

Article

How Urbanization and Land Transfer Shape Carbon Emissions in Agricultural Systems: Evidence from Central China

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Abstract

Reducing agricultural carbon emissions (ACE) requires understanding how urban–rural transformation and land reallocation jointly reshape agricultural production. Using county-level data from Hubei Province, China, for 2019–2021, this study examined the spatial and nonlinear associations among urbanization (URB), agricultural land transfer (ALT), and ACE through spatial autocorrelation analysis, spatial panel models, and geographical convergent cross-mapping. URB, ALT, and ACE exhibited significant spatial dependence, with high-value clusters concentrated mainly in central Hubei. ALT showed a significant level-dependent nonlinear association with URB. URB and ALT were also significantly associated with ACE in a level-dependent nonlinear manner, with negative linear and positive quadratic components, whereas their joint term showed the opposite pattern. The directional-linkage analysis further revealed both recurring and year-specific connections between multiple dimensions of URB and ALT. Taken together, these findings show that the relationships among URB, ALT, and ACE are spatially interdependent, multidimensional, and dependent on local development conditions rather than adequately represented by constant linear relationships. Agricultural carbon mitigation should therefore combine cross-county spatial coordination with differentiated policies that reflect local URB and ALT conditions, particularly in spatially clustered areas.

Keywords: urbanization (URB); agricultural land transfer (ALT); agricultural carbon emissions (ACE); spatial panel data model; geographical convergent cross-mapping (GCCM) model; Hubei province

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1. Introduction

Reducing carbon emissions in agricultural systems has become an important task for sustainable land management and low-carbon agricultural development. In rapidly urbanizing countries such as China, agricultural systems are increasingly influenced by urban–rural transformation rather than by agricultural production factors alone. Urbanization (URB) not only expands cities, but also reshapes urban–rural linkages through the spatial reallocation of population, capital, goods, services, and economic activities [1]. In China, this process has been accompanied by rural labor migration, changes in agricultural land use, and adjustments in agricultural operation scale, thereby changing the

conditions for agricultural production [2]. Under China's rural land system, agricultural land transfer (ALT) enables farmers to transfer land-use rights and adjust farm operation scale, making it an important institutional channel for reallocating agricultural land resources during urban–rural transformation [3]. By changing farm operation scale, production organization, planting structure, input intensity, and land-use efficiency, ALT may influence how urbanization-related factor reallocation is reflected in agricultural carbon emissions (ACE) [4,5]. Clarifying these associations is important for developing land-use management strategies and low-carbon agricultural policies under urban–rural transformation [6,7].

Previous studies have examined the relationship between urbanization (URB) and agricultural land transfer (ALT) from both macro and micro perspectives. At the macro level, studies have mainly focused on regional differences, spatial patterns, and policy contexts of URB and ALT, while household-level studies have emphasized farmers' land transfer decisions, livelihood responses, and welfare outcomes [8–10]. In the Chinese context, URB is often evaluated within the framework of new-type urbanization, which emphasizes population development, economic development, public services, urban–rural coordination, and ecological conditions. Existing evidence suggests that URB may create conditions for ALT through rural labor migration, non-agricultural employment, public service provision, and urban–rural factor mobility. However, there is still no consensus on whether the relationship of URB and ALT is linear or nonlinear. Some studies suggest a mutually reinforcing relationship between URB and ALT based on Granger-type tests [5], whereas others report nonlinear relationships, such as a U-shaped association between URB and ALT [11]. Recent evidence also indicates that urban–rural integration can promote land transfer and labor mobility, thereby improving rural land-use efficiency [12]. These findings suggest that ALT is not merely a land-use adjustment, but is embedded in urbanization-related changes in labor allocation, land resource reallocation, and agricultural operation scale.

Whether URB and ALT exert enhancing or attenuating effects on ACE remains debated. Hu et al. [13] and Chen et al. [14] have reported that URB can reduce ACE by promoting scale operation, industrial upgrading, and agricultural agglomeration. Recent evidence also indicates that urbanization can contribute to the low-carbon transformation of China's agriculture and generate spatial spillover effects [15]. In contrast, Zha et al. [16] and Shi et al. [17] have pointed out that URB may lead to an increase in carbon emissions by intensifying agricultural inputs such as materials and machinery. Similar controversies exist in studies on ALT. Long and Ren [10] as well as Ji, Li and Zhang [8] have found that ALT can promote scale operation and intensive agricultural production, thus significantly increasing ACE. Conversely, Li, Huang, Yang, Su and Guo [5] has suggested that ALT may increase ACE in the short term but decrease it in the long term. More recent studies have further shown that ALT may reduce agricultural carbon-emission intensity, while this effect may depend on operation-scale thresholds [18]. Based on household survey data, Jia et al. [19] also found that the impact of ALT on ACE is not simply linear, but varies with agricultural operation scale. These mixed findings suggest that the effects of URB and ALT on ACE may not be uniform. Instead, their effects may vary across development stages and regions, and may also depend on the interaction between URB and ALT.

URB, ALT, and ACE have been evaluated using different indicators and methods. URB and ALT are commonly measured by either single indicators or composite indices constructed through entropy weighting, principal component analysis, or the analytic hierarchy process [20,21]. Single indicators, such as the population urbanization rate, the proportion of urban land, or the transferred land area, are easy to interpret but may not fully capture the multidimensional characteristics of URB and ALT. More comprehensive

URB indices usually include demographic, economic, social, spatial, and ecological dimensions, while ALT indices may consider both the scale and quality of land transfer [2,22]. For ACE estimation at regional and county scales, the carbon emission coefficient method is widely used because it can link agricultural activity data with emission coefficients from IPCC guidelines or provincial greenhouse gas emission inventories [18,23,24]. These measurement approaches provide a basis for examining URB, ALT, and ACE from a multidimensional and spatial perspective.

However, there remain several research gaps to be filled. First, previous studies have often examined the effects of URB on ACE, the effects of ALT on ACE, or the relationship between URB and ALT as separate issues. Limited attention has been paid to URB and ALT as interconnected components of urban–rural transformation and to how their independent and joint associations with ACE operate within the same analytical framework. Second, although mixed findings have been reported regarding the effects of URB and ALT on ACE, most studies still rely on linear assumptions. The potential nonlinear effects of URB, ALT, and their interaction require further examination. Less is known about whether URB, ALT, and their interaction exhibit nonlinear spatial associations with ACE when considered simultaneously. Third, existing studies have mainly been conducted at provincial or regional scales, while county-level evidence remains relatively limited. Given that counties are important units for implementing land-use management and agricultural low-carbon policies in China, county-level analysis can provide more detailed evidence on the spatial regulation of ACE and the low-carbon transformation of agricultural systems.

This study addresses these gaps using panel data for county- and district-level units in Hubei Province. Its marginal contribution lies in three respects. First, it brings the previously fragmented relationships among URB, ALT, and ACE into a unified analytical framework. Rather than examining URB and ALT only as separate determinants of ACE, the study evaluates their independent and joint associations, thereby providing evidence on whether the relationship between urbanization and agricultural carbon emissions varies with agricultural land-transfer conditions. Second, this study extends the spatial scale of existing evidence from predominantly provincial and regional analyses to the county level. This allows the study to capture spatial differences among counties within the same province that may not be visible in more aggregated analyses. Third, this study combines spatial panel analysis with an exploratory examination of directional linkages among the underlying dimensions of URB and ALT. Composite indices are used to represent the multidimensional characteristics of URB and ALT, while geographical convergent cross-mapping (GCCM) [25] is used to examine directional linkages between their component dimensions. This combination connects the overall spatial associations among URB, ALT, and ACE with the more specific relationships underlying urbanization and agricultural land-transfer processes. These contributions provide county-level evidence for understanding how urban–rural transformation is associated with agricultural carbon emissions and for informing land-use management and low-carbon agricultural strategies.

2. Research Hypotheses and Empirical Testing

2.1. Research Hypotheses

Urbanization (URB) and agricultural land transfer (ALT) are closely connected through the reallocation of rural labor and land resources. As rural households adjust their labor allocation between agricultural and non-agricultural activities, land rental markets provide an important mechanism for reallocating agricultural land among operators [26]. Urbanization can therefore influence ALT by changing rural employment opportunities and households' dependence on agricultural production. Conversely, ALT can alter agricultural operation scale and the allocation of land and other production factors, which

may in turn affect the urban–rural allocation of labor and economic activities. Empirical evidence also indicates that URB and ALT can influence each other rather than operate independently [5]. Because the strength of these mechanisms may differ across counties with different levels of URB and ALT, their association need not remain constant. The relationship between ALT and URB can exhibit nonlinear and spatial characteristics [22]. Therefore, we propose Hypothesis 1.

Hypothesis 1. *URB and ALT exhibit a nonlinear association, accompanied by spatial spillover effects across neighboring counties.*

URB may influence agricultural carbon emissions (ACE) through competing mechanisms. On the one hand, URB can be associated with changes in agricultural production intensity and factor inputs. Where these changes increase reliance on carbon-intensive production factors, such as agricultural machinery and other production inputs, ACE may increase. Empirical evidence suggested that higher levels of URB may be associated with higher ACE [5,9]. On the other hand, URB can facilitate technological innovation and improvements in production efficiency, which may contribute to agricultural carbon reduction [15]. Evidence from regional studies also supports an emission-reducing association between urbanization and ACE [13]. Because these emission-increasing and emission-reducing mechanisms may differ in relative importance across counties with different levels of URB, the association between URB and ACE need not be linear. Moreover, flows of labor, capital, technology, and agricultural production factors across regions provide channels through which the effects of URB may extend to neighboring agricultural systems [15]. Therefore, we propose Hypothesis 2.

Hypothesis 2. *URB has a nonlinear association with ACE, accompanied by spatial spillover effects across neighboring counties.*

ALT may also affect ACE through mechanisms operating in different directions. By changing agricultural operation scale and production organization, ALT can alter the intensity and composition of agricultural inputs, thereby affecting carbon emissions. The expansion of agricultural operation scale associated with land transfer may contribute to higher local ACE under some conditions, and operation scale has been identified as an important mediating mechanism in this relationship [8]. ALT can also change agricultural factor inputs. In particular, increases in agricultural chemical inputs may raise ACE, whereas changes in machinery inputs may have a different carbon effect [27]. However, the carbon consequences of ALT may change when agricultural operation reaches a more suitable scale. Large-scale operators may reduce fertilizer, pesticide, and irrigation-energy inputs after land transfer, thereby lowering agricultural carbon emissions [19]. Consistent with this mechanism, the emission-reducing effect of land transfer has been found to strengthen after agricultural operation scale exceeds a threshold [18]. These competing mechanisms indicate that the association between ALT and ACE may vary across different land-transfer and operation-scale conditions rather than remain uniformly positive or negative. Furthermore, ALT may affect not only local ACE but also ACE in neighboring regions through spatial spillover effects [8]. Therefore, we propose Hypothesis 3.

Hypothesis 3. *ALT has a nonlinear association with ACE, accompanied by spatial spillover effects across neighboring counties.*

URB and ALT may further influence ACE jointly because they affect related components of agricultural factor allocation. Urbanization changes rural labor allocation and non-agricultural employment opportunities, while ALT determines how agricultural land

is reallocated in response to these changes. Consequently, the carbon effect associated with ALT may depend on the level of urbanization, because different urbanization conditions imply different labor availability, production-factor combinations, and agricultural operation conditions. Conversely, the association between URB and ACE may also depend on whether agricultural land can be effectively reallocated as rural labor and other factors move across sectors. Evidence that the effect of ALT on ACE changes across different urbanization conditions provides a basis for expecting such conditional effects [27]. The established interrelationship between URB and ALT further supports considering them jointly [5]. Spatial spillover effects have also been identified separately for the URB–ACE and ALT–ACE relationships [8,15]. Given the interdependence between URB and ALT, their joint association with ACE may therefore also extend beyond local administrative boundaries. Therefore, we propose Hypothesis 4.

Hypothesis 4. *The interaction between URB and ALT has a nonlinear association with ACE, accompanied by spatial spillover effects across neighboring counties.*

In this study, the hypothesized nonlinear relationships refer to level-dependent associations over the observed values of the explanatory variables rather than long-term temporal trajectories within individual counties. The theoretical framework linking URB, ALT, and ACE is presented in Figure 1.

