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The Changes of Farmland by Using Spatial Cluster on the Case of BeiNan Township in Taiwan

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Abstract

The main objectives of this study are, (1) to investigate the influences of farmland policies on land use patterns and, (2) to examine the changes and statuses of land transactions and farmhouse construction projects and determine the influence of changes in the restrictions of farmland use and farmhouse construction on the trends of farmland transactions and transfers and the locations of farmhouse constructions projects, thereby validating the development trends of farmland and farmhouses. A spatial analysis was performed to examine the spatial clustering conditions and locations of farmland transactions and farmhouses in Taitung County. Regional analysis was performed by examining local indicators of spatial association (LISA). A year-over-year analysis was performed on the scope and degree of farmhouse clustering within the target area to determine farmland use patterns, distribution statuses, and the impact of annual location change on rural development in the target area. An analysis of the historical land transaction and building change data revealed that "laws and regulations" were the main factors influencing farmland transaction. The density of farmland transactions increased closer to main traffic routes. The findings of this study highlighted rural change and validated urban sprawl.

Keywords: land use, agricultural policy, spatial autocorrelation, agriculture land-use change

1. Introduction

In agriculture-oriented areas, limited resources and the lack of overall farmland use plan have led to severe population displacement and aging. Land use patterns change rapidly to meet the diverse requirements of fast-growing cities(Wang et al.,2016). Therefore, farmland on the fringe of urban settings compensates for the land demand of urban planning, becoming the most immediate areas for urban sprawl. Urban populations spread outward from the original point of clustering, gradually encroaching on fringing suburban areas and forming low-density, single-function communities highly dependent on private automobiles for transport. According to past spatial development research, the process of urban sprawl is typically decentralized (population dispersion without a clearly defined center), causing leapfrog expansion that creates areas of development with discontinuous open spaces and separated community functions (Reid, 1997). Moreover, the absence of targeted land management and utilization plans during urban sprawl results in inadequate infrastructure to support development, leading to environmental deterioration, aggravated spatial differentiation, and devitalization of existing urban areas(Batty et al., 2003; Audirac et al., 1990; Bhatta et al., 2010; Wu, 2013). Rural settlements change amidst the invasion and development of farmland, consequently altering rural landscapes and impacting the social economy (de Koning, 1998). The actuators of agrarian change can be classified into pulling factors and pushing factors, which include economic determinants(Chen and Liu, 2013; Harris and Todaro, 1970; Patnaik et al.,2015; Chakraborty, 2014; Perz,2000; Vyn and Rude, 2019) and social determinants(Chakraborty, 2014) , and mobility needed(Pojani et al., 2020). In recent years, natural disasters have forced urban dwellers to relocate to rural areas(Kona et al., 2018; Liang and Ma, 2004; Ishtiaque and Nazem, 2017; Husby and Koks, 2017) in search of better security and quality of life. However, those who relocate from cities to the suburbs must acquire land and construction permits regardless of whether their intentions are economic or social. These factors fuel the demand for farmland transactions(Vyn and Rude, 2019; Monkkonen, 2011; Charlotte, 2009) and prompt the alteration and revision of farmland management policies(Kassie, 2017; Chen, 2011; Lin, 2002; Innes, 2003; Vigani and Kathage, 2019; Villoria, 2019). The adjustment of land management policies significantly impacts the scope of farmland use and development, resulting in tangible changes to the landscape, farmland use patterns, and agricultural production(Arkadi, 2016; Njoh, 2010; Assche et al., 2022).

In order to accelerate the modernization of agriculture, respond to the internationalization and liberalization of agriculture, and promote the rational use of agricultural land, the Taiwan government revised the Agricultural Development Regulations in 2000 to guide the management of agricultural land to "relax agricultural land ownership and implement agricultural land use". Along with the variation of land management policies, promoted the increase of agricultural land transaction volume, which in turn affected the changes of agricultural land.

Previous studies for the farmland change have accomplished a great deal by applying literature or on the influence of Acts. However, there are few studies that draw attention to the change of farmland. This research takes a somewhat different approach. We studied on the farmland change with real data of farmland transactions and farmhouse construction data based on BeiNan township, a small town where locate nearby the main urban of Taitung and has been experiencing farmland change. The data are sort out the cadastral registration of the Agricultural Development Act revised in 2000 to the present. Applying spatial statistical analysis theory to carry out spatial correlation analysis, and examine whether non-urban land farming and pastoral land transactions and farm buildings have positive spatial correlations and overall spatial aggregation relationships over the years, and present the research results in terms of spatial changes.

2. Research Literature

Although modern urban development models significantly changed the impact of location distance on land use, the spatial structure of land use remains implicated by various regulatory, political, and social factors(de Koning et al., 1998; Jiang and Cheng, 2020). Under mandatory land management policies, farmland is a crucial factor influencing the urban landscape of a free market.

Studies on farmland changes are typically presented as spatial analysis and spatial distribution results. The applied theoretical models involve applying data mining techniques, decision trees, and artificial neural networks to determine the association results of the data and design a distribution model for the likeliness of change(Wu et al., 2013). Cluster and spatial autocorrelation analyses are generally performed on spatial data to determine spatial distribution scope and density(de Koning et al., 1998; Wu et al., 2013; Anselin and Getis, 1992; Wang et al., 2019; Wong, 2003; Brasington and Hite, 2005; Silverman, 1986). A cellular automaton (CA) model is generally created to run growth simulations and estimate change trends(Wang et al., 2010). Many studies employed the modeling tool of the IDRISI geographical information system (GIS) for spatial simulations(Lee, 2011), de Koning et al.(1998), Weng(2012) and Wei (2013) and performed a regression analysis to investigate the factors influencing farmland change, while also applying data mining techniques to determine the association results of the spatial data to build spatial distribution models that highlighted the likeliness of land change(Chang, 2005). In recent years, many studies have used GISs to analyze data, present spatial distribution, and regional forecast development (Liu and Yang, 2015; Liu et al., 2016).

3. Methodology

3.1 Kernel Density

Kernal density tools are used to calculate the density of specific features within an area. Features can be either points or lines.

The kernel function can be expressed as Eq. (1)(Silverman, 1986):

$$\text{Search Radius} = 0.9 \quad 0.9 \times \min\left(\text{SD}, \sqrt{\frac{1}{\ln(2)}} \times D_m\right) \times n^{-0.2} \tag{1}$$

SD refers to standard distance, and Dm refers to median distance. If the population field is left unused, then n is a point value. Otherwise, n is the sum of all values in the population field.

3.2 Spatial Autocorrelation

Spatial statistics are the statistical analysis of geographical relations, including spatial distribution, spatial autocorrelation, and spatial association. The primary approach incorporates spatial dependence concepts into statistical analysis to better forecast data and produces effective parameter estimates(Wang et al., 2019; Wong, 2003; Griffith, 1992; Unwin, 1996). Subsequently, "autocorrelation" refers to the analysis of similar attribute variables for different observation targets. Spatial autocorrelation is the statistical analysis of spatial attribute variables to determine the degree of autocorrelation. The results show the distribution of spatial units within a given space. The purpose of such an analysis is to determine whether similarities are present between the attributes of a spatial unit and those of its neighboring spatial units or whether the clustering of spatial units is simply a probability error(Flahaut et al., 2003). Theoretical models are used to calculate correlation coefficients. "Spatial clustering" can be confirmed if the analysis outcomes show a positive correlation. If the analysis outcomes show no correlation or the data do not follow a specific set of rules, then "spatial randomness" can be confirmed. The indicators for calculating spatial autocorrelation can be categorized into two groups: global spatial autocorrelation and local spatial autocorrelation. The Moran's I statistical method is most frequently used for the former indicators(Cliff and Ord, 1981). Its function is to describe the overall distribution of a phenomenon and determine whether it has clustering characteristics in a given space. For the latter set of indicators, Anselin (1995) proposed the LISA methodology to deduce the scope of local clustering. A statistical significance test was performed to determine the clustering of spatial units. The outcomes are representative of the spatial clustering of the given region.

