GRIPS Discussion Paper 16-02

Neighborhood Effects in Pesticide Use: Evidence from the Rural Philippines

Takeshi Aida

May 2016

GRIPS
National Graduate Institute
For Policy Studies

National Graduate Institute for Policy Studies
7-22-1 Roppongi, Minato-ku,
Tokyo, Japan 106-8677

Neighborhood Effects in Pesticide Use: Evidence from the Rural Philippines†

Takeshi Aida*

JSPS Research Fellow

National Graduate Institute for Policy Studies

May 2016

Abstract

This study investigates how pesticide use by neighboring farmers affects a given farmer's pesticide use. Although it is common knowledge that pesticide use has spatial externalities, few empirical economic studies directly analyze this issue. Applying the spatial panel econometric model to the plot-level panel data in Bohol, the Philippines, this study shows that the pesticide use, especially for herbicides, is spatially correlated although there is no statistically significant spatial correlation in unobserved shocks. This implies that farmers apply pesticides by mimicking neighboring farmers' behavior rather than rationally responding to the intensity of infestation.

Keywords: pesticide use, neighborhood effects, externality, spatial econometrics, rural Philippines

JEL classification: Q56, Q12, O13

---

† This research was supported by a Grant-in-Aid for JSPS Fellows (14J10587). I am especially grateful to Kei Kajisa for providing the detailed data, Alistair Munro for his encouragement from the early stages of the draft, and Akiko Oguchi for her seminar presentation that inspired this study. I also thank Nobuyoshi Kikuchi, Takashi Kurosaki, Keijiro Otsuka, Daichi Shimamoto, Masahiro Shoji, Ryo Takahashi, and the participants at ABEF 2015 and TEA 2016 for their constructive comments. All remaining errors are my own.

* Address: 7-22-1 Roppongi, Minato-ku, Tokyo 106-8677, Japan.

E-mail: aidatakeshi@gmail.com

1. Introduction

Pesticides, if properly used, can enhance agricultural productivity by reducing crop damage. However, their inappropriate use can cause serious problems, for example, to the environment, farmers' health, and food safety. In addition, especially in developing countries, farmers are often unaware of the proper use of pesticides, which could lead to their acute and/or chronic poisoning as well as to environmental degradation (e.g., Rola and Pingali 1993; Shetty 2004). In fact, some studies argue that the health cost is so high as to offset a large part of the benefit (e.g., Antle and Pingali 1994; Pingali et al. 1994; Soares and Porto 2009). Thus, better understanding of farmers' decisions on pesticide use is very important not only for the field of agricultural research but also for perspectives on policymaking to reduce improper pesticide usage.

In the theoretical economic analysis of pesticide use, farmers are assumed to optimize their application amount by equalizing marginal benefit and marginal cost (e.g., Headley 1972; Sexton et al. 2007). However, this optimization often does not incorporate spatial externalities of pesticide use, and the results might not be socially optimal. In order to fill this gap, this study aims to analyze spatial externalities, that is, neighborhood effects (e.g., Manski 1993; Durlauf 2004; Ioannides and Topa 2010), in pesticide use.

In the case of pesticide use, neighborhood effects are consequential in several ways. First, pesticide application in surrounding plots can directly reduce the weed or pest population, which leads to lower usage in the farmer's own plot. However, regarding insecticides, neighbors' use could increase one's own use because these can kill not only pests but also the beneficial insects that prey them and increase reliance on insecticides (Grogan and Goodhue 2012). Second, pest and weed infestation, which are difficult for econometricians to observe accurately, can be spatially correlated (e.g., Ferguson et al. 2003; Walter and Simmelsgaard 2002). In this case, positive spatial correlation in usage is expected to respond to correlated intensity of infestation. In addition to these effects, it is possible to observe a positive neighborhood effect if farmers simply mimic neighboring farmers' application pattern, which often results in inappropriate use (Escalada and Heong 1993).

In terms of empirical analysis of individual pesticide use, studies have been focusing on the effect of behavioral parameters such as risk and loss aversion (Liu and Huang 2013). Other studies focus on the pesticide reduction effect of integrated pest management (IPM) programs (e.g., Burrows 1983; Fernandez-Cornejo 1996; Ferraioli 1999) and genetically modified crops (e.g., Huang et al 2005; Qaim and de Janvry 2005; Qaim and Zilberman 2003). However, very few empirical studies directly examine the neighborhood effects of pesticide use. An interesting exception is Grogan and Goodhue (2012), who analyze the effect of landscape-level use of pesticide on individual farmers' use in the California citrus industry. However, in the case of Asian countries, where small-scale farming is dominant (e.g., Eastwood et al. 2010), the ownership of individual farm plots is complex. Thus, it is necessary to analyze plot-level data by explicitly incorporating geographical information to discuss externalities of pesticide use.

One of the straightforward ways to incorporate these neighborhood effects into an empirical model is to employ the spatial econometric approach (e.g., Anselin 1988). Spatial econometrics is effective for agricultural and environmental studies, where spatial effects can be an important issue. In fact, using this approach, several studies analyze spatial externality in yield (e.g., Florax et al. 2002; Druska and Horrace 2004) and the response to fertilizers (Anselin et al. 2004). However, to the best of my knowledge, none of the studies applies this approach to the analysis of pesticide use, in which neighborhood effects can be more salient than other inputs of usage because of its direct and indirect neighborhood effects.

The aim of this study is to analyze the neighborhood effects of pesticide use by employing spatial panel econometric approach. This study uses a dataset on rice farmers in Bohol Island in the Philippines. The advantage of the dataset is that plot-level panel data of agricultural input and GPS data are available. Thus, assuming time invariance, including individual fixed effects controls for the effect of preference parameters (e.g., time discounting, risk preference, loss aversion), which are important determinants of pesticide use (e.g., Pannell 1991; Liu and Huang 2013).

The remainder of this article is organized as follows. The next section describes the data and summary statistics. The third section describes the empirical strategy of this article, and the fourth section discusses the estimation results. The final section offers the summary and concluding remarks.

2. Data

The study site is the northeastern part of Bohol Island in the Philippines (Figure 1). Rainfall in this area is mostly evenly distributed throughout the year with comparatively little rainfall from February to May and more rainfall from June to January (JICA and IRRI 2012). Supported by Japanese ODA loans, the Bayongan irrigation system started operation in 2008 to enhance agricultural productivity. Its main canal is 17.5 km long and the actual irrigated area is 2644 ha as of November 2011, covering 14 villages in three municipalities: San Miguel, Ubay, and Trinidad. In order to assess its socio-economic impact, the International

Rice Research Institute (IRRI) conducted a series of household surveys over five cropping seasons: 2008-09 dry, 2009 rainy, 2009-10 dry, 2010 rainy, and 2010-11 dry seasons[1]. However, since the first round of this series focused on irrigation management and covered only the upstream laterals in the irrigation scheme, this study uses the panel data of the last four seasons. The original sampling target was 418 irrigable households that were randomly selected from each irrigation water users' group and 429 randomly selected households from the adjacent villages that were similar to the irrigated area in terms of hydrology, agronomy, and socioeconomics. Note that all sample households are rice farmers and rice has been the dominant crop often cultivated twice a year even before this project. In this survey, the IRRI collected data on agricultural input and output in each farmer's main plot with its GPS coordinates as well as other household characteristics. Upon dropping the missing values, the household-plot-level balanced panel data is available for 665 households, including 348 rain-fed and 317 irrigated households. The average distance between each farm plot is 6.68 km.

