Nonlinear and spatiotemporal dynamics of land finance and urban expansion in China: A GeoXAI-enhanced analysis

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ABSTRACT While land finance is a recognized institutional driver of urban expansion, the nonlinear and spatially heterogeneous dynamics of this fiscal mechanism remain underexplored. This study integrates geospatial explainable artificial intelligence (GeoXAI) with econometric models to decode the spatiotemporal evolution of the land finance – urban expansion nexus across 204 Chinese cities (2005–2020). By overcoming the limitations of traditional methods, we reveal that the impact of land finance on urban expansion is profoundly nonlinear, transitioning from a mitigating effect to a powerful reinforcing driver over time. Furthermore, this fiscal stimulus exhibits stark spatial disparities, with positive spatial interactions diffusing from coastal regions to inland second-tier cities. Ultimately, this research provides a novel methodological paradigm for spatial policy evaluation and extends the theoretical understanding of land urbanization for the emerging economies. These findings offer actionable insights for implementing zoned regulations and polycentric governance to curb inefficient urban sprawl driven by fiscal incentives.

KEY WORDS land finance – urban expansion – GeoXAI – nonlinear dynamics – spatiotemporal dynamics

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1. Introduction

Urban expansion is a global urban issue, especially for developing countries that are experiencing rapid urbanization. According to World Urbanization Prospects, the world's urban population is likely to increase by 2.5 billion people by 2050, with nearly 90% of this growth occurring in Asia and Africa (UN 2014). Urban expansion is reshaping the urban-rural structure of developing countries, and at the same time bringing unprecedented opportunities and challenges to developing countries. On the one hand, urban expansion can lead to more employment opportunities and improve economic incomes (Zhang 2016), while promoting social mobility based on this (Hatab et al. 2022); on the other hand, unorganized urban expansion is believed to lead to biodiversity degradation (McDonald et al. 2020), increased carbon emissions (Wu et al. 2022), higher costs of public services and health inequalities (Garden, Jalaludin 2009). As one of the fastest urbanizing countries in the world (Hu et al. 2024), the average built-up area of Chinese cities was 90.78 km² in 2005, and by 2020, the average built-up area of Chinese cities was 180.16 km², an increase of 98.46% (Ministry of Housing and Urban-Rural Development of China 2005, 2020). This rapid and widespread urban expansion is the result of a combination of factors.

Land finance is recognized as an important driver of urban expansion in China at the institutional level. Since the formal implementation of the tax-sharing fiscal reform in 1994 and the Ministry of Land and Resources of China explicitly promoted land market reform in 2002, land transfer fees have become an important source of revenue for local governments, and a more serious land finance dependence has developed in some regions (Fan, Qiu, Sun 2020; Yu, Zhou 2024). Recent studies have emphasized that land finance is both a driver of China's rapid urbanization and a cause of inefficiency in urban expansion, and that the Chinese government is moving away from an over-reliance on land finance through comprehensive reforms. That is, by exploring a path to address the fiscal needs of local governments while at the same time addressing the environmental and social costs of urban expansion (Gyourko et al. 2022, Zhang et al. 2023). Therefore, scholars have examined the relationship between land finance and urban expansion, as well as their regional heterogeneity, spatial spillovers, and mechanisms (Tong et al. 2023; Yu, Zhou 2024), and based on this, they have provided policy recommendations to help the Chinese government to get rid of the dependence on land finance and to realize the balance between urban expansion and sustainable development. However, existing studies are still insufficient in revealing the nonlinear relationship and spatiotemporal heterogeneity between land finance and urban expansion.

Although some recent studies have begun to focus on the nonlinear relationship between land finance and urban expansion (Chen et al. 2024, Tong et al. 2023, Zhang et al. 2023), these studies usually rely on traditional econometric models (e.g., threshold models or quadratic term models), and thus may oversimplify the polynomial or discontinuous relationship between land finance and urban expansion. In addition, case studies from Chongqing, Wuxi and Foshan, reflect that there may be potential spatiotemporal heterogeneity between land finance and urban expansion (Liu et al. 2018a, Tian 2015). Although preliminary explorations have been conducted using multiscale geographically weighted regression with a spatial Durbin model (Yu, Zhou 2024; Zhang et al. 2023), since both are fundamentally a modeling approach based on linear assumptions, they may lead to model misspecification and performance degradation. At this point, there is an urgent need to introduce emerging geographic machine learning methods to cope with the above dilemma. It is noteworthy that a recent pioneering study has attempted to explore nonlinear and spatial non-stationary effects simultaneously using a geographically weighted-random forest with SHapley Additive exPlanation (SHAP) framework, providing novel insights (Zhang et al. 2025). However, this framework treats spatial features as separate features, which violates the theoretical properties of the Shapley value (Harris, Pymar, Rowat 2021). Additionally, the framework is constrained by the fact that the R software does not provide a module for analyzing interaction effects (Zhang et al. 2025), thus failing to analyze the interaction between land finance and spatial features.

