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Neighborhood Effects in Hybrid Rice Adoption in Davao del Sur, Philippines

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The Philippines adopted the hybrid rice technology in 1998 to increase productivity; however, the adoption rate is 9% of the total rice area in 2016. Thus, it is important to understand the adoption decision of farmers in relation to hybrid rice technology. Previous studies of rice technology adoption in the Philippines did not consider the spatial dependencies, wherein the choice of adoption of a farmer is influenced by the choice of the neighboring farmers. Hence, this study identifies the factors that influence the farmers' adoption decision of hybrid rice technology, focusing on the role of spatial proximity. A survey involving 122 rice farmer-respondents using proportional random sampling was conducted in Padada and Hagonoy, Davao del Sur, Philippines in 2016. Using the Bayesian-Markov Chain Monte Carlo spatial autoregressive probit estimation, this study found that proximity to neighbors is associated with the choice of the farmers to adopt hybrid rice technology. Moreover, the sex of the household head (HH), household size, non-farm income, and rainfall are the major determinants of adopting hybrid rice technology. Thus, the interventions should focus on delivering better access of female farmers to productive resources and those with relatively higher household size, improve access to non-farm livelihood and employment opportunities, and reinforce proven risk mitigation practices in terms of providing stable water sources in the farming community.

Keywords: hybrid rice, neighborhood effect, spatial probit, technology adoption

INTRODUCTION

With the growing population and decreasing land resources devoted to agricultural production, the demand for food and specifically, the need for high-yielding rice (HYR) varieties will continue to increase. By 2030, the demand for rice is expected to be 40% more compared to the current level of rice consumption (Khush 2005). Thus, hybrid rice was introduced as one of the options to address the need for increased rice production while using fewer resources (Khush 2005). Hybrid rice – first introduced in China during the 1970s – is a modern rice variety that has a 20% yield performance advantage compared to inbred rice, high protection against insect pests, improved response to fertilizer use, and better adaptation to various rice environments (Tu *et al.* 2000).

The experience of hybrid rice adoption in some developing nations in Asia was limited. In India, the government has targeted a 25% increase in the area of

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adoption in 2015 but due to challenges such as market and policy constraints, the adoption level is still below the target (Spielman *et al.* 2013). As of 2017–2018, the hybrid rice adoption covered barely 10% of the total rice production in India, which is far from the envisioned target of 25% (Negi *et al*. 2020). Similar findings were also observed in Bangladesh with 6.7% hybrid rice adoption in 2017–2018 rice production (Bangladesh Bureau of Statistics 2018). The adoption rates in other parts of Asia including Vietnam, Indonesia, Pakistan, and Myanmar ranged from 1–7%, while the highest adoption rate was observed in China with 51.7% (FAO 2014). In the Philippines, despite the government's efforts since 1998 to improve hybrid rice adoption through the Hybrid Rice Commercialization Program, the estimated adoption rate remained at only about 4.8% of the total area of rice farms as of 2012 (Sombilla and Quilloy 2014) and increased in 2016 to 9% (Litonjua *et al.* 2017). Compared to inbred rice varieties, the Philippines' experience of hybrid rice adoption has resulted in an 8–14% increased yield productivity with 6.12 t/ha (Dasgupta and Roy 2014).

The drivers affecting the adoption rate of hybrid rice in the Philippines include farm size, irrigation, and training (Digal and Placencia 2020) while in Bangladesh, land characteristics, availability of infrastructure (including irrigation, roads, and seed dealers), and access to credit are the key determinants (Mottaleb *et al*. 2015). On the other hand, factors constraining the adoption of hybrid rice include poor grain quality, expensive seed cost, and limited management skills (Husain *et al.* 2001; Mottaleb *et al*. 2015).

The experience of developing countries with hybrid rice adoption is varied due to economic, socio-cultural, environmental, and institutional reasons. In India, farmers experienced an increase in grain yield by 16%; however, because the market price was lower for hybrid rice compared to inbred rice, the net return declined to –5.1% (Janaiah 2002). Particularly in Karnataka, there was no significant increase in hybrid rice adoption since its introduction in the mid-1990s; while hybrid rice had superior yield performance compared to conventionally bred rice varieties, it was less profitable (Chengappa *et al.* 2003). In Bangladesh, the low adoption rate of hybrid rice was primarily caused by marginal farmlands of the rice farmers while having better education encouraged adoption (Husain *et al.* 2001). Also, other constraints include the high cost of seeds, inadequate management skills, high input usage, pest and disease incidence, insufficient yield advantage, low head-rice recovery, and dependence on external support (Husain *et al.* 2001). The low adoption rate of hybrid rice in Bangladesh was also associated with limited infrastructure – including roads, irrigation, the presence of seed dealers in the locality, land characteristics, and access to loan facilities (Mottaleb *et al.* 2015).

In the Philippines, some insights into Filipino farmers' rice technology adoption decisions suggest the crucial roles of culture, human capital, and infrastructure. The role of the culture such as shared norms in overcoming crop failure and social exclusion in farmer field school training is crucial in adopting integrated pest management in Central Luzon (Palis 2006). Also, the adoption of modern rice technologies is affected by the educational status of the farmers, the marginal land holding, and farmers' entrepreneurial orientation (Mariano *et al.* 2012). Fertility of harvested seeds and yield performance are also common factors, thus encouraging the adoption of rice technologies (Zimmerman and Qaim 2004). Institutional support such as training and extension programs are effective in encouraging farmers to adopt efficient irrigation systems (Rejesus *et al.* 2011). Specific to hybrid rice, the cost of hybrid seeds, insufficient knowledge in hybrid rice management, and lack of irrigation system influenced the relatively low adoption in Central Luzon (Mananesa *et al.* 2012).

