

Article

Impacts of Spatial Clusters on Certified Organic Farming in Taiwan

Chen-Fu Lu ¹ and Chia-Yi Cheng ^{2,*}¹ Department of Economics, Shih Hsin University, Taipei City 106, Taiwan; d98627001@ntu.edu.tw² Department of Applied Economics, National Chung Hsing University, Taichung City 402, Taiwan

* Correspondence: d98627002@ntu.edu.tw or cyc@dragon.nchu.edu.tw

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Abstract: To achieve a balance between agricultural production and environmental protection, organic farming has long been viewed as an alternative for sustainable agricultural development. This study aims to determine the key factors influencing the distribution of organic rice cultivation. Using a unique dataset for the production and environmental characteristics of organic farmland and operations, we assess the impact of spatial clusters, namely cold, hot, and neutral spots, on the certified areas of organic rice. Then, combining the local indicators of spatial association and a multinomial logistic model, we reveal that organic farming is likely to occur in agriculturally less-favored regions, and that improvements in natural productivity is not a favorable incentive for farmers to expand their certified areas. For hot spots, an efficient approach to expand the development of organic farming or certified areas is to increase the scale of agricultural production and marketing groups or even the proportion of individual farmers in operational patterns. Our findings have policy implications for the selection of special regions for organic farming in Taiwan. Further, the analysis of marginal effects provides insight on raising the effectiveness of agricultural sustainability policies.

Keywords: hot spots; LISA; agricultural sustainability; multinomial logistic model; marginal effects

1. Introduction

In recent decades, organic farming has garnered much interest as a sustainable approach to agricultural production while dealing with environmental problems resulting from conventional agricultural methods [1–3]. Given the growing concerns about environmental protection and agricultural sustainability, many nations are attempting to reduce agrochemical material and are pursuing the development of organic farming. A few examples of such efforts are the agri-environmental schemes throughout Europe [4] and the rapid growth of the organic food industry in the United States [5].

Pursuant to environmentally friendly agricultural production practices, a series of policy options, including reduced direct subsidies, lower dependence on chemicals or pesticides, and cheaper and safer production methods, have been considered as responses to the food safety and welfare trend. Among these, organic farming has been viewed as a solution toward more sustainable agricultural development, given the use of little or no pesticide residue and the lower use of inputs [6,7].

A wide body of research focuses on explaining the adoption time and influences of organic operations to gain insight into the distribution, adoption, and conversion process of organic farming from a policy perspective. Their findings on the characteristics of farmers representing human capital assets and farm geographic profiles linked to information interflow among farmers serve as the basis for our empirical work. Related works can be divided into two groups. Some show that the price of agricultural products and the characteristics of farmlands and households are key factors influencing farmers' choice to switch to organic farming [8–10]. Lampkin and Padel [1], for example,

find that concerns about the husbandry of soil degradation are one of the most common factors motivating organic producers. Others reveal that the presence of spatial dependence (Legendre and Legendre [11] define spatial dependence as “the property of random variables taking values, at pairs of locations a certain distance apart, that are more similar (positive autocorrelation) or less similar (negative autocorrelation) than expected for randomly associated pairs of observations.”) reflects the susceptibility of farmers to influences by their geographic and production clusters or surrounding farmland in terms of organic farming distribution [12–16]. Brian [17] reveals the concentration of organic farming in specific regions of England and evidences that the locations between farmlands and regional markets play an important role in spatial differentiation.

In addition to general non-spatial factors, spatial effects on organic operations have become increasingly important. Roe [18] highlights the presence of spatial dependence in the hog production industry, while Hanson [12] suggests that organic operators may benefit from nearby organic farmers. Parker and Munroe [13] reveal that the pattern of surrounding land use influences the conversion to organic farming. Schmidtner [16] explores the spatial distribution of organic farming in Germany. Lapple and Kelley [4] apply the concept of utility and a spatial probit model to demonstrate that organic farmers in close proximity exhibit similar choice behaviors. These studies highlight the importance of identifying spatial clusters (a spatial cluster is a geographically bounded group of occurrences of sufficient size and concentration that is unlikely to have occurred by chance.) given their beneficial impact on sustainable agricultural development.

