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Detecting Multilevel Poverty-Causing Factors of Farmer Households in Fugong County: A Hierarchical Spatial–Temporal Regressive Model

Yuewen Jiang [1,†], Yanhui Wang [1,†], Wenping Qi [2], Benhe Cai [1], Chong Huang [3,*] and Chenxia Liang [4]

1 Key Laboratory of 3Dimensional Information Acquisition and Application, Ministry of Education, Capital Normal University, Beijing 100048, China
2 China Centre for Resources Satellite Data and Application, Beijing 100094, China
3 State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
4 State Key Joint Laboratory of Environment Simulation and Pollution Control, School of Environment, Beijing Normal University, Beijing 100875, China
* Correspondence: huangch@lreis.ac.cn
† These authors contributed equally to this work.

Abstract: Accurate examination of poverty-causing factors and their mechanisms of poverty-stricken farmer households from a fine scale is conducive to policy implementation and long-term effective poverty reduction. The spatial effects in most previous studies are not fully considered, resulting in less reliability of detection results. Therefore, by fully considering background effects and spatial–temporal effects, this study designs a hierarchical spatial–temporal regressive model (HSTRM) to accurately identify the factors as well as mechanisms that cause poverty more reasonably. The empirical study of Fugong County, Yunnan Province, China, shows that: (1) There has been a certain degree of spatial effects in the study area over the years; therefore, spatial effects should be considered. (2) The poverty degree of farmer households in the study area is affected by individual factors and background factors. Therefore, poverty-causing factors should be observed at different levels. (3) Poverty-causing factors feature different action mechanisms. The influence of the village-level factors on poverty is greater than that of the household level. In addition, the village-level factors have a certain impact on the contribution of household-level factors to poverty. This study offers technical support and policy guidance for sustainable poverty reduction and development of poor farmer households.

Keywords: poverty-causing factors; spatial–temporal effects; poor households; HSTRM; action mechanisms

Citation: Jiang, Y.; Wang, Y.; Qi, W.; Cai, B.; Huang, C.; Liang, C. Detecting Multilevel Poverty-Causing Factors of Farmer Households in Fugong County: A Hierarchical Spatial–Temporal Regressive Model. *Agriculture* **2022**, *12*, 1844. https://doi.org/10.3390/agriculture12111844

Academic Editor: Sanzidur Rahman

Received: 20 September 2022
Accepted: 31 October 2022
Published: 3 November 2022

1. Introduction

Poverty has always been a global problem; thus, the international community takes promoting development and eradicating poverty as a long-term important goal. Since the reform and opening up, the Chinese government has attached great importance to the poverty problem and people's livelihoods and has made great contributions to poverty reduction around the world [1–4]. Although China has made great achievements in eradicating extreme poverty, this does not mean the end of poverty alleviation. In recent years, with the continuous development of rural society and economic growth, the poverty problem of farmer households is no longer only manifested in the economic aspect but presents complex diversity. Currently, poverty is caused not only by individual factors but by multidimensional social factors as well. Accurately identifying poverty status, poverty-causing factors at the multilevel and their action mechanism for farmer households is of great significance for the precise implementation of anti-poverty policies under the new situation.

Many studies have detected poverty-causing factors by adopting various methods [5–9] . Kumara et al. [10] used correlation analysis methods to detect the main factors that contribute to differences in multidimensional poverty between disabled families and non-disabled families based on the poverty record data of Sri Lanka. Park et al. [11] investigated the occurrence of poverty in disabled families with the multidimensional poverty index and used correlation analysis methods to detect the causes of multidimensional poverty in disabled families in South Korea. However, the above-mentioned studies only considered the individual factors and did not take into account the influences of the surrounding environment that the individuals live in. Some studies have found that the livelihood opportunities available to farmer households in low-income and middle-income countries are highly dependent on their access to capital at the family level and the community level, which can help them resist social, economic and environmental pressures [12–14]. It can be seen that the factors affecting the poverty situation of farmer households include not only individual factors but also environmental factors. Both of them should be included to analyze the economic situation and poverty formation of farmer households [15].

The hierarchical linear model (HLM) is a statistical method for understanding relationships in hierarchically structured data [16]. It can effectively analyze and measure regression relationships between variables across scales [17]. Therefore, HLM has been employed by recent studies to detect the poverty-causing factors of different levels [18,19]. Relevant studies have also shown that the occurrence of poverty and the degree of poverty of individuals may be affected by others. This impact is related to the distance between individuals. The farther the distance, the more obvious the impact, which may lead to a certain spatial aggregation of them, also referred to as spatial effects [20].

In order to incorporate spatial effects into the HLM model, Wang et al. [15] designed a bi-level hierarchical spatial linear model (HSLM) based on HLM to detect poverty-causing factors at both the village level and the county level. However, HSLM can only deal with the spatial autocorrelation between independent variables at level 1 and cannot solve the spatial autocorrelation between independent variables at level 2 or spatial autocorrelation between dependent variables. Moreover, HSLM is fed with cross-sectional data rather than panel data, which may result in the problem of one-sided analysis because cross-sectional data contain less information than panel data and cannot track the changes of individuals.

To tackle the problems mentioned above, this study first detects whether there are spatial effects and background effects in poverty, then develops a new hierarchical spatial–temporal regressive model (HSTRM) that takes into account the spatial effects, so as to accurately identify poverty-causing factors from both the individual effects and the background effects using panel data. This study selects Fugong County, Yunnan Province, China for empirical research. The detection results can provide insight into the formulation of poverty in Fugong County, China. Meanwhile, the research can also provide reference for poverty reduction research for other developing countries.

2. Study Area and Data Source

2.1. Study Area

This paper selects Fugong County in Yunnan Province, China, as the study area, as shown in Figure 1. Fugong is located in the hinterland of Nujiang Gorge, which is the world's natural heritage and belongs to the Nujiang Lisu Autonomous Prefecture [19]. Fugong belongs to a typical Alpine Canyon landform, and the terrain is high in the north and low in the south; thus, the altitude difference is very large. Fugong County covers a land area of 2756.44 km^2, and has 7 townships, 57 village committees, with a total population of 118,900 from 32,800 households. The people aged over 60 in Fugong County account for 9.52% of the total population, leading to an insufficient labor force and heavy burden of providing for the elderly of farmers. There are more than 20 ethnic minorities living in the territory, and the minority accounts for 98.88% of the total population. Since the implementation of China's poverty alleviation strategy, Fugong County has identified a total of 17,441 registered poverty-stricken families with a population of 73,108. Since most of them can only speak dialects and cannot speak or understand Mandarin Chinese, there exist language barriers for them to communicate with the outside world, which result in poor ability to go out and look for work. They have less scientific and cultural knowledge, which limit their further development. For the rural households in Fugong County, social security is provided by the central and local government, which consists of rural social insurance (including pension, medical care, and so on), rural social assistance (to individuals and families living below the "poverty line" or the minimum standard of living), rural social welfare, etc.; however, the livelihood status there is behind the average living standard in Yunnan Province. Poverty alleviation in Fugong is full of difficulties and challenges. Therefore, taking Fugong County as the study area has typical research significance and important reference value for formulating poverty relief policies.