Moreover, the method can also measure the influence of the spatial units on the autocorrelation of the overall research scope. An enormous impact generally denotes a local "exception," or the point of clustering in a spatial phenomenon. A review of existing literature revealed that the Moran's I method was most frequently used to test global spatial autocorrelation, and the LISA analysis method was most commonly used to test local spatial autocorrelation.

3.2.1 Global Moran's I

Spatial autocorrelation is the quantification of the potential spatial dependency of a geographical phenomenon. It describes the similarities between the location of a phenomenon and its neighboring areas. To elucidate spatial clustering (Goodchild,1986) is to describe the overall distribution situation, which can be achieved by assessing feature locations and related attributes. Subsequently, the cluster models, discrete models, or random models can be obtained by calculating the Moran's I index, Z score (standard deviation), and p-value (probability). (de Koning et al. 1998)

The global Moran's I index can be expressed as Eq. (2):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} Wji} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} Wij\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{2}$$

where n represents the number of regions, x_i the attribute values of the ith and jth areas, and $\bar{x}$ represents the mean variable value in each region. Wij represents the spatial adjacent weight matrix, which illustrates the adjacent relationship of each spatial unit in the ith and jth areas of the research scope. 1 means that i and j are adjacent, and 0 represents that i and j are not contiguous. The Moran's I index is a value between -1 and 1. A value greater than 0 denotes a positive correlation, while a value less than 0 denotes a negative correlation. A high value indicates a strong correlation, or rather, a spatial solid clustering(Chen, 2001). The spatial autocorrelation (Global Moran's I) tool is used for inferential statistical analysis. If the p-values and z scores of the analysis results achieve statistical significance, the null hypothesis can be rejected. If the Moran's I index is a positive value, a clustering trend is confirmed.

We performed a significance test on I. The Z(I) score was an absolute value greater than 1.96, and the p-value was smaller than 0.05, denoting a 95% significance level. Therefore, spatial autocorrelation was confirmed. When using the spatial autocorrelation (Global Moran's I) tool, a spatial weight matrix can be used to select adjacent elements' parameters in the conceptualization of spatial relations to define spatial relations. A spatial weight matrix document can be generated for spatial autocorrelation analysis.

3.2.2 Local Indicators of Spatial Association

Anselin (1995) proposed the LISA methodology to determine local spatial autocorrelation and calculate spatial hot spots. Local spatial autocorrelation can be expressed as Eq. (3).

$$L_i = \frac{\left(x_i - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \sum_{1}^{n} W_{ij}\left(x_j - \bar{x}\right) \tag{3}$$

Equation 3 was used to calculate the significance of the spatial grid. A significant and positive spatial autocorrelation denotes that a specific zone is encapsulated by zones with similar attributes, leading to spatial clustering. A higher significance represents more robust spatial clustering. When the observation values of the target zone and neighboring zones defined by the grid are high, the zones are collectively referred to as a hot spot, highlighted as High-High (HH). When the observation values of the target area and neighboring areas, are collectively regarded as a cold spot, represented as "Low-Low (LL)." When the observation value of the target area is high, and those of the neighboring regions are low, they are collecting represented as "High-Low (HL)." When the observation value of the target area is low and those of the neighboring areas are high, they are collectively represented as "Low-High (LH)" (Anselin, 1995).

In this study, we transferred the local spatial autocorrelation (LISA) results to the ArcGis System for display analysis. The results can be plotted on a fundamental property transaction map of the research area. Then, we examined the development situation of the research area coupled with the LISA value definitions of HH, LH, LL, and HL to elucidate whether farmhouse clustering is present in the research area and distribution of farmhouses.

3.3 Data Sources and Processing

3.3.1 Description of Empirical Research Area

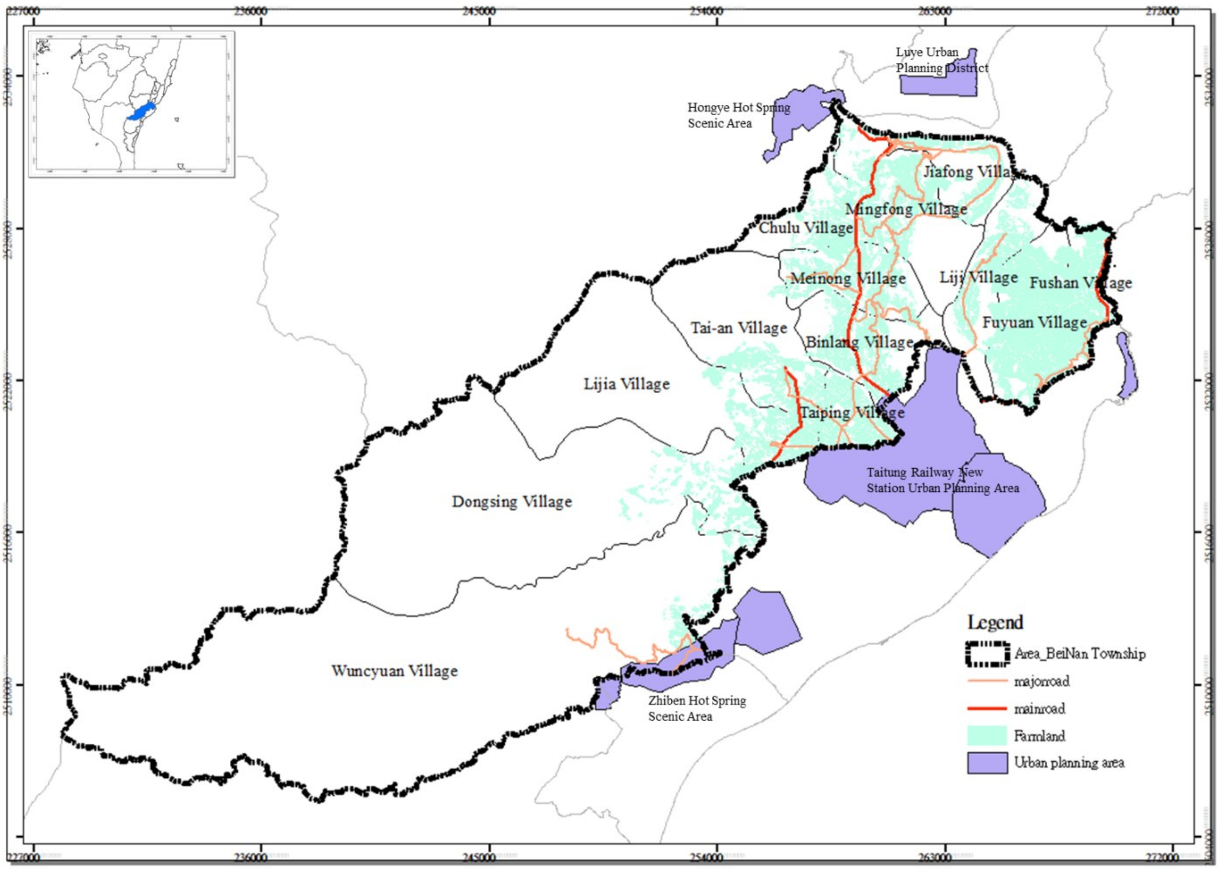


Figure 1. Research Area, a Small Satellite Township Located at Taitung County, Taiwan