However, despite the voluminous literature on clusters and spatial dependence, little is known about spatial correlation in certified organic agriculture. An exception is Marasteanu and Jaenicke [19], who identify the spatial clusters of organic operations in the United States and suggest that such operations do not necessarily follow the same geographic patterns as non-organic agricultural and general business establishments. To the best of our knowledge, no theoretical work suggests a connection between the different types of spatial clusters in certified organic agriculture and also no such work can be found in Taiwan.

Given the lack of detailed regional and local research within the specific areas of spatial agglomeration, this study aims to explore the impact of clusters on Taiwan’s organic industry using a special dataset for certified areas for the cultivation of organic rice. To determine the pattern of spatial autocorrelation in the distribution of organic cultivation, we first test the local indicators of spatial association (LISA) to identify different forms of clusters and determine the degree of spatial dependence. We further explore the types of factors affecting spatial clusters in certified organic farming by performing a multinomial logistic regression. We then attempt to combine the results with the concept of a special agricultural production district (to guide domestic agriculture toward large-scale and centralized management, a special agricultural production district has been established since 2007 and is a critical agricultural policy measure in Taiwan.) and offer suggestions for the site selection of the district at a policy level.

The contributions of this research are twofold. First, the analysis data used in this study are obtained from official verification agencies acknowledged by the Council of Agriculture (COA) in Taiwan. Moreover, the organic operational pattern includes all business types in agriculture, such as individuals; farmers’ associations; agricultural production and marketing groups; and agricultural cooperative, enterprises, and corporations. Second, there is limited evidence on the impact of clustering on organic farming. This study attempts to bridge this knowledge gap by empirically assessing a case study in Taiwan for the spatial effects of clusters on certified organic farming.

The remainder of this paper is organized as below. Section 2 discusses the development of certified organic farming in Taiwan. Section 3 presents the data and variables used in this study. Sections 4–6, explain the theoretical framework, methodology, and empirical results, respectively. Section 7 concludes with a concise summary and policy implications.

2. Background

2.1. Development of Organic Farming in Taiwan

Organic farming is being promoted as the main alternative to conventional farming, which has been viewed as unsustainable in Taiwan since 1986. Following the proposal of certified organic food production, in 1997, the COA implemented the Agricultural Production and Certification Act (APCA) as the official guideline. Since then, the government has sought to promote organic farming by launching numerous policies to significantly increase the amount and size of farmland under organic production [20]. In 2009, the COA introduced regulations for the certification management of both domestic and imported organic agricultural (processed) products to determine an effective verification mechanism and promote the development of organic agriculture in Taiwan.

Given the lack of counseling and promotion of organic agriculture, in 2018, the government promulgated the Organic Agriculture Promotion Act (OAPA) that specifies general principles, certification and verification requirements, management rules, and penalty provisions and aims to more than double the amount of farmland currently under organic production in 10 years. The OAPA takes effect by mid-2019. Under the APCA and OAPA, organic farming practices will be eligible for government support and incentives. Agricultural groups and individuals will need to submit an application that will be reviewed and approved for certification to run an organic farming business.

Figure 1 illustrates the growth paths for organic agricultural development across Taiwanese regions, indicating a changing trend at the regional level for certified areas of organic rice from 2009 to 2013 and for the areas' use with 2009 as the base group. It shows that the growth rate for the certified areas is not consistent at the county level and the distribution of organic operations in certain counties demonstrate possible clustering effects on organic farming.