In summary, this study seeks to address the research question: How does land finance influence urban expansion in China, and how do these effects vary across space and time under fiscal incentives? At the methodological level, we chose to introduce the GeoShapley method proposed by Li (2024), and used Bayesian hyperparameter optimization to obtain the optimal algorithm (XGBoost) and its hyperparameters, constructing a novel geospatial explainable artificial intelligence (GeoXAI) framework. Secondly, we combined the generalized additive model (Hastie, Tibshirani 1986) to capture the nonlinear relationship between land finance and urban expansion. Thirdly, we achieved the exploration of spatiotemporal heterogeneity by drawing spatial distribution maps of GeoShapley values of land finance. Finally, we applied the basic principles of the moderation effect to analyze the spatial interactions of land finance.

2. Theoretical foundations and prior research

2.1. Concepts and measurement of land finance and urban expansion

Land finance is not an internationally standardized term, but rather refers to a distinctive fiscal behavior pattern formed by local governments in China under the institutional context of the tax-sharing fiscal reform and public land ownership, characterized by a heavy reliance on land conveyance and related financing instruments (Qiu 2025). In developed countries, property taxes typically serve as the land-related fiscal source supporting urban operations, whereas in China, the transfer of commercial and residential land use rights constitutes the core extrabudgetary revenue source for local governments to finance urban infrastructure construction (Wang et al. 2020). Against this backdrop, this study follows the mainstream approach and employs land transfer fees as a proxy variable for land finance.

When examining urban spatial evolution, it is essential to distinguish among the concepts of urbanization, urban sprawl, and urban expansion. Urbanization, as a macro-level economic and sociological concept, encompasses a process involving both urban population growth and urban land transformation. In contrast, urban expansion specifically denotes the continuous expansion of urban built-up areas, which can intuitively reflect land use changes during the urbanization process (Li et al. 2025, Mahtta et al. 2022). When the pace of such spatial expansion significantly exceeds the rate of population migration from rural to urban areas, the originally neutral concept of urban expansion evolves into a pejorative notion, namely urban sprawl. Given that land finance directly affects urban construction land, this study adopts changes in built-up area as a proxy variable for urban expansion.

2.2. Urban expansion under fiscal incentives

From a global perspective, the development of human settlements is profoundly shaped by fiscal decentralization and local policies. Within fiscal decentralization systems, the autonomy granted to local governments incentivizes them to maximize fiscal revenue through the utilization of land development permits and land use regulations. Empirical evidence from Europe supports this argument and further suggests that in decentralized countries, fiscal incentives at the local level may provide strong incentives to permit residential development at the outskirts of existing developments (Ehrlich, Hilber, Schöni 2018). Consequently, the outward expansion of urban space transforms from a purely demographic-geographic phenomenon into a fiscally driven economic behavior (Oates 1999).

This phenomenon is particularly pronounced in emerging economies, where local governments face immense pressure to provide public services and infrastructure during rapid urbanization. The resulting escalation of municipal expenditures inevitably renders local governments dependent on land finance. Specifically, land transfer fees and related taxes generate substantial extrabudgetary revenues for municipal budgets, the majority of which are subsequently invested in infrastructure construction on undeveloped land, thereby progressively pulling urban boundaries outward. When land markets remain active, this fiscal feedback loop binds land finance and urban expansion together. However, when land markets begin to contract, the expansionary driving effect of land urbanization weakens accordingly, gradually yielding to population urbanization processes.

From a comparative perspective, urban spatial expansion in developed countries is primarily driven by household residential preferences and property tax dynamics (Chettry 2023; Tikoudis, Dimitropoulos, Oueslati 2018), whereas emerging economies rely more heavily on land finance-driven land urbanization. China represents a paradigmatic case. Against China's distinctive institutional environment and historical backdrop, the local fiscal gap created by the tax-sharing reform has intensified local governments' dependence on land finance. Due to regional variations in land prices, industrial structure, and transportation infrastructure, this local government led urban spatial expansion is bound to exhibit spatial heterogeneity across geographical space. Thoroughly exploring these spatial disparities is of considerable theoretical importance. However, traditional econometric methods possess inherent limitations in capturing localized spatial nonlinearity and heterogeneity, rendering the introduction of GeoXAI imperative.

2.3. GeoXAI and its applications in urban geography

To address the black box problem of machine learning algorithms, explainable artificial intelligence (XAI) has risen to prominence in recent years (Chamola et al. 2023, Dwivedi et al. 2023). Among various frameworks, the SHAP framework-based game theory has gradually become mainstream owing to its rigorous mathematical foundations and intuitive interpretability (Lundberg, Lee 2017). However, this framework assumes feature independence, thereby overlooking the spatial dependence and spatial heterogeneity of locational information during the modeling process (Li 2024; Xing, Sieber 2023). Against this backdrop, improved frameworks incorporating geographical interaction mechanisms, with GeoShapley serving as a representative example, have emerged. Its capacity to not only compute the global contribution of non-spatial features but also decompose such contributions into spatial interaction effects and intrinsic individual effects (Li 2024). Currently, the GeoShapley framework is offering a novel perspective of urban geography. On the one hand, scholars have employed this framework to disentangle the impacts of built environment on elderly walking ability and child friendly perception (Su et al. 2025a, 2025b), thereby expanding the evaluative boundaries of built environment elements such as streetscape and green space coverage. On the other hand, scholars have leveraged this framework to predict road accident risks (Srivastava, Gohil, Ray 2025), consequently improving urban planning and traffic dispatching. More fundamentally, the contribution of GeoXAI to urban geography extends beyond enhancing the predictive accuracy of models, it also facilitates the identification of whether a particular driving factor acts as an enabler or a barrier at different geographical locations. Therefore, the introduction of GeoXAI into the investigation of the relationship between land finance and urban expansion is imperative.