We adopted Beinan Village, a small satellite township located southeast of Taiwan as the area for empirical research. The town's name 'Beinan', in indigenous native language is 'Puyuma', which means centralized or unity. Due to the settlement's around by the main urban planning area such of Taitung New Satation, and Zhiben Hot Spring scenic area, and Hongye Hot Spring Scenic Area, and Luye Urban Planning District, and Siaoyeliu Scenic Area. Traffic connections are convenient and as the portal that must pass to enter the Rift Valley Plain. It also possesses a rich diversity cultural heritage such as foods, handicrafts and natural landscapes(Fig.1), . Tourists come here around the seasons to stay and visit. B&Bs with beautiful natural landscapes and recreational resources have become the goal of the metropolitan area to chase idyllic dreams. Therefore, land transactions are gradually becoming hot. As a small town with a population of nearly 17,000 which living in 3,703 buildings, 296 buildings are located in agricultural and pastoral land. The area of agricultural and pastoral land is 78.09 square kilometer, a partial of 18.9% of the total land area of Beinan Township. Because of its special geographic location, it has become a popular area for farmland trading and farmhouse construction. However, due to the variation of land management policies and changes in land use, it will affect the townscape of Beinan Township.

3.3.2 Data Processing

Statistical data of the area released by the government were collected and compiled. The observation indicators included overall land transaction volume, property transaction reports, and construction permit application volume. After that, the search was narrowed to property transaction reports of farmland and permit applications to construct farmhouses.

(1) Land registration information

To build a database of non-urban land change information over different years, we collected the secondary data released by land administration offices. We collected and sorted the registration records of non-urban land and buildings starting from the end of 2016 and obtained cadastral maps and spatial coordinates based on section number, parcel number, and construction number. Then, a spatial overlay analysis was performed by merging the collected data with road network maps and village border maps.

(2) Property price reports

Property price reports between 2013 and 2016 were collected. The reports were classified by county and township. The data extracted from the reports included (1) total transfer area, (2) land zone and type, (3) date of transaction, and (4) total transaction price and average unit price.

(3) Statistics released by the Ministry of the Interior

Registration and change statistics in different years: Registration statistics between 2001 and 2016 were collected. The data were classified by county. The content of the data included:

A. Reason for registration: division

B. Reason for change in ownership: buying and selling

C. Number of changes and area and total annual area

(4) Construction and Planning Agency: Issuance of construction permits

Data on the issuance of construction permits between 2001 and 2016. The data were classified by county. The content of the data included:

A. Number of cases, number of households, total floor area, project cost

B. Purpose: residence or farmhouse

C. Annual permit issuances, area, and project cost

The data sources of this study were the available statistics related to government organizations and the latest registration records of land administration offices. Land and building registration records were collected from the land administration system. The records were categorized by parcel number and construction number. Each dataset was managed based on the reason for registration and case number, and all data were updated frequently. The changes to each dataset had a reason and date. However, we were unable to compile these changes in chronological order. Therefore, we adopted the end of 2016 as the cut-off point for data collected. The data were then converted to serve as the base data for spatial analysis.

3.3.3 Data Selection

We requested land and building registration records from various land administration offices and selected the columns relevant to this study. The data were sorted and re-tabulated for analysis.

(1) Land data:

The scope of research was BeiNan Village, Taitung County. The farmland information in each zone included section number, parcel number, area, zone, land type, disclosed current value, disclosed land price, the reason for registration, date of registration, and construction number.

(2) Building data:

The building registration data of BeiNan Village were compiled into two categories, construction land in different zones and building information of different land types. We targeted records involving farmhouses in this study. The data included section number, construction number, purpose, total building area, floor area, primary structure, and parcel number.

(3) Change data:

The reason and content for the change in registration were sorted by year. The main screening criteria were:

A. Reason for transaction/transfer: buying and selling

B. Reason for registration: land division

C. Reason for addition: the first building

(4) Cadastral maps

The section numbers and parcel numbers of farmland extracted from the registration records were plotted on cadastral maps to obtain the spatial coordinates and determine spatial distribution.

3.3.4 Data Transformation

The data obtained in this study were the last changes recorded in the current database. Therefore, the data was mainly sorted by parcel number and construction number. The content is then presented sequentially after the parcel number. Thus, flagged data and ownership data were present simultaneously. The data were converted into a text format.

Then, the text format was tabulated into tables used by the database, and the field content was converted into the required format for subsequent analysis. The conversion process is explained below:

(1) Land registration information

A. Based on the legal terminology used in previous studies, the targets of this study were non-urban farmland in various zones. Therefore, the land information consistent with our search criteria was sorted based on section, parcel number, and zone.

B. We then tabulated the land information into datasheets. The key values were section numbers and parcel numbers.

C. We examined the zoning of cultivation land after the revision of relevant laws and regulations. Therefore, the farmlands examined in this study included those located in special farming zones, general farming zones, hillside conservation zones, and forest zones. An extra column was added to the land data to note the different zones. If building data is present in the land data, an additional column was added to note the building data.

D. The date of registration was based on the calendar used in the Republic of China. To maintain consistency, all dates were revised to the Gregorian calendar.

E. For changes in registration, we selected buying and selling, gift, inheritance, auction, trade, the first building, and addition as the reasons for registration. The dates of change were presented in the Gregorian calendar format, and the data were sorted based on section and parcel number. The number of changes recorded was also calculated for subsequent analysis and comparisons.

(2) Building registration information

A. The main reasons for the change in farmhouse registration on the land administration system were first building, addition, and loss. The data were sorted based on year, section, and parcel number.

B. For total floor area and base area, the associated land area corresponding to the parcel number was used to calculate the building coverage ratio.

C. The number of ownership changes was analyzed to determine the ownership period and number of changes for subsequent analysis and comparisons.

D. The parcel numbers and spatial coordinates on the cadastral maps were merged to establish point features for subsequent spatial distribution analysis.

(3) Cadastral map information

A. The cadastral maps of the various sections within the research scope were consolidated into the ArcGIS

(*.shp) polygon feature format.

B. The Feature-To-Point tool was employed to obtain the geometric midpoint coordinates of the polygon feature. Then, the Create Feature Class function in ArcCatalog was used to add features and convert tables with X and Y coordinates into point features.

(4) Combining attribute data and cadastral maps

The cadastral map data were converted into polygon features and point features and stored in the ArcMap Database. The change attribute data were correlated based on year. Section number and parcel number were adopted as the fundamental values to create annual cadastral maps on spatial change.

3.4 Applying Data

A total of 9,466 datasets on registered changes to non-urban farmland between 2001 and 2016 were collected. Of which, 3,695 datasets involved transaction (incl., duplicated transactions; accounting for 39%), 1979 datasets involved gifting (accounting for 21%), 147 datasets involved division (accounting for 17%), and the remaining datasets involved merging, inheritance, co-division, and exchange. The land change statistics are tabulated in Table 1.