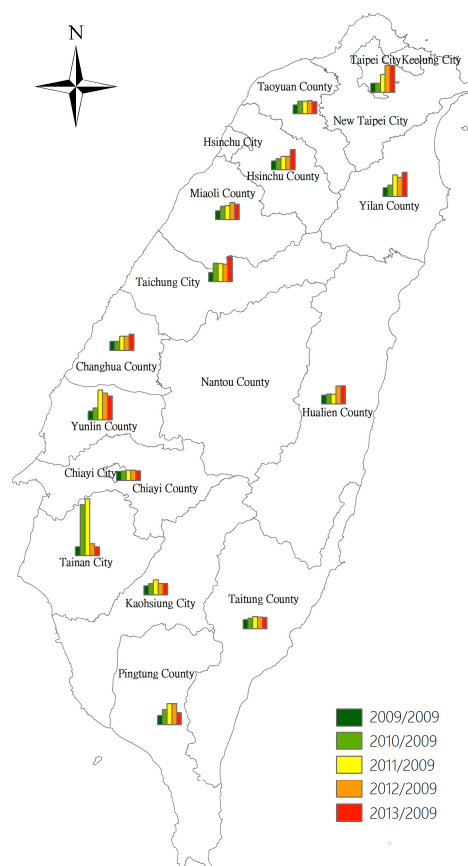


Figure 1. Change in Taiwan's organic certified areas, 2009–2013. Source: Council of Agriculture in Taiwan.

2.2. Framework of Organic Certification in Taiwan

The certification process in Taiwan is mainly based on external and third-party organic verification bodies. As of 2019, there are 13 domestic verification agencies accredited by the COA to inspect and verify organic products. One of their principal duties is to issue the Organic Certified Agricultural Standards (CAS) stamp on domestic organic products. The CAS certification must be renewed every three years. If farmers or agricultural groups are in violation of CAS or related regulations, the agencies can strip them of their organic certification [21]. The verification agencies are under the supervision of the National Accreditation Foundation, which is responsible for annually tracking and managing all certification bodies. If farmers or agricultural groups are not in line with the certified rules, they are disqualified from the verified agencies list.

3. Data and Variables

For the purpose of this study, we construct a dataset of organic rice operations, combining both production and environmental information for Taiwan.

3.1. Production Data

Under the 2007 Certification Management Act of Organic Agricultural Production in Taiwan, the certification body (e.g., individual and farmer associations) certifies organic agricultural products after it has reviewed the application, conducted an on-site inspection, and performed product testing. Once an organic agricultural product has been certified, it issues a certificate listing the type of operators, product category and item, location of certification site, period of validity, and verification agencies.

We collect this information from the official domestic verification agencies acknowledged by Taiwan's COA. Table 1 presents the production characteristics used in this study, including the size of certified areas for organic rice; year in which the certificate was issued; and operational patterns, which can be grouped as individuals, farmer associations, non-farmer private associations, agricultural production and marketing groups, agricultural cooperative, agricultural enterprises, corporations, and public research units.

3.2. Environment Data

Using location information on organic rice operations from the production data, we were able to acquire environmental characteristics by mapping a series of map profiles maintained by different organizations and administrations in Taiwan, such as the Water Conservation Bureau of the Agriculture Committee, the Ministry of the Interior Construction Department, and the Agricultural Land Information System. We extract and combine analytic data for the attributes of organic farmland parcels as environment characteristics (Table 1), such as the magnitude of potential inundation, shortest distance from industrial zones or landslide-prone areas to organic farmlands, natural productivity, and degree of strata subsidence, with the assistance of recent advances in digital land use data and geographic information systems (GIS).

Among these environmental indices, a farmland's natural productivity can be divided into 10 levels, of which the 10th level is the most suitable for agricultural activities and farming. In addition, we use a dummy variable for the strata subsidence of organic farmland, which takes the value of one if the parcel attributes of the mapped results are covered by a range of strata subsidence and zero otherwise.

Table 1. Descriptive statistics of variables for spatial attributes.