Table 1 shows the summary statistics of the variables used in this study. This study focuses on two types of pesticides: herbicide and insecticide. Since the sample farmers use various brands of pesticide, the unit of usage amount is represented in terms of active ingredients (kg per hectare) for comparison[2]. The average size of the surveyed plot is 0.64 ha. Note that the size of the surveyed plot is time variant, albeit slightly, depending on the irrigation water accessibility[3]. Because of the original sampling scheme, about half of the sample plot is irrigated. For these irrigated plots, self-reported irrigation water usage during each season, which is measured by the cumulative depth in an irrigation canal (in meters), is available[4]. In this study area, only 3.3% of farmers adopt hybrid seeds. However, since it is possible that the pattern of pesticide application is different between hybrid and non-hybrid seeds, this variable is included in the main analysis. 15.3% of samples are classified as credit constraint, that is, they could not borrow as much as they wanted or did not apply credit for fear of rejection.

Figures 2 and 3 show the spatial pattern of herbicide and insecticide use, respectively.

[1] See JICA and IRRI (2012) and Tsusaka et al. (2015) for details.

[2] The main ingredients of the commonly used herbicides and insecticides are classified as moderately or slightly hazardous (II or III) in WHO (2010). However, some insecticide brands include extremely hazardous (Ia) ingredients, which require special care for handling.

[3] The correlation between the size of surveyed plot and irrigation water usage is significantly positive at the 1% level.

[4] For rain-fed plots, the irrigation water depth is set to zero.

Comparing to insecticides, there seems to be weak geographical concentration in herbicide use. In contrast, the pattern of insecticide use is more dispersed. However, there is an increasing trend in the amount of usage of insecticides over time. Figure 4 shows the time trend in average pesticide usage amount. As expected, there is a clear increasing trend in insecticide use, whereas there is no clear trend in herbicide use. Since it takes a decade for insects and 10–25 years for plants to gain resistance to pesticides (Palumbi 2001), it is difficult to attribute this trend to the issue of resistant pests. Instead, this increasing trend might reflect the path dependence of pesticide use because of high cost of returning to low-pesticide farming (Cowan and Gunby 1996; Wilson and Tisdell 2001).

In order to test spatial correlation statistically, Moran's I statistics of pesticide usage amount are calculated for each season. Table 2 shows the results. Consistent with graphical analysis, there is significant spatial correlation in herbicide use. In the case of insecticide, the correlation is significant for 2009-10 dry and 2010 rainy seasons.

Although these findings suggest the existence of neighborhood effects in pesticide use, especially for herbicides, the results so far do not control other variables. In addition, spatial correlation in the unobserved intensity of infestation cannot be tested by these analyses. Thus, in order to test neighborhood effects rigorously, it is necessary to employ the spatial econometric approach.

3. Empirical Strategy

In order to test neighborhood effects in pesticide use, this study employs the spatial econometric approach. Spatial econometric models incorporate spatial dependence and heterogeneity (e.g., Anselin 1988; LeSage and Pace 2008). Among these models, the combined spatial lag and error (SAC) model with individual fixed effects (e.g., Elhorst 2003, 2010, 2014; Anselin et al. 2008) is used for the purpose of this study. The model to be estimated is

$$y_t = \rho W y_t + X_t \beta + \tau_t + \eta + u_t \quad (1)$$

$$u_t = \lambda W u_t + \epsilon_t, \quad (2)$$

where y_t is a vector of the amount of herbicide or insecticide use at time t, W is an $n \times n$ inverse-distance weight matrix to capture spatial effects, X_t is a set of control variables at time t, τ_t denotes period fixed effects to control for period-specific aggregate shocks, η

represents household-plot fixed effects to control time-invariant unobserved preference parameters as well as plot characteristics, and ϵ_t is the vector of the well-behaved error term. Note that W is row-standardized for estimation, implying that Wy_t represents the weighted average of neighbors' pesticide usage amount. The coefficient on the spatial lag term, ρ, captures spatial correlation in pesticide use.

After controlling for observed and unobserved characteristics, the residual u_t captures the intensity of infestation, which can be spatially correlated. If unobserved insect or weed infestation correlates spatially, λ should be positive. If λ is not significantly different from zero, it implies that (i) shocks are actually not spatially correlated or that (ii) farmers' pesticide application is not based on the intensity of infestation. Note that case (ii) can happen if farmers use pesticides as preventive measures, which often results in injudicious use[5] (e.g., Plianbangchang et al. 2009).

The main parameters of interest are ρ and λ, which capture spatial dependence ("endogenous effect") and heterogeneity ("correlated effect"), respectively. One possible scenario of neighborhood effects in pesticide use arises from spatially correlated shocks. If the farmers respond to spatially correlated shocks, both ρ and λ are expected to be positive. On the other hand, if the intensity of infestation is not spatially correlated ($\lambda = 0$), the spatial lag term should be 0 as long as the farmers are rational and there is no other type of spatial externality in pesticide use. In contrast to these cases, $\rho > 0$ and $\lambda = 0$ imply that farmers are mimicking the pattern of pesticide application in surrounding farm plots, because otherwise, there is no rational reason for the application pattern to be spatially correlated without significant spatially correlated shocks. In addition to these cases, neighborhood effects in pesticide use arise from the endogenous effect. In the case of insecticides, ρ can be positive or negative because neighboring farmers' insecticide use can kill both pests and their predator insects. If the impact of killing pests outweighs that of killing predator insects, the net impact would be negative ($\rho < 0$) because surrounding farmers' usage leads to lower application. Conversely, if the impact of killing predator insects outweighs that of killing pests, the net impact would be positive. Thus, the sign of ρ is an empirical question for rational insecticide use. As for herbicides, the expected endogenous effect is negative, though negligible, because herbicide drift from surrounding farm plots can reduce the weed population in one's own plot, which leads to lower herbicide use. Thus, positive ρ without a significant spatial error term implies mimicking behavior in herbicide use.

[5] Preventive use is common for herbicides in this area.

Note that model (1) is a structural form in the sense that y_t is present on both sides. Thus, the OLS estimators are known to be inconsistent (e.g., Anselin 1988; LeSage and Pace 2008). In order to handle this problem, this study employs the maximum likelihood approach by solving (1) and (2) for ϵ_t and assuming it to be independent and identically distributed following a normal distribution. In addition, the transformation approach proposed by Lee and Yu (2010) is also employed for bias correction.[6]

Although the most preferable specification is the SAC model with individual fixed effects to control unobserved individual heterogeneities, it is also informative to discuss the impact of time-variant variables. For this purpose, pooled OLS regression and corresponding cross sectional SAC models are also estimated. In addition, there are many cases where farmers did not use any herbicides or insecticides during each survey period. Thus, linear probability models are also estimated to analyze the decision whether to apply pesticide.[7]

4. Empirical Results

Using the econometric models discussed above, this section analyzes the neighborhood effects for herbicides and insecticides, respectively.

4.1 Herbicide Use

The first four columns of Table 3 show the estimation results of the neighborhood effects in herbicide use when the dependent variable is the usage amount. The spatial lag term is significantly positive with and without fixed effects. In contrast, the spatial error term is not significant in both cases. Thus, the farmers' usage pattern is correlated without spatially correlated shocks, implying that they mimic their neighbors.