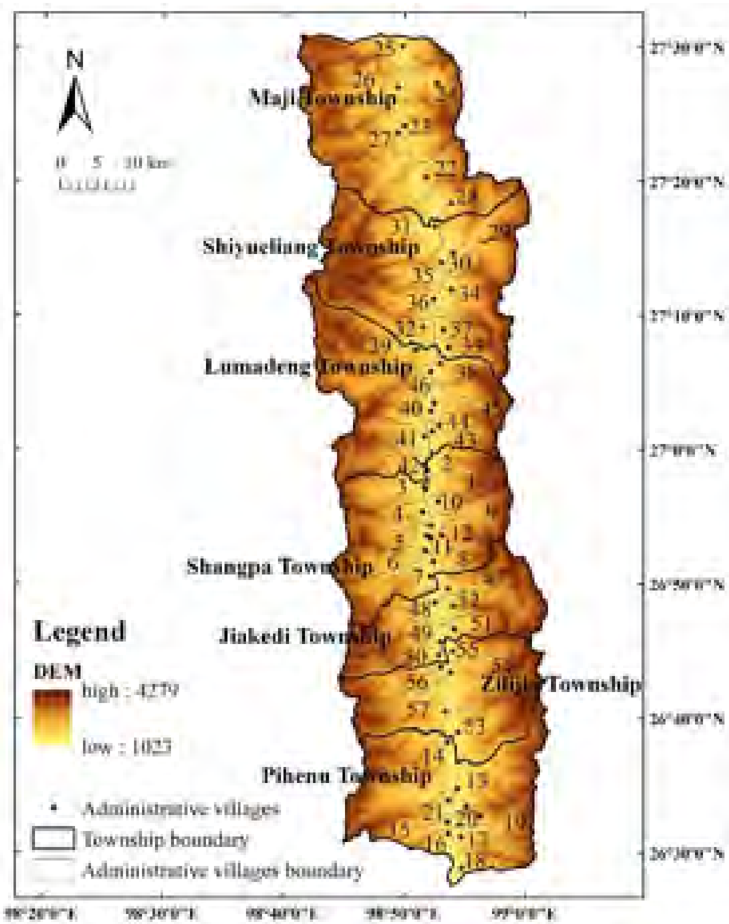

Figure 1. An overview of the study area; Note: Administrative Village No.: 1. Lazhudi Village 2. Dapulo Village 3. Shidi Village 4. Zhuminglin Village 5. Latudi Village 6. Guquan Village 7. Mugujia Village 8. Jiziluo Village 9. Shangpa Village 10. Dayou Village 11. Labu Village 12. Shuangmidi Village 13. Shawa Village 14. Wawa Village 15. Jiajiu Village 16. Tuoping Village 17. Puluo Village 18. Guoke Village 19. Zhiziluo Village 20. Laomden Village 21. Miangu Village 22. Qiaodi Village 23. Maji Village 24. Gudang Village 25. Bura Village 26. Mujiajia Village 27. Majimi Village 28. Wangjidu Village 29. Shimendeng Village 30. Lishadi Village 31. Ramadi Village 32. Yaduo Village 33. Zali Village 34. Zuolodi Village 35. Miolo Village 36. Ziguduo Village 37. Zhiluo Village 38. Chisadi Village 39. Yaping Village 40. Bajiaduo Village 41. Buladi Village 42. Chihengdi Village 43. Lumadeng Village 44. Lamaluo Village 45. Majadi Village 46. Watuwa Village 47. Ada Village 48. Weidu Village 49. Jiake Village 50. Liwudi Village 51. Nan'anjian Village 52. Dadako Village 53. Yagu Village 54. Zilija Village 55. Okolo Village 56. Lamujia Village 57. Jinxiugu Village.

2.2. Data Sources

The statistical data in this study are mainly from the monitoring data and the statistical yearbook of Yunnan Province, involving household-level data and the village-level data from 2015 to 2018. There are four dimensions at the household level, including geographical location, family characteristics, social security, and economic development. The factors at the village level include five dimensions: geographical environment, infrastructure, labor situation, social security, and economic development. The geographic data come from the geospatial data cloud website (http://www.gscloud.cn (accessed on 10 March 2019). Before the experiment, we pre-processed the statistical data such as sampling, index screening and multi-collinearity detection, and pre-processed the geographic data such as image clipping, mosaic, and geo-referencing. We matched and connected the processed statistical data and geographic data so that we can accurately detect spatial effects and significant poverty-causing factors.

3. Methods

3.1. Spatial–Temporal Correlation Analysis

In this study, we attempt to explore the spatial–temporal effects of poverty in Fugong, that is, the spatial effects from 2015 to 2018. Spatial effects include spatial dependence and spatial heterogeneity. Spatial dependence refers to the phenomenon that there are correlations between geographical entities in certain geographical spaces [21,22]. The closer the distance, the stronger the correlation. Spatial heterogeneity means that geographical entities in different spatial units show various properties due to the difference in geographical location [23,24]. Because of the existence of spatial dependence or spatial heterogeneity, a spatial autocorrelation test should be carried out before analyzing spatial data.

Because spatial effects are related to the distance between geographical entities, it is necessary to identify the proximity relationship between them before spatial effects detection. The spatial weight matrix (W) is a mathematical expression that reflects the proximity between geographical entities, and it is the premise and basis for calculating spatial autocorrelation statistics and spatial data analysis. It defines the proximity relationship between them and determines the influence of any geographical entity on its adjacent geographical entities. The expression of the spatial weight matrix is as follows [25]:

$$W = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ \cdots & \cdots & \cdots & \cdots \\ w_{n1} & w_{n2} & w_{n3} & w_{nn} \end{bmatrix}$$

Tobler's first law points out that the correlation between geographical entities is inversely proportional to the distance between them. We adopt the inverse of the Euclidean distance to reflect the proximity relationship between poor farmer households or poverty-stricken villages. The formula is as follows:

$$W_{ij} = \frac{1}{d_{ij}} \tag{1}$$

where i and j represent two different households or villages; d is the distance between the two households or two villages; W_{ij} is equal to W_{ji}.

Global Moran's I can describe the spatial distribution and the correlation of geographical entities as a whole. It was used to detect spatial dependence among the poverty levels of farmer households, household-level factors and village-level factors, respectively, in the study. *Local Moran's I* or *Getis-Ord* index (Gi*) can reflect the difference in poverty status and farmer households' correlation in local areas and can be used to detect spatial heterogeneity between them.

The calculation formula for *Global Moran's I* is as follows [26]:

$$Moran'sI = \frac{N}{\sum_{ij} w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \tag{2}$$

In the formula, i and j represent different households or villages, and i is not equal to j; N is the number of households or villages; x is the poverty level of farmer households or the residual of OLS regression at the household level or the village level, and w is the spatial weight matrix. *Moran's I* is generally between -1 and 1. The closer its absolute value is to 1, the stronger the aggregation of farmer households.

Local Moran's I is calculated as follows:

$$I_i = \frac{(x_i - \overline{x})}{S^2} \sum_j w_{ij}(x_j - \overline{x}) \tag{3}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n} (x_i - \overline{x})^2; \quad \overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

A positive I_j indicates that the property values of geographical entities are positively correlated with others, exhibiting high value aggregation (high-high) or low value aggregation (low-low). A negative I_j indicates that a high value is surrounded by other low values, showing a high–low value aggregation phenomenon, or a low value is surrounded by other high values, showing a low–high value aggregation phenomenon. In this study, a positive I_j means that farmer households with high or low poverty levels gather together (high-high or low-low). A negative I_j means that a farmer household with a high poverty level is surrounded by others with low poverty levels, or a farmer household with a low poverty level is surrounded by others with high poverty levels.

*Gi** is calculated as follows:

$$G_i{}^* = \frac{\sum_{j \neq i}^{n} w_{ij} x_j}{\sum_{j \neq i}^{n} x_j} \tag{4}$$

In the formula, i and j represent different households or different villages, n is the number of households or villages, and w is the spatial weight matrix.

Normalize *Gi** to obtain $Z = \frac{G_i^* - E(G_i^*)}{\sqrt{Var(G_i^*)}}$, where $E(G_i^*)$ and $Var(G_i^*)$ represent the expectation and variance of *Gi**, respectively.

Under the original hypothesis without spatial autocorrelation, when the absolute value of Z is greater than 1.96, the original hypothesis is rejected at the 5% confidence level, and there is spatial autocorrelation, and the greater the absolute value of Z, the more obvious the spatial heterogeneity.

We use *Global Moran's I* and *Gi** to detect the spatial dependence and the spatial heterogeneity of the poverty levels of farmer households, respectively. If there are significant spatial effects between the poverty levels, we multiply W (spatial weight matrix of the households) with Y (the poverty level of households) and obtain the spatial lag explanatory variable WY for the model estimation [27].