Table 1. Count of Transactions in Each Land Use Zoning

Reason for change	Land use zoning									
	Specific agri-cultural area	General agri-cultural area	Hillside Conser-vation Area	Scenic area	Forest area	Rural area	Specific dedicated area	River area	transaction Quality	Percentage of total transaction volume (%)
Segmentation	538	115	719	147	0	0	49	5	1573	17
Merge	138	41	164	29	0	0	7	0	379	4
Trading	1478	279	1522	330	0	0	79	7	3695	39
Give	983	97	799	72	0	0	19	9	1979	21
Inheritance	684	118	719	54	0	0	14	7	1596	17
Co-segmentation	102	14	94	11	0	0	2	0	223	2
Exchange	15	0	3	3	0	0	0	0	21	0%

4. Results and Discussion

4.1 Change of Farmland Transactions and Farmhouses

In this study, we examined land transactions and above-ground building registration data to determine the status and trends of farmland transactions after the Agricultural Development Act was revised to allow the free trade of farmland. After eliminating duplicate transaction data, there were 3,671 datasets on post-transaction farmland change. Figure 2 is a statistical charge of farmland transactions between 2001 and 2016. The number of transactions in BeiNan Village, Taitung County, reached a high point starting in 2000. The trend tapered between 2001 and 2005, yet average transaction cases remained high. The number of transactions increased exponentially in 2006, reaching a record high, and then gradually declined in 2009 and 2012. After the overhaul of the Regulations for Farmlands and Construction of Farmhouses in 2013, the number of transactions reached another record high, and the high number of cases persisted for two years. An analysis of major government policies showed that opening up to foreign investment, completing the Huadong Railway Electrification Project, strengthening tourism promotion in Taitung County – and other beneficial policies – attracted foreign investments and drove up farmland prices. The level of transactions dropped to near average in 2015, and the revision of farmhouse regulations in 2016, which incentivized natural citizens from procuring farmhouses, led to an evident reduction in transaction volume. Because farmland must serve the dual purpose of residence and business, most land sold in the scope and research period was used to build farmhouses, agricultural production plants, and cargo yards. There were 3,703 buildings within the research area. Of which, 296 (8%) were farmhouses. These results show that government policies evidently led to the trend of farmland change and were key tools in utilizing farmland.