The results of the pooled OLS and cross-sectional SAC models show that the distance to the agricultural supplier in the nearest town is negatively associated with the usage of herbicides, suggesting that the cost of the herbicide is a hindrance for application. Although the irrigation dummy itself is not statistically significant, the amount of irrigation water usage has a significantly negative effect and its magnitude is not considerably affected even after controlling for fixed effects. This implies that irrigation water generally prevents the growth of weed population. The sign on the size of the surveyed plot is negative, which represents

[6] Because of this approach, the sample size reduces from *NT* to *N*(*T*-1) for spatial fixed-effect model.

[7] Since the estimation of spatial Tobit models did not converge, they are not reported.

economy of scale (Liu and Huang 2013). Though credit constraint is negatively associated with the usage amount, it becomes insignificant in the fixed-effect models. Thus, credit constraint is not necessarily a barrier for herbicide use. Larger household size is associated with lower herbicide use, suggesting that herbicides can be substituted for weeding by the household members. Note that the qualitative results remain virtually unchanged between the models with and without the spatial terms.

The remaining four columns show the estimation results when the dependent variable is a dummy for whether the farmers applied herbicides. Consistent with the first four columns, the spatial lag term is significantly positive but the spatial error term is insignificant. Thus, this finding is robust and supports the possibility of farmers' mimicking use of herbicides. As for other variables, the results do not change qualitatively except for the sign of the surveyed plot size. Combined with the findings above, larger plot size is associated with higher probability of application and lower amount, which supports the existence of scale economy. However, the positive coefficient on plot size becomes significant when time-invariant heterogeneities are controlled for.

4.2 Insecticide Use

The first four columns of Table 4 show the estimation results of the neighborhood effects in insecticide use when the dependent variable is the usage amount. In contrast to the herbicide use, both spatial lag and error are insignificant. This can be reasonable because the insignificant spatial lag term can result from the lack of spatially correlated pest infestation. Similar to the herbicide case, the size of the surveyed plot has negative impact on the insecticide use, implying the effect of scale economy. The coefficient on distance to the agricultural suppler in the nearest town is negative but insignificant. As for the irrigation variables, though the irrigated dummy is significantly negative, irrigation water use is insignificant and robust to the inclusion of fixed effects, suggesting higher insecticide use in the rain-fed area. This might reflect the fact that the intensity of pests is lower in the irrigated area because the timing of transplanting is synchronized due to the timing of irrigation water supply[8] (Litsinger et al. 2009). The coefficient on household size is negative but insignificant, which contrasts with the herbicide case. This is because pest infestation is more difficult to monitor or predict than weed infestation. Consistent with the graphical analysis (Figures 2-4),

---

[8] In fact, the standard deviation of the timing of transplanting is significantly smaller in the irrigated area than in the rain-fed area for all seasons. Note that direct sowing is not common in this area.

the magnitudes of the coefficients on the season dummies are increasing, suggesting path dependence in insecticide use.

The remaining four columns show the estimation results when the dependent variable is a dummy for whether they applied insecticides or not. The spatial error term is significantly positive in the pooled SAC model, indicating that pest damage might be spatially correlated. However, the spatial lag term is insignificant. This inconsistency also implies that farmers do not properly respond to pest damage. However, in the SAC model with fixed effects, the spatial lag term becomes significantly positive and the spatial error term becomes insignificant. This finding is consistent with the herbicide case and supports mimicking use in insecticide use. Similar to the herbicide case, the coefficient on plot size is positive but insignificant in the fixed-effect models.

Comparing to the robust positive coefficient on the spatial lag term in herbicide use, significance is much lower in insecticide use. This contrast might imply that negative externalities arising from reducing pest insect population is much stronger than that from herbicide drift, which results in less precise estimates.

4.3 Irrigated vs. Rain-fed Samples

Further, it is informative to analyze the neighborhood effects separately for irrigated and rain-fed households because the pattern of pesticide application and unobserved intensity of infestation might be different. Note that dividing the sample implicitly assumes that there is no neighborhood effect between irrigated and rain-fed households. Tables 5 and 6 show the estimation results for herbicide and insecticide use, respectively. Since the introduction of the spatial terms has virtually no effect on other coefficients, the estimation results are reported only for the spatial models.

The first four columns of Table 5 show the results for irrigated households and the last four columns for rain-fed households, respectively. There is no clear difference between irrigated and rain-fed samples for herbicide use. The spatial lag term in the SAC model with fixed effects is significantly positive for columns (2) and (8), but the spatial error term is always insignificant. This result also supports, albeit weakly, the hypothesis of mimicking the neighboring households. Compared to the significant spatial lag term in Table 3, this lack of significance might imply salient endogenous effects between the irrigated and the rain-fed households. Overall tendency of the other coefficients is not very different from those of Table 3 except that the coefficients are less precisely estimated.

Similarly, Table 6 shows the results for insecticide use. In contrast to the ambiguous difference for herbicide use, there is a clear difference in the spatial error terms for insecticide use. Although λ is insignificant in all specifications for irrigated households, it is significantly positive for rain-fed households except for column (8). As mentioned above, these significant coefficients might indicate higher intensity of pests in the rain-fed area because of the lack of synchronized transplanting. The spatial lag term is significantly negative in column (5), implying that the negative endogenous effect from reducing the pest population is larger than the positive effect from killing predator insects. However, it becomes insignificant when plot fixed effects are controlled for. Another interesting finding is that the increasing trend in insecticide use can be found only in the rain-fed area, implying that the path dependence issue is more salient—and thus, the problem of insecticide use is more serious—in the rain-fed area than in the irrigated area.

5. Concluding Remarks

This study investigates neighborhood effects in pesticide use by employing the spatial econometric approach. By exploiting the plot-level panel data in the rural Philippines, this study controls for time-invariant individual characteristics, which affect pesticide use but are difficult to observe. The estimation results show that although there is no significant spatial correlation in an unobserved degree of infestation, the usage is spatially correlated, especially for herbicide use. This finding indicates that when farmers apply pesticide, they do not respond to the degree of infestation but mimic the neighboring farmers' application. Thus, the current usage amount may not be optimal and there is room for pesticide reduction. To the best of my knowledge, this is the first statistical evidence that suggests mimicking behavior in pesticide use.

Another important finding is that sufficient irrigation water use can reduce herbicide use. Since irrigation water is a common pool resource, effective allocation requires community-level involvement. In this sense, collective action among neighbors can indirectly lead to pesticide reduction through irrigation management as well as direct effects of joint pest management (e.g., Regev et al. 1976).

In addition to these results from econometric analysis, there are some anecdotal evidences from an open-ended interview. In the interview, an elder farmer answered that others refer to his pesticide use by asking him what type of pesticide he is spraying. However, they do not coordinate in crop protection except for few farmers who engage in synchronized transplanting as a method of IPM. Intriguingly, another farmer also answered that she was trying to reduce pesticide use by employing traditional pest control methods because of food safety concerns. These evidences suggest that there continues to be room for pesticide reduction and improving farmers' welfare.

Some policy implications can be drawn from these findings. First, since farmers may apply pesticide by mimicking neighboring farmers, policy interventions such as agricultural training programs that provide them with proper knowledge about the usage of pesticides, are effective to reduce pesticide use. In addition, since there is an increasing trend in insecticide use, reducing the current use can lead to the reduction of insecticide use in the future. The training should provide information not only on the timing and the amount of pesticide application but also on the proper use of protective cover to prevent acute and chronic poisoning. Giving this training to selective farmers would be sufficient because it will be disseminated among the neighboring farmers through the mimicking process, thus being a cost-effective intervention (e.g., Krishnan and Patnam 2013; Nakano et al. 2015).

Reference

Anselin, Luc. *Spatial Econometrics: Methods and Models*. Dordrecht, The Netherlands: Kluwer Academic Publishers, 1988.