For the spatial autocorrelation test between explanatory variables, we take the poverty level as the dependent variable and the poverty-causing factors (household level or village level) as the independent variables, and implement linear regression analysis using the Ordinary Least Squares (OLS) method. Then, *Global Moran's I* and *Local Moran's I* are adopted to detect the spatial dependence and spatial heterogeneity of OLS residuals, respectively [28]. If there is spatial autocorrelation in OLS residuals, it means that there are spatial effects among those factors. Then, we multiply spatial weight matrix with poverty-causing factors to obtain the endogenous explanatory variable for the model estimation [29,30].

3.2. Background Effects Identification

Before detecting poverty-causing factors, it is necessary to check whether there are background effects. In other words, we first need to check whether the poverty level of farmer households is affected by village-level background factors except for the household-level factors. We adopt the null model and the analysis of variance method to determine the proportion of individual differences (intra-group differences, each village is a group) at the household level and village differences (inter-group differences) at the village level in the overall difference. Inter-group differences are expressed by the ICC index (Intra-Class Correlation Coefficient). The larger the ICC index, the larger the proportion of inter-group differences and the more significant the background effects. According to relevant studies [31], when the ICC index is greater than 0.059, the background effects cannot be ignored, and it is necessary to adopt a multi-level regression model to detect poverty-causing factors at both the household level and the village level, respectively. The null model is as follows:

$$\text{Level 1}: Y_{ijt} = \beta_{0j} + \gamma_{ij} \tag{5}$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \mu_{0j} \tag{6}$$

Level 1 is the household level, and level 2 is the village level. i represents the household (i = 1, 2, . . . , n; n is the number of farmer households); j represents the village (j = 1, 2, ..., J; J is the number of administrative villages in the study area); t represents the year. Y_{ijt} is the poverty level of farmer households; β_{0j} is the average value for Y_{ijt}; γ_{00} is the average value for β_{0j}. r_{ij} is the random effect of Y_{ijt} and represents variation at level 1 (the household level); μ_{0j} is the random effect of β_{0j} and represents variation at level 2 (the village level).

The variance proportion of intra-group difference and inter-group difference is calculated as follows:

Intra-group variance ratio:

$$\rho_1 = \frac{\sigma^2}{\tau_{00} + \sigma^2} \tag{7}$$

Inter-group variance proportion:

$$ICC = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \tag{8}$$

The overall variance:

$$Var(poverty) = \tau_{00} + \sigma^2 \tag{9}$$

σ^2 represents the differences between households within a village; τ_{00} represents the differences between villages. ρ_1 and ICC represent the proportion of the variance at the household level and village level, respectively. *Var (poverty)* represents the overall variance of the poverty level of farmer households.

3.3. Poverty-Causing Factors Detection

Considering that there are both individual differences and group differences in the poverty level of farmer households, and the poverty-causing factors may come from both themselves and the village they live in, we first construct a two-level index system to detect significant poverty-causing factors at different levels. Then, considering the nested structure of the research data and the possible spatial effects in the study area, we try to design a new model based on the HSLM model to achieve three goals: first, to detect the significant poverty-causing factors at the household level and the village level at the same time by the panel data; second, to highlight the impact of neighborhood effects on the poverty status of farmer households [32,33]; third, to weaken the influence of the spatial autocorrelation of independent variables on the accuracy of the detection results of significant poverty-causing factors [15].

3.3.1. Candidate Indicator System

According to the actual situation of Fugong county, and referring to relevant research on poverty-causing factors, from the perspective of sustainable development, based on the multi-dimensional poverty analysis framework [34–37], we construct a multi-level indicator system as Table 1. At the household level, there are four dimensions: geographical location, family characteristics, social security and economic development [38–41]. The reasons for the selection of these four dimensions are as follows: the geographical location can reflect the living environment, traffic convenience and living convenience of farmer households. The family characteristics can reflect the obstacles to poverty alleviation and the development potential of families. Social security can reduce the burden of family life to a certain extent, thereby reducing the resistance of families to poverty alleviation. Economic development can directly reflect the economic situation of farmers and the difficulty of poverty alleviation.

Table 1. Candidate indicators and screening at both household level and village level.

Level	Dimension	Variable	Variable Interpretation	Screening Results by Coefficient of Variation (Retain or Not)	Screening Results by Complex Correlation Coefficient (Retain or Not)
Household	Dependent variable	*Y_poverty*	Poverty level	-	-
	Geographical location	*F_distance*	Distance from the main road (m)	yes	yes
		F_road	Road access type	yes	yes
		F_altitude	Elevation of the natural village where the household is located	yes	yes
	Family characteristics	*F_health*	Ratio of the healthy family members (%)	yes	yes
		F_labour	Ratio of the family labor force (%)	yes	yes
		F_education	Ratio of students in non-compulsory education (%)	yes	yes
		F_mandarin	Ratio of the population who can speak mandarin in the family (%)	yes	yes
	Social security	*F_allowance*	Ratio of the population supported by the allowance for the lowest living standard in the family (%)	yes	yes
		F_medical	Ratio of the population enrolled in the new rural cooperative medical insurance of China in the family (%)	yes	yes
		F_insurance	Ratio of the population enrolled in urban and rural basic pension insurance in the family (%)	yes	yes
	Economic development	*F_per_inc*	Per capita annual income of the family (yuan)	yes	yes
		F_per_cularea	Per capita cultivated land area of the family (mu)	yes	yes
Village	Geographical environment	*V_terrain*	Terrain relief	yes	yes
		V_altitude	Altitude (m)	yes	yes
		V_slope	Slope	no	-
	Infrastructure	*V_broadband*	Ratio of households with broadband in the village (%)	yes	yes
		V_school	Number of primary schools with broadband in the village	yes	yes
		V_road	Is there an asphalt road in the village (Yes, 1; No, 0)	no	-
		V_shuttle	Is there a passenger bus in the village (Yes, 1; No, 0)	no	-
	Labor situation	*V_labour*	Ratio of the village labor force (%)	yes	yes
		V_worker	Ratio of migrant workers in the village (%)	yes	yes
	Social security	*V_medical*	Ratio of the population enrolled in the new rural cooperative medical insurance of China in the village (%)	yes	yes
		V_pension	Ratio of the population enrolled in urban and rural basic pension insurance in the village (%)	yes	yes
	Economic development	*V_peo_inc*	Per capita annual income of the village (yuan)	yes	yes
		V_coll_inc	Collective income of the village (yuan)	yes	yes

At the village level, there are five dimensions: geographical environment, infrastructure, labor situation, social security and economic development [42–47]. At the village level, the reasons for the selection of these five dimensions are as follows: the geographical environment directly reflects the overall topography of the village, which will have a certain impact on the living convenience of farmer households and agricultural production. The geographical environment directly reflects the overall topography of the village, which will have a certain impact on the convenience of farmers' lives and agricultural production. The infrastructure in the village will affect families' lives, study and communication with the outside world. The labor situation reflects the overall development potential of the villagers. Social security reflects the coverage of medical insurance and pension insurance in the village. The higher the coverage, the more conducive it is for the villagers to overcome poverty. In the dimension of economic development, promoting the development of the village collective economy is conducive to driving farmers out of poverty.

The indicators at the household level and the village level are shown in Table 1. According to the national poverty line standards over the years and the government documents related to poverty reduction policies, we divide the poverty level of poor farmer households into five grades and assign 1~5 as the dependent variables. The higher the grade, the deeper the poverty level. Further, we screen the indexes by the variation coefficient method and the complex correlation coefficient method: Firstly, we use the variation coefficient method to screen out the indicators with a coefficient of variation greater than 15%. Then, the complex correlation coefficient method is used to carry out the complex correlation simulation on the indicators of each dimension at the household level and the village level, respectively. In addition, to make the results of regression coefficients comparable, we use the Z-score method to standardize the indexes.