3. Methodology

3.1. Variables

The land finance revenue of local governments in China consists of land transfer fees and land-related taxes. Considering that land transfer fees are the most important source of local government revenue and that land tax-related data are difficult to collect, we draw on the idea of Sun and Zhou (2013) to use land transfer fees as a proxy variable for land finance and logarithmically treat them in the modeling process.

Urban expansion in China mainly manifests as the excessive expansion of urban space and urban population (Lyu, Huang, Sun 2025). Considering that this study mainly explores the driving role of land finance in the urbanization process. Therefore, we set 2002 as the base period and measure urban expansion by the ratio of the built-up area of each prefecture-level city in the study year to the built-up area in the base period, as shown below:

$$URBS = \left(\frac{S_t}{S_0} - 1\right) \times 100\% \tag{1}$$

Based on previous literature (Osman, Divigalpitiya, Arima 2016; Sudhira, Ramachandra, Jagadish 2004), we will select control variables from three aspects: economics, population, and geography. In the economic dimension, this study selects GDP per capita and industrial structure as control variables. GDP per capita serves as an intuitive indicator of a region's overall level of economic development, while industrial structure directly determines the spatial pattern and intensification degree of land use. In the population dimension, population size and urbanization level are incorporated into the model. The sustained growth of the urban permanent population generates rigid demand for housing, and the large-scale migration of the rural population to cities constitutes the fundamental driving force behind the outward expansion of urban built-up areas. In the geographical dimension, location, geographic region, and topographic relief are introduced as control variables. Location and geographic region are constructed as dummy variables, typically reflecting structural differences in fiscal resources and development trajectories across different regions of China, whereas the topographic relief derived from remote sensing image processing directly captures the natural constraints that geomorphological features impose on urban construction. The multisource panel dataset thus constructed provides a solid foundation for revealing the complex relationship between land finance and urban expansion.

3.2. Data source

After removing missing values from the variables, a sample of 204 prefecture-level cities in China was retained, with the study years including 2005, 2010, 2015, and 2020. In terms of data sources, land finance was obtained from the *China Land and Resources Statistical Yearbook*, urban expansion from the *China Urban Construction Statistical Yearbook*, and the remaining control variables from the *China City Statistical Yearbook*, the GTOPO30, and statistical yearbooks of various provinces and cities. The descriptive statistics of each variable are shown in Table 1.

Table 1 – Descriptive statistics

Variables	Symbol	N (%)	Mean ± Std	Definition
Land finance	Lnx		3.821 ± 1.557	Natural logarithm of (total land transfer revenue + 1) in the year
Urban expansion	Y		2.136 ± 1.244	Growth rate of built-up area compared to the baseline period
Per Capita GDP	E1		10.395 ± 0.816	Natural logarithm of per capita GDP
Industrial Structure	E2		41.131 ± 10.246	Share of tertiary industry value added in GDP (%)
Urbanization	P1		0.522 ± 0.176	Urbanization rate
Population Size	P2		5.987 ± 0.697	Natural logarithm of resident population
Geographic Region	G1			Defined by National Bureau of Statistics of China
Eastern		328 (40.20%)		
Central		268 (32.84%)		
Western		212 (25.98%)		
Northeastern		8 (0.98%)		
Location	G2			Coastal or Inland
Inland		472 (57.84%)		
Coastal		344 (42.16%)		
Topographic Relief	G3		0.671 ± 0.736	Terrain relief derived from remote sensing image processing

3.3. Research methods

To comprehensively examine the evolutionary characteristics of land finance and urban expansion and their complex nexus, this study develops an integrated analytical framework. First, kernel density estimation is employed to characterize the distribution patterns and polarization phenomena of land finance and urban expansion, and further to analyze their dynamic evolution. Second, a two-way fixed effects model is constructed to conduct a global test of the basic linear relationship between land finance and urban expansion, thereby establishing links with previous quantitative research. Third, considering that traditional econometric models struggle to capture the intricate nonlinear relationships and spatial heterogeneity between land finance and urban expansion, this study adopts XGBoost as the base learner and utilizes GeoShapley along with the generalized additive model to present the estimation results in a more intuitive manner. Finally, drawing on the principle of moderation effects, a temporal analysis is performed on the spatial interaction terms derived from GeoShapley. The detailed flowchart is illustrated in Figure 1.