The analysis of spatial dependence in technology adoption is beneficial in planning and resource allocation (Holloway *et al.* 2002). Studies on the determinants of adoption of modern agricultural technologies show that a farmer's decision to adopt technology is influenced by the decision of neighboring farmers (Holloway *et al.* 2002; Wollni and Andersson 2014). Furthermore, recent studies demonstrate the usefulness of social networks in terms of measuring the effect of farmer-to-farmer interaction on technology adoption or influence in farm practices (Mekonnen *et al.* 2018; Maertens and Barrett 2012; Takahashi *et al.* 2020). More specifically, Mekonnen *et al.* (2018) demonstrated – using spatial neighborhood analysis – that the existing social networks among farmers can be an effective delivery system of information dissemination.

In the Philippines, several studies have included the spatial aspect in modeling rice production (Nalica 2010; Villanueva *et al*. 2017; Pede *et al.* 2018; Villano *et al*. 2016). More specifically, by incorporating spatial dependence, the farmers' production performance was found to be influenced by their proximity to their neighboring conventional rice farmers (Villanueva *et al.* 2017; Pede *et al.* 2018). Thus, it is in this context that the study aims to determine the drivers of hybrid rice adoption while taking into account the effect of spatial proximity of neighboring farms.

MATERIALS AND METHODS

Bayesian Spatial Probit

Probit and logit models are commonly used techniques in modeling discrete choices in agricultural technology adoption to determine the factors that influence the farmer's choice to adopt or not to adopt the technology (Bahinipati and Venkatachalam 2015). These factors usually include household and weather information, farm assets, and access to local institutions (Bahinipati and Venkatachalam 2015). However, standard probit and logit models do not consider some form of spatial aspect in their estimation, and neglecting spatial relations may cause inconsistent estimates (Holloway *et al.* 2002).

Holloway *et al.* (2002) applied the Bayesian spatial probit model in estimating the neighborhood effect in the adoption of HYV among rice farmers in Bangladesh. The authors found that spatial dependence matters and the significant drivers of HYV adoption include education, farm size, and rented farmland. Wollni and Andersson (2014) also employed the same method to analyze the factors that drive the decision of farmers in Honduras to adopt organic agriculture. Their results showed that farmers who act correspondingly to their neighbor's decision, and those who have access to the information within the neighborhood are more likely to adopt organic agriculture (Wollni and Andersson 2014).

Generally, the Bayesian approach has become the standard method in spatial econometrics using simulation estimators such as Monte Carlo Markov Chain and Gibbs sampler (Anselin 2010). The Bayesian estimation samples from a posterior distribution of the model parameters p(z, β, ρ|y) given the independent variable y and some prior distributions p(z), p(β), p(ρ). The study utilized Bayesian estimation of the spatial autoregressive probit model (SAR probit model), where $\rho = 0.75$, MCMC iterations = 1000, MCMC burn-in = 100, and thinning factor equal to 1.

This study posits that a farmer's decision to adopt the hybrid rice technology is affected by other neighboring farmers. Thus, a Bayesian spatial autoregressive probit model was denoted as (LeSage *et al.* 2011; Wollni and Andersson 2014):

$$L = \rho WL + X\beta + \varepsilon \tag{1}$$

or equivalently:

$$L = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} \varepsilon \tag{2}$$

where $\varepsilon \sim N(0, I_n)$. The variable L, which represents the adoption or non-adoption of hybrid rice technology, is considered a latent variable that cannot be observed. Thus, the binary choice is expressed as:

$$y_i = \begin{cases} 1, & if\ L_i \geq 0 \\ 0, & if\ L_i < 0 \end{cases} \tag{3}$$

where y_i reflects the binary outcome of an observation's choice of adoption.

The spatial weight matrix W captures the dependence structure between neighboring observations, WL is a linear combination of neighboring observations, and the scalar rho (ρ) is the dependence parameter which is assumed as $abs\ (\rho) < 1$. The term $X\beta$ represents a fixed matrix of covariates $X(n \times m)$ of the explanatory variables such as sex, age, education, household size, farm experience, farm size, land ownership, irrigation access, farm income, non-farm income, farm training, and rainfall, which is associated with the parameter vector $\beta(m \times 1)$, such that:

$$X\beta = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix} \tag{4}$$

where x_{ij} is the input of observation *i* on variable *j*, where *i* $= 1, \ldots, n$ observations and $\beta(m \times 1)$ explanatory variables.

The marginal effects as proposed by LeSage and Pace (2009) are utilized to analyze the impacts of independent variables on the adoption decision while taking into account the neighborhood effect. The spatial effect dependence parameter – namely, the "neighborhood effect" represented by rho, in which the choice of technology adoption of one observation, is assumed to be affected by the decisions of other nearby farmers (Case 1992). A non-zero rho (ρ) suggests that spatial dependence among farmers exists. Otherwise, if ρ is statistically equal to zero, farmers' adoption decisions are independent of each other and the spatial proximity of the farmers will not matter (Wollni and Andersson 2014).