3.3.2. Poverty-Causing Factors Discrimination

Based on the hierarchical spatial linear model (HSLM), we designed a hierarchical spatial–temporal regressive model (HSTRM) to accurately discriminate the poverty-causing factors by introducing the spatial weight matrix at each level and constructing endogenous explanatory variables and spatial lag explanatory variables. Both the HSTRM model and the HSLM model can be used to detect the significant poverty-causing factors and their mechanisms at the household level and the village level. However, different from the HSLM model, the HSTRM model adds *WY* and *MZ* in addition to *WX*. That is, HSLM only adds *WX* at level 1, HSTRM adds *WX* and *WY* at level 1 and adds *MZ* at level 2. The detailed description of HSTRM is as follows: When there are spatial effects between the dependent variables (the poverty level of farmer households), we construct the spatial lag explanatory variable *WY* and put it at level 1 to explore how it affects the dependent variable. When there are spatial effects between the independent variables at level 1 (the household-level factors), we construct the endogenous explanatory variable *WX* and put it at level 1 to weaken the impact of spatial effects on the detection of household-level factors and achieve a more accurate detection of significant household-level factors. When there are spatial effects between the independent variables at level 2 (the village-level factors), we construct the endogenous explanatory variable *MZ* and put it at level 2 to weaken the impact of spatial effects on the detection of village-level factors and achieve a more accurate detection of significant village-level factors. In addition, we put *MZ* into the equation of β_{ij} (Formula (11)) at level 2 to explore how village-level factors affect the contribution of household-level factors to the poverty level of farmer households. The HSTRM model is as follows:

HSTRM:

Level 1:

$$Y_{ijt} = \beta_{0j} + \rho WY_{ijt} + \beta_{1j} WX_{ijt} + \gamma_{ij} \quad (10)$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} MZ_{jt} + \mu_{0j} \quad (11)$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} MZ_{jt} + \mu_{1j} \tag{12}$$

W is the inverse distance spatial weight matrix for poverty-stricken households, and M is the inverse distance spatial weight matrix for villages. X_{ijt} is the explanatory variable at the household level. Z_{jt} is the explanatory variable at the village level. ρ is the regression slope of WY; β_{1j} is the fixed effect that represents the regression slope of WX_{ijt}; γ_{01} is the fixed effect that represents the regression slope of MZ_{jt}; γ_{10} is the average values of β_{1j}; μ_{1j} is the random effects of β_{1j} and represents the variation at the village level. The interpretations of other parameters are the same as the null model.

In the analysis of detection results, we adopt the variance change ratio to measure the difference proportion that the household-level factors and the village-level factors can explain. The calculation formula for the variance change ratio is as follows [48]:

Variance change ratio of the household level:

$$Var_{\_ratio1} = \frac{\sigma_0^2 - \sigma^2}{\sigma_0^2} \tag{13}$$

Variance change ratio of the village level:

$$Var_{\_ratio2} = \frac{\tau_0^2 - \tau^2}{\tau_0^2} \tag{14}$$

Var_ratio_1 and Var_ratio_2 are the variance change ratios of level 1 (the household level) and level 2 (the village level), respectively. σ_0^2 and τ_0^2 are the variances of level 1 and level 2 of the null model, respectively. σ^2 and τ^2 are the variances of level 1 and level 2 of the HATRM model, respectively. By calculating the variance change ratio of each level, we can judge the explanation degree of independent variables to dependent variables in the HSTRM model, that is, we can judge the explanation degree of the household-level factors and the village-level factors to the difference of the poverty level.

4. Results and Analysis

4.1. Spatial–Temporal Effects of Poverty

We detected spatial effects through the spatial autocorrelation analysis method. The detection results of the spatial dependence effect by *Global Moran's I* are shown in Table 2. It can be seen that from 2015 to 2018, there was significant global spatial autocorrelation (*p value* < 0.01) between dependent variables (Y, the poverty level of farmer households), that is, there were significant spatial dependence effects between the poverty levels over the four years.

Table 2. Spatial–temporal dependence effects of poverty levels from 2015 to 2018.

Year	2015	2016	2017	2018
Moran's I	0.129 ***	0.286 ***	0.376 ***	0.324 ***
Z-score	10.567	23.413	30.736	26.581
p value	0.000	0.000	0.000	0.000

Note: *** $p < 0.01$.

The detection results of the spatial heterogeneity effect by *Gi** are shown in Table 3. It can be seen that from 2015 to 2018, there was a certain degree of local spatial autocorrelation between the poverty levels, but it was only significant in 2016. That is, there were significant spatial heterogeneity effects between the poverty levels over the past four years. The spatial heterogeneity effect was only significant in 2016 (*p value* < 0.01). Nevertheless, because there are also significant spatial dependence effects between the poverty levels of farmer households over the four years, there are significant spatial effects between the poverty levels in general. Therefore, the spatial lag explanatory variable *WY* should be included in the model when detecting the poverty-causing factors.

Table 3. Spatial–temporal heterogeneity effects of poverty levels from 2015 to 2018.

Year	2015	2016	2017	2018
*Gi**	0.000032	0.000033 **	0.000032	0.000033
Z-score	0.447	3.167	0.045	1.623
p value	0.655	0.002	0.964	0.104

Note: * $p < 0.1$; ** $p < 0.05$.

The spatial aggregation of farmer households at different poverty levels is shown in Figure 2. Red represents the significant aggregation of high value, that is, the aggregation of farmer households with high poverty levels. Blue represents the significant aggregation of low value, that is, the aggregation of farmer households with low poverty levels. Yellow indicates that the aggregation is not significant. It can be seen that there is a certain degree of local spatial aggregation between farmer households, that is, there are spatial heterogeneity effects in Fugong County.

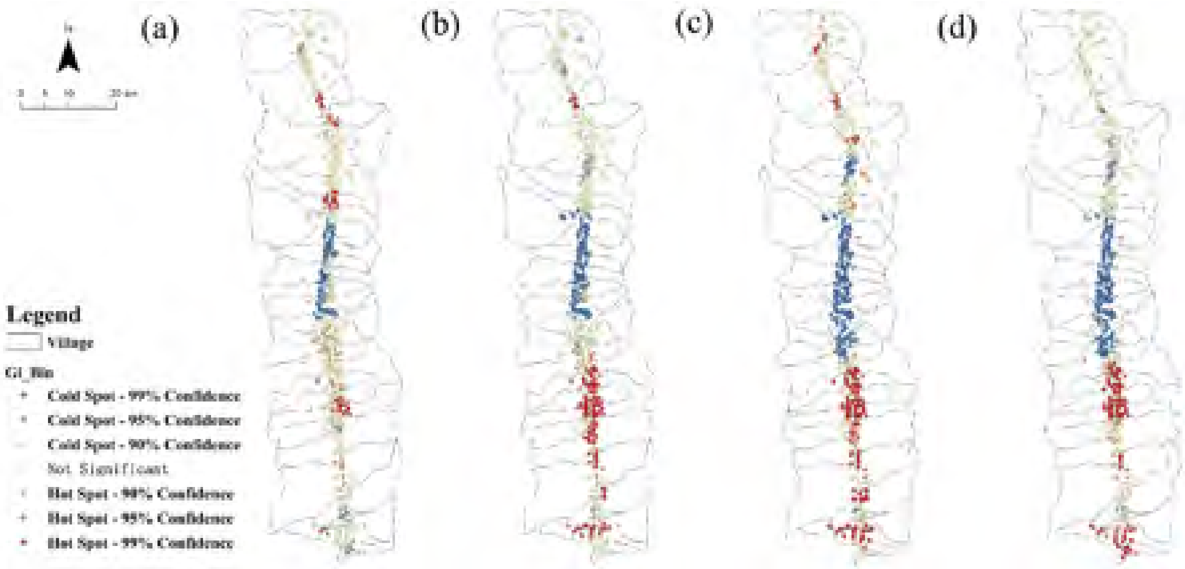

Figure 2. Hot spots of local spatial autocorrelation of farmer households from 2015 to 2018 (**a**–**d**).