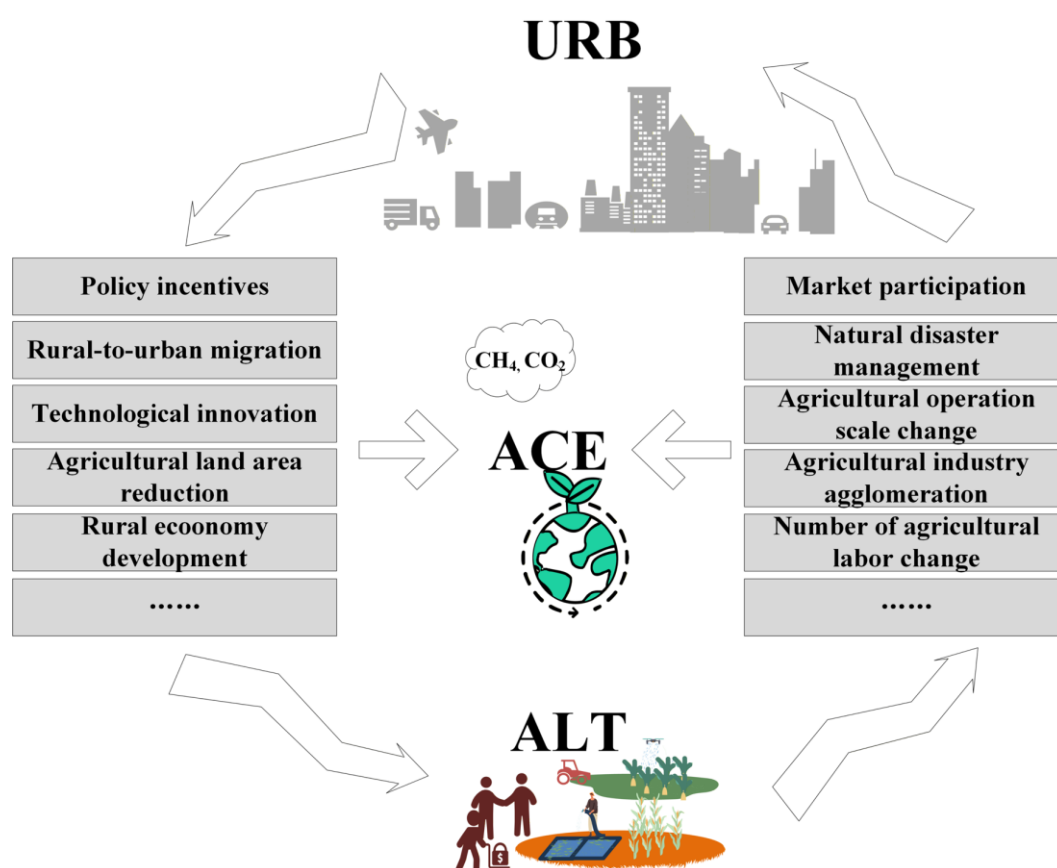


Figure 1. Theoretical framework linking urbanization (URB), agricultural land transfer (ALT), and agricultural carbon emissions (ACE).

2.2. Model Construction

Seven major modeling steps are applied to test the above four hypotheses, following (Figure 2).

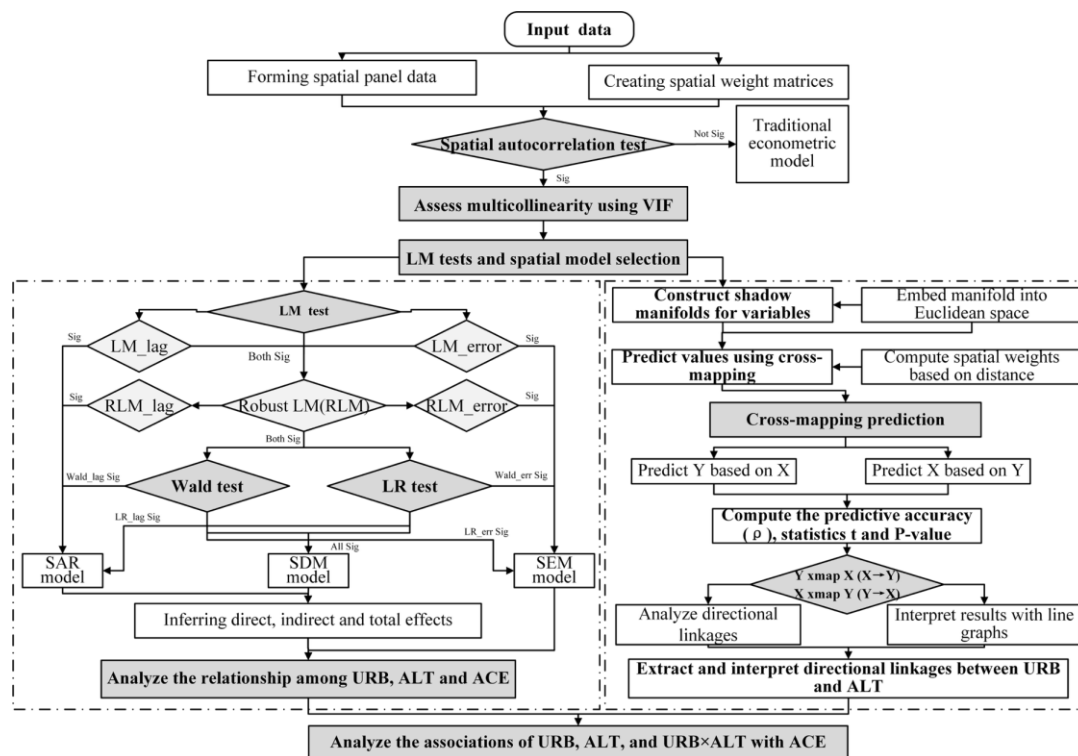


Figure 2. Modeling framework. URB, urbanization; ALT, agricultural land transfer; ACE, agricultural carbon emissions; VIF, variance inflation factor; LM, Lagrange multiplier; RLM, robust Lagrange multiplier; LR, likelihood-ratio test; SAR, spatial autoregressive model; SEM, spatial error model; SDM, spatial Durbin model. The spatial panel branch is used to examine spatial and level-dependent nonlinear associations among URB, ALT, and ACE, whereas the geographical convergent cross-mapping branch is used to explore directional linkages between dimensions of URB and ALT.

Step 1: Spatial weight matrix is used to quantify adjacency relationships among different regions. Given that the effects of URB, ALT, and ACE on neighboring regions may be influenced by distances and adjacency, we constructed two spatial weight matrices. Spatial weight matrix 1 (W1) was created using the criterion of geographical spatial distance, while Spatial weight matrix 2 (W2) was constructed based on the criterion of geographical adjacency relationships.

Step 2: Global and local spatial autocorrelations were used to measure the spatial distribution pattern. The former reflects spatial dependence, while the latter reflects spatial heterogeneity [28]. Moran's I [29] was used to measure global and local spatial autocorrelations, and global and local Moran's indices were calculated according to Equations (A1) and (A2) in Appendix A.

Step 3: Spatial panel data models can capture the interaction effects among spatial units, also known as spatial spillover effects, reflecting spatial dependence. If a dependent variable is spatial-dependent, the model is a spatial lag model, also known as a spatial autoregressive model (SAR); if the error term is spatial-dependent, the model is spatial error model (SEM) [30]. In addition, spatial panel data exhibit time and individual dimensions, allowing for the control of specific spatial and temporal effects [31]. In this study, time-individual (two-way) fixed effects are employed to control potential unobserved heterogeneity in the model to ensure accuracy and robustness of estimated results. When it is difficult to choose a certain model, spatial Durbin model (SDM) can be the preferential

one [32]. To investigate the nonlinear relationships among URB, ALT, and ACE, the quadratic terms of the independent variables should be included in the modeling process [33]. The specific model is presented in Equations (1) and (2).

$$URB_{it} = \rho WURB_{it} + \beta_1 ALT_{it} + \beta_2 ALT_{it}^2 + \theta WALT_{it} + u_i + v_t + \epsilon_{it}, \quad (1)$$

$$\begin{aligned} \ln ACE_{it} = & \rho W \ln ACE_{it} + \beta_1 URB_{it} + \beta_2 URB_{it}^2 + \theta_1 WURB_{it} \\ & + \beta_3 ALT_{it} + \beta_4 ALT_{it}^2 + \theta_2 WALT_{it} + \\ & \beta_5 (URB \times ALT)_{it} + \beta_6 (URB \times ALT)_{it}^2 + \theta_3 W(URB \times ALT)_{it} + u_i + v_t + \epsilon_{it}, \end{aligned} \quad (2)$$

where URB is the abbreviation for urbanization; i and t represent regions and time, respectively; X_{it} and Y_{it} denote the independent and dependent variables of region i at time t , respectively; ρ is the spatial autoregressive coefficient; W represents the spatial weight matrix; β indicate the coefficient to be estimated for the independent variables; θ is the coefficient to be estimated for the spatial lagged terms of the independent variables; u_i and v_t are the individual and time fixed effects, respectively; ϵ_{it} is the error term; and URB_{it} , ALT_{it} , and $\ln ACE_{it}$ are the composite indexes of URB, ALT, and ACE, respectively.

Step 4: Multicollinearity among the underlying explanatory variables was assessed using variance inflation factors (VIFs) following O'Brien (2007) [34]. The diagnosis was conducted for the standardized forms of URB, ALT, and the control variables. The quadratic and interaction terms were not included in this base-variable diagnostic, as they were constructed to capture the hypothesized nonlinear and joint associations. The stability of these nonlinear terms was further examined using alternative spatial model specifications and spatial weight matrices.

Step 5: Anselin et al. [35] used the Lagrange multiplier (LM) test originally in cross-sectional models to investigate interaction effects among the dependent variables and error terms in spatial panel data models. Elhorst [30] further applied a robust LM (RLM) test to spatial panel data model. When the LM or RLM test results reject the null hypothesis of the ordinary least squares model, but fail to reject the that of SAR or/and SEM, SDM should be adopted. SDM may be simplified into SAR or SEM, which was the two null hypotheses proposed by Elhorst [36]. Elhorst [30] pointed out that in addition to the LM test, the likelihood ratio (LR) test and the Wald test can be used to determine whether the specific model should be adopted. When the statistics between SDM and SAR/SEM exceed the 10% significance level in the chi-squared test, SDM cannot be determined as simplified one. The final selection of the most appropriate model in this study is based on all above diagnostic test results.

Step 6: The regression coefficient of SDM and SAR cannot fully reflect the effects of the explanatory variables on the dependent variable due to the presence of feedback effects. To measure the spatial effect, the total effect is decomposed into direct and indirect (spillover) effects by utilizing the partial differential method proposed by LeSage and Pace [32]. In SEM, the coefficient of variables represents the direct effect, while the spatial lag coefficient of variables signifies the indirect effect.

Step 7: To complement the analysis of nonlinear associations between URB and ALT, this study employed the GCCM model to examine exploratory directional dependence patterns between URB-related and ALT-related dimensions from 2019 to 2021. GCCM was a model proposed by Gao, Yang, Chen, Sugihara, Li, Stein, Kwan and Wang [25], based on dynamical system theory and generalized embedding theory. For details on the principles of the GCCM model, refer to Equations (A3)–(A12) in Appendix B. A line graph of the prediction results is generated based on the Appendix B-mentioned steps, with ρ values as the vertical axis and library sizes as the horizontal axis. If the Y cross-mapping prediction of X (Y xmap X) line is at a high position in this line graph, then X can cause Y (noted as $X \rightarrow Y$) [37]. However, if the causal effect of X is sufficiently strong to subordinate Y to X , leading to synchronization, then the ability of X to predict Y (X xmap Y) is strong.

Therefore, strong cross-mapping prediction capacity in both directions ($X \rightarrow Y$ and $Y \rightarrow X$) suggest bidirectional causal associations or the subordination of the effect variable to the cause variable. Given the short observation period of this study, the GCCM results are used as exploratory evidence of directional linkages rather than definitive proof of causal effects.

2.3. Materials

2.3.1. Data Sources

The data used for calculating the composite index of urbanization (URB) and agricultural land transfer (ALT) are primarily derived from the *China City Construction Statistical Yearbook*, *China County Statistical Yearbook*, *Hubei Statistical Yearbook* (provincial and municipal), and *Annual Report on Rural Policy Reform in Hubei Province* in the period of 2019 to 2021. The data for estimating ACE are primarily obtained from the *Hubei Statistical Yearbook* and *Hubei Rural Statistical Yearbook*. In the cases where partial data are missing, we made data public disclosure requests to municipal agricultural and rural bureaus, natural resources and planning bureaus, and other relevant authorities.

2.3.2. Study Region

As one of the key grain-producing regions in China, Hubei province experiences rapid urbanization and an active agricultural land transfer market, making it a suitable research region. The study time frame spanning from 2019 to 2021 is appropriate since it represents the accomplishment of the *13th Five-Year Plan* in China and Hubei Province, alongside the commencement of the *14th Five-Year Plan*.

Hubei Province is located in the central part of China ($29^{\circ}01'53''$ – $33^{\circ}6'47''$ N and $108^{\circ}21'42''$ – $116^{\circ}07'50''$ E), covering a total area of 18.59×10^4 km². The administrative divisions of the province are illustrated in Figure 3. Hubei Province is a typical province that has been advancing urbanization in the central region of China. Mountainous regions account for 56% of the total area of the province; hilly regions, 24%; and plain-lake regions, 20% [38]. The regions cover different terrains for agricultural production in Hubei Province. In this study, considering the limited agricultural production in certain regions, some municipal districts have been consolidated, and finally 82 county- or district-level research units were obtained.