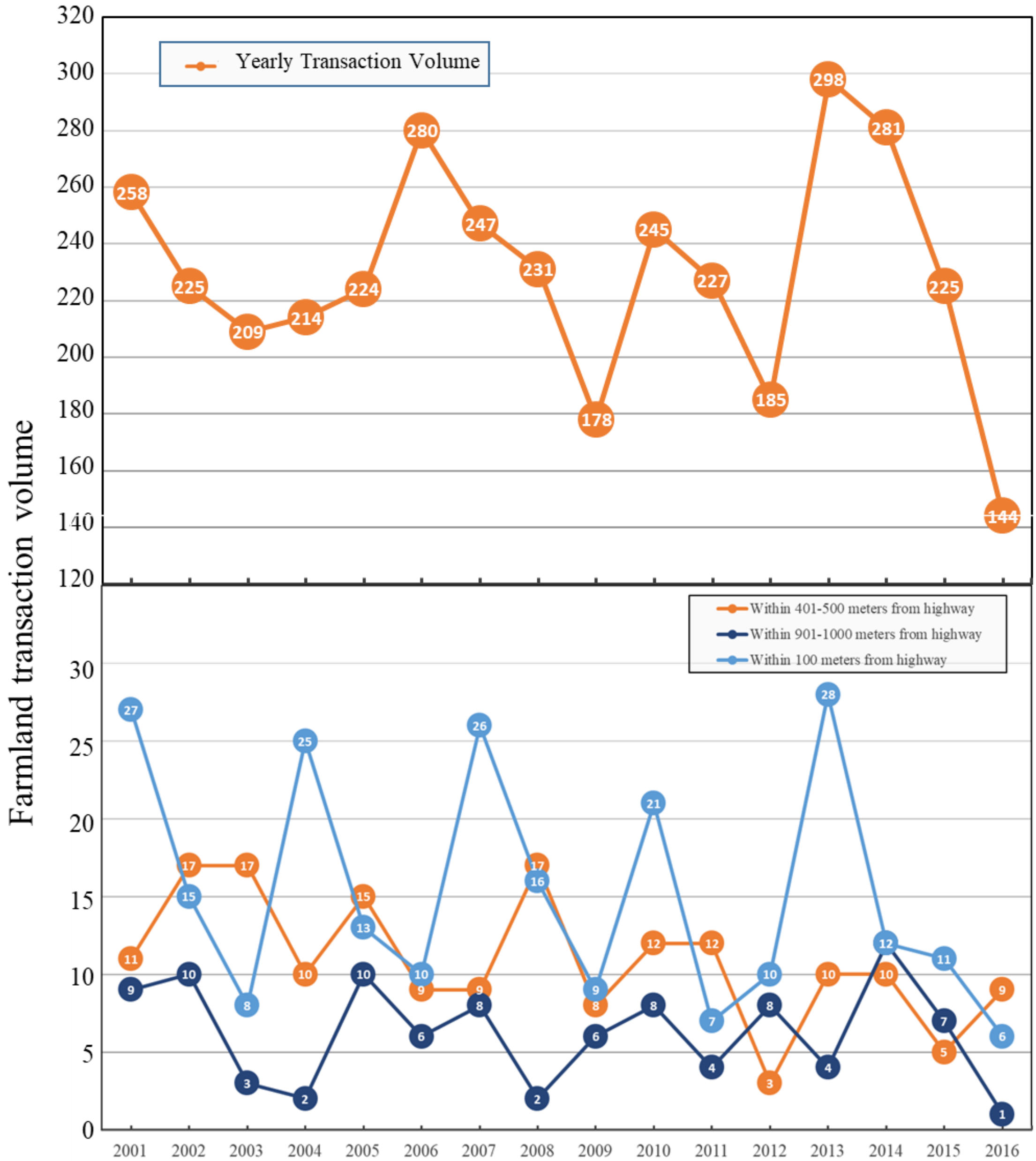


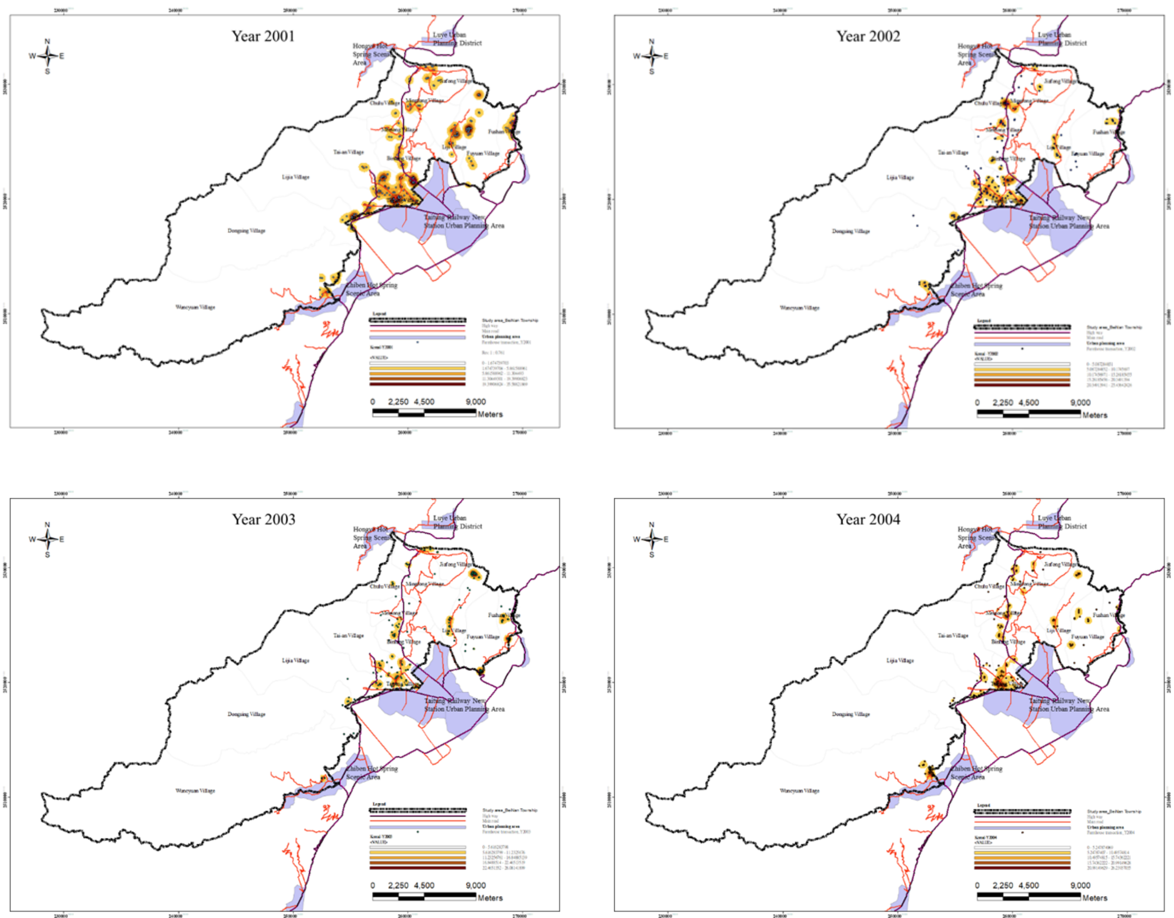
Figure 2. Yearly Statistical of Farm-land Transaction

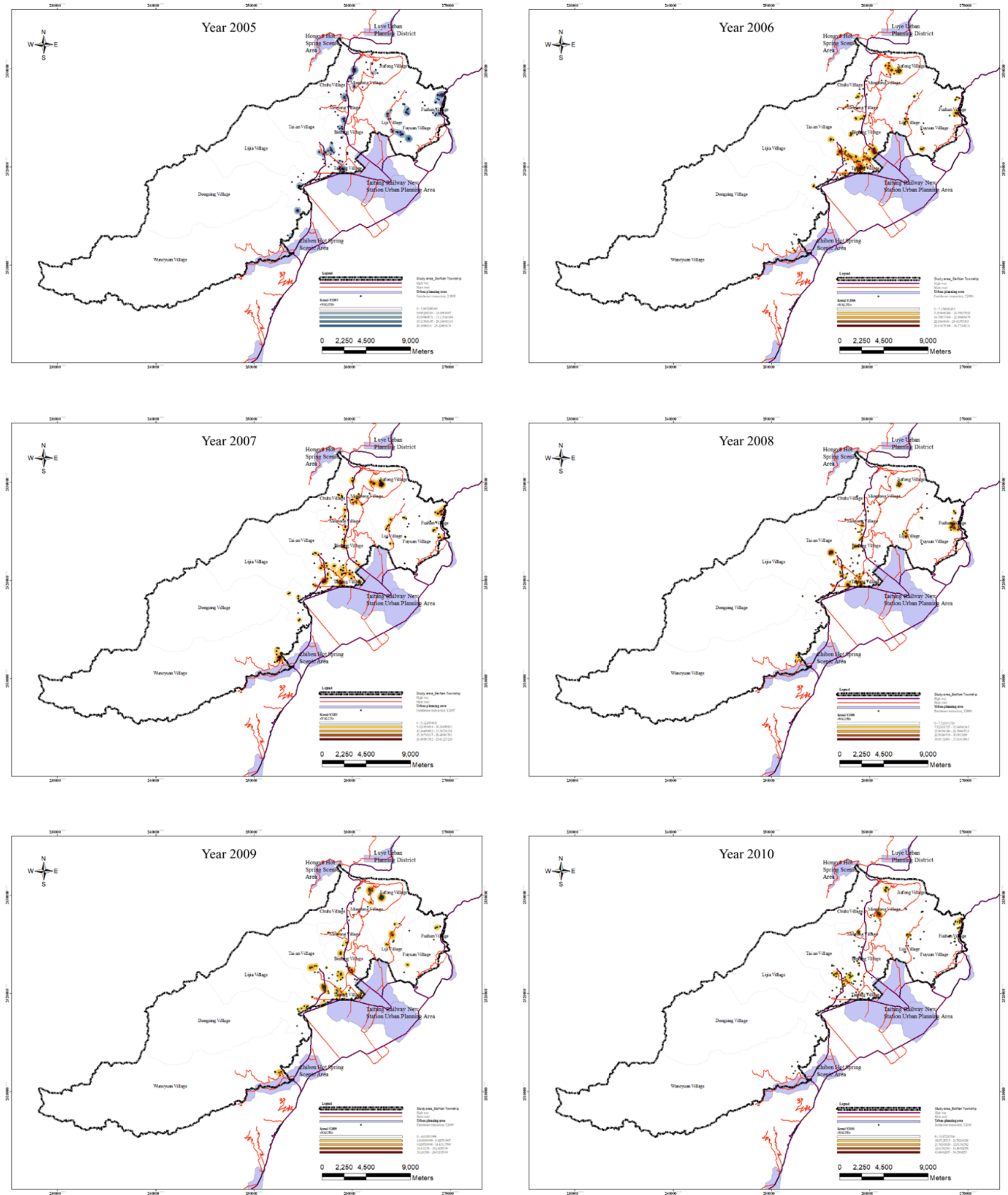
4.2 The Cluster and Changes of Traded Farmland

Land use patterns and prices are influenced by various factors(Ehwi et al., 2019; Wu, 1994). In this study, we used density analysis and spatial statistics to determine the spatial distribution of farmland transactions in BeiNan Village, Taitung County, and analyze land transaction hot spots and clustering characteristics. We used the ArcGIS analysis tool to estimate kernel density. We also used Moran's I and LISA to determine global and local spatial autocorrelation.