Variables		Description	Hot Spots		Neutral Spots		Cold Spots	
			Mean	SD	Mean	SD	Mean	SD
Production characteristic	certified areas	verified areas of organic rice cultivation (unit: ha)	0.572	1.557	0.488	1.705	0.284	1.173
	c_year	If the issued year of the certificate in or after 2009 (=1)	0.331	0.471	0.431	0.495	0.598	0.490
	operator_1	If organic operator is the agricultural production and marketing groups (=1)	0.721	0.449	0.230	0.421	0.364	0.481
	operator_2	If organic operator is individual farmers (=1)	0.163	0.370	0.719	0.449	0.630	0.483
	operator_others	If organic operator is neither operator_1 nor operator_2 (=1)	0.116	0.320	0.050	0.218	0.006	0.077
Environmental characteristic	Inundation	Potential inundation of the organic farmland (unit: meter)	0.060	0.163	0.082	0.195	0.023	0.114
	dis_landslides	The closest distance to landslides from organic farmland (unit: km)	7.598	8.631	2.223	2.609	2.133	2.244
	dis_indust	The closest distance to the industrial zones from organic farmland (unit: km)	22.086	13.953	30.863	17.429	16.145	21.972
	natural productivity	The level of natural productivity for organic farmland (unit: rank ¹)	3.762	3.074	3.712	3.374	3.325	3.680
	d_subsiden	If there is the condition of strata subsidence for organic farmland (=1)	0.033	0.180	0.001	0.032	0.000	0.000
Sample size of the organic rice farming			n = 631		n = 998		n = 1358	

¹ A farmland's natural productivity level can be divided into 10 levels, of which the 10th level is the most suitable for agricultural activities and farming. Source: authors' research using Stata.

3.3. Descriptive Statistics

Table 1 presents the primary descriptive statistics for the variables that are based on the spatial attributes of clusters grouped according to the results for the LISA statistics. Statistically significant spatial clusters that comprise certified areas of high value are defined as hot spots and those with a low value are deemed cold spots. Spatial clusters with certified areas of an insignificant size are grouped as neutral spots. The sample size of each cluster is 631,998, and 1358 from 2009 to 2013 and the average certified area of each farmland is about 0.572, 0.488, and 0.284 ha, respectively. The average size of the certified areas for hot spots is the largest and a majority of these organic parcels (66.9%) were verified prior to 2009. On the other hand, the average certified area for cold spots is the smallest and 59.8% were certified in or after 2009. As for the operational patterns, a majority of the hot spot operators are agricultural production and marketing groups (72.1%), while the operators of neutral (71.9%) and cold (63%) spots are individual farmers.

We simultaneously include positive and negative measures to reflect the environmental information for organic farmland. The variable for natural productivity denotes a positive measure and that the average level of each cluster is roughly the same. There is no significant difference in the fertile degree of organic agricultural land. Negative measures include possible pollution factors, interruptions in organic farmland, and the shortest distance from industrial zones to hot spots is 7.598 km. Compared to cold spots, the distance from landslide-prone areas to hot and neutral spots is large on average.

4. Theoretical Framework

4.1. Tobler's First Law of Geography

The concern of spatial dependence has received increasing attention in agricultural economic research since Tobler [22] proposed the first law of geography. Tobler believes “everything is related to everything else, but near things are more related than distant things.” Failure to account for spatial dependence may lead to cognitive errors [23–27]. This concept is important because it highlights that the intensity of certain phenomena depends on their spatial location.

The statistical exploration of these phenomena has gained much interest with the aim to identify spatial distribution, spatial patterns, and the occurrence of outliers in the data [28]. A spatial arrangement can be clustered, dispersed, or random depending on the observed spatial dependence. Spatial association measures can be global or local. Local measures indicate associations between each location and its neighbors on the basis of defined distances and Anselin's [29] proposed criteria to classify statistics within a class of LISA.

4.2. Unordered Discrete Choice Models

To analyze for heterogeneity in the spatial clusters of certified areas, we formulate a multinomial logistic regression drawing on the theory of unordered discrete choice models [30]. The approach can be motivated by a random utility model. For each data point, I , with a possible outcome, k , we suppose that the utility of outcome, k , is:

$$U_{ik} = Z'_{ik}\theta + \varepsilon_{ij}. \quad (1)$$

If the certified areas belong to spatial cluster k , then we assume that U_{ik} is the maximum among the K utilities. Thus, the statistical model is driven by the probability that cluster k is determined, which is:

$$\text{Prob}(U_{ik} > U_{ij}) \text{ for all other } j \neq k. \quad (2)$$

According to Equation (2), we compute a particular unordered statistic for a set of values, or what is called a multinomial logit model.