Three types of marginal effects can be observed in the estimation of spatial autoregressive models: direct, indirect, and total effects, which are presented in confidence intervals and posterior mean. The significance of these effects can be observed through the consistency of the sign of the boundaries of the confidence intervals (LeSage *et al.* 2011). Intervals with a negative lower limit and positive upper limit are regarded as insignificant and *vice versa*.

The average direct effect is the overall average effect of the change of an explanatory variable of farmer *i* to their own choice of adoption. The average indirect effect, on the other hand, measures how a change associated with the independent variables impacts neighboring farmer j (where $j \neq i$) (LeSage and Pace 2009). Whereas, the average total effect – which is the sum of indirect and direct effects – pertains to the total change in probability of adopting hybrid rice technology, resulting from a change in the farmers' explanatory variables (LeSage and Pace 2009).

Spatial Weight Matrix

Spatial weight matrices used in this study are row-standardized to allow for the comparison of parameter estimates between different models. The spatial weight matrix is an n x n positive matrix containing the "neighborhood sets" of each observation in the form of:

$$W = \begin{bmatrix} 0 & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & 0 \end{bmatrix} \tag{5}$$

where w_{ij} represents the spatial relationship of observations i and j such that $i = 1, \ldots, n$ and $j = 1, \ldots, n$ (Anselin 2002).

Different spatial weight matrices are incorporated in the model to determine which representation of spatial dependence best fits the data. Specifically, four methods in generating spatial weight matrices that are applicable to point coordinates were used in this study – namely, 1) inverse distance, 2) fixed distance, 3) k-nearest neighbors, and 4) Delaunay triangulation (ESRI 2018). Inverse distance creates a spatial weight matrix such that the effect of one point-feature on another point declines with distance. In the fixed distance, it considers all data points within a specified distance threshold of each point feature. Both distance-based methods need a specified threshold distance in which three critical distances were analyzed: 2, 2.5, and 3 km. The radius of 2–3 km is reasonable to approximate the reach of spillover effects in rural areas where there is limited infrastructure (Wollni and Andersson 2014). On the other hand, the k-nearest neighbor's approach examines the closest k point-features, wherein k is a specified numeric parameter – specifically, $k = 6$ for this study, where $k = 6$ neighbors have equal weights. According to LeSage and Pace (2009), the contiguity weight matrix usually will have an average of approximately six neighbors for each observation for spatially random data on a plane. Lastly, the Delaunay triangulation generates a spatial weight matrix by creating a mesh of non-overlapping triangles from feature centroids and then marks as neighbors those points associated with triangle nodes sharing edges. Spatial probit models utilizing different spatial weight matrices are then compared using the Akaike information criterion (AIC) and Bayesian information criterion (BIC) with the lowest values used in this study (LeSage and Pace 2009).

Study Areas

Davao region is one of the regions considered as highly agricultural in the southern part of the Philippines. In 2017, it contributed 393,250 mt (2.7%) out of 14.55 million mt of irrigated paddy rice production (PSA 2017). The region has experienced improving technological change in terms of rice production (Umetsu *et al.* 2003). According to the statistics bureau, within the Southern Mindanao region, Davao del Sur contributed 32% of the production, which is equivalent to 125,656 mt (PSA 2017). There was an advantage of hybrid rice production in Davao del Sur, wherein the revenues of hybrid rice farmers in three planting seasons were significantly higher compared to inbred rice farmers (David 2006).

Hagonoy is a third-class municipality of Davao del Sur covering 12,433 ha and in 2004, 18% of the total land area (2,192 ha) was devoted to rice farming (Hondrade 2007). Rice farmers in this municipality earn a net profit of not less than PHP 40,000. In particular, the municipality targets to institutionalize One-Town-One-Product Hagonoy Hybrid Rice; Hagonoy has nine milling stations supporting the rice industry (Hondrade 2007; MCDLUP 2014).

Padada is also a third-class municipality of Davao del Sur, which is located in the mid-northern part of the region with 8,300 ha. Its major sources of livelihood are coconut, banana, corn, and rice production with high rice production sufficiency (Hondrade 2007). The Padada-Mainit River Basin, which is one of the main river systems in Davao del Sur, supports the irrigation of rice fields in the municipality (Balicanta *et al.* 2017).

Both municipalities are highly dependent on agriculture for food and livelihood. Furthermore, aside from being fully irrigated areas, the Hagonoy and Padada municipalities are supported by their respective local government units in terms of support for credit, seed production and delivery, communication infrastructure, and marketing assistance (Hondrade 2007; MCDLUP 2014). More specifically, both municipalities are being serviced by the Padada (Hagonoy) River Irrigation System of the National Irrigation Administration (NIA), which covers seven lowland barangays plus two mini-dams in Sacub and Sinayawan; rice farms in the southwestern barangays are served by the Mal Irrigation System from Matanao (MCDLUP 2014). Aside from the services from the NIA, communal schemes also exist in Davao del Sur, which are considered more efficient in terms of cropping intensity compared with the national schemes (Cisneros 2021). Thus, these two municipalities have high levels of rice supply sufficiency.

Data Source

The study utilized the dataset from Philippine Light Detection and Ranging (Phil-LiDAR) 2.B.13 Vulnerability

Assessment Study of the University of the Philippines Mindanao. A household survey was conducted among smallholder rice farmers in Padada and Hagonoy, Davao del Sur, wherein information such as socio-demographic characteristics and household records, crop production, and other farm activities, and global positioning system coordinates expressed in latitude and longitude were collected. The project coordinated with the Municipal Agriculture Offices of Padada and Hagonoy, and they provided the master list of rice farmers. Based on the master list, a proportional random sampling was applied, which involves a total of 603 farmers. Out of these farmers, 20% were rice farmer-respondents (122 samples) coming from two municipalities surveyed in 2016. Prior to the conduct of the survey interview, enumerators were trained in data collection. Moreover, the consent of the participants was sought before the start of the survey.