Anselin, Luc, Rodolfo Bongiovanni, and Jess Lowenberg-DeBoer. “A Spatial Econometric Approach to the Economics of Site-specific Nitrogen Management in Corn Production,” *American Journal of Agricultural Economics* 86.3 (2004): 675–687

Antle, John M., and Prabhu L. Pingali. “Pesticides, Productivity, and Farmer Health: A Philippine Case Study,” *American Journal of Agricultural Economics* 56 (1994): 418-30.

Burrows, Thomas M. “Pesticide Demand and Integrated Pest Management: A Limited Dependent Variable Analysis.” *American Journal of Agricultural Economics* 65 (1983): 806–810.

Cowan, Robin and Philip Gunby. “Sprayed to Death: Path Dependence, Lock-in and Pest Control Strategies,” *Economic Journal*, 106.436 (1996): 521-542.

Druska, Viliam and William C. Horrace. “Generalized Moments Estimation for Spatial Panel Data: Indonesian Rice Farming,” *American Journal of Agricultural Economics* 86.1 (2004): 185–198.

Durlauf, Steven N. “Neighborhood Effects,” in *Handbook of Regional and Urban Economics*, vol. 4, J. Vernon Henderson and Jacques-François Thisse, eds., Amsterdam: North Holland, 2004.

Eastwood, Robert, Michael Lipton, and Andrew Newell. “Farm Size,” In: *Handbook of Agricultural Economics*, Volume 4. Amsterdam: North Holland Publishing Company, 2010.

Elhorst, J. Paul. “Specification and Estimation of Spatial Panel Data Models,” *International Regional Science Review* 26.3 (2003): 244–68.

Elhorst, J. Paul. “Spatial Panel Data Models,” In *Handbook of Applied Spatial Analysis*, ed. M. M. Fisher and A. Getis, 377-408. New York: Springer, 2010.

Elhorst, J. Paul. *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, New York: Springer, 2014.

Escalada MM, Heong KL. “Communication and implementation of change in crop protection.” In *Crop Protection and Sustainable Agriculture*, CIBA Foundation Symposium 177, pp. 191–207. Chichester, UK: Wiley, 1993.

Ferguson, Andrew W, Zdisław Klukowski, Barbara Walczak, Suzanne J Clark, Moira A Mugglestone, Joe N Perry, and Ingrid H Williams. “Spatial distribution of pest insects in oilseed rape: implications for integrated pest management," *Agriculture, Ecosystems & Environment*, 95. 2–3 (2003): 509–521.

Fernandez-Cornejo, Jorge, and Jennifer Ferraioli. "The Environmental Effects of Adopting IPM Techniques: The Case of Peach Producers." *Journal of Agricultural and Applied Economics* 31 (1999): 551–564.

Florax, Raymond J. G. M., Roelf L. Voortman, Joost Brouwer. "Spatial dimensions of precision agriculture: a spatial econometric analysis of millet yield on Sahelian coversands," *Agricultural Economics* 27 (2002): 425-443

Grogan, Kelly A. and Rachael E. Goodhue. "Spatial Externalities of Pest Control Decisions in the California Citrus Industry," *Journal of Agricultural and Resource Economics* 37.1 (2012): 156–179.

Headley, J. C. "Defining the Economic Threshold," In: *Pest Control Strategies for the Future*, Agricultural Board, Washington, DC: National Academy of Sciences, 1972.

Huang, Jikun, Ruifa Hu, Scott Rozelle, Carl Pray. "Insect-Resistant GM Rice in Farmers' Fields: Assessing Productivity and Health Effects in China," *Science* 308 (2005): 688–690.

Ioannides, Yannis M. and Giorgio Topa. "Neighbourhood Effects: Accomplishments and Looking Beyond them." *Journal of Regional Science* 50.1 (2010): 343–62.

Japan International Cooperation Agency and International Rice Research Institute. "Impact Evaluation of the Bohol Irrigation Project (Phase 2) in the Republic of the Philippines," 2012.

Krishnan, Pramila and Manasa Patnam. "Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?" *American Journal of Agricultural Economics* 96.1 (2013): 308–327.

Lee, Lung-fei, and Jihai Yu "Estimation of Spatial Autoregressive Panel Data Models with Fixed Effects," *Journal of Econometrics* 154 (2010): 165–185.

Litsinger, J.A., B.L. Canapi, J.P. Bandong, M.D. Lumaban, F.D. Raymundo, and A.T. Barrion. "Insect pests of rain-fed wetland rice in the Philippines: population densities, yield loss, and insecticide management," *International Journal of Pest Management* 55.3 (2009): 221–242.

Liu, Elaine M. and JiKun Huang. "Risk preferences and pesticide use by cotton farmers in China," *Journal of Development Economics* 103 (2013): 202–215.

Manski, Charles F. "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60 (1993): 531–542.

Nakano, Yuko, Takuji W. Tsusaka, Takeshi Aida, and Valerien O. Pede (2015) "The Impact of

Training on Technology Adoption and Productivity of Rice Farming in Tanzania: Is Farmer-to-Farmer Extension Effective?,” *JICA-RI Working Paper* No.90.

Palumbi, Stephen R. “Humans as the World’s Greatest Evolutionary Force.” *Science* 293 (2001): 1786–1790.

Pannell, David J. “Pests and pesticides, risk and risk aversion,” *Agricultural Economics* 5 (1992): 61-383

Pingali, Prabhu L., Cynthia B. Marquez, and Florencia G. Palis. “Pesticides and Philippine Rice Farmer Health: A Medical and Economic Analysis,” *American Journal of Agricultural Economics*, 76.3 (1994): 587-592.

Regev, Uri, Andrew P. Gutierrez, Gershon Feder. “Pests as a Common Property Resource: A Case Study of Alfalfa Weevil Control,” *American Journal of Agricultural Economics* 58.2 (1976): 186-197.

Rola, Agnes C. and Prabhu L. Pingali. *Pesticide, Rice Productivity and Farmer’s Health: An Economic Assessment*. Washington, DC: World Resources Institute and Los Banos, Philippines: IRRI, 1993.

Qaim, Matin and Alain de Janvry. “Bt cotton and pesticide use in Argentina: economic and environmental effects,” *Environment and Development Economics* 10 (2005): 179–200.

Qaim, Matin and David Zilberman. “Yield Effects of Genetically Modified Crops in Developing Countries,” *Science* 299 (2003): 900–902

Sexton, Steven E., Zhen Lei, and David Zilberman. “The Economics of Pesticides and Pest Control,” *International Review of Environmental and Resource Economics* 1.3 (2007): 271–326.

Shetty, P. K. “Socio-ecological Implications of Pesticide Use in India,” *Economic and Political Weekly* 39.49 (2004): 5261-5267.

Soares, Wagner Lopes and Marcelo Firpo de Souza Porto. “Estimating the social cost of pesticide use: An assessment from acute poisoning in Brazil,” *Ecological Economics* 68 (2009): 2721-2728.

Tsusaka, Takuji W., Kei Kajisa, Valerien O. Pede, and Keitaro Aoyagi. “Neighborhood effects and social behavior: The case of irrigated and rain-fed farmers in Bohol, the Philippines,” *Journal of Economic Behavior & Organization* 118 (2015): 227–246.

Walter, A. M., S. Christensen, and S. E. Simmelsgaard. “Spatial correlation between weed species densities and soil properties,” *Weed Research* 42 (2002): 26–38.