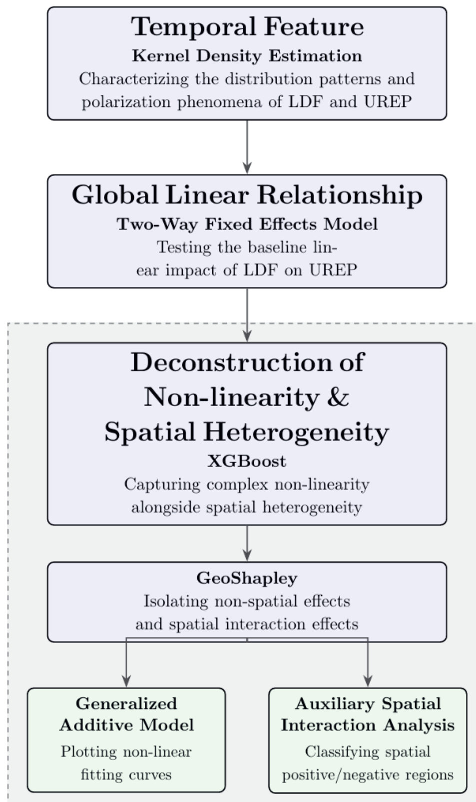

Fig. 1 – Comprehensive methodology framework

3.3.1. Kernel density function

The distribution location, distribution shape, extension characteristics, and polarization phenomena of land finance and urban expansion are characterized by the Gaussian kernel function to measure their dynamic evolution characteristics. The formula is as follows:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{D_i - \overline{D}}{h}\right) \tag{2}$$

In this formula, n is the number of prefecture-level cities; h is the smoothing bandwidth; $\overline{D}$ is the mean of the core variables; and $K(\cdot)$ denotes the kernel density function.

3.3.2. Two-way fixed effects

Test the linear effect of land finance on urban expansion by constructing a two-way fixed effects model:

$$Y_{i,t} = \delta_0 + \delta_1 Lnx_{i,t} + \delta_2 Z_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{3}$$

In equation (3), δ_0 is the intercept term, δ_1 and δ_2 represent the estimated coefficients of land finance and control variables, respectively, and μ_i, λ_t, and $\varepsilon_{i,t}$ represent the city (individual) fixed effect, year (time) fixed effect, and random disturbance term, respectively.

3.3.3. XGBoost

XGBoost is an efficient and scalable ensemble learning algorithm based on the gradient boosting framework, which can be applied to both regression and classification tasks. Its core idea lies in iteratively training decision trees to gradually optimize the model, with the objective of minimizing the model's loss function in each iteration. Furthermore, compared with the traditional GBDT, XGBoost further enhances the model's generalization ability and robustness by introducing a regularization mechanism (Chen, Guestrin 2016). The calculation formula of its objective function is:

$$\varphi(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}^{(t)}) + \sum_{k=1}^{t} \Omega(f_k) \tag{4}$$

Among them, $\varphi(\theta)$ is the objective function, which consists of two parts: the loss function and the regularization term. $l(y_i, \hat{y}^{(t)})$ is the loss function, which is used to measure the prediction error of the model. $\Omega(f_k)$ is the regularization term, which is used to control overfitting.

3.3.4. GeoShapley

Generally, traditional regression analysis and the econometric methods extended from it mainly focus on identifying linear relationships, while the emerging machine learning models in recent years have significant advantages in recognizing complex relationships among variables (Cao, Tao 2023). Meanwhile, considering that the core variables in this study exhibit significant spatial agglomeration effects, if spatial heterogeneity is not considered during modeling and machine learning algorithms are directly applied to construct a global model, it will be impossible to accurately describe the local relationships between spatial variables, leading to weak model interpretability (Yang et al. 2023). Therefore, we chose to apply GeoShapley, the geospatial extension of the SHAP framework – the most popular explainable machine learning framework – to strengthen the analysis of spatial heterogeneity and improve the interpretability of modeling results (Foroutan, Hu, Li 2025; Li 2024). Its final output formula consists of four parts (Li 2024):

$$\hat{y} = \phi_0 + \phi_{GEO} + \sum_{j=1}^{p} \phi_j + \sum_{j=1}^{p} \phi(GEO, j) \quad (5)$$

Among these, ϕ_0 is the global intercept calculated based on the average predicted value of the given data, ϕ_j represents the location-independent effect provided for each non-location variable, ϕ_{GEO} is the inherent location effect in the model, and $\phi(GEO, j)$ represents the interaction effect between location and a specific variable. When there is no location information in the model, ϕ_{GEO} and $\phi(GEO, j)$ will be 0, and the equation will revert to the classic Shapley value calculation equation.

3.3.5. Generalized additive model

To better explain the nonlinear relationship between land finance and urban expansion, we combined machine learning algorithms with generalized additive model to plot the fitted curve (Hastie, Tibshirani 1986), as shown in the following formula:

$$g(E(y)) = \beta_0 + s(v) \quad (6)$$

Among them, $g(E(y))$ represents the expected response $E(y)$ of the dependent variable y after being acted upon by the link function g, where β_0 is the intercept term, and $s(v)$ is a smooth function of the GeoShapley values of the independent variables.