The independent variables included in the model are the following information pertaining to the HH such as sex, age, educational attainment, years of farming experience and rice farming-related training, and information relevant to the household that includes the household size, farm size, land ownership, access to irrigation and post-harvest facilities, farm income, and non-farm income, and rainfall. Equality of standard deviations (variances) test for homogeneity of variance followed by t-test using equal and unequal variances are utilized to test the significant difference between the adopters and non-adopters involving continuous variables. Moreover, the chi-squared test was used for categorical covariates. The dependent variable is the adoption or non-adoption of a high-yielding variety of hybrid rice technology represented by 1 and 0, respectively. ArcGIS 10.2.1 and R version 4.0.3 software were used in this study to estimate the spatial weight matrices and binary outcome models, respectively. Specifically, the *spatialprobit* package was used for the estimation of spatial probit, probit, and logit models (Wilhelm and Godinho de Matos 2013).

RESULTS

Descriptive Statistics

The descriptive statistics are reported in Table 1. The majority of the sample (83%) are male farmers and half of the sample have elementary education (52%), followed by high school education (29%) and graduate-level education (19%). The average farm size is 1.2 ha, and most of the farmers owned their land (63%). The remaining farmers (37%) are categorized as tenant/renter (29%) and maintainer (8%). Less than half of the farmers (44%) have access to irrigation, while only 6% have access to post-harvest facilities. About 60% of the farmer-respondents have attended at least one training session. The average age is 59 yr, and the average household size is 4.3 household members. Farmers have approximately 35 yr of farming experience. Furthermore, the average annual farm- and non-farm income are approximately PHP 130,000 and 111,000, respectively. Farmers receive an average rainfall of 1.80 mm. The descriptive statistics of the adopters and non-adopters plus the test for statistical significance are also shown in Table 1. Adopters are relatively older (61 yr old), with more years of farming experience (37 yr), and have higher annual non-farm income (PHP 143,000) compared to non-adopters (56 yr old, 30 yr of farming experience, and PHP 56,000 annual non-farm income). Finally, 63% of the samples are composed of hybrid rice adopters, while 37% are non-adopters. However, while the majority (92%) of the farmers in the sample who are owners/tenants/renters have partial to full rights in deciding which variety to plant including hybrid rice, the remaining 8% consisting of maintainers/farm workers depend on the owners' decision.

Spatial Dependence Parameter

It can be observed through visual inspection that most of the hybrid rice adopters are located in the northern part of study sites, while the majority of the non-adopters are located in the southern part. Figure 1 shows the location of each adopter farmer (blue dots) and non-adopter farmer (red stars). The models generated with different spatial weight matrices were compared using the AIC and BIC (Appendix I). Among the different models, the spatial probit model using the k-nearest neighbor with $k = 6$ as the spatial weight matrix had the lowest AIC and BIC (AIC = 140, BIC = 185). The correlogram of the estimated parameters is shown in Appendix II.

The spatial dependence parameter ρ is estimated at 0.28 with a standard deviation of 0.16 and p-value of 0.08 (Table 2). The non-zero ρ suggests that spatial correlation exists in the choice of adoption of hybrid rice among farmers. The results of the estimation using spatial probit, probit, and logit models were compared. The parameter estimates of spatial probit show that the sex of the HH and household size are statistically significant at 5%, while non-farm income and rainfall are statistically significant at 1%. The non-spatial probit model, on the other hand, showed that the sex of the HH and rainfall are significant at 5 and 1% levels, respectively, while the household size and non-farm income are significant at the 10% level (Appendix III). Moreover, the non-spatial logit model showed that sex of the HH, household size, and non-farm income are significant at 10% level, while rainfall is significant at 1% level (Appendix IV).

Total Effects

The estimates of the marginal effects of the spatial probit model were calculated using the total effects approach,

Table 1. Descriptive statistics of explanatory variables.

Explanatory variable	Pooled n = 122		Non-adopters n = 45		Adopters n = 77		*p*-value
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Sex of HH (indicator variable)							
Male	0.83	0.38	0.76	0.43	0.87	0.34	0.11
Female	0.17	0.38	0.24	0.43	0.13	0.34	0.11
Education of HH (indicator variable)							
Elementary level/ graduate	0.52	0.50	0.62	0.49	0.47	0.50	0.10
High school level/ graduate	0.29	0.45	0.22	0.42	0.32	0.47	0.23
College level/ graduate	0.19	0.39	0.16	0.37	0.21	0.41	0.48
Farm size (hectares)	1.20	1.35	0.93	0.81	1.37	1.57	0.22
Land ownership							
Owned/ tenured	0.63	0.48	0.60	0.50	0.65	0.48	0.59
Leased/ maintainer	0.37	0.48	0.40	0.50	0.35	0.48	0.59
Irrigation access	0.44	0.50	0.42	0.50	0.45	0.50	0.73
Access to post-harvest facilities	0.06	0.23	0.90	0.29	0.40	0.20	0.25
Training of HH (indicator variable)							
No training	0.40	0.49	0.42	0.50	0.39	0.49	0.72
At least one training	0.60	0.49	0.58	0.50	0.61	0.49	0.72
Age of HH (yr)	59.19	11.94	56.42	11.55	60.81	11.94	0.05
Household size (number)	4.30	2.04	4.38	1.98	4.25	2.09	0.73
Farming experience of HH (yr)	34.77	15.67	30.44	13.15	37.30	16.63	0.02
Farm income (PHP '000)	129.98	201.64	104.87	149.66	144.66	227.40	0.25
Non-farm income (PHP '000)	110.99	300.05	55.81	78.49	143.24	371.62	0.05
Average daily rainfall (mm)	1.80	0.22	1.68	0.20	0.45	0.50	0.00