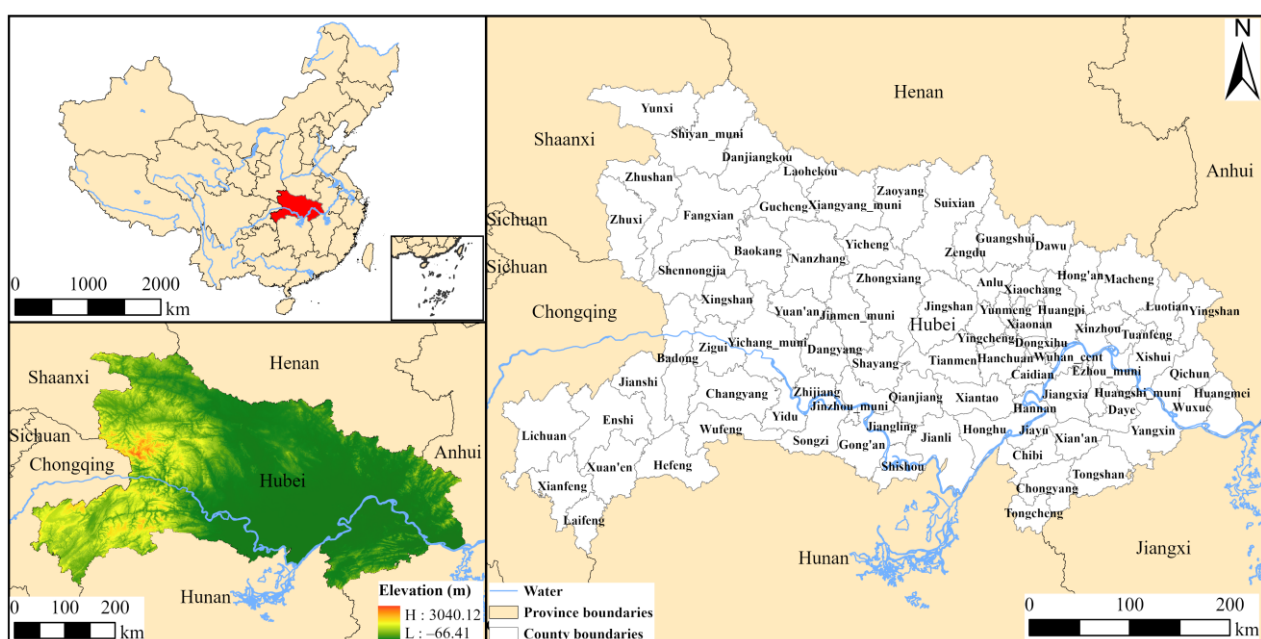


Figure 3. Location of Hubei Province.

2.4. Variables

2.4.1. Estimation of URB ALT, and ACE

(1) Composite index of urbanization (URB)

In this study, urbanization is operationalized through a composite index developed based on the new-type urbanization framework. Since 2014, the Chinese government has issued a series of policy documents related to new-type urbanization, which provide important institutional references for constructing a multidimensional urbanization index in the Chinese context. These documents include the *Implementation of New Urbanization in 14th Five-Year Plan* formulated by the China central government and the *Opinions on Promoting Urbanization with Counties as Important Carriers*. The government of Hubei Province also made requirements on new-type urbanization in some related documents. Based on the existing research findings [2,22], this study selected the indicators from the perspectives of population urbanization, economic urbanization, public service urbanization, spatial urbanization, and ecological urbanization (Table 1). The composite index of URB in each county and district was calculated using the entropy weight method.

(2) Composite index of agricultural land transfer (ALT)

The composite index of agricultural land transfer (ALT) was selected across four dimensions including market participation, transfer target liberalization, market effectiveness, and market stability, which comprehensively reflects the macroeconomic characteristics of the agricultural land transfer market. Market participation is quantified as the proportion of transferred land in total contracted agricultural land area per household, and it reflects market activity levels [21]. Transfer target liberalization refers to the scope and category flexibility of agricultural land transfers. A liberalized market facilitates optimal resource flow towards entities with comparative advantages or higher production efficiency [39]. In this study, transfer target liberalization is quantified as the proportion of agricultural land transferred to non-local entities in total transferred land. Market effectiveness is used to evaluate the efficiency of the transfer process. An effective transfer market contributes to the optimization of land-use efficiency, channeling resources into the most productive activities, thereby enhancing overall agricultural productivity [26]. This market effectiveness dimension is calculated as the proportion of agricultural land transferred to new agricultural business entities in total transferred land area, including specialized farms, family farms, and agricultural enterprises engaged in intensive production. Market stability is used to evaluate the long-term stability of ALT, which is quantified as the proportion of transferred land area in signed contracts in total transferred land area. Stable transfer agreements can enhance transaction security and credibility, thus creating a favorable environment for sustainable market development. The composite index of ALT in each region is also calculated by the entropy weight method.

(3) Simulation of Agricultural carbon emissions (ACE)

The current study investigates carbon emissions arising from agricultural cultivation. Energy consumption during cultivation is the major source of ACE, including the consumption of coal, refined oil, electricity, straw, firewood, and biogas. In addition, ACE also includes carbon emissions from production activities, such as methane (CH₄) emissions from paddy fields and carbon dioxide (CO₂) emissions from fertilizers, pesticides, films, and irrigation [40]. ACE is estimated using the carbon emission coefficient method according to Equation (4). Table A1 (in Appendix C) presents the details of the emission coefficients of diverse agricultural production activities as well as their respective reference sources.

$$ACE = \sum ACE_m = \sum \partial_m Q_m, \quad (2)$$

where ACE is the total carbon emission from agricultural cultivation; ACE_m refers to carbon emission from agricultural activity m ; ∂_m indicates the carbon emission coefficient

of agricultural activity m , and Q_m is the quantity (energy and cultivation area) consumed by agricultural activity m .

2.4.2. Variable Description

URB and ALT simultaneously serve as both independent and dependent variables, influencing each other. In addition, URB and ALT act as independent variables affecting the dependent variable ACE. Many factors are considered to significantly influence URB or ALT, such as the number of agricultural labor forces, agricultural operation scale, property right reform, agricultural industry agglomeration, agricultural technology, non-agricultural market activity, and agricultural development level [20,41,42]. Similarly, multiple factors are reported to influence ACE, including urban–rural disparity, agricultural operation scale, property rights reform, agricultural industry agglomeration, agricultural technology, availability of clean energy, non-agricultural market activity, agricultural development, natural disaster management, agricultural waste utilization degree, agricultural market participation, rural economy, and climate [4,40,43]. The descriptive statistics of the variables are shown in Table 1.

Table 1. Definitions and descriptive statistics of study variables.

Elements	Variable	Indicator	Mean	Standard deviation
URB	Population development	Population urbanization rate (%)	53.950	13.359
		Urban registered unemployment rate	2.968	0.863
	Economic development	Per capita GDP (CNY 10,000 per person)	7.192	8.529
	Public services	Number of hospital beds per thousand people	0.007	0.002
	Urban–rural coordinated development	Proportion of secondary and tertiary industries (%)	0.828	0.092
		Proportion of built-up areas (%)	4.172	11.077
	Ecological environment	Green coverage rate in built-up regions	38.669	4.747
ALT	Market participation	Proportion of transfer area (%)	0.347	0.190
	Transfer target (market) liberalization	Proportion of agricultural land transferred to non-local entities in total transferred land (%)	0.315	0.366
	Market effectiveness	Proportion of land area transferred to new agricultural management entities in total transferred land area (%)	0.641	0.254
	Market stability	Proportion of transferred land area in signed contracts in total transferred land area (%)	0.725	0.249
	ACE	Agricultural carbon emission, (t C)	375,314.100	290,075.700
Control variables	Urban–rural disparity	Ratio of urban to rural residents' income	2.024	0.373
	Agricultural operation scale	Cultivated area of crops by the agricultural labor force (ha per 10,000 agricultural workers)	11,016.620	6638.890
	Property rights reform	Number of contracted agricultural land certificates	107,444.100	57,736.590

Agricultural industry agglomeration	Proportion of total agricultural labor force in the study (area) unit in provincial agricultural labor force (%)	0.120	0.007
Agricultural technology	Number of agriculture products awarded “Three Products and One Standard” certificate in each study unit	29.646	30.500
Availability of clean energy	Proportion of households using clean energy in total rural households (%)	0.470	0.290
Non-agricultural market activity	Proportion of perennial migrant labor force in total migrant labor force (%)	0.413	0.237
Agricultural development	Per capita output value of the primary industry (people per billion yuan)	3.829	2.533
Natural disaster management	Comprehensive control area of soil erosion	0.077	0.313
Agricultural waste utilization degree	Straw utilization rate (%)	0.935	0.306
Agricultural market participation	Proportion of household agricultural labor force in total household labor force (%)	0.283	0.135
Rural economy	Total economic income of the village collective (CNY 10,000)	20,994.380	27,109.180
Climate	Annual average precipitation (mm)	1239.163	300.986

Notes: URB, urbanization; ALT, agricultural land transfer; ACE, agricultural carbon emissions.

3. Results

3.1. Spatiotemporal Characteristics of URB, ALT, and ACE

3.1.1. Spatiotemporal Evolution of URB, ALT, and ACE

As shown in Figure 4, from 2019 to 2021, the URB index exhibited fluctuating growth with a notable concentration trend, and over 3 years, the spatial distribution of the URB index presented an inverted U-shaped in the east–west (X-axis trend line) and north–south directions (Y-axis trend line), implying a high URB index in central regions of Hubei Province. However, the disparities in the URB index across regions diminished from 2019 to 2021, as evidenced by the gradual flattening curves in the X-axis and Y-axis.

From 2019 to 2021, an overall trend of decrease in the ALT index across regions was observed, with a more concentrated distribution of the ALT index and a reduced disparities among regions. Over 3 years (2019–2021), the central region of Hubei Province consistently exhibited high ALT index in the east–west direction (X-axis), including counties (such as Suizhou) and cities (such as Guangshui, Zhongxiang, Jingshan, Shayang, and Jiangling) (Figure 4). The regions at both ends in the north–south direction exhibited higher ALT index than central regions.

From 2019 to 2021, ACE in Hubei Province exhibited a fluctuating decrease, with a significant concentration trend. The total annual ACE in 2019, 2020, and 2021 was 3136.71×10^4 , 3030.75×10^4 , and 3065.27×10^4 t C, respectively. Over the 3-year period, only Daye county in the southeastern region and Fang county in the northwestern region witnessed an annual increase in ACE. The central regions exhibited the highest ACE (Figure 4).

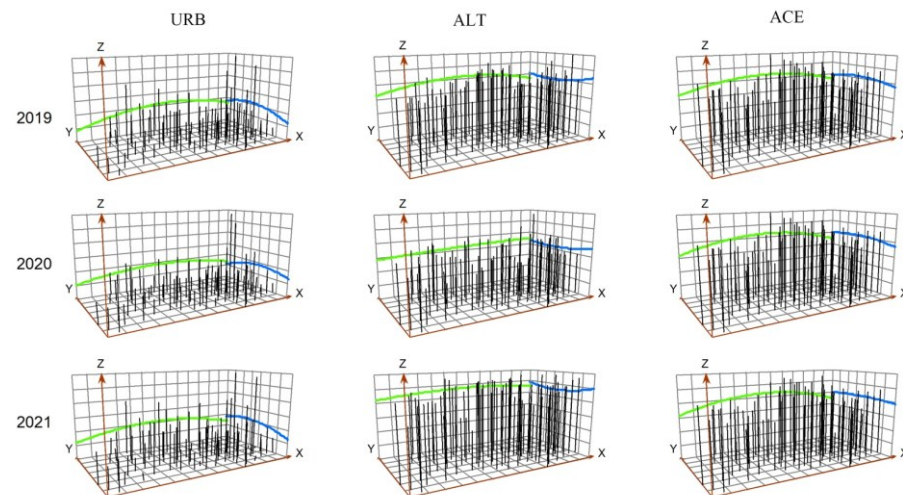


Figure 4. Spatial distributions of urbanization (URB), agricultural land transfer (ALT), and agricultural carbon emissions (ACE) in Hubei Province, 2019–2021. The green and blue curves distinguish the data distributions along the X and Y axes, while the black vertical lines represent the corresponding values along the Z axis.

3.1.2. Spatial Correlation of URB, ALT, and ACE

The estimation results of global *Moran's I* and P value of URB, ALT, and ACE were basically consistent between spatial weight matrices W1 and W2 (Table A2 in Appendix D). A global positive spatial autocorrelation of URB, ALT, and ACE was observed in each county or district of Hubei Province from 2019 to 2021. Even after 999 randomization tests, the P values remained at the 10% significance level. Similarly, the local spatial autocorrelation of URB, ALT, and ACE was also observed in each county and district of Hubei Province, and it demonstrated consistency between weight matrices W1 and W2. The regions with spatial clustering of ACE, ALT, and URB were basically consistent among 3 years, and those regions with high comprehensive indices were more prone to clustering.

3.2. Model Diagnostic Tests

The multicollinearity diagnostic results indicated that the VIF values of the underlying explanatory variables ranged from 1.13 to 2.00, with a mean VIF of 1.41. These results suggested that serious multicollinearity was not present among the underlying explanatory variables included in the subsequent spatial econometric analysis.

As shown in Table 2, the LM and RLM test results were generally consistent under W1 and W2, although some differences were observed in the LR and Wald tests for model specification.

Table 2. Diagnostic tests for spatial econometric model selection.