WHO, *The WHO Recommended Classification of Pesticides by Hazard and Guidelines to Classification 2009*, Geneva: World Health Organization, 2010.

Wilson, Clevo and Clem Tisdell. “Why farmers continue to use pesticides despite environmental, health and sustainability costs," *Ecological Economics* 39 (2001): 449–462.

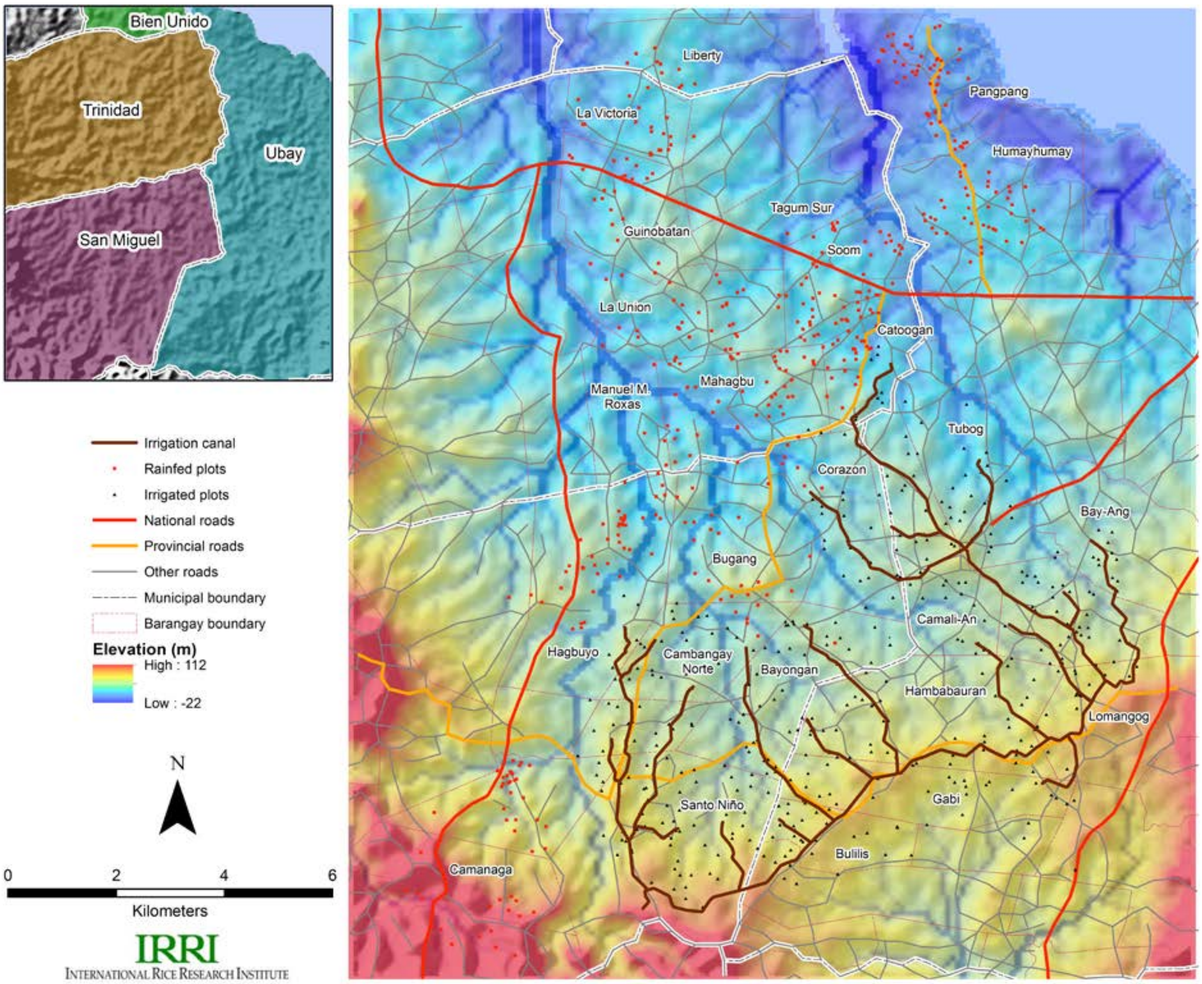

Figure 1: Map of the Study Site (cited from JICA-IRRI (2012))

Table 1: Summary Statistics

	Count	Mean	S.D.
Herbicide (kg per ha; active ingredients)	2660	0.073	0.193
Insecticide (kg per ha; active ingredients)	2660	0.051	0.140
Irrigated dummy	2660	0.477	0.500
Size of surveyed plot	2660	0.635	0.498
Log (irrigation water use +1)	2660	1.322	1.645
Hybrid dummy	2660	0.033	0.179
Credit-constrained dummy	2660	0.153	0.360
Distance to the nearest agricultural supplier (km)	2660	16.348	3.172
Age of household head	2660	52.856	12.186
Education level of household head	2660	6.177	3.216
Female household head dummy	2660	0.057	0.232
Household size	2660	5.677	2.504

Note: Irrigation water use is self-reported amount of irrigation water usage measured by the cumulative depth in an irrigation canal (in meters) and replaced with 0 for rain-fed households.