SD test for homogeneity of variance followed by T-test using equal and unequal variances was used for continuous variables, and the chi-squared test was used for categorical variables.

which can be decomposed into direct and indirect effects (Wollni and Andersson 2014). The total effects are the effects when all the samples experience one unit of shock in the variable. Following Holloway *et al.* (2002), the 95% highest posterior density expressed as confidence intervals with the consistent sign within the boundaries are statistically significant at the 5% level. The results showed four explanatory variables are significant: sex of HH, household size, non-farm income, and rainfall (Table 2). Relative to the female head, male HHs are associated with a higher probability of hybrid rice technology adoption by 27.17%. An additional member in the household is correlated with a decreasing probability of adoption by 5.35%. Also, for every PHP 1,000 increase in non-farm income, the likelihood of hybrid rice adoption is associated with an increase by 0.12%. An additional 1 mm in rainfall is correlated with an increase in the probability of adoption by 76.86%. The marginal effects of the four explanatory variables were also statistically significant in the regular probit and logit models (Appendices III and IV).

Direct and Indirect Effects

The average direct and indirect effects of the sex of the HH, household size, non-farm income, and rainfall are reported in Table 2. Direct effects measure the effect of the explanatory variable on the *i*th farmer's choice of adoption (LeSage and Pace 2009; Wollni and Andersson 2014). The positive estimate of the sex variable suggests that families with male HHs are associated with a higher

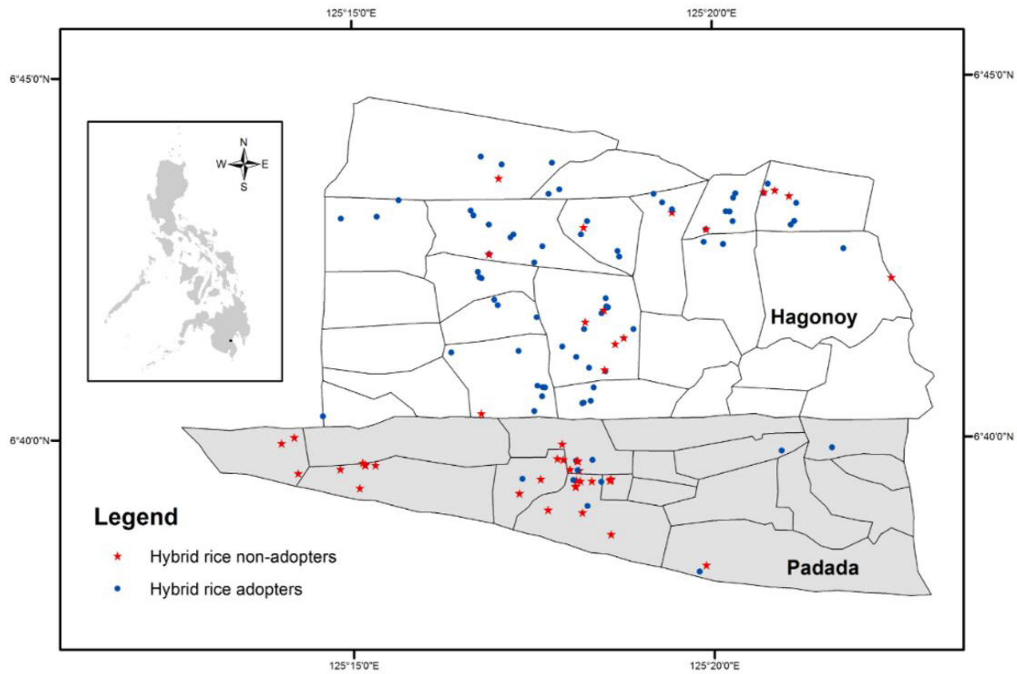

Figure 1. Adopters and non-adopters of the hybrid rice variety in Padada and Hagonoy, Davao del Sur, Philippines.

Table 2. Spatial probit estimates and marginal effects.