5. Empirical Methodology

The analysis of spatial clusters in this study can be introduced in the following two steps. First, to test for a local spatial autocorrelation, we adopt the indices of LISA statistics and convert them into a latent dummy variable as a dependent to estimate the multinomial logistic model in the next step. Second, after identifying and classifying the spatial clusters, we assess the relationship between the dependent and independent variables and further compute the marginal effects of a unit change in the independent variables on the dependent variable.

5.1. Local Indicators of Spatial Association

To analyze the outcome of local spatial agglomeration, as proposed by Anselin [29], we use the following LISA statistics test:

$$I_i = \frac{(Y_i - \bar{Y})}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \times \sum_{j=1}^n W_{ij}(Y_j - \bar{Y}), \quad (3)$$

where I_i is the LISA value for parcel i , n is the number of observations, Y_i and Y_j are the values of the certified areas for parcel i and j , $\bar{Y}$ is the mean of the certified areas for the entire region, and W_{ij} is the spatial weight matrix used to define the relationship between parcel i and j .

To identify the spatial scale of clustering, we use LISA statistics to group the spatial clusters of certified areas, namely hot, neutral, and cold spots. Once the LISA index, I_i , is computed as in Equation (3), we estimate the Z-test statistics as follows:

$$Z_i = \frac{1 - E(I_i)}{\text{Var}(I_i)}. \quad (4)$$

Under the null hypothesis of no spatial autocorrelation in Equation (4), the significance level or p -value allows us to test for a local spatial autocorrelation.

We extend Marasteanu and Jaenicke's [19] work to maintain the test results of the univariate LISA statistics, which compares the level of certified areas in an organic parcel to that of the same attribute in a neighboring parcel. Then, we use the latent dummy variable for the outcome of the LISA statistics to estimate the multinomial logistic model in the next stage. Thus, the value of the dummy for hot spots defined as parcels with positively correlated and high-value certified areas is two, whereas that for cold spots defined as parcels with positively correlated and low-value certified areas is one. Similarly, the value is zero for neutral spots whose size of certified areas is not statistically significant.

5.2. Multinomial Logistic Model

We identify three groups of spatial clusters for certified areas: Hot spots with a high mean value surrounded by high, cold spots with low mean value surrounded by low, and neutral spots with a high (low) mean value surrounded by low (high). Since there are multiple choices and we are particularly interested in the spatial effects of the independent variables on each outcome, the adoption decisions for operators regarding important factors are modeled using a multinomial logistic model.

The unordered response of the dependent variable, that is, the level of significance for LISA's Z-test, can be converted into a latent dummy variable since Y_i^* takes the values of $j = 2, 1, 0$ for different spatial clusters. In particular, the model explores the probability of hot ($j = 2$), cold ($j = 1$), or neutral ($j = 0$) spots. The determinants associated with each group can be contrasted with the base group, which comprises neutral spots in this study. We examine how, ceteris paribus, changes in the elements of the independent variables affect response probabilities [31], assuming the estimated coefficients for the base group is zero [32].

The mode is as shown in Equation (5):

$$\Pr(Y_i^* = j) = \frac{\exp(\beta_j' x_{ij})}{1 + \sum_{k=1}^J \exp(\beta_k' x_{ij})} \quad j = 0, 1, 2, \quad (5)$$

where k is one of the j subgroups, $\Pr(Y_i^* = j)$ is the probability that the i th organic farmland parcel belongs to the k subgroup, and x_{ij} denotes the characteristics of production and the environment for an organic farmland excluding the certified areas in Table 1. In line with Amemiya [33], the model performs well, although the alternatives are dissimilar, and it reveals significant differences between the hot and cold spots of organic rice farming in Taiwan relative to the neutral spots.