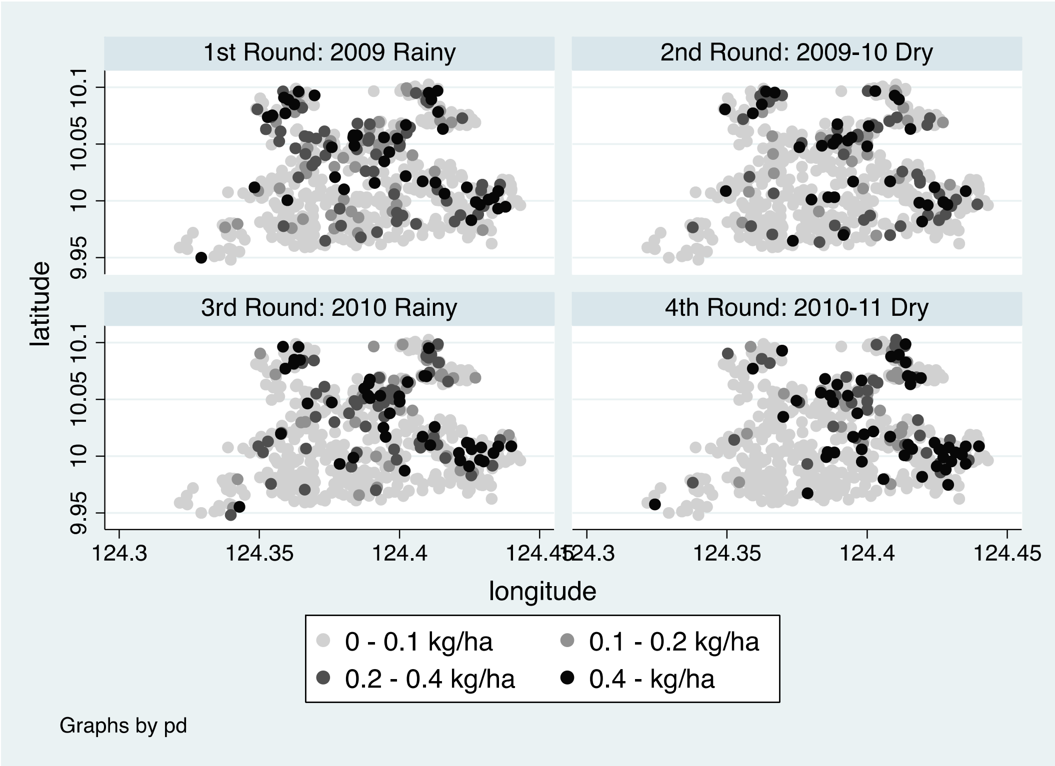

Figure 2: Spatial Pattern of Herbicide Usage Amount

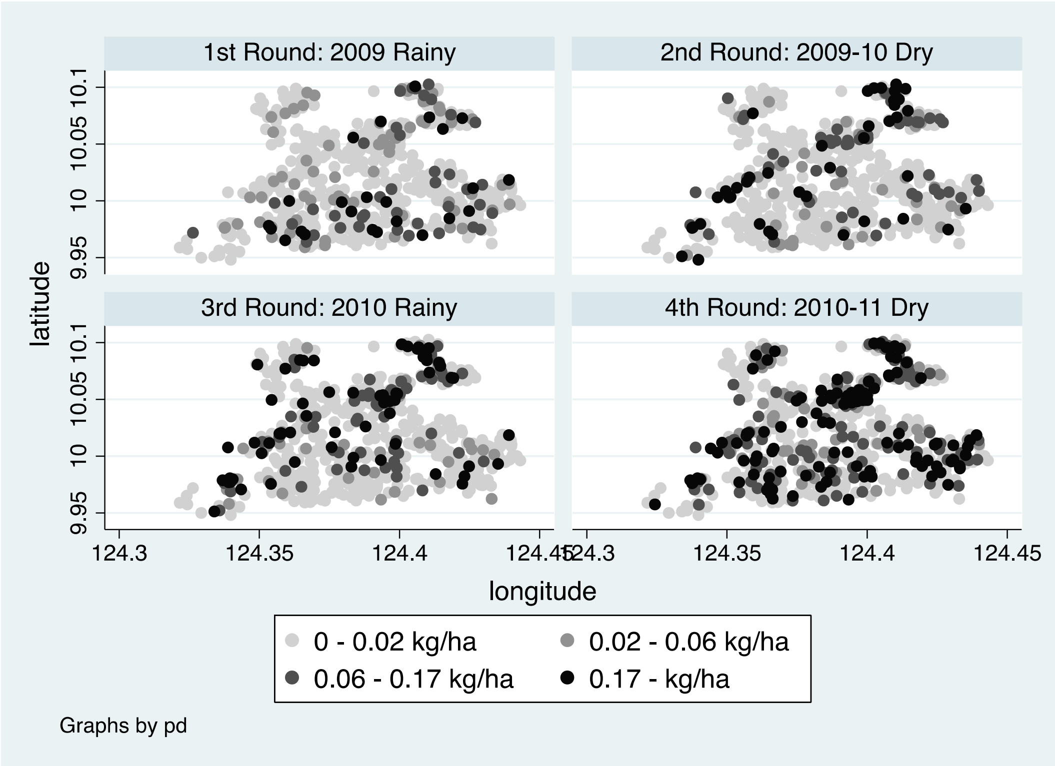

Figure 3: Spatial Pattern of Insecticide Usage Amount

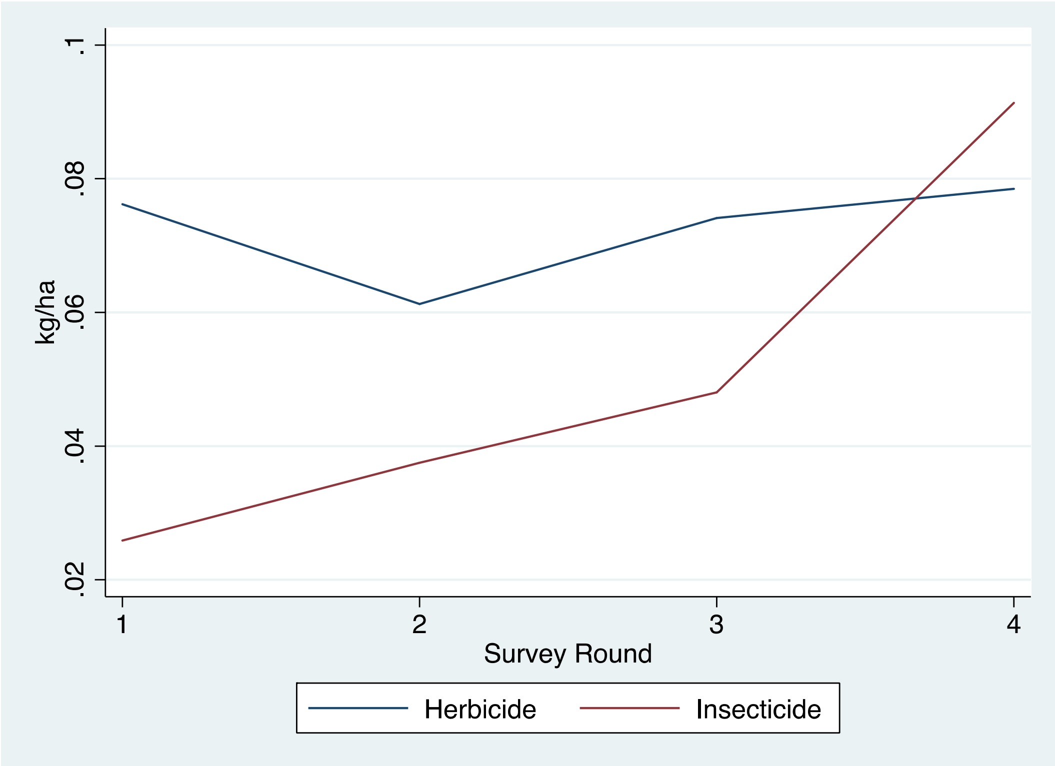

Figure 4: Time Trend in Average Pesticide Usage Amount

Table 2: Moran's *I* of Pesticide Use

	Herbicide	Insecticide
2009 Rainy	0.018***	0.002
	(0.004)	(0.004)
2009-10 Dry	0.007**	0.005**
	(0.004)	(0.004)
2010 Rainy	0.016***	0.009***
	(0.004)	(0.004)
2010-11 Dry	0.029***	0.002
	(0.004)	(0.004)