Explanatory variable	Spatial probit (k-nearest neighbors, k = 6)			Total marginal effects mean posterior (lower, upper)	Direct marginal effects mean posterior (lower, upper)	Indirect marginal effects mean posterior (lower, upper)
	Estimate	Std. dev.	*p*-value			
Intercept	–5.7209	1.6922	0.0010			
Sex of HH	0.8451	0.4062	0.0396	0.2717 (0.0532,0.493)	0.1955 (0.0369, 0.3420)	0.0762 (–0.0057, 0.2010)
Age of HH	0.0134	0.0156	0.3943	0.0043 (–0.004,0.0130)	0.0031 (–0.0029, 0.0090)	0.0012 (–0.0011, 0.0050)
Education of HH (base = Elementary level/graduate)						
High school level/ graduate	0.3950	0.3252	0.2270	0.1249 (–0.0443,0.294)	0.0913 (–0.0319, 0.2120)	0.0337 (–0.0147, 0.1120)
College level/graduate	–0.0021	0.4104	0.9960	–0.0028 (–0.2178,0.2200)	–0.0015 (–0.1625, 0.1590)	–0.0013 (–0.0722, 0.0680)
Household size	–0.1658	0.0759	0.0308	–0.0535 (–0.0955, –0.012)	–0.0387 (–0.0695, –0.0100)	–0.0149 (–0.0379, 0.0010)
Farm experience of HH	0.0185	0.0114	0.1092	0.0060 (–0.0002,0.013)	0.0044 (–0.0002, 0.0090)	0.0017 (–0.0003, 0.0050)
Farm size	–0.5079	0.3512	0.1507	–0.1635 (–0.3641,0.016)	–0.1181 (–0.2486, 0.0120)	–0.0455 (–0.1404, 0.0110)
Land ownership	0.4533	0.3232	0.1633	0.1469 (–0.0292,0.331)	0.1053 (–0.0230, 0.2300)	0.0417 (–0.0095, 0.1340)
Irrigation access	0.1703	0.3058	0.5785	0.0558 (–0.1069,0.233)	0.0398 (–0.0805, 0.1600)	0.0160 (–0.0306, 0.0810)
Access to post-harvest facilities	–0.6008	0.5763	0.2993	–0.1951 (–0.5181,0.113)	–0.1403 (–0.3585, 0.0860)	–0.0548 (–0.1925, 0.0280)
Farm income of household	0.0002	0.0014	0.8791	0.0001 (–0.0007,0.001)	0.0001 (–0.0005, 0.0010)	0.0001 (–0.0003, 0.0000)
Non-farm income of household	0.0036	0.0013	0.0072	0.0012 (0.0005,0.0020)	0.0009 (0.0004, 0.0010)	0.0004 (–0.0001, 0.0010)
Farm training of HH	–0.3418	0.2973	0.2526	–0.1106 (–0.2653,0.047)	–0.0800 (–0.1961, 0.0350)	–0.0307 (–0.1001, 0.0140)
Average daily rainfall	2.4480	0.7440	0.0013	0.7686 (0.4545,1.029)	0.5668 (0.3139, 0.8290)	0.2018 (–0.0122, 0.4300)
Rho	0.2831	0.1613	0.0818			

N = 122; spatial probit: log likelihood = –53.91; [a]95% highest posterior density regions (confidence intervals) are presented in parentheses; intervals with consistent sign are significant at 5% (Holloway *et al.* 2002) likelihood of adoption than female-led households by 19.55%. An increase of one member in the household is correlated with the adoption of the same household by 3.87%. Also, an increase of PHP 1,000 income from non-farm activities is associated with an increase in the probability of adoption by 0.09%. The same is true for the rainfall variable, which is also associated with an increase in the probability of adoption by 56.68% for every 1-mm increase of rainfall.

On the other hand, indirect effects are the effects when all the farmers j, other than i ($i \neq j$), experience one unit of change in the variable (LeSage and Pace 2009). The results in the indirect effects indicate that changes in a unit of the explanatory variables of the farmer's neighbor – including sex of the HH, non-farm income, and rainfall – are significantly associated with an increase in adoption by 7.62, 0.04, and 20.18%, respectively. Moreover, the neighbor's household size is negatively correlated with the likelihood of hybrid rice adoption by 1.49% for every additional member of the household.

DISCUSSION

The non-zero estimate of the spatial dependence parameter suggests that the decision of a farmer is affected by the spillover effects of the decision of other neighbors within its neighborhood. This result is consistent with the HYV rice adoption in Bangladesh (Holloway *et al.* 2002). The influence of neighbors is crucial in modern agricultural technology adoption and farm management (CIMMYT 1993; Wollni and Andersson 2014). In developing countries, the adoption of modern technology and the application of fertilizer are mainly influenced by farmers' neighbors such as in Ethiopia (Krishnan and Patnam 2014) and Mozambique (Langyintuo and Mekuria 2008). Furthermore, learning from neighbors has been found to sustain the adoption rate relative to contact with extension agents (Krishnan and Patnam 2014). In Bangladesh, having a relatively nearer network of neighbors adopting hybrid rice technologies influences more the decision of the farmer to adopt the same technology (Ward and Pede 2014). In this study, the neighboring farmers also influence the farmers' hybrid rice adoption decision – specifically in terms of the sex of the HH, farm experience, farm size, and non-farm income. These changes have a direct effect on farmers' adoption decisions and indirect effects *via* the farmers' neighbors.

Male farmers, compared to their female counterparts, have a higher likelihood of adopting hybrid rice technology. According to CIMMYT (1993), the necessary operations for hybrid rice can be challenging for women as they are less likely to allocate more resources to adopt new technologies. Some studies suggest that the drivers for agricultural technology adoption differ by gender; male-headed households' decisions are influenced by the farm size and extension service while for women, the main drivers of adoption are farm size and asset ownership (Peterman *et al.* 2014). Moreover, women have typically less access to agricultural technologies due to socio-cultural norms and beliefs about gender roles and they have insufficient resources (Rola-Rubzen *et al.* 2020).