6. Results and Discussion

6.1. Spatial Clusters

We computed the indices for the LISA statistics in Equation (3) to examine the certified areas of organic rice. According to the significance level noted in the previous section, we plotted a map of the LISA clusters, as shown in Figure 2. The red points represent hot spots in certified areas where the organic farmland parcels and its surrounding area are significantly higher than the average value. More specifically, the certified areas of these parcels are positively spatially correlated with the higher values for the size of the certified areas. Further, we find evidence of a local spatial autocorrelation in the certified and their neighboring areas with similarly high proportions of organic rice cultivation.

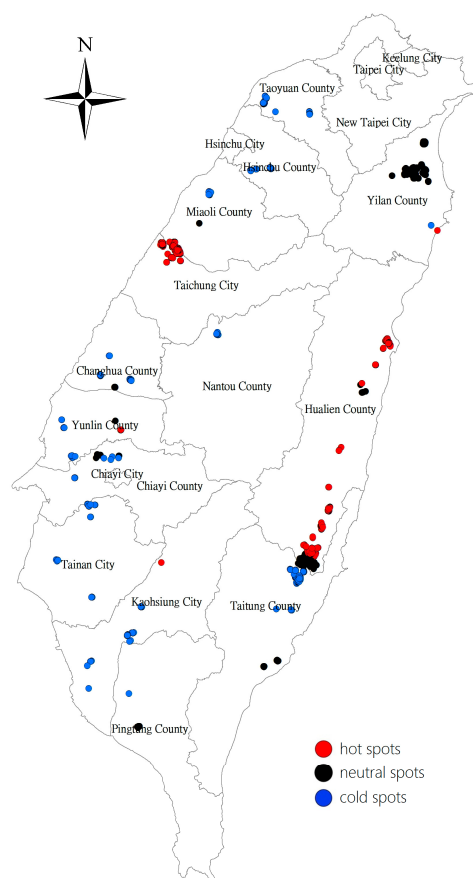


Figure 2. Result of LISA. Source: authors' research using ArcGIS.

The blue points denote cold spots where organic farmland and its surroundings are positively spatially correlated with certified areas of lower value. The black points are neutral spots classified as spatial outliers whose certified areas report no statistical significance. The results for LISA show that a majority of the hot spots are distributed in the eastern region and a portion of the western region in Taiwan, namely the counties of Hualien, Taichung, and Miaoli. In addition, the neutral spots are largely located in Yilan and the junction between Hualien and Taitung. Clusters of cold spots are mainly diffused along the western region, particularly in its central and southern counties, where there are principal agricultural production areas for rice that employ conventional agriculture methods. In such areas where organic agriculture already has a foothold, we believe a policy aimed at promoting organic agriculture will be more effective.

In sum, there is spatial dependence in the spatial clustering effects on certified areas of organic rice and this empirical result is consistent with those of previous studies highlighting the influence of spatial clustering on the distribution of organic farming [34–36]. In addition, we find statistically significant hot and cold spots of certified organic rice farming in line with the definition proposed by LISA. From a policy perspective, it is imperative that the COA accounts for spatial dependence when offering assistance to organic farmers.

6.2. Multinomial Logistic Model Results

Table 2 summarizes the estimation results for the multinomial logistic model. The total sample size is 2987 and the log-likelihood value is -2082.35 . In addition, the pseudo- R^2 is about 0.338 and the probability of the likelihood ratio test is 0.000, indicating that the model works well and helps determine the differing significance between the hot and cold spots of organic rice farming in Taiwan relative to the base group of neutral spots.