Diagnostic Test	Parameters	URB~ALT		ACE~URB + ALT + (URB × ALT)	
		W1	W2	W1	W2
		Statistic (p Value)	Statistic (p Value)	Statistic (p Value)	Statistic (p Value)
LM test	LM_err	22.016 (0.000)	20.059 (0.000)	6.171 (0.013)	4.483 (0.034)
	LM_lag	28.430 (0.000)	25.840 (0.000)	16.306 (0.000)	15.085 (0.000)
	RLM_err	0.002 (0.965)	0.012 (0.912)	0.006 (0.936)	0.157 (0.692)

LR test	RLM_lag	6.415 (0.011)	5.794 (0.016)	10.142 (0.001)	10.759 (0.001)
	LR_lag_both	11.630 (0.311)	18.230 (0.051)	21.860 (0.112)	23.890 (0.070)
	LR_err_both	14.320 (0.159)	20.200 (0.027)	22.790 (0.089)	24.550 (0.055)
Wald test	Wald_lag_both	14.800 (0.139)	24.810 (0.006)	22.740 (0.090)	27.910 (0.022)
	Wald_err_both	18.490 (0.047)	28.230 (0.002)	23.680 (0.071)	28.76 (0.017)

Notes: URB, urbanization; ALT, agricultural land transfer; ACE, agricultural carbon emissions. LM and RLM denote the Lagrange multiplier and robust Lagrange multiplier tests, respectively; _err and _lag refer to spatial error and spatial lag dependence. LR denotes the likelihood-ratio test. Two-way FE refers to county and year fixed effects. Spatial weight matrix 1 (W1) was constructed based on geographical distance, whereas Spatial weight matrix 2 (W2) was constructed based on geographical adjacency. Values in parentheses are P values.

For the relationship between URB and ALT, the SAR with two-way fixed effects was selected as the baseline specification. The LM and RLM tests indicated significant spatial lag dependence under both W1 and W2. The LR and Wald tests generally supported the simplification of the SDM to SAR under W1, although some differences were observed under W2.

For the effects of URB and ALT on ACE, the SAR with two-way fixed effects was also selected as the baseline specification. The LM and RLM test results similarly indicated significant spatial lag dependence under both spatial weight matrices. The LR and Wald tests provided somewhat mixed evidence regarding the simplification of the SDM, particularly under W2. Therefore, the SDM and SEM were further employed as alternative spatial specifications for robustness analysis.

3.3. Hypothesis Testing

In spite of slight differences in the regression coefficients, the regression results under matrices W1 and W2 displayed overall similarity. In our analytical framework, the main coefficient represents the estimated association between the independent and dependent variables in the SAR specification, whereas the direct, indirect, and total effects further account for the spatial feedback mechanism. The parameter Rho denotes the spatial autoregressive coefficient and quantifies the degree of spatial dependence in the model. The direct effect (LR_Direct) represents the average association of an independent variable with the dependent variable within the same spatial unit after accounting for spatial feedback. The indirect effect (LR_Indirect) reflects the association transmitted to neighboring spatial units through the spatial dependence mechanism and therefore represents the spatial spillover effect. The total effect (LR_Total) is the sum of the direct and indirect effects and reflects the overall association of an independent variable with the dependent variable across the spatial system.

3.3.1. Nonlinear Relationship Between URB and ALT

The significant nonlinear association between URB and ALT provided support for hypothesis 1 (H1). The results under matrix W1 (Table 3) were used as a representative example for subsequent analysis, while the regression results under matrix W2 are presented in Table A3 (Appendix E). The signs, magnitudes, and significance patterns of the key coefficients under W2 were highly consistent with those under W1, suggesting that the main finding was not sensitive to the choice of spatial weight matrix. Rho was positive and statistically significant, indicating significant positive spatial dependence in URB. In

the SAR model with two-way fixed effects, the LR_Direct, LR_Indirect, and LR_Total effects reflecting the association between ALT and URB demonstrated generally consistent patterns. Specifically, the linear coefficients of ALT were negative, whereas the corresponding quadratic coefficients were positive. The total effect of ALT on URB exhibited a linear coefficient of -0.469 and a quadratic coefficient of 0.559, both of which were statistically significant. These results jointly revealed a significant convex nonlinear association between ALT and URB, indicating that the association between ALT and URB varied across different levels of ALT rather than remaining constant. Further analysis showed that the urban–rural disparity was negatively associated with URB, whereas agricultural operation scale and agricultural development exhibited positive associations with URB. The remaining control variables did not show statistically significant associations.

Table 3. Spatial panel estimates of the level-dependent nonlinear association between agricultural land transfer (ALT) and urbanization (URB).

Variables	Main	Spatial	LR_Direct	LR_Indirect	LR_Total
ALT	−0.344*** (0.008)	/	−0.346** (0.011)	−0.123* (0.057)	−0.469** (0.012)
ALT ²	0.410*** (0.001)	/	0.412*** (0.002)	0.147** (0.034)	0.559*** (0.002)
Urban–rural disparity	−0.528*** (0.005)	/	−0.519*** (0.004)	−0.184** (0.041)	−0.703*** (0.005)
Agricultural operation scale	0.053* (0.052)	/	0.054** (0.048)	0.019 (0.121)	0.073* (0.053)
Property rights reform	−0.158 (0.545)	/	−0.155 (0.555)	−0.054 (0.593)	−0.209 (0.559)
Agricultural industry agglomeration	0.062 (0.472)	/	0.067 (0.434)	0.024 (0.472)	0.091 (0.434)
Agricultural technology	0.042 (0.475)	/	0.043 (0.489)	0.016 (0.531)	0.059 (0.494)
Availability of clean energy	0.038 (0.365)	/	0.037 (0.364)	0.013 (0.431)	0.050 (0.373)
Non-agricultural market activity	0.005 (0.856)	/	0.007 (0.789)	0.003 (0.804)	0.010 (0.790)
Agricultural development	0.083** (0.023)	/	0.086** (0.023)	0.030* (0.082)	0.116** (0.025)
ρ	/	0.275*** (0.00)	/	/	/
Observations	246	246	246	246	246
R-squared	0.150	0.150	0.150	0.150	0.150

Notes: ρ denotes the spatial autoregressive coefficient. Direct, indirect, and total effects refer to spatial impact estimates. All continuous explanatory variables were standardized before estimation. Values in parentheses are P values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The model includes county and year fixed effects.

3.3.2. Nonlinear Relationship Among URB, ALT, and ACE

The empirical results showed significant level-dependent nonlinear associations of URB and ALT with ACE, as well as a significant level-dependent nonlinear joint association of URB and ALT with ACE, thereby providing support for hypotheses H2, H3, and H4. The regression results under matrix W1 are presented in Table 4, while those under matrix W2 are shown in Table A4 (Appendix E). The signs, magnitudes, and significance patterns of the key coefficients under W2 were highly consistent with those under W1, suggesting that the main findings were not sensitive to the choice of spatial weight matrix.

Table 4. Spatial panel estimates of the level-dependent nonlinear associations of urbanization (URB), agricultural land transfer (ALT), and their joint term (URB×ALT) with agricultural carbon emissions (ACE).

Variables	Main	Spatial	LR_Direct	LR_Indirect	LR_Total
URB	−0.463*** (0.007)	/	−0.468*** (0.009)	−0.185* (0.066)	−0.653** (0.011)
URB ²	0.560*** (0.000)	/	0.567*** (0.000)	0.226** (0.038)	0.793*** (0.001)
ALT	−0.374** (0.026)	/	−0.371** (0.029)	−0.146* (0.093)	−0.517** (0.030)
ALT ²	0.390*** (0.000)	/	0.391*** (0.000)	0.155** (0.031)	0.546*** (0.000)
URB×ALT	0.418** (0.046)	/	0.417** (0.048)	0.165 (0.122)	0.582* (0.051)
(URB×ALT) ²	−0.459*** (0.001)	/	−0.461*** (0.001)	−0.184** (0.042)	−0.645*** (0.001)
Natural disaster management	0.307 (0.486)	/	0.318 (0.492)	0.127 (0.559)	0.445 (0.503)
Agricultural industry agglomeration	−0.070** (0.045)	/	−0.073** (0.033)	−0.030 (0.155)	−0.103** (0.049)
Agricultural technology	−0.029 (0.202)	/	−0.028 (0.218)	−0.011 (0.308)	−0.040 (0.231)
Availability of clean energy	−0.004 (0.786)	/	−0.004 (0.807)	−0.001 (0.856)	−0.005 (0.818)
Agricultural waste utilization rate	0.036 (0.396)	/	0.035 (0.403)	0.013 (0.487)	0.048 (0.416)
Agricultural market participation	0.008 (0.454)	/	0.009 (0.429)	0.004 (0.483)	0.013 (0.435)
Climate	−0.004 (0.906)	/	−0.005 (0.874)	−0.002 (0.89)	−0.007 (0.878)
Rural economy	0.003 (0.835)	/	0.004 (0.795)	0.002 (0.818)	0.006 (0.800)
Agricultural development	0.082*** (0.000)	/	0.081*** (0.000)	0.033** (0.035)	0.114*** (0.000)
ρ	/	0.291*** (0.000)	/	/	/
R-squared	0.104	0.104	0.104	0.104	0.104

Notes: ρ denotes the spatial autoregressive coefficient. Direct, indirect, and total effects refer to spatial impact estimates. All continuous explanatory variables were standardized before estimation. Values in parentheses are p values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The model includes county and year fixed effects.

Under W1, the linear term of URB was negative and statistically significant (−0.463, $p = 0.01$), whereas its quadratic term was positive and statistically significant (0.560, $p < 0.01$). Similarly, the linear term of ALT was significantly negative (−0.374, $p = 0.03$), while its quadratic term was significantly positive (0.390, $p < 0.01$). These results indicated significant level-dependent nonlinear associations of both URB and ALT with ACE. For the joint association of URB and ALT, the coefficient of the URB×ALT term was positive and statistically significant (0.418, $p = 0.05$), whereas the coefficient of its quadratic term was negative and statistically significant (−0.459, $p < 0.01$), indicating that the joint association also varied across different levels of URB and ALT.

In the SAR with two-way fixed effects, the spatial autoregressive coefficient Rho was 0.291 ($p < 0.01$), indicating significant positive spatial dependence in ACE, which was

consistent with the spatial autocorrelation identified by the Moran's I results in Section 3.1.2. The estimated direct, indirect, and total effects generally exhibited consistent coefficient directions. For URB, the total effect of the linear term was -0.653 ($p = 0.01$), whereas that of the quadratic term was 0.793 ($p < 0.01$). For ALT, the corresponding total effects were -0.517 ($p = 0.03$) and 0.546 ($p < 0.01$), respectively. The total effect of the URB $\times$ ALT term was 0.582 ($p = 0.05$), while that of its quadratic term was -0.645 ($p < 0.01$). These results further supported the level-dependent nonlinear associations of URB, ALT, and their joint term with ACE. Additionally, other factors such as agricultural industry agglomeration and agricultural development also had effects on ACE, in spite of different influence direction (positive or negative) and degree.

3.4. Robustness and Sensitivity Analyses

To examine whether the main findings were dependent on a particular spatial weight matrix, spatial econometric specification, or fixed-effects structure, a series of robustness and sensitivity analyses were conducted. The baseline specification was the SAR model under W1 with county and year fixed effects. The models were re-estimated using the alternative spatial weight matrix W2, the SDM and SEM under W1, and a county fixed-effects SAR specification under W1. The results are presented in Tables 5 and 6.

For the relationship between URB and ALT, the results were highly stable across the alternative specifications (Table 5). The coefficient of ALT remained negative and statistically significant, ranging from -0.308 to -0.380 , whereas the coefficient of ALT² remained positive and statistically significant, ranging from 0.404 to 0.432 . The coefficient directions, magnitudes, and significance patterns were therefore broadly consistent across the alternative spatial weight matrix, spatial econometric models, and fixed-effects specifications. These results indicate that the identified level-dependent nonlinear association between ALT and URB was not driven by a particular model specification.

For the associations of URB and ALT with ACE, the results were highly consistent when the spatial weight matrix was changed from W1 to W2 (Table 6). The coefficient directions of URB, URB², ALT, ALT², URB $\times$ ALT, and (URB $\times$ ALT)² were almost unchanged. Under the alternative SDM and SEM specifications, the directions of all six core terms also remained consistent with those of the baseline SAR, although the statistical significance of some linear terms weakened. In the county fixed-effects specification, the signs of the core nonlinear terms were generally preserved, but the magnitudes and statistical significance of several linear terms decreased substantially after year fixed effects were excluded. Thus, the main level-dependent nonlinear patterns were robust to the choice of spatial weight matrix and broadly consistent across alternative spatial econometric specifications, while some sensitivity to the fixed-effects structure was observed. This sensitivity further indicates the importance of controlling for common year-specific shocks in the baseline two-way fixed-effects specification.

Table 5. Robustness and sensitivity analyses of the level-dependent nonlinear association between urbanization (URB) and agricultural land transfer (ALT).