3.3.6. Methods for auxiliary analysis of spatial interactions

Since the spatial interactions in GeoShapley essentially represent interaction terms between independent variables and spatial features, their numerical values cannot be directly analyzed. Therefore, we chose to draw on the fundamental principles of the moderation effect (Cohen et al. 2013; James, Brett 1984) for analysis. Specifically, when the sign of land finance is the same as that of its spatial interaction term, it is regarded as a spatial reinforcing effect; conversely, it is a spatial weakening effect. According to the sign of land finance, this can be further subdivided into four categories: positive spatial reinforcement, negative spatial reinforcement, positive spatial weakening, negative spatial weakening. In the results section, we will also conduct an analysis following this logic.

Except for the two-way fixed effects models constructed using Stata/MP 17.0 and the spatial feature maps drawn using ArcGIS 10.8, all other data processing, modeling, and visualization were implemented via Python 3.11.7. The research framework diagram of this study is shown in Figure 1.

4. Results

4.1. Temporal characterization of land finance and urban expansion

Figures 2 and 3 illustrate the temporal changes in land finance and urban expansion of China's prefecture-level cities from 2005 to 2020[1]. The figures show that both land finance and urban expansion exhibited a sustained growth trend during the study period. The mean value of land finance increased from 24.582 to 298.810, representing a 1116% growth, while the mean value of urban expansion rose from 1.346 to 2.950, a 119% increase. Additionally, the medians of land finance and urban expansion continuously increased, but the box sizes of their boxplots also expanded. The kernel density curves shifted rightward overall, yet the peak values of the main peaks significantly decreased, and the amplitude widths substantially widened. In summary, the continuous growth of land finance and urban expansion during the study period was accompanied by an expanding regional disparity.

4.2. Average direct effect of land finance on urban expansion

Before constructing the regression model, we analyzed whether there was a correlation between the independent variables and the dependent variable, and the results showed that there was a positive correlation between land finance and urban expansion ($r = 0.355$, $P < 0.001$). Figure 4 shows the univariate regression equation of the land finance and urban expansion and its fitted line, which also verifies the positive correlation between the land finance and urban expansion. Secondly, we also tested for multicollinearity between the variables. The results of the test showed that the maximum value of VIF was 3.35 (< 10) and the mean value was 2.45 (< 5), indicating that the possibility of multicollinearity among the selected variables is not significant. Meanwhile, the result of Hausman test ($\chi^2 = 83.04$, $P < 0.001$) rejected the original hypothesis of accepting the random

[1] For a more intuitive presentation, we did not logarithmically process the land finance in the process of plotting the temporal and feature maps.