In general, the estimated coefficients for the model cannot directly explain the effect of dependent variables on the probability of organic certified areas. In other words, the coefficients are not quantities of interest. Therefore, we further estimated the marginal effects of each cluster. As reported in Table 2, the effects of independent variables are all statistically significant for hot spots. For instance, for the negative environmental measures, we find that once the magnitude of potential inundation becomes more severe, the probability of an organic farmland becoming a hot spot declines (0.887), whereas that of areas becoming cold spots increases (0.923). According to Chen [37], the extent of potential inundation is spatially correlated with agricultural damage and loss in Taiwan. Therefore, our results further evidence the impact of potential inundation on the pattern of spatial clusters and implies that the magnitude of potential inundation influences the development or size of certified areas for organic rice cultivation.

As for the impact of strata subsidence, once the degree of subsidence increases, the probability of an organic farmland becoming a hot spot decreases (0.487), whereas that of areas becoming cold spots increases (0.566). That is, the severity of strata subsidence will result in significantly smaller and clustered organic certified areas of rice. In addition, agricultural activities that rely on irrigation may contribute to groundwater depletion in aquifer systems [38]. Thus, undoubtedly, the rate of ground subsidence is likely to peak in areas where agricultural activities rely on groundwater exploitation. Our study documents the problem of strata subsidence in the spatial clustering of certified areas for organic rice and appeals to the government that it remains increasingly aware of this concern given that irrigation water for rice accounts for the largest proportion of agricultural water consumption in Taiwan.

Table 2. Estimated results for the multinomial logistic model.

Multinomial Logistic Model						
Variable	Estimate		SE	Marginal Effect		SE
Cold Spots						
c_year	0.060		0.103	0.055		0.226
Inundation	−3.976	***	0.349	0.923	***	0.178
dis_landslides	−0.131	***	0.023	0.013		0.053
dis_indust	−0.060	***	0.003	0.011		0.007
operator_1	3.215	***	0.413	−0.590	***	0.200
operator_2	3.353	***	0.411	−0.301		0.381
natural productivity	−0.135	***	0.016	0.029	***	0.004
d_subsiden	−8.992		485.693	0.566	***	0.070
constant terms	−0.061		0.417			
Hot Spots						
c_year	−1.682	***	0.155	0.087	**	0.034
inundation	−2.507	***	0.611	−0.887	***	0.199
dis_landslides	0.365	***	0.027	−0.048	***	0.011
dis_indust	0.035	***	0.005	−0.016	***	0.003
operator_1	1.227	***	0.273	0.630	***	0.132
operator_2	−2.761	***	0.297	0.737	**	0.287
natural productivity	−0.026		0.022	−0.033	***	0.008
d_subsiden	−3.269	**	1.349	−0.487	***	0.070
constant terms	−1.382	***	0.335			
Neutral Spots						
c_year				−0.142		0.201
inundation				−0.036		0.342
dis_landslides				0.035		0.043
dis_indust				0.005		0.004
operator_1				−0.039		0.078
operator_2				−0.436	***	0.101
natural productivity				0.003		0.005
d_subsiden				−0.079	***	0.012
constant terms						
Log-likelihood	−2082.35					
pseudo-R ²	0.338					

Source: authors' research using Stata. Note: ** and *** denote significance at the 5% and 1% level, respectively.

Meanwhile, if the distance to landslide-prone areas from the organic farmland increases, the probability of hot spots will significantly decrease, *percentile* = 0.048. That is, if the farmland of hot spots is located away from a hillside, the clustering phenomenon will be weakened. Our result is in line with that of Koesling [39], who finds that the locations of organic farmers are a key factor. As a result, it reflects that most of the agricultural production areas are far from the urban regions in Taiwan.

In terms of the positive environmental measures, we find that natural productivity has a considerable marginal impact on the certified areas (Table 2). For instance, once the level of natural productivity improves, the probability of certified areas becoming a hot spot decreases (*percentile* = 0.033), whereas that of areas becoming cold spots significantly increases (*percentile* = 0.029). In other words, the improved fertility of organic farmland is not a favorable factor or incentive for farmers to further engage in organic farming. As reported in Table 1, the average level of natural productivity for each cluster is nearly the same, ranging between 3.325 and 3.762. Further, since the 10th level is the most suitable level of natural productivity for agricultural activities and the average level for the sample is 3.547, organic farming is likely to occur in agriculturally less-favored areas, a result which is consistent with that of Gabriel [14].