Variables/Specification	Baseline: SAR-W1, Two-Way FE	SAR-W2, Two- Way FE	SDM-W1, Two-Way FE	SEM-W1, Two-Way FE	SAR-W1, County FE
ALT	-0.344^{***} (0.008)	-0.347^{***} (0.008)	-0.380^{***} (0.005)	-0.341^{***} (0.011)	-0.308^{***} (0.014)
ALT ²	0.410^{***} (0.001)	0.415^{***} (0.001)	0.424^{***} (0.002)	0.404^{***} (0.002)	0.432^{***} (0.000)
Rho/lambda	0.275^{***} (0.000)	0.268^{***} (0.001)	0.227^{***} (0.004)	0.253^{***} (0.002)	0.325^{***} (0.000)

Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No
Spatial weight matrix	W1	W2	W1	W1	W1
Observations	246	246	246	246	246
R-squared	0.150	0.148	0.123	0.170	0.158

Notes: Tables 5 reports the estimated main coefficients of the core explanatory terms to facilitate comparability across alternative model specifications. ρ denotes the spatial autoregressive coefficient and λ denotes the spatial error coefficient. All specifications include the same set of control variables. Values in parentheses are p values. *** indicate statistical significance at the 1% levels, respectively.

Table 6. Robustness and sensitivity analyses of the level-dependent nonlinear associations among urbanization (URB), agricultural land transfer (ALT), and agricultural carbon emissions (ACE).

Variables/Specification	Baseline: SAR-W1, Two-Way FE	SAR-W2, Two- Way FE	SDM-W1, Two-Way FE	SEM-W1, Two-Way FE	SAR-W1, County FE
URB	−0.463*** (0.007)	−0.460*** (0.008)	−0.399** (0.020)	−0.367*** (0.040)	−0.256 (0.129)
URB ²	0.560*** (0.000)	0.559*** (0.000)	0.516*** (0.001)	0.475*** (0.003)	0.368*** (0.013)
ALT	−0.374*** (0.026)	−0.372*** (0.027)	−0.306* (0.072)	−0.290* (0.099)	−0.097 (0.538)
ALT ²	0.390*** (0.000)	0.390*** (0.000)	0.369*** (0.001)	0.338*** (0.002)	0.168* (0.063)
URB×ALT	0.418** (0.046)	0.415** (0.048)	0.344* (0.100)	0.323 (0.137)	0.103 (0.607)
(URB×ALT) ²	−0.459*** (0.001)	−0.458*** (0.001)	−0.429*** (0.001)	−0.395*** (0.004)	−0.241* (0.057)
Rho/lambda	0.291*** (0.001)	0.295*** (0.001)	0.263*** (0.004)	0.304*** (0.001)	0.336*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No
Spatial weight matrix	W1	W2	W1	W1	W1
Observations	246	246	246	246	246
R-squared	0.104	0.100	0.112	0.095	0.003

Notes: Tables 6 reports the estimated main coefficients of the core explanatory terms to facilitate comparability across alternative model specifications. ρ denotes the spatial autoregressive coefficient and λ denotes the spatial error coefficient. All specifications include the same set of control variables. Values in parentheses are p values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4. Discussion and Policy Implications

4.1. Relationships Among URB, ALT, and ACE

4.1.1. Directional Linkages Between URB and ALT

The spatial panel results indicated a significant level-dependent nonlinear association between ALT and URB. The negative linear term and positive quadratic term of ALT suggest that the association between ALT and URB varied across the observed levels of ALT rather than remaining constant. Given the short observation period, this pattern should not be interpreted as a long-term temporal transition in which individual counties move sequentially through different development stages. Instead, it represents a

nonlinear association over the observed values of ALT within the county-level panel. The positive spatial autoregressive coefficient further indicated that URB exhibited significant spatial dependence across counties.

The GCCM results provided complementary evidence on the directional linkages between specific dimensions of ALT and URB. The directional linkages between ALT-related variables and URB-related variables during the study period were visualized using line graphs (Figures A1–A3 in Appendix F). Specific quantitative results, including predictive capability (ρ) and statistical significance (p value), are presented in Tables A5–A7 in Appendix F.

From 2019 to 2021, the directional linkages between URB and ALT exhibited both recurring patterns and year-specific differences, with the linkage structure varying across dimensions and years (Figure 5). Market participation and public services, as well as market effectiveness and urban–rural coordinated development, showed repeated unidirectional or bidirectional linkages. Urban–rural coordinated development also showed recurrent directional linkages with market liberalization, while population development was consistently linked with market stability over the three years. These results suggest that the development of the ALT market was closely associated with several dimensions of URB, particularly population development, public services, and urban–rural coordination.

Compared with 2020, 2019 and 2021 showed directional linkages among a broader range of variable pairs, including market liberalization and economic development, market liberalization and public services, market effectiveness and public services, and market stability and economic development. Market liberalization and population development showed a unidirectional linkage in 2019 and a bidirectional linkage in 2020. Market effectiveness and ecological environment also exhibited directional linkages in opposite directions in 2020 and 2021. These year-specific differences further indicate that the linkage structure between URB and ALT was not temporally uniform during the study period.

The observed association between URB and ALT may be related to differences in land-market development, labor mobility, and local economic conditions. Land tenure insecurity and concerns about losing access to farmland may discourage households from transferring land or reallocating labor away from agriculture, thereby weakening the connection between land transfer and urbanization [44]. By contrast, stronger land-tenure security can reduce mobility frictions and facilitate labor reallocation, while greater expected returns from land transfer may increase households' willingness to participate in land markets [44,45]. Differences in resource endowments, public services, and market development across counties may therefore contribute to variation in the association between ALT and URB across observed ALT levels. The present findings should nevertheless be interpreted as evidence of level-dependent association and exploratory directional linkages rather than as definitive evidence of causal effects.

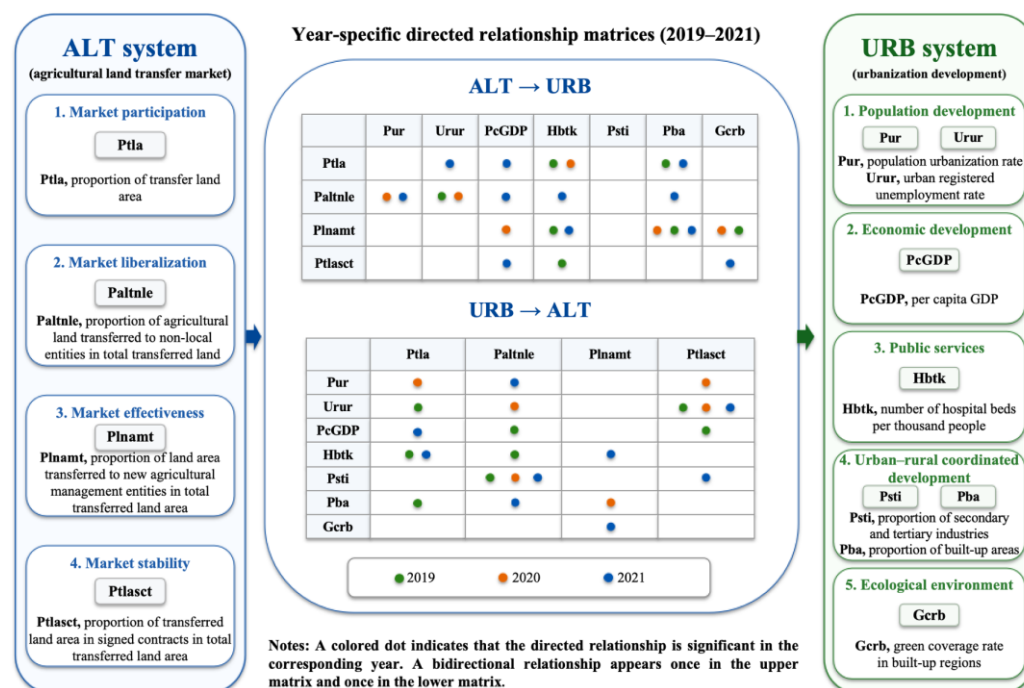


Figure 5. Directed relationship between URB and ALT from 2019 to 2021

4.1.2. Level-Dependent Nonlinear Associations with ACE

The spatial panel results showed significant level-dependent nonlinear associations of both URB and ALT with ACE, together with a significant nonlinear joint association of URB and ALT. For both URB and ALT, the linear coefficients were negative and the quadratic coefficients were positive, whereas the URB×ALT term was positive and its quadratic term was negative. These results indicate that the associations of URB, ALT, and their joint term with ACE varied across their observed levels rather than remaining constant. Given the short observation period and the absence of a formal turning-point test, these patterns are interpreted as level-dependent nonlinear associations rather than as U-shaped or inverted U-shaped temporal trajectories.

The level-dependent association between URB and ACE may reflect the coexistence of mechanisms operating in different directions. Urbanization can promote technological innovation, knowledge diffusion, and agricultural structural adjustment, thereby improving resource-use efficiency and facilitating the adoption of lower-carbon agricultural technologies. Lei et al. (2025) [15], for example, identified technological innovation and high-quality economic development as important channels through which urbanization contributes to agricultural low-carbon transformation. At the same time, urbanization may also increase demand for agricultural production and alter labor, energy, and other factor inputs. Li et al. (2023) [5] similarly reported that urbanization can be associated with higher agricultural carbon emissions under some conditions. The coexistence of these mechanisms provides a plausible explanation for why the association between URB and ACE may vary across different levels of urbanization.

A similar mechanism may underlie the relationship between ALT and ACE. Agricultural land transfer can alter operation scale, production organization, and the intensity of agricultural inputs. Ji et al. (2023) [8] found that rural land transfer could increase agricultural carbon emissions partly through changes in agricultural operation scale, while Tang and Chen (2022) [27] identified agricultural factor inputs as an important transmission channel. By contrast, Chen and Zhang (2025) [18] found that agricultural land-use-rights transfer reduced cultivated-land carbon-emission intensity and that this relationship

varied with operation scale. Household-level evidence also suggests heterogeneous carbon consequences of farmland transfer: land transfer among small-scale farmers may increase fertilizer and pesticide inputs, whereas larger-scale farmers may reduce irrigation electricity consumption and fertilizer and pesticide use [19]. These contrasting mechanisms are consistent with the finding that the association between ALT and ACE varies across observed ALT levels rather than remaining uniform.

The significant $URB \times ALT$ terms further suggest that the association with ACE cannot be understood solely from the separate relationships of URB and ALT. Urbanization and agricultural land transfer jointly affect the allocation of labor, land, capital, and technology between agricultural and non-agricultural activities. Urbanization may facilitate labor mobility, technological diffusion, and changes in agricultural demand, while land transfer may promote scale adjustment and resource reallocation. Their combination can therefore alter both production efficiency and input intensity. The positive coefficient of $URB \times ALT$ and the negative coefficient of its quadratic term indicate that this joint association also varies across different configurations of URB and ALT. This finding is broadly consistent with Tang and Chen (2022) [27], who found that the effect of agricultural land transfer on agricultural carbon emissions varied with the level of urbanization. However, the present analysis does not identify a specific threshold or causal mechanism.

The spatial results also suggest that these associations extend beyond individual counties. The positive spatial autoregressive coefficient of ACE and the presence of statistically significant indirect effects for several core terms indicate spatial feedback in agricultural carbon emissions. This is consistent with previous evidence that agricultural carbon emissions and the associations of urbanization and land transfer with ACE may exhibit spatial dependence and spillovers [4,8,15]. The robustness analysis further showed that the coefficient directions and general nonlinear patterns were broadly preserved across alternative spatial weight matrices and spatial specifications, although the statistical significance of several linear terms weakened when year fixed effects were excluded. These findings reinforce the importance of considering both spatial interactions and model specification when examining the relationships among URB, ALT, and ACE. Accordingly, the identified level-dependent nonlinear patterns should be interpreted as conditional associations rather than fixed structural relationships, and the mechanisms discussed above should be regarded as plausible explanations rather than directly identified causal pathways.

4.2. Policy Implications

The findings of this study suggest that agricultural carbon mitigation in Hubei Province should account for both spatial dependence and differences in the observed levels of urbanization (URB) and agricultural land transfer (ALT) across counties. Spatial analysis showed significant spatial autocorrelation in URB, ALT, and agricultural carbon emissions (ACE), with high-value clusters concentrated particularly in central Hubei Province. Meanwhile, the spatial panel models identified significant level-dependent nonlinear associations of URB, ALT, and their joint term with ACE, indicating that uniform policy responses may not be equally appropriate for counties with different development conditions. The GCCM results further revealed multidimensional and year-specific directional linkages between ALT and URB, particularly involving population development, economic development, public services, and urban–rural coordination. Accordingly, agricultural carbon mitigation should combine spatially coordinated governance with differentiated policy priorities according to local URB and ALT conditions. Here, low, medium, and high levels refer to counties' relative positions within the observed distributions of URB and ALT rather than to statistically identified thresholds.

First, greater attention should be given to counties in central Hubei Province where high-value spatial clusters of URB, ALT, and ACE were concentrated. The significant spatial dependence of ACE and the presence of spatial indirect effects indicate that agricultural carbon management in one county may be associated with conditions in neighboring counties. Therefore, counties within these clusters should strengthen cross-county coordination in agricultural input management, land-use regulation, low-carbon technology diffusion, and carbon-emission monitoring. For counties with relatively high levels of both URB and ALT, policy priorities should focus less on further quantitative expansion and more on land-use efficiency, environmental performance, and the quality of agricultural modernization. Monitoring of fertilizer, pesticide, agricultural film, diesel, and machinery use should be strengthened, while low-carbon machinery, precision agriculture, water-saving irrigation, straw recycling, and other resource-efficient technologies should be promoted. Environmental constraints should also be strengthened in ecologically sensitive and urban–rural fringe areas to prevent inefficient land expansion and excessive agricultural intensification.