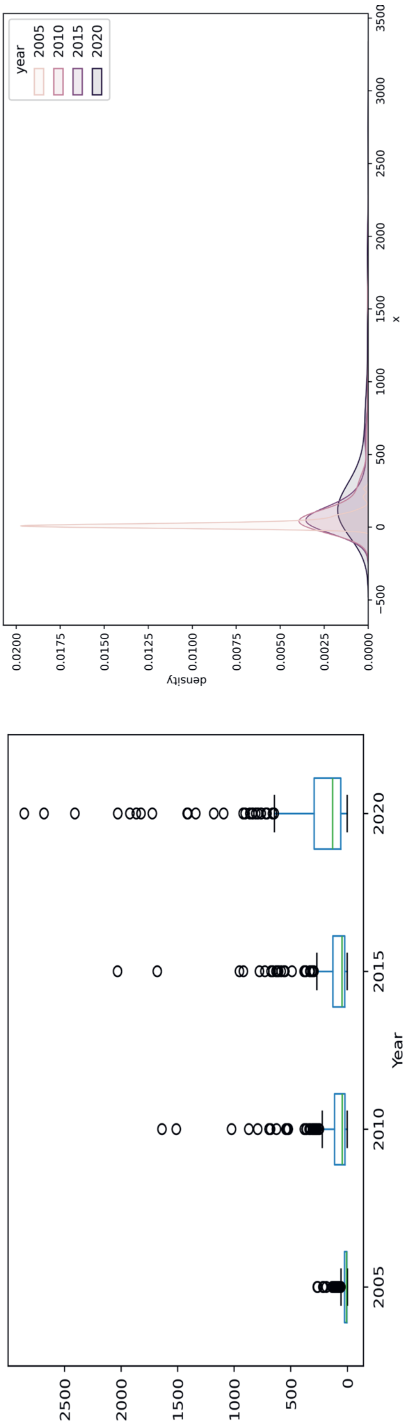

Fig. 2 – Temporal changes of land finance

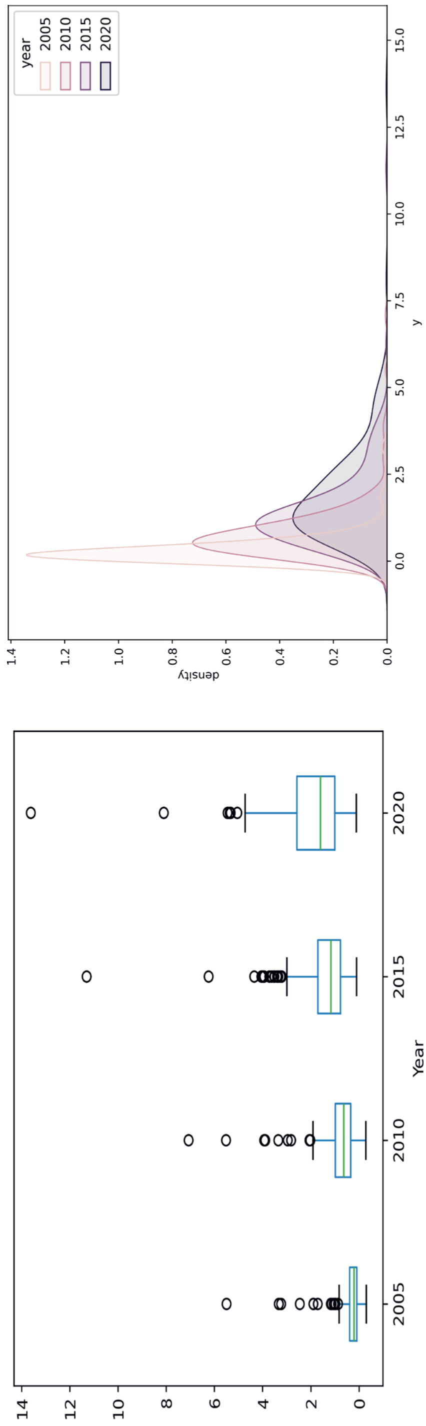

Fig. 3 – Temporal changes of urban expansion

Table 2 – Estimation results of the two-way fixed effects model

	Model 1	Model 2	Model 3	Model 4
Independent variable	0.458*** (0.022)	0.181*** (0.031)	0.148*** (0.032)	0.091* (0.043)
Covariates	×	√	√	√
City effect	×	×	√	√
Year effect	×	×	×	√
Constant	0.387*** (0.110)	0.354 (0.383)	-0.461 (0.244)	0.949** (0.323)
N	816	816	816	816
R^2	0.126	0.199	0.157	0.241

Note: * p < 0.05, ** p < 0.01, *** p < 0.001.

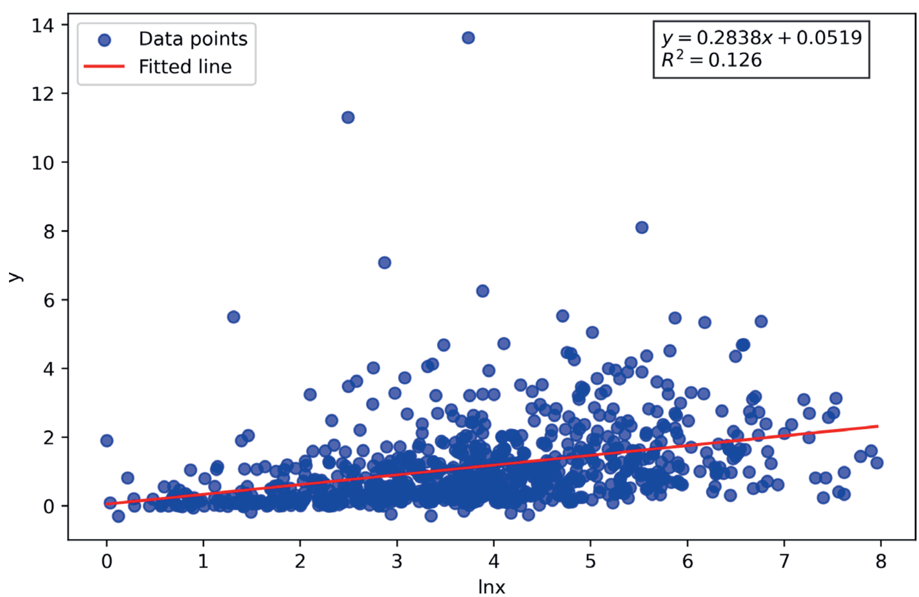

Fig. 4 – Fitted plot of land finance and urban expansion

effect model and initially identified the use of fixed effect model. Furthermore, we found that the estimated coefficients of the time term were significant and the R^2 of the model was improved after we added the time fixed effect, so we chose to use the two-way fixed effects model as the benchmark model.

The regression results are shown in Table 2. Among them, Model 1 is the OLS model, and Model 2, Model 3 and Model 4 are based on which control variables, individual fixed effects and time fixed effects are added, respectively. In the following, Model 4 will be analyzed as the benchmark model. Since the independent variables have been taken as logarithms and the units of the dependent variables are percentages, it can be concluded from Model 4 that for every 1% increase in land finance, there will be a 0.091% increase in urban expansion ($B = 0.091$, $P < 0.05$). In addition, land finance significantly and positively affects urban expansion regardless of the inclusion of fixed effects with control variables, which validates the robustness of the benchmark results.