The detection results of spatial effects between explanatory variables are as follows. At the household level, we take the poverty level as the dependent variable and use the Ordinary Least Squares tool in ArcGIS 10.2 software (Environmental Systems Research Institute, Inc., RedLands, CA, America) to carry out OLS regression for the household-level factors, and then, the spatial autocorrelation analysis methods are used to detect the spatial effects of residual terms in OLS regression results. The detection results of spatial dependence effects and spatial heterogeneity effects of residual terms are shown in Figures 3 and 4, respectively. The Moran scatter diagram in Figure 3 shows the spatial dependence of OLS residual terms. *Global Moran's I* index of OLS residuals from 2015 to 2018 were 0.018 (p = 0.02), 0.005 (p = 0.25), 0.164 (p = 0.01) and 0.062 (p = 0.01), respectively. Except for 2017, the *p values* of other years were less than 0.05, indicating that the residuals of OLS regression for household-level factors in 2015, 2016 and 2018 did not meet the independence. This indicates that the spatial dependence effects between household-level factors are significant at the level of 0.05. Although *p value* was not significant in 2017, the detection results of *Global Moran's I* index in 2017 showed that there was a certain degree of spatial dependence effects between household-level factors. We used *Local Moran's I* to obtain the Lisa diagram, as shown in Figure 4, which shows the local spatial autocorrelation of the residual terms, that is, there are spatial heterogeneity effects between the household-level factors. It can be found from Figure 4 that the OLS residual terms in 2015–2018 show a certain degree of spatial aggregation, such as high–high, low–low, high–low and low–high, which indicates that the residual terms in 2015–2018 do not meet the independence. Therefore, it can be judged that there are spatial heterogeneity effects between the household-level factors. Given the spatial dependence effects and spatial heterogeneity effects of the household-level factors, it is necessary to put the endogenous explanatory variable *WX* into the model to detect significant factors at the household level.

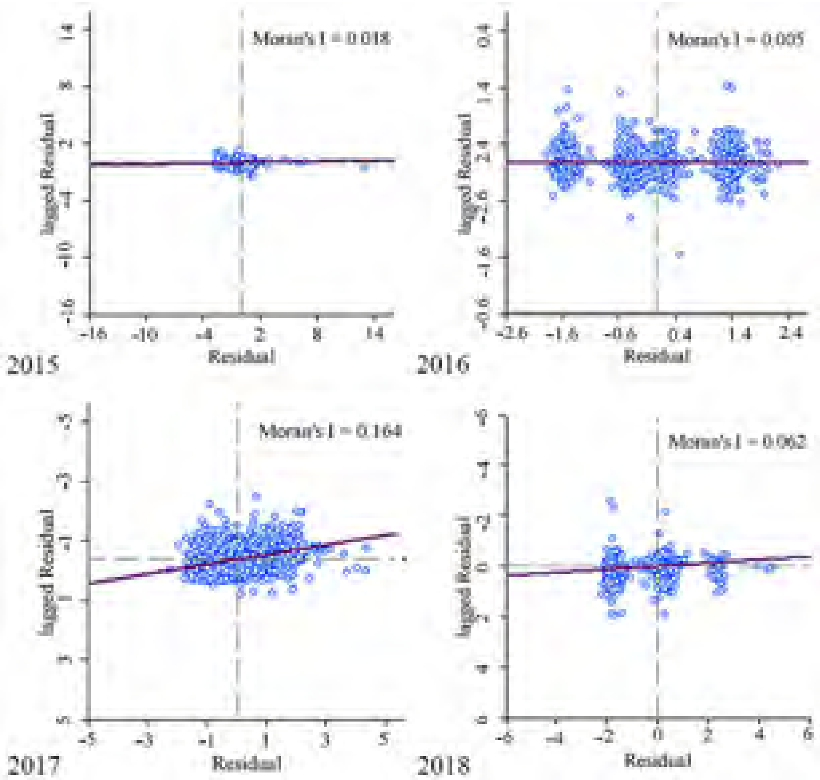

Figure 3. Moran scatter diagram of OLS regression residual terms of the household-level factors from 2015 to 2018.

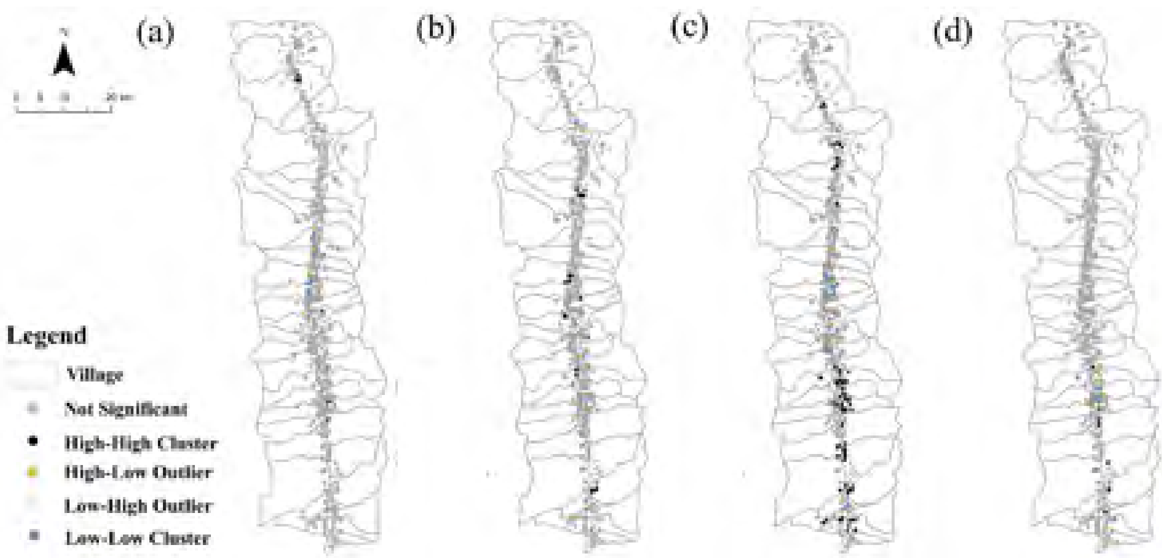

Figure 4. Lisa diagram chart of OLS residual terms of the household-level factors from 2015 to 2018 (**a**–**d**).

At the village level, the process of spatial effect detection is the same as at the household level. We take the average poverty level of farmer households in the village as the dependent variable and use the Ordinary Least Squares tool in ArcGIS software to carry out OLS regression for the village-level factors, and then, the spatial autocorrelation analysis methods are used to detect the spatial effects of residual terms in OLS regression results. The detection results of spatial dependence effects and spatial heterogeneity effects of residual terms are shown in Figures 5 and 6, respectively. The Moran scatter diagram in Figure 5 shows the spatial dependence of OLS residual terms. *Global Moran's I* indexes of OLS residuals from 2015 to 2018 were 0.092 (p = 0.10), 0.201 (p = 0.03), −0.047 (p = 0.49) and −0.04 (p = 0.46), respectively. Only the *p value* in 2016 is less than 0.05, indicating that the residuals of OLS regression of the village-level factors in 2016 did not meet the independence, and there are significant spatial dependence effects between the village-level factors at the level of 0.05. Although they are not significant in other years, the detection results of the *Global Moran's I* show that there is also a certain degree of spatial dependence effects. We use *Local Moran's I* to obtain the Lisa diagram, as shown in Figure 6, which shows the local spatial autocorrelation of the residual terms, that is, there are spatial heterogeneity effects between the village-level factors. It can be found from Figure 6 that the OLS residual terms in 2015–2018 show a certain degree of spatial aggregation, such as high–high, low–low, high–low and low–high, which indicates that the residual terms in 2015–2018 do not meet the independence. Therefore, it can be judged that there are spatial heterogeneity effects between the village-level factors. Given the spatial dependence effects and spatial heterogeneity effects of the village-level factors, it is necessary to put the endogenous explanatory variable *MZ* into the model to detect significant factors at the village level.