Second, counties with intermediate relative levels of URB and ALT should prioritize the coordination of land transfer, agricultural modernization, and resource-use efficiency. The identified level-dependent nonlinear associations indicate that the relationships of URB and ALT with ACE are not constant across their observed levels. Therefore, these counties should closely monitor whether changes in land allocation and operation scale are accompanied by improvements in production efficiency or by increases in carbon-intensive inputs. Policy support should encourage family farms, cooperatives, agricultural enterprises, and other management entities to adopt precision farming, efficient agricultural machinery, organic fertilizer substitution, straw recycling, and water-saving technologies. At the same time, land-transfer policies should be coordinated with technical extension services and environmental management so that changes in agricultural operation scale contribute to more efficient resource use rather than simply greater input intensity.

Third, counties with relatively low levels of URB and ALT should focus primarily on improving the institutional and service conditions required for orderly land and labor reallocation. The GCCM results showed that ALT was directionally linked with multiple dimensions of URB, including population development, public services, economic development, and urban–rural coordination. These counties should therefore improve land transfer market institutions, standardize transfer contracts, strengthen land-tenure security, reduce transaction barriers, and improve access to rural public services, agricultural technologies, and non-agricultural employment opportunities. However, increasing the scale of land transfer should not itself be treated as a policy objective. ALT should remain voluntary and orderly, and its development should be matched with local land resources, agricultural production conditions, and environmental capacity.

Finally, the spatial clustering and level-dependent associations identified in this study support the establishment of a county-level monitoring framework integrating URB, ALT, agricultural production intensity, land-use efficiency, and ACE. Such a framework could help identify changes in local development conditions and spatial clustering patterns and support adaptive policy adjustment. Counties within the same high-value cluster should strengthen regional coordination, whereas counties with different relative levels of URB and ALT may require different combinations of institutional improvement, efficiency enhancement, technological upgrading, and environmental regulation. This differentiated and spatially coordinated approach may provide a more appropriate basis for promoting agricultural modernization and low-carbon urban–rural development in Hubei Province.

4.3. Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the three-year panel limits the examination of long-term dynamics, and the identified nonlinear relationships are therefore better understood as level-dependent associations rather than temporal trajectories. Although county and year fixed effects help account for unobserved heterogeneity and common annual shocks, potential reverse causality, simultaneity, and time-varying omitted factors may remain. Accordingly, the spatial panel estimates are interpreted as conditional associations, while the GCCM results provide exploratory evidence of directional linkages rather than definitive causal identification. Second, the relatively modest R^2 values suggest that some county-level variation remains unexplained, possibly reflecting measurement limitations, omitted time-varying factors, spatial heterogeneity, and the short observation period. Finally, although the main nonlinear patterns were broadly supported by alternative spatial weight matrices and spatial econometric specifications, some sensitivity to the fixed-effects structure remained in the ACE models. Future research using longer panels, richer county-level data, and stronger identification strategies could further examine the underlying mechanisms and causal relationships among URB, ALT, and ACE.

5. Conclusions

This study examined the spatial and nonlinear relationships among urbanization (URB), agricultural land transfer (ALT), and agricultural carbon emissions (ACE) using county-level evidence from Hubei Province, China. The results show that URB, ALT, and ACE are spatially interdependent rather than randomly distributed, with high-value clusters concentrated particularly in central Hubei Province. These spatial patterns indicate that county-level urban–rural transformation and agricultural carbon mitigation should not be considered in isolation, but within a broader regional context.

The findings further show that the relationship between URB and ALT is both level-dependent and multidimensional. ALT is not associated with URB in a constant linear manner, and the directional linkages between their underlying dimensions vary across years and development conditions. Similarly, URB, ALT, and their joint configuration are associated with ACE through level-dependent nonlinear relationships. Taken together, these results suggest that the carbon consequences of urban–rural transformation depend on how population, land, production factors, and agricultural organization are configured locally, rather than on any single factor operating independently. The main nonlinear patterns were broadly supported by the robustness and sensitivity analyses.

These findings have two main implications. First, agricultural carbon mitigation in Hubei Province requires stronger cross-county coordination, particularly in spatially clustered areas where urbanization, land transfer, and agricultural carbon emissions are closely interconnected. Second, policy design should be differentiated according to local URB and ALT conditions rather than relying on uniform county-level measures. Counties at different relative levels of URB and ALT may require different combinations of institutional improvement, resource-use efficiency, technological upgrading, and environmental regulation.

Given the short observation period and potential endogeneity arising from reverse causality and time-varying omitted variables, these findings should be interpreted as conditional associations rather than definitive causal effects. Future research using longer panel data and stronger identification strategies could further examine the dynamic and causal mechanisms linking urbanization, agricultural land transfer, and agricultural carbon emissions.

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Data Availability Statement: The data used in this study were derived from publicly available statistical yearbooks and third-party administrative sources. Public data were obtained from the China City Construction Statistical Yearbook, China County Statistical Yearbook, Hubei Statistical Yearbook, and Hubei Rural Statistical Yearbook. Restrictions apply to data obtained from the Annual Report on Rural Policy Reform in Hubei Province and from government data disclosure requests. These restricted data are not publicly available from the authors because the authors do not have permission to redistribute them. Requests should be directed to the original data providers or relevant government departments.

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

Abbreviations

The following abbreviations are used in this manuscript:

URB	Urbanization
ALT	Agricultural Land Transfer
ACE	Agricultural Carbon Emissions
GCCM	Geographical Convergent Cross-Mapping

Appendix A

$$\text{Global Moran's } I = \frac{N \sum_{i=1}^N \sum_{j=1}^N w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{S_0 \sum_i (y_i - \bar{y})^2}, \quad (\text{A1})$$

$$\text{Local Moran's } I_i = \frac{y_i - \bar{y}}{S_i^2} \sum_{j=1, j \neq i}^N w_{ij} (y_i - \bar{y})(y_j - \bar{y}), \quad (\text{A2})$$

N is the number of observed spatial units; y_i and y_j denote the observed values of variable y in spatial units i and j , respectively; $\bar{y}$ represents the mean value of variable y ; w_{ij} denotes the element in the spatial weight matrix; and S_0 represents the sum of all the elements in the spatial weight matrix. The range of Moran's I is $[-1, 1]$, where -1 indicates complete spatial dispersion, 0 signifies spatial randomness, and 1 indicates complete spatial clustering.

Appendix B

In this GCCM model, the Earth system is viewed as a dynamical system, and spatial cross-sectional data as snapshots at a specific time point. According to the generalized embedding theory, the manifold M of the dynamical system can be embedded into

Euclidean space $\mathbb{R}^L$ [46] where $L=2d+1$, and d is the dimension of the manifold. For a compact d -dimensional manifold M and a set of observation functions $\{h_1, h_2, \dots, h_L\}$, the mapping $\varphi_\emptyset, h(x)$ is defined as Equation (A3).

$$\varphi_\emptyset, h(x) = \langle h_1(x), h_2(x), \dots, h_L(x) \rangle, \quad (\text{A3})$$

This mapping is an embedding, allowing a one-to-one mapping of the original manifold. The observation function h_i can be either the lags of single/multiple time-series observation values or lags of single/multiple observation functions. Therefore, a specific spatial unit s and its i -th order spatial lag $s(i)$ can be embedded into the spatial data using Equation (A4).

$$\varphi_\emptyset, h, s(x) = \langle h_s(x), h_{s(1)}(x), \dots, h_{s(L-1)}(x) \rangle, \quad (\text{A4})$$

Suppose X and Y are two spatial variables, and their shadow manifolds M_x and M_y can be constructed using the aforementioned embedding. If X and Y belong to the same dynamical system, their manifolds can be predicted through cross-mapping. For a given spatial unit s , Y value can be predicted based on the nearest neighbors of this spatial unit s on M_x using Equation (A5).

$$\hat{Y}_s | M_x = \sum_{i=1}^{L+1} (w_{si} Y_{si} | M_x) \quad (\text{A5})$$

where w_{si} represents the spatial weight, and it is determined in the shadow manifold through neighbor relationships. The neighbors are determined based on the similarity between states, and similarity refers to the distance between states in the embedded shadow manifold, and the spatial weight is calculated according to Equations (A6) and (A7).

$$w_{si} | M_x = \frac{\text{weight}(\varphi(x, s_i), \varphi(x, s))}{\sum_{i=1}^{L+1} \text{weight}(\varphi(x, s_i), \varphi(x, s))}, \quad (\text{A6})$$

$$\text{weight}(\varphi(x, s_i), \varphi(x, s)) = \exp\left(\frac{\text{dis}(\varphi(x, s_i), \varphi(x, s))}{\text{dis}(\varphi(x, s_1), \varphi(x, s))}\right), \quad (\text{A7})$$

$\exp$ is the exponential function, and $\text{dis}()$ represents the distance between two states in the shadow manifold. The distance functions vary with the type of data. This study adopts the polygon data, and the corresponding distance function is presented in Equations (A8) and (A9).

$$\text{dis}(\varphi(x, s_i), \varphi(x, s)) = \frac{1}{L} \left(|h_{si}(x) - h_s(x)| + \sum_{k=1}^{L-1} \text{abs}[h_{si(k)}(x), h_{s(k)}(x)] \right), \quad (\text{A8})$$

$$\text{abs}_v[h_{si(k)}(x), h_{s(k)}(x)] = \left| \frac{1}{D_1} \sum_d^{D_1} u_{si(k,d)}(x) - \frac{1}{D_2} \sum_d^{D_1} u_{s(k,d)}(x) \right|, \quad (\text{A9})$$

where $u_{si(k,d)}(x)$ is the spatial unit of the k -th order spatial lag of si in the d direction. D refers to the number of k -th order spatial units (or directions). The predictive accuracy ρ is measured by the Pearson correlation coefficient between the actual observation values and corresponding predictive values according to Equation (A10). The range of ρ values for Y is dependent on various library sizes. Sugihara et al. (2012) [37] infer causal associations by the convergence of ρ . In the GCCM model, convergence is observed, as ρ increases with library size, exhibiting statistical significance. The significance of ρ is tested using the null hypothesis $H_0: \rho = 0$, using statistics t in Equation (A11) to determine the p value. The confidence interval of ρ is estimated using statistics z in Equation (A12). This study used a significance level of 10%. The ρ , t , and z are calculated according to Equations (A10)–(A12), respectively.

$$\rho = \frac{Cov(Y, \hat{Y})}{\sqrt{Var(Y)Var(\hat{Y})}}, \quad (A10)$$

$$t = \rho \sqrt{\frac{n-2}{1-\rho^2}}, \quad (A11)$$

$$z = \frac{1}{2} \ln \left(\frac{1+\rho}{1-\rho} \right), \quad (A12)$$

where $Cov(Y, \hat{Y})$ is the covariance; $Var(Y)Var(\hat{Y})$ is the variance; and n represents the number of observation values to be predicted. Finally, the causal relationships are analyzed.

Appendix C

Table A1. Emission coefficients used to estimate agricultural carbon emissions (ACE).

Input elements	Meaning	Coefficient	Reference
Fertilizer	Nitrogenous fertilizer	3.392 kg C kg ⁻¹	(Chen et al., 2015)[47], (Deng et al., 2016) [48]
	Phosphate fertilizer	0.636 kg C kg ⁻¹	
	Potash fertilizer	0.180 kg C kg ⁻¹	(Deng et al., 2016) [48]
	Compound fertilizer	0.38097 kg C kg ⁻¹	
Pesticide	Pesticide application rate	4.9341 kg C kg ⁻¹	(Zhi and Gao, 2009) [49], (Zhang and Fang, 2013) [50]
Agricultural film	Plastic mulch usage	5.18 kg C kg ⁻¹	IREEA
Irrigation	Irrigated area	266.48 kg C ha ⁻¹	(Duan et al., 2011) [51]
Plowing	Plowed/Tilled land area	312.6 kg C km ⁻²	(Wu et al., 2007) [52]
Diesel	Diesel fuel consumption	0.5927 kg C kg ⁻¹	IPCC (2007)
Rice growing (1 t CH ₄ =6.82 tC)	Early rice	0.1751 kg CH ₄ m ⁻²	(Min and Hu, 2012) [53]
	Late rice	0.039 kg CH ₄ m ⁻²	
	Mid-season rice	CH ₄ : 0.05817 kg CH ₄ m ⁻²	
Straw burning	All crops	1515 g CO ₂ kg ⁻¹ , 2.7 g CH ₄ kg ⁻¹	(Andreae and Merlet, 2001) [54]

Notes: C, carbon; CH₄, methane; CO₂, carbon dioxide; IREEA, Institute of Resource, Ecosystem, and Environment of Agriculture. All emission sources were converted to a common carbon-based unit before aggregation into agricultural carbon emissions (ACE).

Appendix D

Table A2. Global *Moran's I* statistics for urbanization (URB), agricultural land transfer (ALT), and agricultural carbon emissions (ACE), 2019–2021.