Standard deviations are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Estimation Results for Herbicide Use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MODEL	OLS	SAC	FE	SAC FE	OLS	SAC	FE	SAC FE
VARIABLES	kg/ha	kg/ha	kg/ha	kg/ha	dummy	dummy	dummy	dummy
Irrigated dummy	0.0183	0.0209			-0.00802	0.0152		
	(0.0167)	(0.0137)			(0.0389)	(0.0302)		
Size of surveyed plot	-0.0185**	-0.0178**	-0.0359**	-0.0352**	0.0769***	0.0774***	0.0220	0.0225
	(0.00758)	(0.00758)	(0.0155)	(0.0154)	(0.0251)	(0.0165)	(0.0285)	(0.0284)
Log (irrigation water use +1)	-0.0103**	-0.00949**	-0.0120**	-0.0103**	-0.0296***	-0.0279***	-0.0325***	-0.0313***
	(0.00433)	(0.00430)	(0.00492)	(0.00497)	(0.0103)	(0.00930)	(0.00933)	(0.00935)
Hybrid dummy	-0.00232	-0.00258	0.0141	0.0122	-0.0528	-0.0529	-0.00354	-0.00621
	(0.0166)	(0.0207)	(0.0150)	(0.0147)	(0.0378)	(0.0451)	(0.0379)	(0.0371)
Credit constrained	-0.0234***	-0.0234**	-0.00507	-0.00634	-0.0378*	-0.0373	-0.00875	-0.0105
	(0.00897)	(0.0106)	(0.00894)	(0.00892)	(0.0229)	(0.0231)	(0.0228)	(0.0227)
Distance to the nearest agricultural	-0.00844***	-0.00603***			-0.0198***	-0.0133***		
	(0.00137)	(0.00126)			(0.00332)	(0.00297)		
Age of household head	0.00303	0.00291			0.0128*	0.0126***		
	(0.00265)	(0.00217)			(0.00660)	(0.00473)		
Age squared (divided by 100)	-0.00280	-0.00271			-0.0116*	-0.0114***		
	(0.00250)	(0.00201)			(0.00618)	(0.00437)		
Education level of household head	0.000408	0.000357			0.000495	0.000445		
	(0.00148)	(0.00121)			(0.00370)	(0.00264)		
Female household head dummy	-0.0166	-0.0161			-0.0676	-0.0671*		
	(0.0214)	(0.0162)			(0.0419)	(0.0353)		
Household size	-0.00680***	-0.00679***			-0.0165***	-0.0165***		
	(0.00200)	(0.00154)			(0.00426)	(0.00335)		
2009 dry season dummy	-0.0231***	-0.0142	-0.0192**	-0.0139*	-0.0838***	-0.0449**	-0.0773***	-0.0640***

	(0.00827)	(0.00886)	(0.00822)	(0.00833)	(0.0199)	(0.0217)	(0.0196)	(0.0225)
2010 wet season dummy	-0.0100	-0.00971	-0.00756	-0.00781	-0.0222	-0.0217	-0.0187	-0.0204
	(0.00904)	(0.00846)	(0.00905)	(0.00915)	(0.0213)	(0.0182)	(0.0213)	(0.0234)
2010 dry season dummy	-0.00953	-0.0108	-0.00785	-0.00839	-0.0823***	-0.0514**	-0.0800***	-0.0698***
	(0.0107)	(0.00901)	(0.0108)	(0.0110)	(0.0219)	(0.0217)	(0.0216)	(0.0232)
Spatial lag (ρ)		0.619***		0.396**		0.604***		0.226*
		(0.189)		(0.163)		(0.181)		(0.118)
Spatial error (λ)		-0.317		0.0249		-0.331		0.108
		(0.287)		(0.166)		(0.265)		(0.124)
Constant	0.201***	0.115*	0.120***	NA	0.368**	0.0911	0.313***	NA
	(0.0685)	(0.0648)	(0.0136)	NA	(0.174)	(0.153)	(0.0290)	NA
Observations	2,660	2,660	2,660	1,995	2,660	2,660	2,660	1,995
Log likelihood	650.4261	655.69448	1411.859	1366.1933	-1415.89	-1411.079	-552.614	-600.332

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

Table 4: Estimation Results for Insecticide Use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MODEL	OLS	SAC	FE	SAC FE	OLS	SAC	FE	SAC FE
VARIABLES	kg/ha	kg/ha	kg/ha	kg/ha	dummy	dummy	dummy	dummy
Irrigated dummy	-0.0263***	-0.0284**			-0.0763*	-0.0744*		
	(0.00990)	(0.0114)			(0.0412)	(0.0411)		
Size of surveyed plot	-0.0112**	-0.0115**	-0.0280*	-0.0279*	0.0892***	0.0873***	0.0145	0.0154
	(0.00544)	(0.00553)	(0.0152)	(0.0151)	(0.0323)	(0.0191)	(0.0319)	(0.0317)
Log (irrigation water use +1)	0.00343	0.00295	0.00285	0.00246	0.00148	-0.00454	0.0156	0.0120
	(0.00256)	(0.00325)	(0.00310)	(0.00320)	(0.0122)	(0.0113)	(0.0133)	(0.0138)
Hybrid dummy	0.0179	0.0179	0.0235	0.0234	0.0433	0.0431	0.0437	0.0410
	(0.0200)	(0.0152)	(0.0205)	(0.0206)	(0.0522)	(0.0527)	(0.0645)	(0.0641)
Credit constrained	-0.00676	-0.00645	-0.000997	-0.000484	-0.0554**	-0.0514*	-0.0252	-0.0238
	(0.00905)	(0.00775)	(0.0116)	(0.0118)	(0.0281)	(0.0267)	(0.0286)	(0.0284)
Distance to the nearest agricultural	-0.00125	-0.00148			-0.00517	-0.00596		
	(0.000953)	(0.00109)			(0.00414)	(0.00426)		
Age of household head	0.00500***	0.00505***			0.0182**	0.0180***		
	(0.00156)	(0.00157)			(0.00711)	(0.00540)		
Age squared (divided by 100)	-0.00509***	-0.00513***			-0.0198***	-0.0196***		
	(0.00141)	(0.00145)			(0.00659)	(0.00499)		
Education level of household head	-0.00146	-0.00141			-0.00485	-0.00484		
	(0.000991)	(0.000884)			(0.00397)	(0.00305)		
Female household head dummy	0.00764	0.00811			-0.0777	-0.0656		
	(0.0187)	(0.0117)			(0.0516)	(0.0403)		
Household size	-0.00123	-0.00131			-0.00758	-0.00797**		
	(0.00126)	(0.00111)			(0.00464)	(0.00381)		
2009 dry season dummy	0.0118*	0.0163	0.0131*	0.0108	-0.177***	-0.147*	-0.166***	-0.105***

	(0.00715)	(0.0156)	(0.00754)	(0.0102)	(0.0233)	(0.0860)	(0.0237)	(0.0401)
2010 wet season dummy	0.0228***	0.0294*	0.0236***	0.0185*	-0.126***	-0.116	-0.117***	-0.0768**
	(0.00636)	(0.0167)	(0.00666)	(0.0111)	(0.0242)	(0.0810)	(0.0246)	(0.0355)
2010 dry season dummy	0.0680***	0.0882***	0.0684***	0.0534**	-0.0174	-0.0335	-0.00484	-0.00673
	(0.00898)	(0.0282)	(0.00929)	(0.0254)	(0.0257)	(0.0680)	(0.0263)	(0.0289)
Spatial lag (ρ)		-0.346		0.213		0.206		0.381**
		(0.410)		(0.325)		(0.315)		(0.174)
Spatial error (λ)		0.485		0.0628		0.602**		0.0854
		(0.321)		(0.328)		(0.257)		(0.228)
Constant	-0.0382	-0.0246	0.0378***	NA	0.230	0.172	0.427***	NA
	(0.0438)	(0.0487)	(0.0125)	NA	(0.196)	(0.248)	(0.0367)	NA
Observations	2,660	2,660	2,660	1,995	2,660	2,660	2,660	1,995
Log likelihood	1522.141	1523.25	2070.159	2021.8134	-1790.737	-1770.601	-998.7405	-1043.2734