The research area was BeiNan Village, Taitung County. The entire area contained 35,553 registered plots of land across 413 square kilometers. BeiNan Village was not within the scope of urban planning. However, the east side borders the densely populated Xinzhan Urban Planning Zone, the south side is the location of the famous Jhih Ben Scenic Area, and the north leads to the Hongye Hot Spring Scenic Area and Luye Urban Planning Zone. Moreover, the highway and major roads run through BeiNan. Most of the buildings and farmlands are located to the east of the area, while the west side is mostly mountainous terrain. Therefore, farmland transactions were concentrated to the east of the research area. We performed a kernel analysis on farmland transactions conducted between 2001 and 2016. The results for each year are illustrated in Fig. 3 and Fig. 4. The figures show that transactions were concentrated near main roads and highways, presenting a shift from south to north. To verify that farmland transaction is the key factor influencing the diffusion of urban development to the suburbs, we focused on the following two aspects:

(1) The largest spatial cluster is the east area bordering the central urban planning zone in Taitung. Although the main urban planning zone in Taitung City provides excellent public facilities and access systems, the area is densely populated, and land for development is difficult to obtain due to scarcity and high land prices. By comparison, the price of farmland in suburban areas is low. Therefore, these suburban areas have become the main locations of construction. Land acquisition and construction are necessary regardless of whether the shift to suburban areas gains economic benefits or meets social needs. Once regulations on the trade and development of farmland are relaxed, the outflow of farmland development from the city to the suburbs will accelerate. Figure 5 is a spatial distribution map of farmland overlaid with farmhouse locations. The figure shows that the farmhouse construction hot spots coincided with the spatial distribution of farmland transactions and that the hot spots approximated the Taitung Railway New Station Urban Planning Area, suggesting that farmhouse construction and convenience of land use are correlated to the integrity of public facilities. To elucidate the impact of sold farmland on surrounding land transactions, we performed a spatial analysis of past land transaction locations using Anselin Local Moran's I to calculate the LISA, determine local spatial autocorrelation, and estimate the clusters of farmland transactions in BeiNan Village, Taitung County. Figure 6 illustrates the transaction zones based on the four LISA definitions. The results show that the farmland transaction hot spots (HH) coincided with the kernel analysis results. The hot spots were located near Taitung's main urban planning area and on either side of the main roads.




Year 2005
Year 2006
Year 2007
Year 2008
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Year 2010
Luye Urban Planning District
Taitung Railway New Station Urban Planning Area
0 2,250 4,500 9,000
Meters

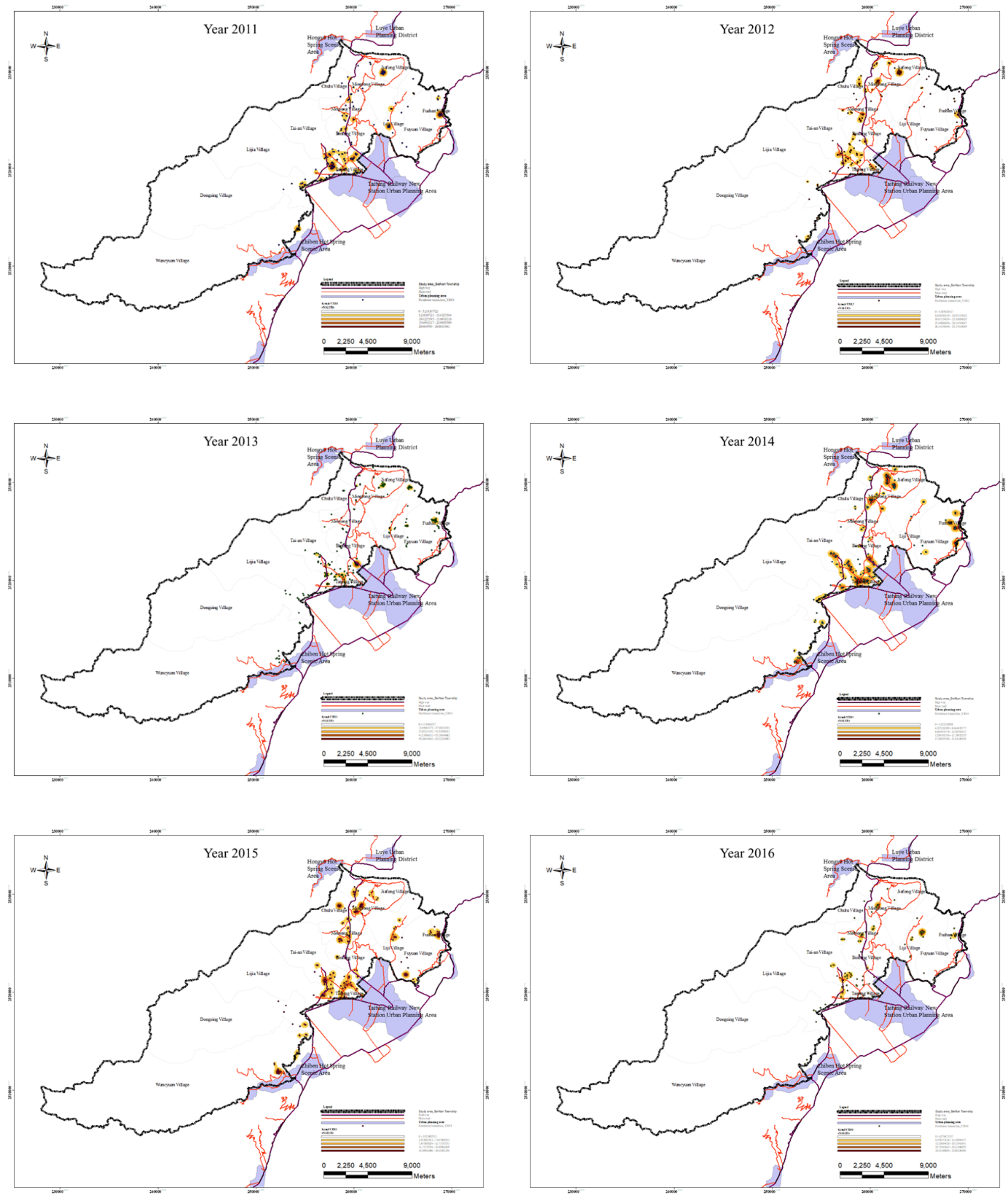

Figure 3. Yearly Kernal Analysis of Agricultural Land Transactions (from 2001 to 2016)