Variables	Year	W1		W2	
		Moran's I	p-Value	Moran's I	p-Value
URB	2019	0.14	0.02	0.14	0.02
	2020	0.10	0.05	0.10	0.05
	2021	0.08	0.09	0.08	0.09
ALT	2019	0.23	0.01	0.23	0.01
	2020	0.15	0.02	0.15	0.02
	2021	0.27	0.00	0.27	0.00
ACE	2019	0.44	0.00	0.44	0.00
	2020	0.46	0.00	0.46	0.00
	2021	0.47	0.00	0.47	0.00

Notes: W1 denotes Spatial weight matrix 1, constructed based on geographical distance; W2 denotes Spatial weight matrix 2, constructed based on geographical adjacency. Positive Moran's I values indicate positive spatial autocorrelation. Reported p values correspond to the significance tests of Moran's I.

Appendix E

Table A3. Spatial panel estimates of the level-dependent nonlinear association between agricultural land transfer (ALT) and urbanization (URB) under W2.

Variables	Main	Spatial	LR_Direct	LR_Indirect	LR_Total
ALT	−0.347*** (0.008)	/	−0.349** (0.010)	−0.121* (0.063)	−0.470** (0.011)
ALT ²	0.415*** (0.001)	/	0.416*** (0.002)	0.145** (0.040)	0.561*** (0.002)
Urban–rural disparity	−0.536*** (0.004)	/	−0.526*** (0.004)	−0.182** (0.046)	−0.709*** (0.004)
Agricultural operation scale	0.053* (0.052)	/	0.054** (0.048)	0.019 (0.130)	0.073* (0.054)
Property rights reform	−0.160 (0.543)	/	−0.156 (0.552)	−0.053 (0.594)	−0.209 (0.557)
Agricultural industry agglomeration	0.062 (0.471)	/	0.067 (0.433)	0.023 (0.475)	0.091 (0.433)
Agricultural technology	0.043 (0.460)	/	0.045 (0.474)	0.016 (0.522)	0.061 (0.480)
Availability of clean energy	0.037 (0.373)	/	0.036 (0.373)	0.013 (0.445)	0.049 (0.382)
Non-agricultural market activity	0.005 (0.849)	/	0.008 (0.782)	0.003 (0.798)	0.010 (0.783)
Agricultural development	0.083** (0.023)	/	0.086** (0.023)	0.030* (0.089)	0.116** (0.025)
ρ	/	0.275*** (0.001)	/	/	/
R-squared	0.148	0.148	0.148	0.148	0.148

Notes: W2 denotes Spatial weight matrix 2. ρ denotes the spatial autoregressive coefficient. Direct, indirect, and total effects refer to spatial impact estimates. All continuous explanatory variables were standardized before estimation. Values in parentheses are p values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The model includes county and year fixed effects.

Table A4. SAR estimates of the level-dependent nonlinear associations among urbanization (URB), agricultural land transfer (ALT), and agricultural carbon emissions (ACE) under W2.

Variables	Main	Spatial	LR_Direct	LR_Indirect	LR_Total
URB	−0.460*** (0.008)	/	−0.464*** (0.010)	−0.189* (0.073)	−0.653** (0.012)
URB ²	0.559*** (0.000)	/	0.565*** (0.000)	0.232** (0.043)	0.797*** (0.001)
ALT	−0.372** (0.027)	/	−0.369** (0.030)	−0.149* (0.100)	−0.518** (0.032)
ALT ²	0.390*** (0.000)	/	0.390*** (0.000)	0.160** (0.036)	0.549*** (0.000)
URB×ALT	0.415** (0.048)	/	0.414** (0.050)	0.169 (0.130)	0.583* (0.053)
(URB×ALT) ²	−0.458*** (0.001)	/	−0.459*** (0.001)	−0.189** (0.048)	−0.648*** (0.002)

Natural disaster management	0.318 (0.471)	/	0.330 (0.478)	0.137 (0.549)	0.467 (0.489)
Agricultural industry agglomeration	−0.068* (0.052)	/	−0.071** (0.039)	−0.030 (0.169)	−0.101* (0.056)
Agricultural technology	−0.029 (0.210)	/	−0.028 (0.227)	−0.011 (0.320)	−0.039 (0.240)
Availability of clean energy	−0.004 (0.822)	/	−0.003 (0.843)	−0.001 (0.895)	−0.004 (0.856)
Extent of agricultural waste utilization	0.034 (0.411)	/	0.034 (0.419)	0.013 (0.508)	0.047 (0.434)
Agricultural market participation	0.008 (0.467)	/	0.009 (0.442)	0.004 (0.497)	0.013 (0.448)
Climate	−0.005 (0.883)	/	−0.006 (0.850)	−0.002 (0.871)	−0.008 (0.855)
Rural economy	0.003 (0.832)	/	0.004 (0.792)	0.002 (0.816)	0.006 (0.796)
Agricultural development	0.082*** (0.000)	/	0.082*** (0.000)	0.034** (0.040)	0.115*** (0.000)
ρ	/	0.295*** (0.001)	/	/	/
R-squared	0.100	0.100	0.100	0.100	0.100

Notes: W2 denotes Spatial weight matrix 2. ρ denotes the spatial autoregressive coefficient. Direct, indirect, and total effects refer to spatial impact estimates. All continuous explanatory variables were standardized before estimation. Values in parentheses are p values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The model includes county and year fixed effects.

Appendix F

Table A5. GCCM directional linkages between urbanization and agricultural land transfer in 2019.

X	Y	ρ (largest lib_sizes)		p-value (largest lib_sizes)	
		x_xmap_y_means	y_xmap_x_means	x_xmap_y_Sig	y_xmap_x_Sig
Ptla	Pur	0.00	0.13	0.50	0.12
	Urur	0.16	0.00	0.07	0.50
	PcGDP	0.04	0.00	0.35	0.50
	Hbtk	0.18	0.23	0.05	0.02
	Psti	0.00	0.11	0.50	0.16
	Pba	0.30	0.45	0.00	0.00
	Gcrb	0.00	0.02	0.50	0.43
Paltnle	Pur	0.00	0.00	0.50	0.50
	Urur	0.00	0.22	0.50	0.02
	PcGDP	0.33	0.00	0.00	0.50
	Hbtk	0.17	0.00	0.07	0.50
	Psti	0.15	0.00	0.09	0.50
	Pba	0.09	0.00	0.20	0.50
	Gcrb	0.00	0.00	0.50	0.50
Plnamt	Pur	0.00	0.00	0.50	0.50
	Urur	0.00	0.00	0.50	0.50
	PcGDP	0.14	0.04	0.11	0.36
	Hbtk	0.00	0.20	0.50	0.04
	Psti	0.08	0.00	0.25	0.50
	Pba	0.00	0.25	0.50	0.01

	Gcrb	0.00	0.33	0.50	0.00
	Pur	0.00	0.00	0.50	0.50
	Urur	0.18	0.02	0.06	0.42
	PcGDP	0.16	0.00	0.07	0.50
Ptlasct	Hbtk	0.00	0.21	0.50	0.03
	Psti	0.00	0.00	0.50	0.50
	Pba	0.00	0.00	0.50	0.50
	Gcrb	0.00	0.09	0.50	0.20

Notes: (1) Ptla, proportion of transfer land area; Paltnle, proportion of agricultural land transferred to non-local entities in total transferred land; Plnamt, proportion of land area transferred to new agricultural management entities in total transferred land area; Ptlasct, proportion of transferred land area in signed contracts in total transferred land area; Pur, population urbanization rate; Urur: urban registered unemployment rate; PcGDP, per capita GDP; Hbtk, number of hospital beds per thousand people; Psti, proportion of secondary and tertiary industries; Pba, proportion of built-up areas; Gcrb: green coverage rate in built-up regions. (2) For instance, in 2019, the q values for Ptla xmap Pba (Pba (proportion of built-up areas)→ Ptla (proportion of transfer land area)) and Pba xmap Ptla (Ptla (proportion of transfer land area)→ Pba (proportion of built-up areas)) at the maximum library sizes are 0.00 (p=0.50) and 0.13 (p=0.12), respectively.

Table A6. GCCM directional linkages between urbanization and agricultural land transfer in 2020.

X	Y	ρ (largest lib_sizes)		P-value (largest lib_sizes)	
		x_xmap_y_means	y_xmap_x_means	x_xmap_y_Sig	y_xmap_x_Sig
Ptla	Pur	0.16	0.13	0.08	0.12
	Urur	0.00	0.00	0.50	0.50
	PcGDP	0.01	0.00	0.47	0.50
	Hbtk	0.00	0.20	0.50	0.03
	Psti	0.02	0.00	0.42	0.50
	Pba	0.00	0.10	0.50	0.19
	Gcrb	0.00	0.05	0.50	0.34
Paltnle	Pur	0.04	0.33	0.38	0.00
	Urur	0.15	0.16	0.10	0.07
	PcGDP	0.00	0.00	0.50	0.50
	Hbtk	0.02	0.11	0.44	0.15
	Psti	0.14	0.00	0.10	0.50
	Pba	0.00	0.00	0.50	0.50
	Gcrb	0.00	0.00	0.50	0.50
Plnamt	Pur	0.00	0.08	0.50	0.25
	Urur	0.00	0.05	0.50	0.34
	PcGDP	0.00	0.14	0.50	0.10
	Hbtk	0.01	0.00	0.45	0.50
	Psti	0.03	0.00	0.41	0.50
	Pba	0.17	0.14	0.07	0.10
	Gcrb	0.00	0.19	0.50	0.04
Ptlasct	Pur	0.19	0.00	0.04	0.50
	Urur	0.19	0.14	0.04	0.11
	PcGDP	0.03	0.00	0.38	0.50
	Hbtk	0.00	0.00	0.50	0.50
	Psti	0.00	0.00	0.50	0.50

Pba	0.10	0.00	0.18	0.50
Gcrb	0.13	0.00	0.13	0.50

Notes: Ptla, proportion of transfer land area; Paltnle, proportion of agricultural land transferred to non-local entities in total transferred land; Plnamt, proportion of land area transferred to new agricultural management entities in total transferred land area; Ptlasct, proportion of transferred land area in signed contracts in total transferred land area; Pur, population urbanization rate; Urur: urban registered unemployment rate; PcGDP, per capita GDP; Hbtk, number of hospital beds per thousand people; Psti, proportion of secondary and tertiary industries; Pba, proportion of built-up areas; Gcrb: green coverage rate in built-up regions.

Table A7. GCCM directional linkages between urbanization and agricultural land transfer in 2021.

X	Y	ρ (largest lib_sizes)		P-value (largest lib_sizes)	
		x_xmap_y_means	y_xmap_x_means	x_xmap_y_Sig	y_xmap_x_Sig
Ptla	Pur	0.00	0.08	0.50	0.23
	Urur	0.00	0.18	0.50	0.05
	PcGDP	0.26	0.21	0.01	0.03
	Hbtk	0.21	0.09	0.03	0.20
	Psti	0.00	0.08	0.50	0.23
	Pba	0.00	0.20	0.50	0.03
	Gcrb	0.00	0.00	0.50	0.50
Paltnle	Pur	0.23	0.19	0.02	0.04
	Urur	0.03	0.00	0.39	0.50
	PcGDP	0.00	0.14	0.50	0.10
	Hbtk	0.00	0.18	0.50	0.05
	Psti	0.15	0.04	0.09	0.35
	Pba	0.28	0.25	0.01	0.01
	Gcrb	0.00	0.00	0.50	0.50
Plnamt	Pur	0.00	0.04	0.50	0.36
	Urur	0.04	0.06	0.36	0.30
	PcGDP	0.00	0.00	0.50	0.50
	Hbtk	0.28	0.30	0.01	0.00
	Psti	0.00	0.00	0.50	0.50
	Pba	0.09	0.36	0.21	0.00
	Gcrb	0.17	0.09	0.06	0.21
Ptlasct	Pur	0.00	0.07	0.50	0.26
	Urur	0.15	0.12	0.09	0.13
	PcGDP	0.00	0.26	0.50	0.01
	Hbtk	0.04	0.00	0.37	0.50
	Psti	0.16	0.00	0.08	0.49
	Pba	0.01	0.09	0.46	0.20
	Gcrb	0.00	0.17	0.50	0.07

Notes: Ptla, proportion of transfer land area; Paltnle, proportion of agricultural land transferred to non-local entities in total transferred land; Plnamt, proportion of land area transferred to new agricultural management entities in total transferred land area; Ptlasct, proportion of transferred land area in signed contracts in total transferred land area; Pur, population urbanization rate; Urur: urban registered unemployment rate; PcGDP, per capita GDP; Hbtk, number of hospital beds per thousand people; Psti, proportion of secondary and tertiary industries; Pba, proportion of built-up areas; Gcrb: green coverage rate in built-up regions.