The negative relationship between household size and hybrid rice adoption may be attributed to the underutilization of labor for rice farming livelihood. Mariano *et al.* (2012) found an inverse relationship of household size and adoption of certified rice seeds, and this is driven by the underutilization of labor in rice farming, which competes with more profitable non-farm activities in the rural area. Also, the lack of interest of younger rice farming household members may likely contribute to the negative effect of household size on the adoption of modern rice varieties (Bannor *et al.* 2020). Catudan and Arocena (2004) also found that household size has a negative effect on the adoption of the F1 hybrid rice variety in the country.

The income from non-farm sources also significantly influences hybrid rice adoption decisions. For example, farmers who receive remittances or other sources of non-farm income are more likely to utilize labor-saving technologies in rice production (Tisch and Paris 1994). In hybrid rice production, the cost of seed is relatively high due to its non-reusable characteristic, and it is one of the cited reasons for farmers' non-adoption of the technology (Mananesa *et al.* 2012). To improve the adoption of high-cost technology, there is a need to augment farm income with nonfarm sources (Savadogo *et al*. 1998). Access to non-farm livelihood and employment can also encourage farm households to improve agricultural productivity such as through the adoption of modern rice varieties (Estudillo and Otsuka 1999; Rashidin *et al.* 2020) and managing risk (Velandia *et al.* 2009).

Finally, water supply is crucial in irrigated areas, especially when there are changes in run-off patterns brought by erratic rainfall (Turral *et al.* 2008). Hence, more stable rainfall distribution is needed to re-charge rivers and aquifers in order for irrigation to provide a steady supply of water, particularly in irrigated areas (Turral *et al.* 2008). Since food production is generally sensitive to future water deficits, it will also affect the decision of farmers to likely adopt more varieties, especially those dependent on stable water supply (Cai 2005). Furthermore, provision of water catchment and adoption of other water-saving practices in rice irrigation systems will likely further reduce the risk of water deficits and, hence, encourage farmers to adopt relatively modern rice farming technologies.

CONCLUSION

This study found that the hybrid rice adoption decision of farmers is influenced by the proximity of their neighboring farmers. Specifically, the sex of the HH, non-farm income, and rainfall are positively associated with the likelihood of hybrid rice technology adoption, while the household size is negatively associated. To increase the adoption of female farmers, access to productive assets must be pursued especially that hybrid rice production is resource-intensive. For farming households with relatively more members, in order to spark interest among younger household members, information and educational campaign should be introduced early on and access to start-up loans be made more accessible to young farmer entrepreneurs. An example of this program includes the "KAYA" (*Kapital* Access for Young Agripreneurs) program of the Department of Agriculture. Non-farm activities also play a crucial role in terms of generating household savings that can help the farmers minimize risk with the adoption of new technology and improve their productive capacity. Some of the non-farm activities and employment opportunities in the locality include jobs related to plant and machine operators and assemblers, service and sales workers, and craft and related trades workers, which can provide viable opportunities in terms of earning income from non-farm activities. Lastly, in anticipation of future water deficits, mitigating measures such as a rainwater catchment system can help stabilize water supply in irrigated areas while practicing alternate wetting and drying as a rice management practice can help cushion future impacts of reduced rainfall.

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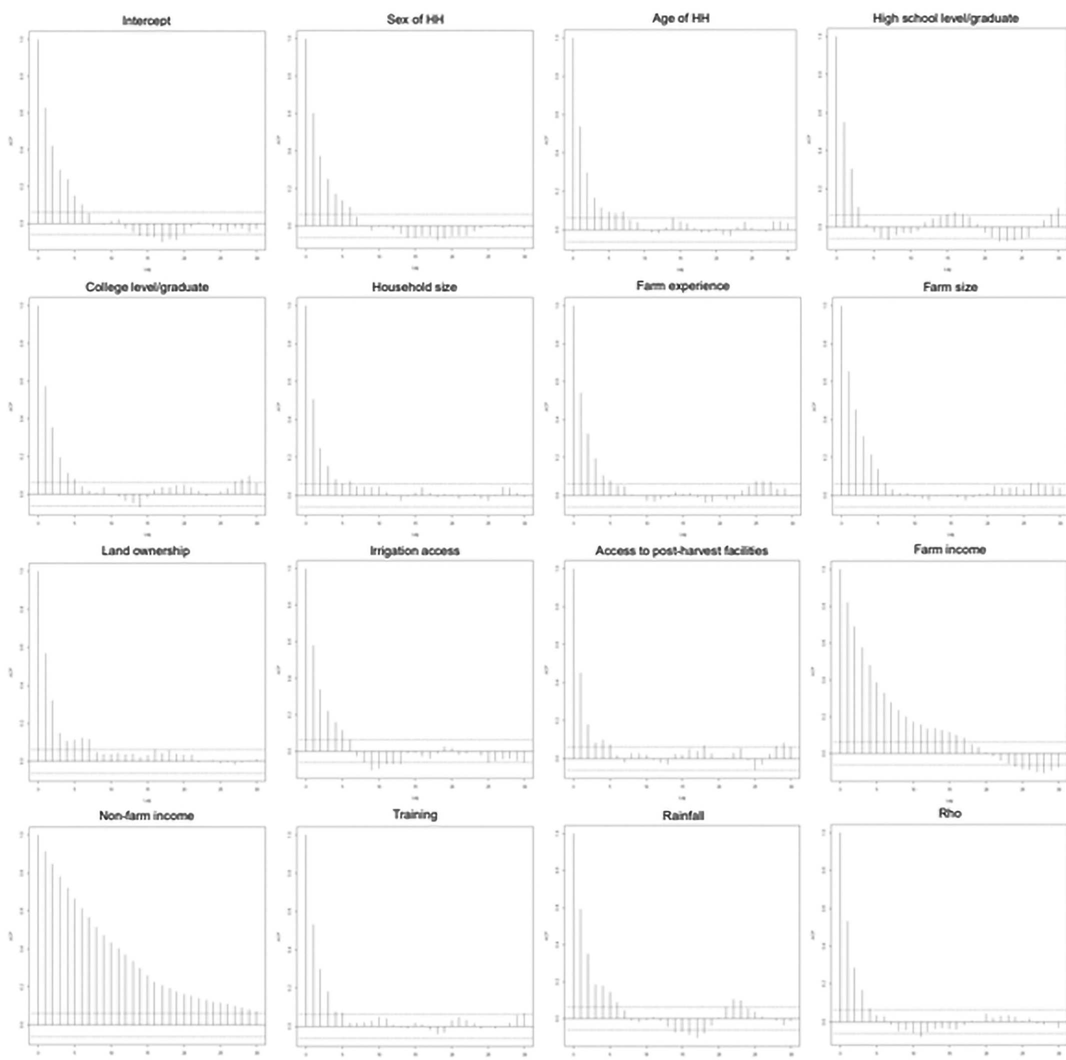
APPENDICES