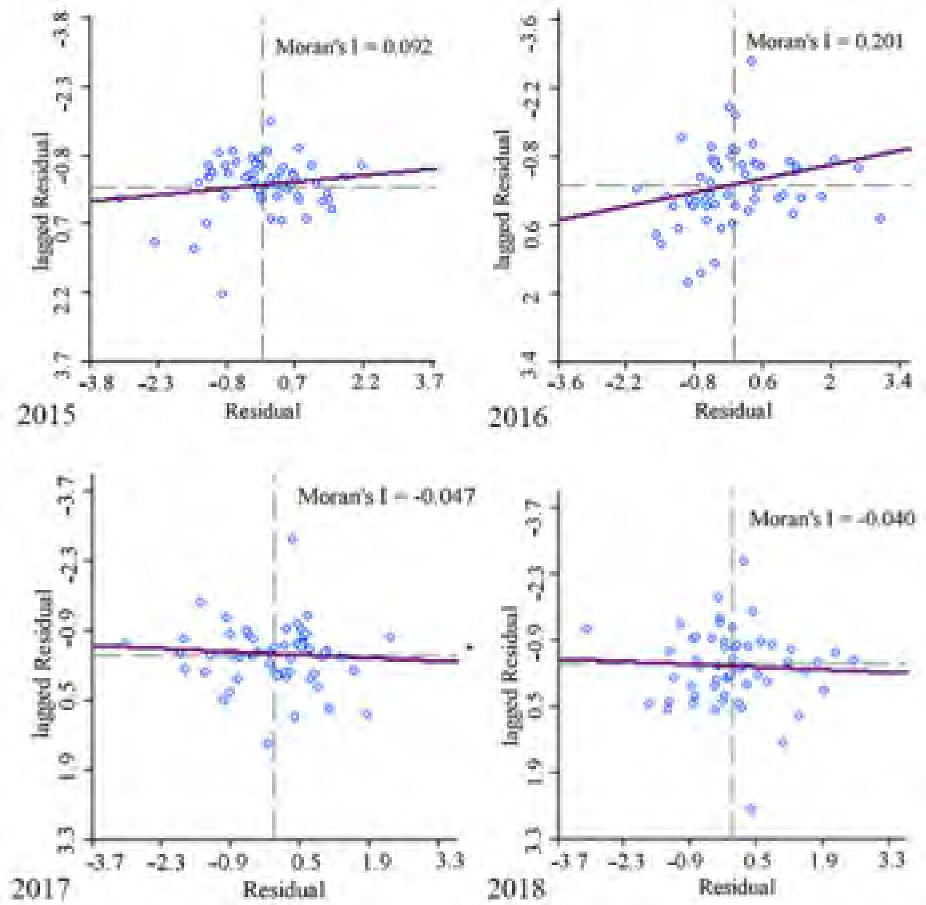

Figure 5. Moran scatter diagram of OLS regression residual terms of the village-level factors from 2015 to 2018.

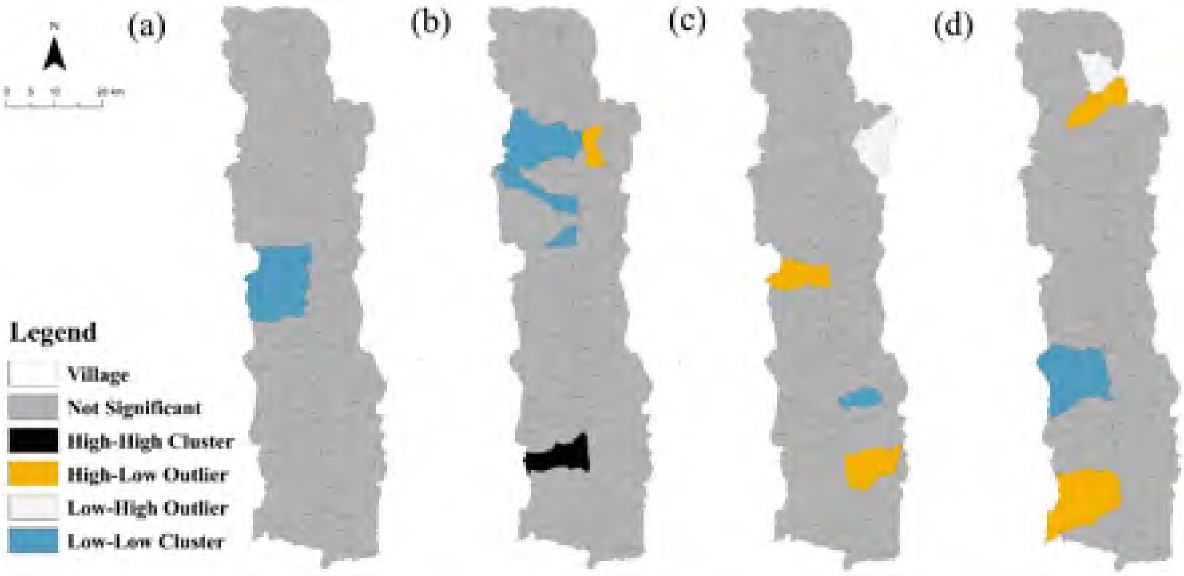

Figure 6. Lisa diagram chart of OLS residual terms of the village-level factors from 2015 to 2018 (**a**–**d**).

Based on the detection results, we can find that there are spatial effects among the poverty levels and the poverty-causing factors that are at both the household level and the village level. The poverty status of neighboring farmer households who live in a similar environment shows similarity to a certain degree. The closer they are, the stronger the similarity is, and the spatial autocorrelation among the household-level factors or the village-level factors leads to their aggregation.

4.2. Background Effects Analysis

The estimation results of random effects of the null model are shown in Table 4. It can be seen that the variance at level 1 (the household level) and level 2 (the village level) was 1.2633 and 0.2298, respectively. According to Formula (7), Formula (8), and Formula (9), ρ_1 was 84.91% and *ICC* was 15.39%, which is larger than 0.059. This indicates that 84.91% of the overall difference in poverty level resulted from differences between households, and 15.39% resulted from differences between villages. It shows that the poverty level of farmer households is affected by both the household-level factors and the village-level factors. It is necessary to build a multi-level regression model to detect the poverty-causing factors.

Table 4. The random effects of the null model.

Level	Variance	Std.Dev.
Household level	1.2633 (σ^2)	1.1240
Village level	0.2298 (τ_{00})	0.4793

4.3. Multilevel Poverty-Causing Factors Analysis

4.3.1. Significant Factors at the Household Level

According to the detection results of HSTRM (Table 5), there are five significant factors at the household level, *F_per_inc* (per capita annual income of the family), *F_medical* (ratio of the population enrolled in the new rural cooperative medical insurance of China in the family), *F_insurance* (ratio of the population enrolled in urban and rural basic pension insurance in the family), *F_per_culturea* (per capita cultivated land area of the family), *F_labour* (ratio of the family labor force).

Table 5. The detection results of the HSTRM model.

Indicator Dimension	Variables	Coefficient	Std. Error	*t* Value	Pr (>|t|)
Spatial lag factor	*WY*	(ρ) 0.3295 ***	0.0611	5.393	0.0000
the household level					
Geographical location	*F_distance*	−0.0142	0.0624	−0.227	0.8200
	F_road	0.0147	0.0486	0.303	0.7620
	F_altitude	−0.0178	0.0541	−0.329	0.7420
Family characteristics	*F_health*	−0.0270	0.0633	−0.426	0.6700
	F_labour	−0.1135 *	0.0600	−1.892	0.0586
	F_education	−0.0555	0.0652	−0.851	0.3950
	F_mandarin	0.0405	0.0476	0.851	0.3950
Social security	*F_allowance*	0.0037	0.0417	0.09	0.9280
	F_medical	−0.1576 ***	0.0561	−2.809	0.0050
	F_insurance	0.1499 ***	0.0472	3.175	0.0015
Economic development	*F_per_inc*	−0.1717 ***	0.0609	−2.822	0.0048
	F_per_cularea	0.1362 ***	0.0482	2.823	0.0048
the village level					
Geographical environment	*V_terrain*	−0.0450	0.0428	−1.052	0.2930
	V_altitude	−0.0498	0.0491	−1.015	0.3110
Infrastructure	*V_broadband*	−0.0113	0.0355	−0.319	0.7500
	V_school	−0.0729	0.0476	−1.531	0.1260
Labor situation	*V_labour*	−0.1199 ***	0.0439	−2.735	0.0064
	V_worker	−0.1076 *	0.0583	−1.612	0.1080
Social security	*V_medical*	0.1179 ***	0.0315	3.745	0.0002
	V_pension	0.2579 ***	0.0395	6.535	0.0000
Economic development	*V_peo_inc*	0.0123	0.0418	0.295	0.7680
	V_coll_inc	0.1381 ***	0.0471	2.930	0.0035
the interaction					
	F_education: V_school	0.2415 ***	0.0908	2.66	0.0078
	F_education: V_broadband	−0.2575 ***	0.0791	−3.257	0.0011
	F_mandarin: V_school	0.2686 ***	0.0886	3.031	0.0025
	F_road: V_altitude	0.0178	0.0667	0.267	0.7900

Note: *** $p < 0.01$; * $p < 0.1$.