Our findings for the characteristics of production suggest that if the proportion of operational patterns for individual or agricultural production and marketing groups increases, the probability of certified areas becoming hot spots significantly increases by 0.737 or 0.630, respectively. For cold spots, once the proportion of agricultural production and marketing groups increases, the probability to be in these clusters dramatically decreases to 0.59. This result coincides with Qiao's [40] findings, which reveal that organic farming contributes to a greater increase in farmer income for individual operators than those using conventional agriculture methods. Our research further evidences the role of spatial dependence in organic farming: That is, compared to large-scale operational patterns, an increase in small-scale farmers or production groups significantly increases the cluster size of certified areas as hot spots.

The descriptive statistics in Table 1 highlight that a majority of the operational patterns for hot and cold spots is agricultural production and marketing groups (72.1%) or individual farmers (63%). Thus, for hot spots, an efficient way to expand the development of organic farming or certified areas is to expand the scale of agricultural production and marketing groups or even the number of individual farmers.

The results for hot spots in Table 2 suggest that if the number of organic certificates issued in or after 2009 increases, the probability of certified areas becoming hot spots significantly rises by 0.087. This result also reflects the effectiveness of the COA's new regulations proposed in 2009 for the certification management of organic agricultural products. In sum, it essentially urges the development of organic farming and the expansion of certified areas for the clustering of hot spots.

7. Conclusions and Policy Implications

Organic farming has been viewed as an effective alternative to achieve a balance between agricultural production and environmental protection, and thus, the sustainable development of agriculture. This study, therefore, aimed to evaluate the impact of spatial clusters for certified areas of organic rice farming using a unique dataset for production and environment characteristics, which were derived and extracted from official organic certified agencies and a series of map profiles. This study goes beyond a sizable body of the literature on clusters and spatial dependence by analyzing the relationship between local spatial clusters and organic farming.

Further, it employed an econometric approach that combines LISA statistics and a multinomial logistic model to evidence statistically significant hot, neutral, and cold spots of certified areas for organic rice farming and compared the results with those for organic spatial clusters. The results confirm the spatial spillover effects on certified areas in Taiwan and thus, can be used to interpret factors contributing to spatial clusters. In other words, it is necessary that the COA accounts for spatial dependence when designing incentives or subsidies for organic farmers.

Moreover, our analysis of factors contributing to the distribution of spatial clusters for organic rice cultivation serves as a starting point for further discussion on the formation of hot spots. The results highlight the impact of the magnitude of potential inundation and strata subsidence on the spatial cluster pattern and the development or size of certified areas. Further, the increasing distance to landslide-prone areas indicates that the clustering effects of organic hot spots will decrease. Thus, the government must increase its awareness about the sustainability of organic farming location and farmland protection.

This study also suggests that organic farming is likely to occur in agriculturally less-favored areas and improved fertility in organic farmland is not a favorable factor or incentive for farmers to expand their certified areas for spatial clusters. As for operational patterns, a majority of the organic operators for hot or cold spots are agricultural production and marketing groups or individual farmers. Thus, an efficient way to expand the development of organic farming or certified areas is to increase the number of agricultural production groups and individual farmers.

Our findings have key policy implications. First, to promote the development of organic farming, the spatial clustering results in our study can be referenced to select a special district for agricultural

production. Second, in terms of a verification mechanism, the formation and implementation of regulations may lead to large-scale organic certified areas reporting a spatial agglomeration effect. Finally, given that the organic operational patterns for individuals or agricultural production and marketing groups are mainstream for hot spots of certified areas, offering incentives to expand the scale of such operators or associations seem to be an efficient approach at a policy level.

8. Limitations

As highlighted in previous studies [8–10], the prices of agricultural products are an important factor for farmers who chose to shift to organic farming. However, the lack of data on the sales or consumption of organic products hinders our ability to explore demand and consumption behavior in Taiwan.

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