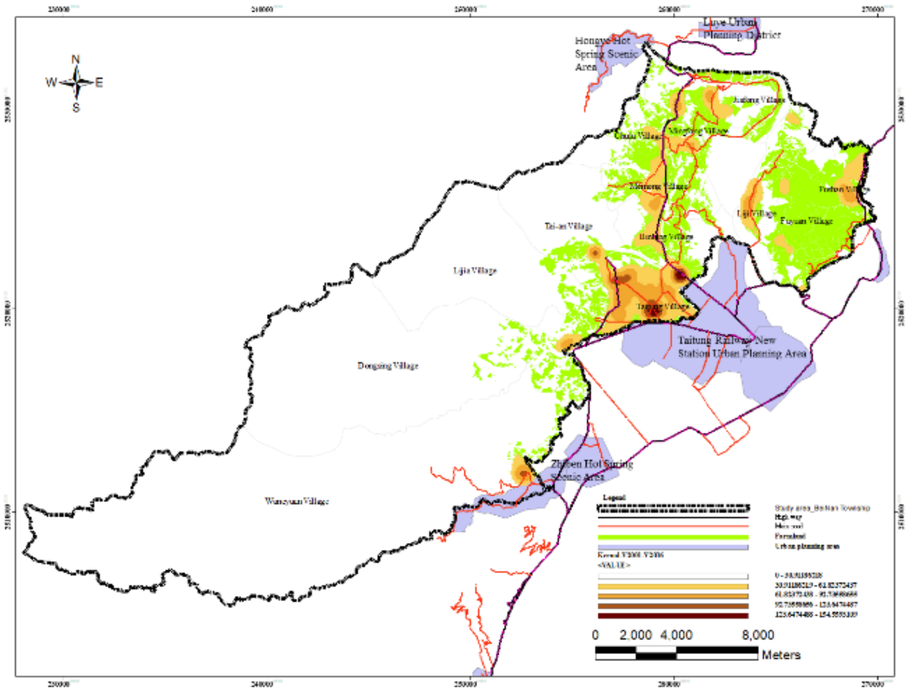

Figure 4. Kernel Density of All the Number of Transactions from 2001 to 2016

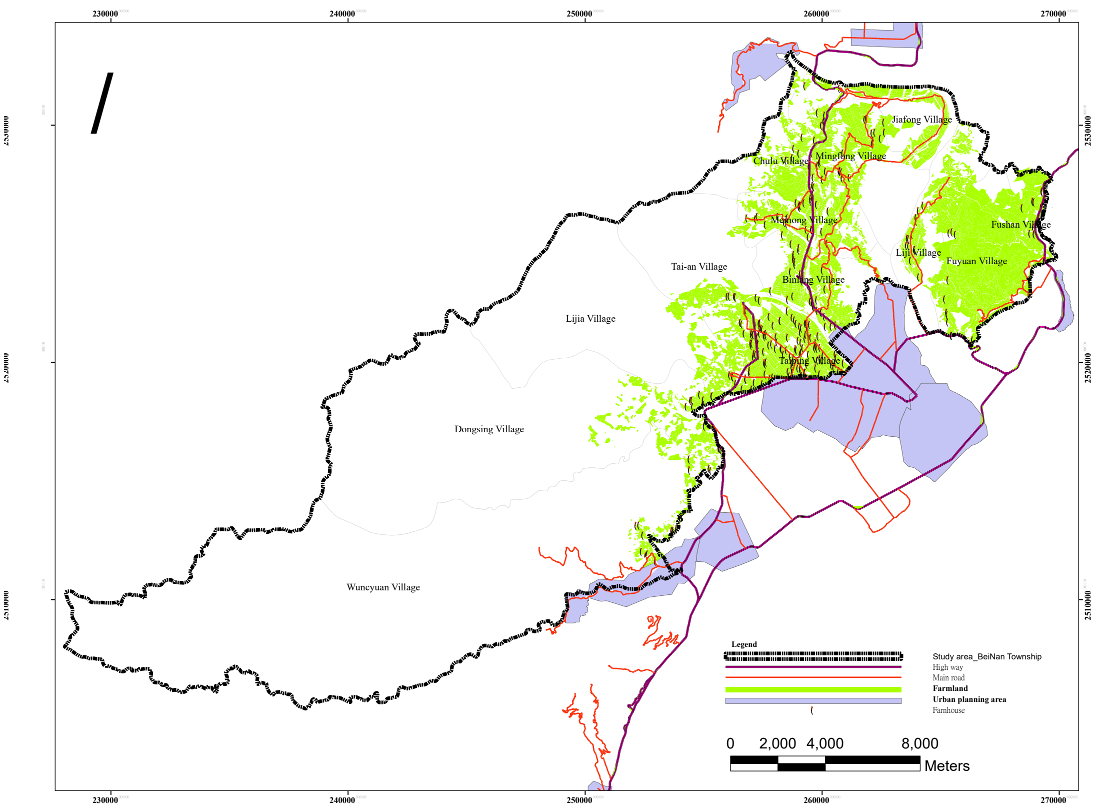

Figure 5. Distribution of Farm House

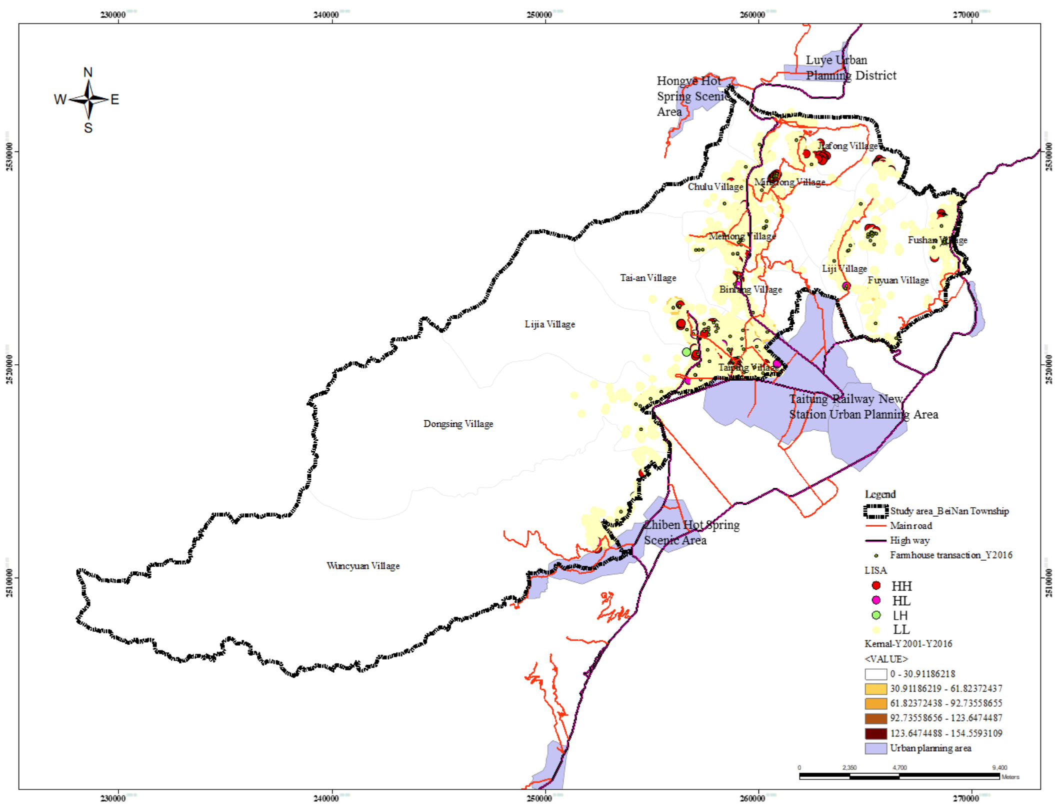

Figure 6. Spatial Correlation of Farm-Land Transaction

(2) For rural areas, agricultural production and transportation rely heavily on the transportation system. Roadside land is favorable for development and utilization. Therefore, transactions are more likely to occur in these areas. Figure 7 shows statistics on farmland transaction volume within 1000 meters on both sides of the road at 100-meter intervals. The data highlight that farmland transaction volume was inversely proportional to distance. Areas with 100 meters from the highway were transaction hot spots. Transaction volume decreased rapidly as distance increased, which validated that the transportation system was a significant factor influencing farmland transactions.