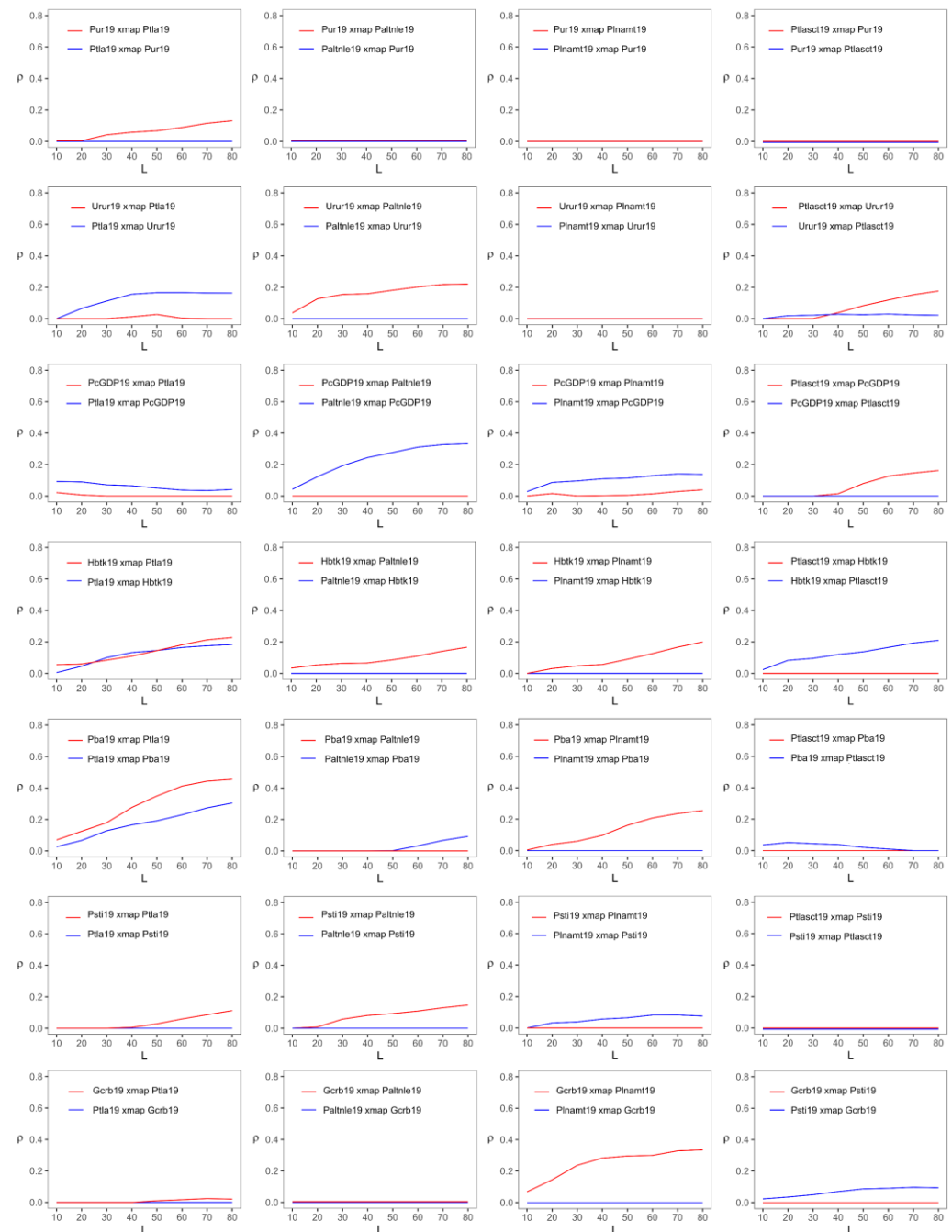


Figure A1. Cross-mapping predictive skill (ρ) between agricultural land transfer (ALT) and urbanization (URB) variables across library sizes in 2019. Notes: ρ , cross-mapping predictive skill; L , library size. Red and blue curves represent the two-directional cross-mapping predictions identified in the legends of each panel. Ptla, proportion of transfer land area; Palt19, proportion of agricultural land transferred to non-local entities in total transferred land; Pnamt, proportion of land area transferred to new agricultural management entities in total transferred land area; Ptlact, proportion of transferred land area in signed contracts in total transferred land area; Pur, population urbanization rate; Urur: urban registered unemployment rate; PcGDP, per capita GDP; Hbtk, number of hospital beds per thousand people; Psti, proportion of secondary and tertiary industries; Pba, proportion of built-up areas; Gcrb: green coverage rate in built-up regions.

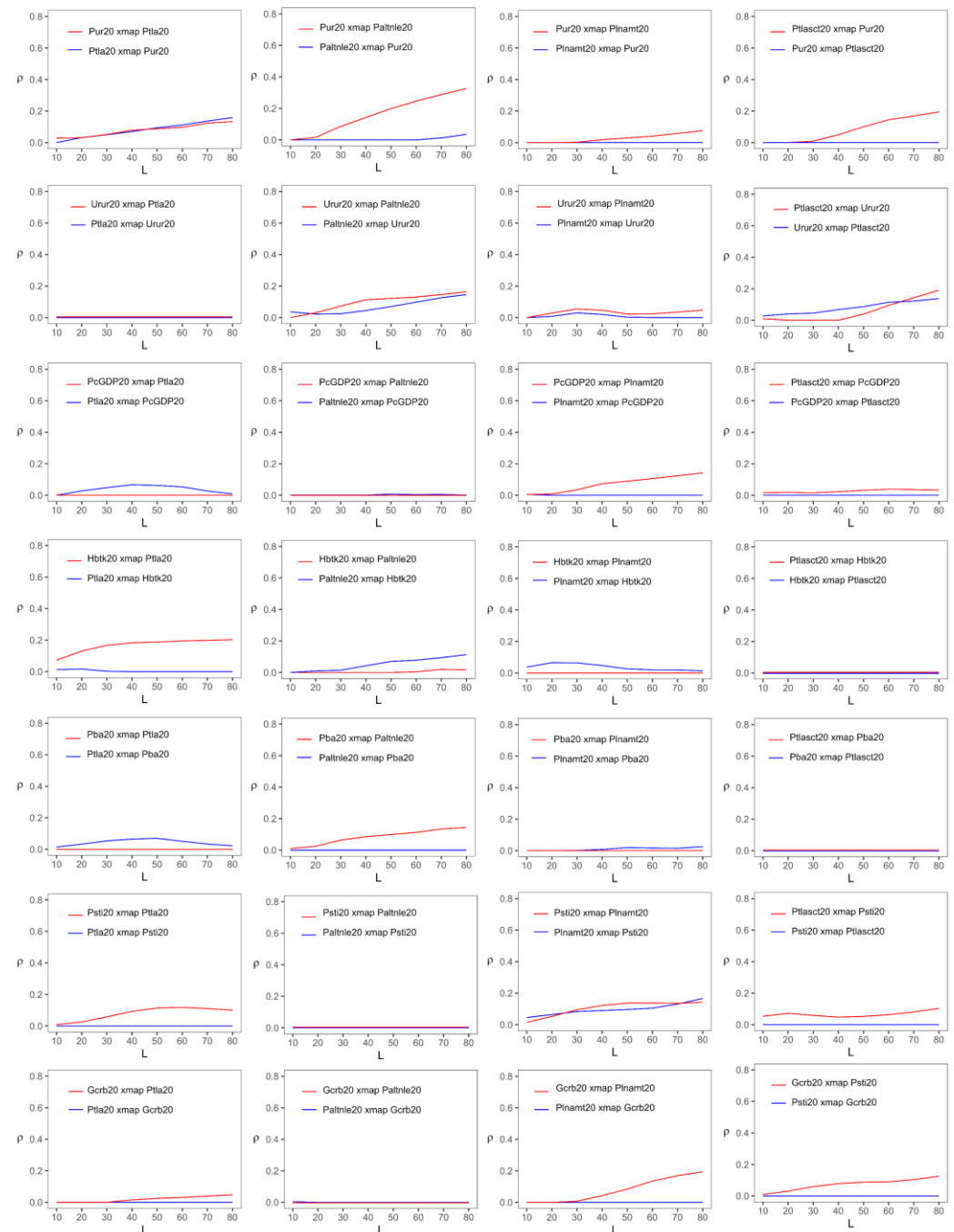


Figure A2. Cross-mapping predictive skill (ρ) between agricultural land transfer (ALT) and urbanization (URB) variables across library sizes in 2020. Notes: ρ , cross-mapping predictive skill; L , library size. Red and blue curves represent the two-directional cross-mapping predictions identified in the legends of each panel. Ptla, proportion of transfer land area; Paltlne, proportion of agricultural land transferred to non-local entities in total transferred land; Plnamt, proportion of land area transferred to new agricultural management entities in total transferred land area; Ptlasct, proportion of transferred land area in signed contracts in total transferred land area; Pur, population urbanization rate; Urur: urban registered unemployment rate; PcGDP, per capita GDP; Hbtk, number of hospital beds per thousand people; Psti, proportion of secondary and tertiary industries; Pba, proportion of built-up areas; Gcrb: green coverage rate in built-up regions.

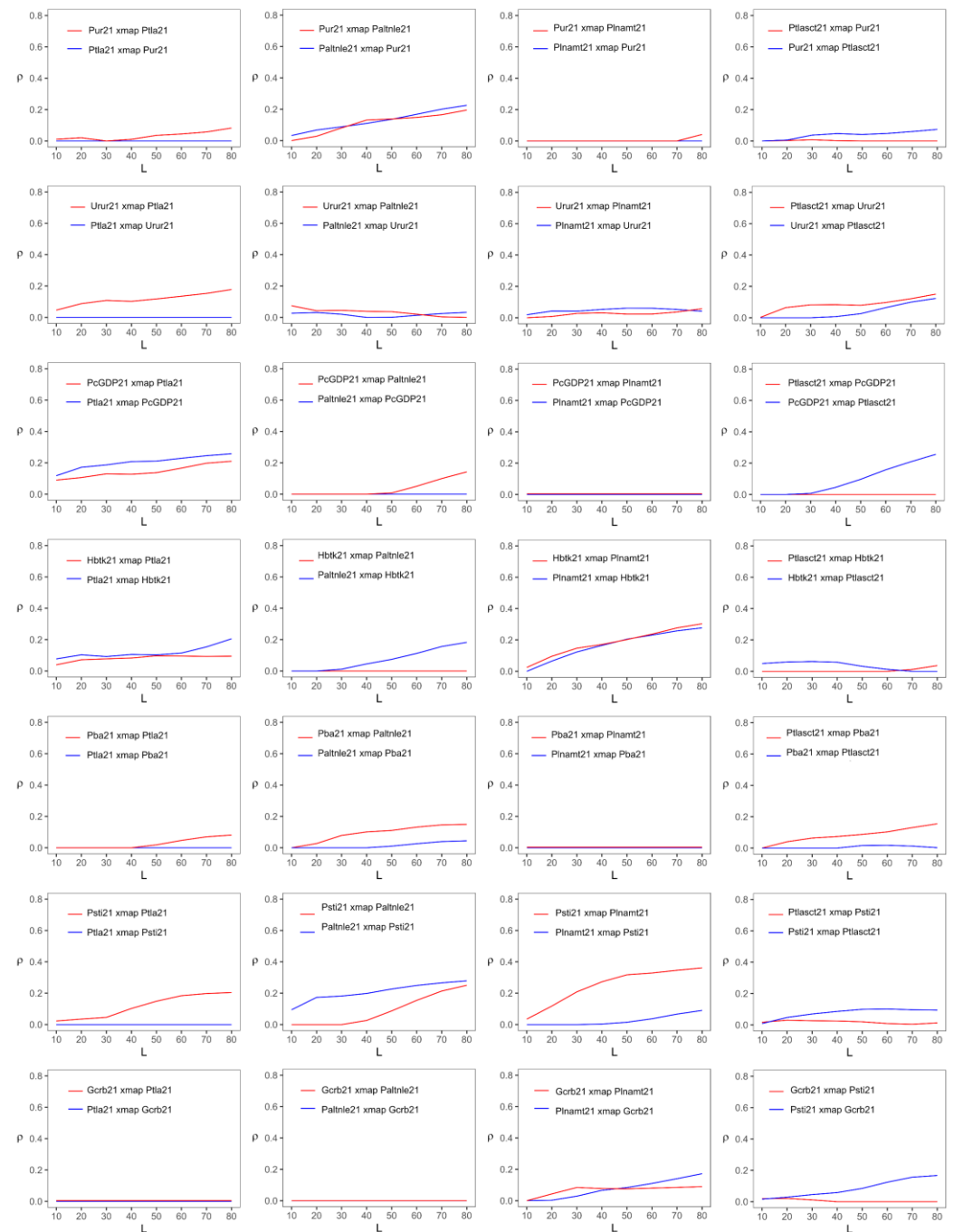


Figure A3. Cross-mapping predictive skill (ρ) between agricultural land transfer (ALT) and urbanization (URB) variables across library sizes in 2021. Notes: ρ , cross-mapping predictive skill; L , library size. Red and blue curves represent the two-directional cross-mapping predictions identified in the legends of each panel. Ptla, proportion of transfer land area; Paltnle, proportion of agricultural land transferred to non-local entities in total transferred land; Pinamt, proportion of land area transferred to new agricultural management entities in total transferred land area; Ptlasc21, proportion of transferred land area in signed contracts in total transferred land area; Pur, population urbanization rate; Urur: urban registered unemployment rate; PcGDP, per capita GDP; Hbtk, number of hospital beds per thousand people; Psti, proportion of secondary and tertiary industries; Pba, proportion of built-up areas; Gcrb: green coverage rate in built-up regions.

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