4.3. Nonlinear characterization of the relationship between land finance and urban expansion

Due to the performance of machine learning regressors being largely influenced by hyperparameters (Probst, Boulesteix, Bischl 2019), we adopted BayesSearchCV from scikit-optimize to tune the hyperparameters of XGBoost, RandomForest, AdaBoost, and LightGBM. BayesSearchCV is a Bayesian optimization method designed for efficiently searching global optimization problems (Mesquita,

Table 3 – Models and their hyperparameter tuning

Algorithm	Hyperparameter Name	Hyperparameter Type	Hyperparameter Range
XGBoost	learning_rate	Real	0.01–0.3 (prior = 'log-uniform')
	max_depth	Integer	3–10
	n_estimators	Integer	100–1,000
RandomForest	n_estimators	Integer	100–500
	max_depth	Integer	3–20
	min_samples_split	Integer	2–10
AdaBoost	n_estimators	Integer	50–200
	learning_rate	Real	0.01–1.0 (prior = 'log-uniform')
	loss	Categorical	['linear', 'square', 'exponential']
LightGBM	learning_rate	Real	0.01–0.3 (prior = 'log-uniform')
	max_depth	Integer	3–15
	n_estimators	Integer	100–1,000
	subsample	Real	0.6–1.0
	colsample_bytree	Real	0.6–1.0

Table 4 – Model evaluation results

	MAE	RMSE	R^2
XGBoost	0.447	0.658	0.766
RandomForest	0.592	0.853	0.608
AdaBoost	0.737	0.976	0.487
LightGBM	0.583	0.805	0.651