Appendix I. Model comparison among spatial weight matrices.

Model specification	BIC value	AIC value
Spatial autoregressive probit model		
W1: Fixed distance (d = 2 km)	190.2520	145.3877
W2: Fixed distance (d = 2.5 km)	190.2269	145.3626
W3: Fixed distance (d = 3 km)	189.0948	144.2305
W4: Inverse distance (d = 2 km)	190.8006	145.9363
W5: Inverse distance (d = 2.5 km)	190.8228	145.9584
W6: Inverse distance (d = 3 km)	190.7978	145.9334
W7: Delaunay triangle	189.7202	144.8559
W8: K-nearest neighbor (k = 6)	184.6938	139.8295

Appendix II. Autocorrelation function of variables.



Appendix III. Probit estimates and marginal effects.

Explanatory variable	Estimate	Std. error	*p*-value	Marginal effects	*p*-value
Intercept	–6.6800	1.6260	0.0000		
Sex of HH	0.7587	0.3772	0.0443	0.2830	0.0511
Age of HH	0.0127	0.0155	0.4112	0.0044	0.4140
Education of HH (base = elementary level/graduate)					
High school level/graduate	0.3830	0.3383	0.2575	0.1240	0.2320
College level/graduate	0.1015	0.4156	0.8070	0.0341	0.8040
Household size	–0.1594	0.0854	0.0619	–0.0545	0.0541
Farm experience of HH	0.0166	0.0115	0.1491	0.0057	0.1430
Farm size	–0.4346	0.3371	0.1973	–0.1420	0.1750
Land ownership	0.3465	0.3162	0.2731	0.1210	0.2820
Irrigation access	0.1398	0.2958	0.6366	0.0475	0.6330
Access to post-harvest facilities	–0.4825	0.5585	0.3876	–0.1800	0.4120
Farm income of household	0.0001	0.0014	0.9635	0.0000	0.9630
Non-farm income of household	0.0033	0.0019	0.0787	0.0011	0.0594
Farm training of HH	–0.3161	0.3009	0.2934	–0.1060	0.2790
Average daily rainfall	3.1530	0.7217	0.0000	1.0800	0.0000

N = 122; log likelihood = –53.91; probit: log likelihood = –56.75, LR chi-squared (df = 14) = 47.137, prob > chi-squared = 0.00, pseudo-R-squared = 0.29; variance inflation factor: minimum = 1.08, average = 1.33, maximum = 1.64.

Appendix IV. Logit estimates and marginal effects.

Explanatory variable	Estimate	Std. error	*p*-value	Marginal effects	*p*-value
Intercept	–11.220	2.8810	0.0001		
Sex of HH	1.2490	0.6435	0.0523	0.2840	0.0634
Age of HH	0.0202	0.0265	0.4454	0.0041	0.4490
Education of HH (base = elementary level/graduate)					
High school level/graduate	0.6414	0.5873	0.2748	0.1210	0.2430
College level/graduate	0.1851	0.7160	0.7961	0.0364	0.7910
Household size	–0.2517	0.1477	0.0884	–0.0508	0.0780
Farm experience of HH	0.0286	0.0195	0.1425	0.0058	0.1340
Farm size	–0.6479	0.5795	0.2636	–0.1240	0.2400
Land ownership	0.5569	0.5441	0.3061	0.1160	0.3190
Irrigation access	0.2338	0.5120	0.6479	0.0469	0.6440
Access to post-harvest facilities	–0.8203	0.9354	0.3805	–0.1870	0.4140
Farm income of household	0.0003	0.0024	0.9094	0.0001	0.9090
Non-farm income of household	0.0053	0.0032	0.0943	0.0011	0.0694
Farm training of HH	–0.5526	0.5177	0.2858	–0.1090	0.2680
Average daily rainfall	5.2810	1.2660	0.0000	1.0700	0.0000

N = 122; log likelihood = –57.00, LR chi-squared (df = 14) = 46.628, prob > chi-squared = 0.00, pseudo-R-squared = 0.29; variance inflation factor: minimum = 1.09, average = 1.34, maximum = 1.60.