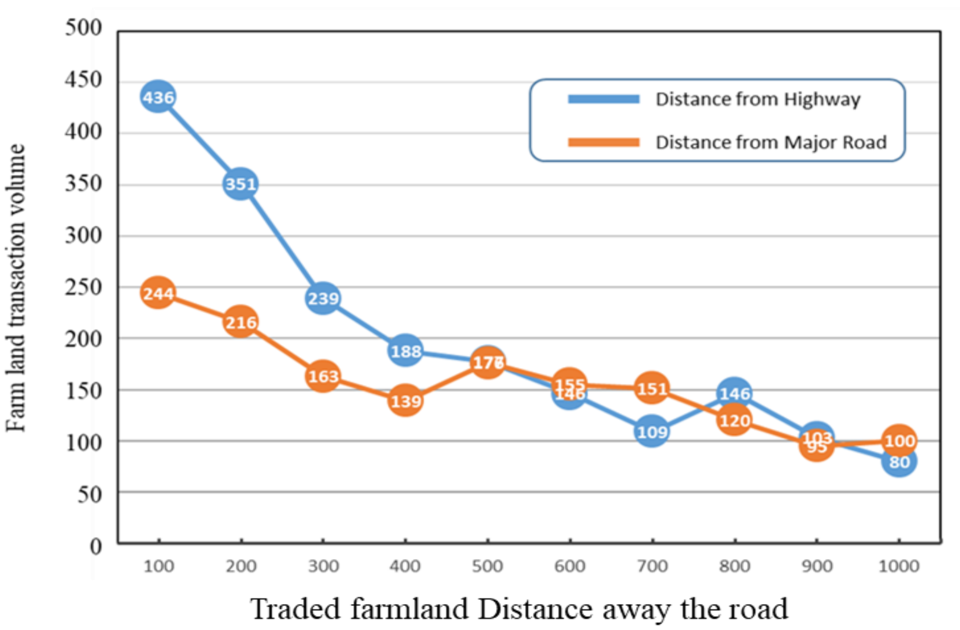

Figure 7. Relation between Farmland Transaction and Distance from the Road

4.3 Spatial Autocorrelation Analysis

We examined kernel density to elucidate the farmland transaction spatial distribution over time. Moran's I index was used to examine whether a positive correlation existed between the land transaction and above-ground buildings of non-urban farmland and their overall spatial clustering relationships. We analyzed Moran's I index, p-value, and z-score. The analysis results are tabulated in Table 2.

(1) For the data in 2001, 2003, 2004, 2005, 2006, 2010, 2011, 2012, 2013, 2014, and 2016, only 1% of the data were likely to be randomly distributed. The likeliness of data clustering was greater than that of random distribution, and the null hypothesis was significantly rejected. The aforementioned annual data showed clustering features and achieved spatial correlation.

(2) The data in 2002, 2007, 2008, and 2009 exhibited significant random distribution. Therefore, the null hypothesis was not rejected.

Table 2. The Analysis Result of Global Moran's I of Farm-Land Trading

Year	Moran's Index:	z-score:	p-value:	Significance	Degree of aggregation
2001	0.172580	4.189844	0.000028	99%	Positive
2002	0.047631	1.240597	0.214755	----	none
2003	0.832121	17.546970	0.000000	99%	Positive
2004	0.243048	4.739340	0.000002	99%	Positive
2005	0.170056	3.966721	0.000073	99%	Positive
2006	0.205408	5.533239	0.000000	99%	Positive
2007	-0.004500	-0.004090	0.996735	----	none
2008	-0.016090	-0.300940	0.763457	----	none
2009	-0.011850	-0.127230	0.898756	----	none
2010	0.346448	8.127913	0.000000	99%	Positive
2011	0.429810	9.340661	0.000000	99%	Positive
2012	0.535310	9.959086	0.000000	99%	Positive
2013	0.104828	2.970663	0.002972	99%	Positive
2014	0.619675	14.609150	0.000000	99%	Positive
2015	0.049658	1.163557	0.244604	----	none
2016	0.558575	10.440980	0.000000	99%	Positive

Note: Significance (----) means the null hypothesis was not rejected, none space cluster.

The global spatial autocorrelation of above-ground buildings on farmland was determined using Moran's I index, p-value, and z-core. The data showed significant random distribution. Therefore, the null hypothesis was not rejected, suggesting that the above-ground buildings on the farmlands of BeiNan Village had no clustering features and that farmland construction policies did not lead to the intensive construction of farmhouse. The calculation results are as follows:

Global Moran's I summary of above-ground buildings on the farmlands of BeiNan Village:

Moran's Index: 0.015382

z-score: 0.870038

p-value: 0.384280

5. Conclusion

Urban planning is affected by various factors, including land utilization patterns, policy incentives, and infrastructure integrity (Wu et al., 2013). Moreover, an extended transition period is required. In particular, suburban areas neighboring highly developed urban areas are hot spots for urban development. The research area is non-urban. However, this area neighbors the highly developed Taitung Urban Planning District. Geographically, the research area is a satellite city of a developed city. It has a large area of low-utility farmland and relies on the highway and major roads to access neighboring regions. Due to the urgency of urban development, the farmland in this area has become hot spots for land development.

We collected the land transaction data from BeiNan Village, Taitung County, between 2001 and 2016 to examine the farmland transactions and the promotion of farmland management policies. We also conducted a spatial autocorrelation analysis to determine spatial clustering and change.

(1) The farmland transaction volume over time indicated that farmland transaction volume was positively correlated to land management policies. These policies also lead to changes in farmland utilization. The number

of transactions in BeiNan Village, Taitung County, reached a high point starting in 2000. The trend tapered between 2001 and 2005, yet average transaction cases remained high. The open and free trade of farmland drove land transaction volume. The number of transactions increased exponentially in 2006, reaching a record high. This increase coincided with the relaxation of farmland transaction laws and regulations, which eliminated agricultural activities as a mandatory criterion for farmland procurement and reduced the administration process for farmland transactions. Farmland management policies were overhauled in 2013, relaxing the construction and development restrictions of farmland. This revision contributed to a record high in farmland transactions. This trend continued for the next three years. In 2015, farmland management policies were revised once again to tighten the eligibility for procuring farmland. The revision reduced the incentive of natural persons from procuring farmland, and transaction volume dropped by 40%.

(2) We performed a kernel analysis and a spatial statistics analysis to determine the spatial distribution and change of farmland transactions. The kernel analysis results indicated that the degree of farmland transaction clustering was inversely proportional to the farmland's distance from densely populated urban planning areas with comprehensive infrastructure. These results verified urban proliferation to the suburbs and changes in farmland utilization. LISA analysis results showed that hot spots (HH) and transportation accessibility had the highest correlation, whereby transaction volume increased concurrently with transportation accessibility. Moreover, traded farmland drove investor willingness in peripheral farmland.

(3) We used the Moran's I index to elucidate the correlation between the transaction of non-urban farmland and above-ground buildings and overall spatial clustering. Global spatial autocorrelation results indicated significant random distribution in the data from 2002, 2007, 2008, and 2009. Therefore, the null hypothesis was not rejected. For the remaining years, the likeliness of data clustering was higher than that of random distribution. Therefore, the data of these years significantly rejected the null hypothesis. The aforementioned annual data showed clustering features and achieved spatial correlation.

(4) We performed a global spatial autocorrelation analysis to explore the transition of traded farmland development into construction. Data distribution results indicated significant random distribution. Therefore, the null hypothesis was not rejected, suggesting that the above-ground buildings on the farmlands of BeiNan Village had no clustering features and that farmland construction policies did not lead to the intensive construction of farmhouse.

(5) For deeply research, more influencing indicators of urban development such as transaction unit price should be induced to explore transaction changes.

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