The interpretations of them are as follows: (1) Per capita annual income of the family (*F_per_inc*, $\beta = -0.1717$, $p < 0.01$). In the study area, there is a significantly negative correlation between the per capita annual income of the family and the poverty level at the level of 0.01. The per capita annual income of the family is the most direct manifestation of the family's economic situation. In a period, the higher the family income, the greater the possibility of eradicating poverty. This means that, to achieve sustainable and high-quality poverty alleviation, the key is to maintain a steady increase in income [49]. (2) Ratio of the population enrolled in the new rural cooperative medical insurance of China in the family (*F_medical*, $\beta = -0.1576$, $p < 0.01$). There is a significantly negative correlation between the ratio of the population enrolled in the new rural cooperative medical insurance of China in the family and the poverty level at the level of 0.01. For most farmers, medical expenses are likely to account for a large proportion of household expenditure, which will make it impossible for farmer households to sustain their sustainable livelihoods. Participating in the new rural cooperative medical insurance can alleviate the medical pressure and reduce the medical burden of poor families to a certain extent, reduce the obstacles for poor households to escape poverty, and reduce the possibility of families becoming poor or returning to poverty due to illness to a certain extent. (3) Ratio of the population enrolled in urban and rural basic pension insurance in the family (*F_insurance*, $\beta = 0.1499$, $p < 0.01$). There is a significantly positive correlation between the ratio of the population enrolled in the new rural cooperative medical insurance of China in the family and the poverty level at the level of 0.01. In the family, the more family members that participate in urban and rural basic pension insurance, the larger the proportion of the elderly in the family, and the smaller the proportion of the population with the ability to work. The burden of supporting the elderly and the low income due to the lack of labor force may aggravate the poverty level of the family and is not conducive to poverty alleviation in poor households. Reasonable basic pension insurance provides the elderly with basic living security and provides them with security, thus reducing the economic difficulty of poverty alleviation. (4) Per capita cultivated land area of the family (*F_per_cularea*, β = 0.1362, $p < 0.01$). There is a significantly positive correlation between the per capita cultivated land area of the family and the poverty level at the level of 0.01. Generally, when the per capita cultivated land area is larger, the agricultural income will be higher, which is more conducive to poverty alleviation. However, the opposite conclusion is presented in this study. This suggests that the large per capita cultivated land area may be related to the decrease in the number of people in the family. When disasters lead to personnel loss and insufficient family labor force, the poverty level of the family is likely to deepen. (5) Ratio of the family labor force (*F_labour*, $\beta = -0.1135$, $p < 0.1$). There is a significantly negative correlation between the ratio of the family labor force and the poverty level at the level of 0.1. When more people in the family can work, the family may obtain higher income, to reduce the economic burden on the family and help the family to escape poverty.

In addition, it can be seen from Table 5 that the spatial lag factor *WY* has a positive correlation with the poverty level of farmer households at the level of 0.01. It shows that the poverty level of the family in the study area is closely related to the poverty level of others around, that is, the poverty level of the family may be affected by the poverty status of their neighbors, and there is a neighborhood effect. If the other families around a family are poor, the more likely the family is to be poor, and their enthusiasm to eradicate poverty may not be high, thus affecting the family's poverty reduction development.

4.3.2. Significant Factors at the Village Level

According to the detection results of HSTRM (Table 5), there are five significant factors at the village level, i.e., *V_pension* (ratio of the population enrolled in urban and rural basic pension insurance in the village), *V_coll_inc* (collective income of the village), *V_labour* (ratio of the village labor force), *V_medical* (ratio of the population enrolled in the new rural cooperative medical insurance of China in the village), *V_worker* (ratio of migrant workers in the village).

The interpretations of them are as follows: (1) Ratio of the population enrolled in urban and rural basic pension insurance in the village (*V_pension*, γ = 0.2579, $p < 0.01$). In the study area, there is a significantly positive correlation between the ratio of the population enrolled in urban and rural basic pension insurance in the village and the poverty level at the level of 0.01. When the proportion of the population participating in urban and rural basic pension insurance in the village is larger, it means that the population ageing phenomenon in the village may be more serious, and the proportion of young people is low, which is not conducive to the development of the village and poverty relief. However, it does not mean that there is no need for the pension insurance. On the contrary, villages should increase the security of endowment insurance to ensure the material life needs of the elderly. (2) Collective income of the village (*V_coll_inc*, γ = 0.1381, $p < 0.01$). There is a significantly positive correlation between the collective income of the village and the poverty level, which is opposed to general cognition. It shows that due to the lack of self-development capacity, when farmer households want to overcome poverty, they need to rely on the development of village collective to a great extent. (3) Ratio of the village labor force (*V_labour*, $\gamma = -0.1199$, $p < 0.01$). There is a significantly negative correlation between the ratio of the village labor force and the poverty level. When more people can work, it will help the overall development of the village, which is conducive to villagers shaking off poverty. Although the poverty-stricken people still face many outstanding problems in terms of stable employment and continuous income increase, labor employment is still an important way to promote farmers' income increase and help farmers out of poverty. The transfer and employment of poor labor force can improve the nonfarm income of farmers and the overall income of families, and promote the poverty alleviation of poor people.

(4) Ratio of the population enrolled in the new rural cooperative medical insurance of China in the village (*V_medical*, $\gamma = 0.1179$, $p < 0.01$). There is a significantly positive correlation between the ratio of the population enrolled in the new rural cooperative medical insurance of China in the village and the poverty level. It appears to be contrary to general cognition. It may be because the local medical conditions are poor and the medical level is low, which is consistent with the poverty level; thus, a positive correlation is detected. However, from the perspective of reducing the burden of farmers and meeting their needs for a better life, villages should improve the coverage of medical insurance and increase medical security of farmers to prevent families from returning to poverty due to illness. (5) Ratio of migrant workers in the village (*V_worker*, $\gamma = -0.1076$, $p < 0.1$). There is a significantly negative correlation between the ratio of migrant workers in the village and the poverty level. Migrant workers are relatively less affected by natural factors; thus, the income of farmer households is more stable, which can drive the overall development of poor villages and reduce the degree of poverty.