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

Table 5: Estimation Results for Herbicide Use (Irrigated vs. Rain-fed)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SAMPLE			Irrigated				Rain-fed	
MODEL	SAC	SAC FE	SAC	SAC FE	SAC	SAC FE	SAC	SAC FE
VARIABLES	kg/ha	kg/ha	dummy	dummy	kg/ha	kg/ha	dummy	dummy
Size of surveyed plot	0.00255	-0.0455*	0.119***	0.0468	-0.0316***	-0.0242	0.0423*	-0.00225
	(0.0114)	(0.0269)	(0.0227)	(0.0424)	(0.0102)	(0.0149)	(0.0241)	(0.0345)
Log (irrigation water use +1)	-0.00390	-0.00297	-0.0231**	-0.0228**				
	(0.00476)	(0.00540)	(0.00945)	(0.0100)				
Hybrid dummy	-0.0103	0.00386	-0.0864*	-0.0472	0.0564	0.0486	0.0843	0.144
	(0.0243)	(0.0135)	(0.0483)	(0.0333)	(0.0431)	(0.0451)	(0.102)	(0.110)
Credit constrained	-0.0306*	-0.00881	-0.0307	0.00684	-0.0220	-0.0120	-0.0563	-0.0461
	(0.0157)	(0.0122)	(0.0311)	(0.0251)	(0.0148)	(0.0140)	(0.0350)	(0.0381)
Distance to the nearest agricultural	-0.00918***		-0.0174***		-0.00496***		-0.0155***	
	(0.00248)		(0.00488)		(0.00159)		(0.00475)	
Age of household head	-0.000641		-0.000927		0.00469		0.0230***	
	(0.00341)		(0.00676)		(0.00294)		(0.00695)	
Age squared (divided by 100)	0.000690		0.000962		-0.00432		-0.0201***	
	(0.00327)		(0.00647)		(0.00263)		(0.00622)	
Education level of household head	-0.00229		-0.00729**		0.00257		0.00712*	
	(0.00183)		(0.00363)		(0.00163)		(0.00387)	
Female household head dummy	-0.0309		-0.0585		-0.00371		-0.0594	
	(0.0276)		(0.0547)		(0.0199)		(0.0473)	
Household size	-0.00860***		-0.0187***		-0.00520**		-0.0149***	
	(0.00232)		(0.00458)		(0.00206)		(0.00487)	
2009 dry season dummy	-0.00604	-0.00356	-0.0280	-0.0295	-0.0257*	-0.0284**	-0.0952**	-0.105***
	(0.0139)	(0.0118)	(0.0309)	(0.0302)	(0.0151)	(0.0128)	(0.0450)	(0.0333)

2010 wet season dummy	0.00347	0.00708	-0.0105	-0.00697	-0.0174	-0.0200	-0.0264	-0.0256
	(0.0149)	(0.0141)	(0.0311)	(0.0321)	(0.0138)	(0.0135)	(0.0328)	(0.0348)
2010 dry season dummy	0.0163	0.0239	-0.0265	-0.0212	-0.0296*	-0.0362**	-0.0951**	-0.108***
	(0.0200)	(0.0183)	(0.0339)	(0.0329)	(0.0169)	(0.0147)	(0.0460)	(0.0360)
Spatial lag (ρ)	0.450	0.306**	0.298	-0.0133	0.273	0.0559	0.311	0.182**
	(0.279)	(0.141)	(0.290)	(0.175)	(0.293)	(0.0886)	(0.274)	(0.0883)
Spatial error (λ)	-0.144	0.138	-0.0247	0.155	-0.201	-0.0206	-0.0890	0.0573
	(0.387)	(0.147)	(0.344)	(0.144)	(0.352)	(0.0838)	(0.322)	(0.0998)
Constant	0.274***	NA	0.603***	NA	0.0698	NA	-0.102	NA
	(0.0988)	NA	(0.208)	NA	(0.0927)	NA	(0.245)	NA
Observations	1,268	951	1,268	951	1,392	1,044	1,392	1,044
Log likelihood	284.9907	605.6397	-580.50448	-182.4868	388.7026	774.6842	-808.33569	-395.5922

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Estimation Results for Insecticide Use (Irrigated vs. Rain-fed)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SAMPLE		Irrigated				Rain-fed		
MODEL	SAC	SAC FE	SAC	SAC FE	SAC	SAC FE	SAC	SAC FE
VARIABLES	kg/ha	kg/ha	dummy	dummy	kg/ha	kg/ha	dummy	dummy
Size of surveyed plot	-0.00149	-0.0308	0.108***	0.0395	-0.0213***	-0.0258	0.0609**	-0.0127
	(0.00808)	(0.0252)	(0.0281)	(0.0511)	(0.00751)	(0.0164)	(0.0260)	(0.0387)
Log (irrigation water use +1)	0.00142	-0.000108	-0.00984	0.00117				
	(0.00337)	(0.00333)	(0.0117)	(0.0151)				
Hybrid dummy	0.0237	0.0277	0.0669	0.0695	-0.0128	0.00308	-0.0508	-0.0300
	(0.0172)	(0.0255)	(0.0601)	(0.0766)	(0.0324)	(0.0230)	(0.112)	(0.114)
Credit constrained	0.00218	0.00507	-0.0401	-0.0490	-0.00896	0.00104	-0.0666*	0.00274
	(0.0111)	(0.0197)	(0.0385)	(0.0408)	(0.0108)	(0.0118)	(0.0373)	(0.0399)
Distance to the nearest agricultural	-0.000563		0.00193		-0.00320*		-0.0153*	
	(0.00125)		(0.00498)		(0.00180)		(0.00780)	
Age of household head	0.00370		0.00363		0.00652***		0.0250***	
	(0.00240)		(0.00831)		(0.00214)		(0.00740)	
Age squared (divided by 100)	-0.00404*		-0.00453		-0.00622***		-0.0269***	
	(0.00230)		(0.00796)		(0.00192)		(0.00664)	
Education level of household head	-0.00138		-0.00528		-0.00128		-0.00457	
	(0.00130)		(0.00451)		(0.00121)		(0.00416)	
Female household head dummy	0.0225		-0.0503		-0.00157		-0.0683	
	(0.0195)		(0.0673)		(0.0145)		(0.0500)	
Household size	-0.00296*		-0.00548		-8.27e-05		-0.00937*	
	(0.00163)		(0.00565)		(0.00149)		(0.00515)	
2009 dry season dummy	-0.0126	-0.0129	-0.126*	-0.107***	0.0623*	0.0595**	-0.229*	-0.188***
	(0.0117)	(0.0101)	(0.0685)	(0.0404)	(0.0366)	(0.0285)	(0.127)	(0.0452)

2010 wet season dummy	-0.00429	-0.00583	-0.141*	-0.121***	0.0753**	0.0744**	-0.135	-0.0958**
	(0.0110)	(0.00862)	(0.0723)	(0.0418)	(0.0354)	(0.0313)	(0.117)	(0.0403)
2010 dry season dummy	0.0568***	0.0504***	-0.0813	-0.0591	0.121***	0.120***	0.000480	0.0314
	(0.0202)	(0.0169)	(0.0590)	(0.0467)	(0.0366)	(0.0352)	(0.106)	(0.0384)
Spatial lag (ρ)	-0.0447	0.00543	0.0398	0.151*	-0.709***	-0.571	0.00196	0.0930
	(0.325)	(0.130)	(0.383)	(0.0907)	(0.253)	(0.510)	(0.355)	(0.122)
Spatial error (λ)	-0.0490	-0.00790	0.213	0.0809	0.699***	0.606*	0.665***	0.141
	(0.328)	(0.0997)	(0.364)	(0.120)	(0.152)	(0.329)	(0.248)	(0.121)
Constant	-0.0139	NA	0.360	NA	-0.0527	NA	0.288	NA
	(0.0649)	NA	(0.279)	NA	(0.0698)	NA	(0.351)	NA
Observations	1,268	951	1,268	951	1,392	1,044	1,392	1,044
Log likelihood	727.48979	957.2583	-847.26575	-551.54	809.47291	1077.0624	-910.20426	-477.1891

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