4.3.3. Multilevel Poverty-Causing Factor Interactions

Through the detection results of the interaction mechanism in Table 5, it can be found that (1) *V_school* has a significantly positive impact on the poverty contribution of *F_education* at the level of 0.01 (*F_education*: *V_school*, $\gamma = 0.2415$, $p < 0.01$). When the number of primary schools with broadband in the village increases, it will enhance the impact of the ratio of students in non-compulsory education on the poverty level of farmer households. This means that when the number of schools increases, the education level in the village is likely to be improved and the thoughts of students will be more progressive, and many students will choose to continue to study in high school and improve their academic qualifications to change the poverty situation. (2) *V_broadband* has a significantly negative impact on the poverty contribution of *F_education* at the level of 0.01 (*F_education*: *V_broadband*, $\gamma = -0.2575$, $p < 0.01$). When the proportion of households with broadband in the village increases, it will weaken the impact of the ratio of students in non-compulsory education on the poverty level of farmer households. When the broadband facilities in the village are improved, the villagers can learn new knowledge from the outside world through the network to emancipate their minds and actively seek a way out of poverty, which will weaken the impact of education on poverty alleviation to a certain extent. (3) *V_school* has a significantly negative impact on the poverty contribution of *F_mandarin* at the level of 0.01 (*F_mandarin*: *V_school*, $\gamma = 0.2686$, $p < 0.01$). When the number of primary schools with broadband in the village increases, it will enhance the impact of the ratio of the population who can speak Mandarin in the family on the poverty level of farmer households. When the number of primary schools increases, the enrollment rate of school-age children in the village will increase to a certain extent so that the proportion of Mandarin speakers in the household will increase. In Fugong County, the proportion of ethnic minorities is very large. Being able to speak Mandarin will help villagers communicate with the outside world, thereby increasing the opportunities to learn advanced ideas and technologies from the outside world and helping themselves to develop and eradicate poverty.

The estimation results of random effects of the HSTRM model are shown in Table 6. Combined with the estimation results of the random effects of the null model in Table 4, we use Formula (13) and Formula (14) to obtain that the variance change ratio of the household level and the village level is 12.08% and 31.70%, respectively. It shows that the household-level factors have explained 12.08% of the overall difference in the poverty level, and the village-level factors have explained 31.70% of the overall difference.

Table 6. The random effects of the HSTRM model.

Level	Variance	Std. Dev.
Household level	1.2065	1.0984
Village level	0.0969	0.3112

5. Policy Implications

According to the above analysis, we propose some targeted policy suggestions based on the significant poverty-causing factors at the different levels as a scientific reference for the poverty reduction and development of Fugong County.

First, since the labor force in households and villages has a great impact on the level of poverty, collective labor skills training can be used to improve the quality of the labor force, which in turn can contribute to the growth of household income. Villagers can also work outside to obtain more stable income and alleviate poverty through their own efforts. Second, the ratio of the insured population in medical insurance and basic pension insurance also has a great impact on the poverty level; therefore, the coverage rate of medical insurance and pension insurance in the villagers should be increased to relieve the medical pressure and pension pressure of villagers and reduce the burden of poor families. Finally, since annual per capita household income and per capita arable land area, and collective village income have a significant impact on the poverty status of farm households, villagers should be encouraged to develop a collective village economy to increase household income.

In addition, the impact of the external natural environment and infrastructure security level on farmers' poverty alleviation and income increase should also be considered. Fugong County is at a high altitude and is mountainous, which is not suitable for traditional agriculture, but the villagers can try to increase their income by developing side businesses. For example, the practice of Maji village shows that developing the fruit industry and the goat breeding industry are effective ways to increase income. In Laomden village, the channels of economic resources can be broadened by improving traffic conditions, developing tourism and promoting the development of service industries, increasing the economic income of villagers and achieving long-term effective poverty reduction. In addition, from the detection results of the interaction mechanism, it can be seen that the impact of education and networking on the development of farmer households cannot be ignored. Therefore, the villages can strengthen the infrastructure construction such as schools and communication base stations to increase the villagers' access to knowledge, improve their ability to communicate with the outside world and their enthusiasm to eradicate poverty, and achieve long-term effective poverty reduction and sustainable development in Fugong County.

6. Discussions and Conclusions

This paper has constructed a multi-dimensional index system from both the household level and the village level and designed the HSTRM model to detect the poverty-causing factors and mechanisms at different levels. Previous studies have shown that the causes of poverty come from not only individuals, but also economic, social, policy and other aspects [11,50,51]. The study of Park et al. [11] indicated that the poverty rate is higher for householders with disabilities than it is for non-disabled householders in South Korea. Behruz et al. [51] showed that the most important factors affecting spatial distribution of poverty in the rural area in India include the elements of assets, education and banking credit. When checking the factors determining poverty in Pakistan, Latif et al. [52] found that GDP growth, the unemployment rate and the hospital numbers have a significant impact on poverty. However, these studies have only detected multidimensional influencing factors at a single level. When taking Fugong County, China, as a case study, we found that the poverty is caused not only by the household-level factors, but by the village-level background factors as well. Therefore, when building models to detect the poverty-causing factors, we should consider not only the spatial lag explanatory variable of the dependent variable (poverty level), but also the endogenous explanatory variable at the household level and at the village level, to enhance the goodness of model fit and improve the accuracy.

Since poverty-causing factors are multidimensional and multilevel, these factors are very likely to interact with and influence each other in geographical space. Therefore, under the background of economic mobility and open development of social resources, the spatial interaction and spatial effect among natural environment and social economic factors on which poor households live should be considered [13,14,20,38,41]. In our study, spatial effects have been detected among the poverty levels and the poverty-causing factors. There are many differences in poverty levels across Fugong County; however, poverty levels show high correlations in geographical spaces. Spatial effects in poverty have also been validated by other research [49,53]. Furthermore, regional and spatial differences in poverty have different impacts on people. For example, COVID-19-positive patients who resided in high-poverty areas had a higher prevalence of comorbidities when compared to individuals living in low-poverty areas [54]. Considering the impacts of spatial effects, if we adopt traditional linear regression for detection, we are likely to obtain inaccurate or unreliable results. Harrison et al. showed that after considering endogeneity and spatial relationships, the research results on the interrelationship between social capital and poverty in the western United States will be more reliable, and the poverty reduction policy based on it will be more effective [53]. In this study, the proposed HSTRM method integrates both spatial effects and background effects, and the different action mechanisms of independent variables (poverty causing factors) in different spatial locations on dependent variables (poverty level) can be well explored. Moreover, HSTRM can employ panel data for analysis. Compared with cross-sectional data, which cannot track the development of poor farmer households over time, panel data provide richer information about the changes of individuals, with more freedom, less collinearity and higher estimation efficiency [55–59]. Such advantages enable us to have a more comprehensive and accurate understanding of the causes of poverty in the study area. Only then can targeted solutions be found to effectively help poor households eradicate poverty and prevent farmers from falling back into poverty [34–36].

When applying the HSTRM to detect the multilevel poverty-causing factors and the mechanisms based on the panel data in Fugong County, the main conclusions are as follows:

(1) During the research period, spatial effects were found among poverty levels and the poverty-causing factors. Local spatial autocorrelation or spatial dependence is found among the neighboring households. Therefore, the impact of spatial effects on model estimation needs to be considered when detecting the poverty-causing factors of farmer households.

(2) The poverty level of farmer households in the study area is affected by the factors at both the household level and the village level. Therefore, when detecting the poverty-causing factors, it is necessary to detect the factors at both levels.

(3) Significant influencing factors at the household level include per capita annual income of the family and ratio of the population enrolled in the new rural cooperative medical insurance of China in the family, while ratio of the population enrolled in urban and rural basic pension insurance in the village and collective income of the village are the most important factors at the village level. The household-level factors account for 12.08% of the overall difference in poverty level, and the village-level factors account for 31.70% of the overall difference.

(4) Our results have the potential to help the local government identify the specific causes of poverty in farmer households. However, due to limitations in data access, the dynamic poverty situation has not been reflected. In future research, we will take time series statistical data, in combination with field investigations, to detect the short-term and long-term factors affecting households' poverty alleviation, which should contribute to more accurately understand the poverty situation and take targeted measures for poverty reduction.

Author Contributions: Conceptualization, Y.W. and C.H.; Data curation, Y.J. and W.Q.; Formal analysis, Y.J. and C.H.; Funding acquisition, Y.W.; Investigation, Y.W. and Y.J.; Methodology, Y.J., Y.W. and C.L.; Software, Y.J.; Supervision, Y.W. and C.H.; Validation, Y.J. and C.H.; Visualization, Y.J. and B.C.; Writing—original draft, Y.J. and Y.W.; Writing—review & editing, C.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China (42171224), the Great Wall Scholars Program (CIT&TCD20190328), the CAS Earth Big Data Science Project, (XDA19060302), Key Research Projects of National Statistical Science of China(2021LZ23).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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