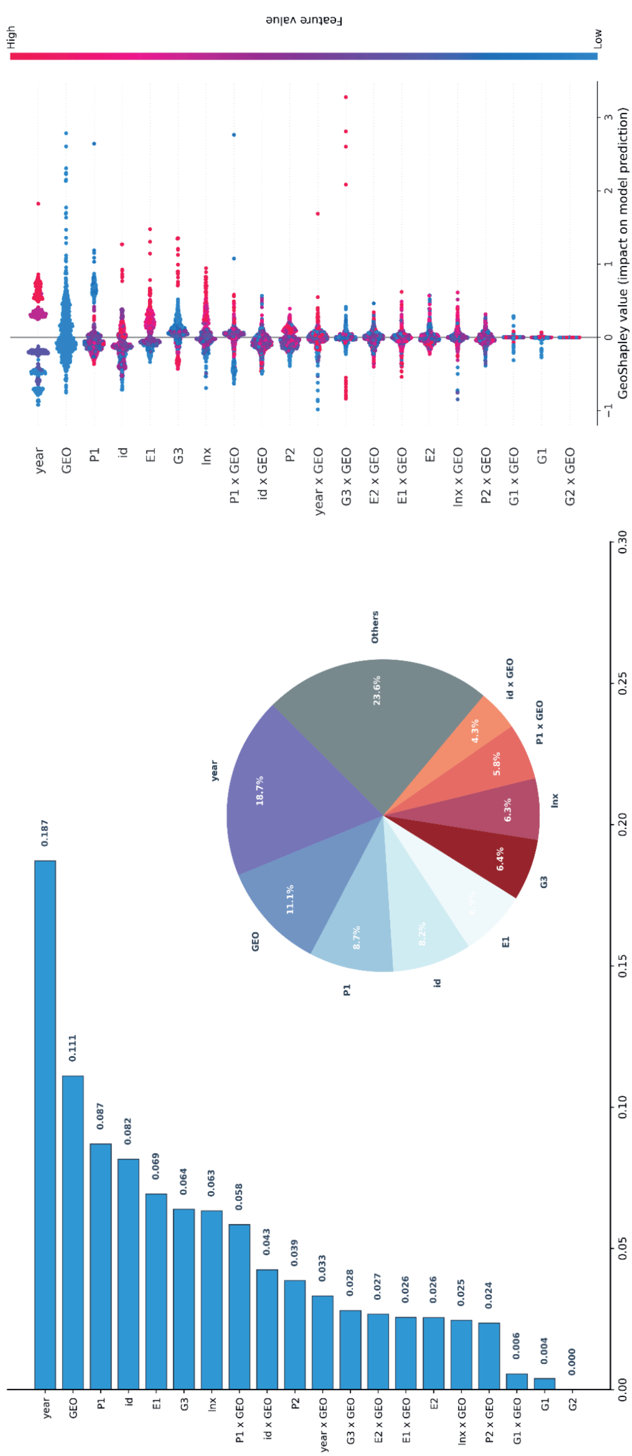

Fig. 5 – Variable importance and contribution percentage for the model

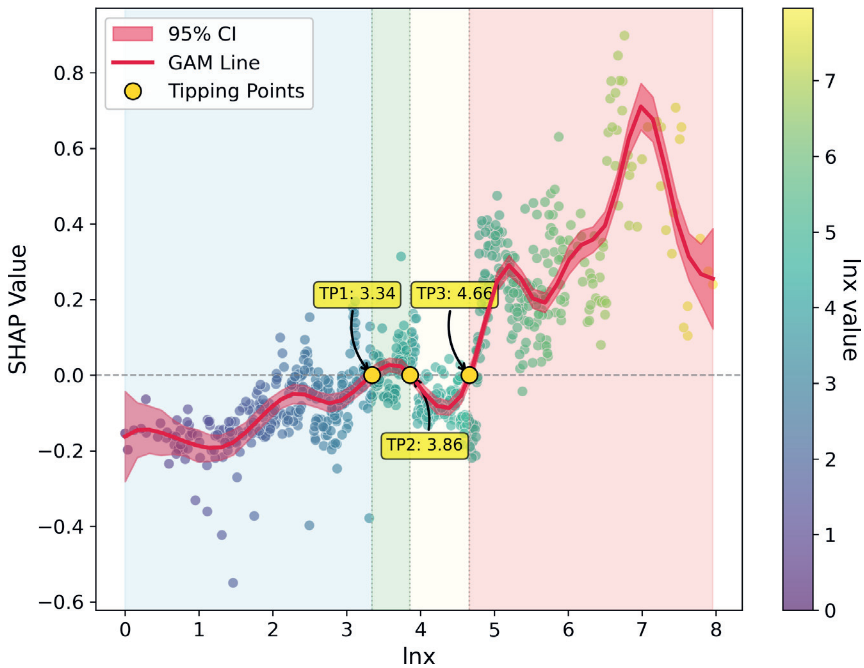

Fig. 6 – Nonlinear relationship between land finance and urban expansion

Marques 2024). During the hyperparameter optimization, all algorithms employed 5-fold cross-validation to ensure the robustness of model performance evaluation, with 30 iterations set and R^2 as the evaluation metric. The specific hyperparameter optimization items and ranges are shown in Table 3.

By comparing the evaluation indicators of each algorithm in Table 4, it can be found that XGBoost outperformed the other three models in R^2, *RMSE*, and *MAE* metrics (*MAE* = 0.447, *RMSE* = 0.658, R^2 = 0.766). Thus, based on the optimal hyperparameters, we constructed a GeoXAI framework to analyze the nonlinearity and spatiotemporal heterogeneity of the relationship between land finance and urban expansion in China's prefecture-level cities.

By taking the absolute values of GeoShapley values for each variable of every sample, averaging them, and sorting them sequentially, a variable importance summary plot was obtained (Figure 5)[2]. As shown in Figure 5, temporal effects, spatial effects, and individual effects are the three most important influencing

[2] Since the schematic diagram only supports displaying the top 20 variables and their spatial interaction effects, and the impacts of the last few variables and their spatial interaction effects on the model are almost negligible, we only present the top 20 variables and their spatial interaction effects here.

factors. land finance ranks 7th in the importance ranking of all variables and their spatial interaction effects, with a feature contribution of 6.3%, which is higher than that of population size and industrial structure – factors traditionally considered to have significant impacts (Li, Li 2019; Liu et al. 2018b). Meanwhile, Figure 6 indicates that when land finance is at a lower value, its impact on urban expansion is predominantly negative, whereas when land finance is at a higher value, the impact is predominantly positive. In other words, the relationship between land finance and urban expansion is not a simple linear one.

To further explore the potential nonlinear relationship, we plotted a partial dependence plot of land finance's GeoShapley values and combined it with a generalized additive model to draw a fitting line for better visualization of the nonlinear effect. Figure 6 shows that the fitting line between land finance and urban expansion has three tipping points, corresponding to the original data values of 27.22($e^{3.34}-1$), 46.47($e^{3.86}-1$), and 104.64($e^{4.66}-1$). This indicates that when land finance is less than 27.22, its overall impact on urban expansion is negative; when its value is between 27.22 and 104.64, it exhibits an inverted U-shape followed by a U-shape relationship; and when the value exceeds 104.64, the impact on urban expansion is overall positive. In essence, the relationship between land finance and urban expansion is characterized by complex nonlinearity.

4.4. Spatiotemporal heterogeneity of the relationship between land finance and urban expansion

To more intuitively characterize the spatiotemporal heterogeneity of the impact of land finance on urban expansion, the GeoShapley values of land finance for each study year were visualized using the equal interval classification method (Figure 7). Based on Figure 7, it was found that during the study period, the impact of land finance on urban expansion gradually shifted from negative to positive, with continuously enhanced effects. High-positive-value regions were mainly concentrated in second-tier cities and showed a trend of diffusion from the coast to the inland. Specifically: In 2005, except for some cities in the Yangtze River Delta, some cities in the Bohai Rim, and a few inland cities, land finance in the remaining regions had a negative impact on local urban expansion. Only 12.75% of prefecture-level cities showed that land finance had a positive impact on urban expansion. In 2010, 45.59% of prefecture-level cities had land finance exerting a positive impact on urban expansion, presenting a trend of diffusion from the coast to the inland. The positive impacts of land finance on urban expansion were particularly prominent in Ningbo, Suzhou, and Dalian. In 2015, 48.53% of prefecture-level cities had land finance positively affecting urban expansion. The number of positive value regions slightly increased, but the polarization

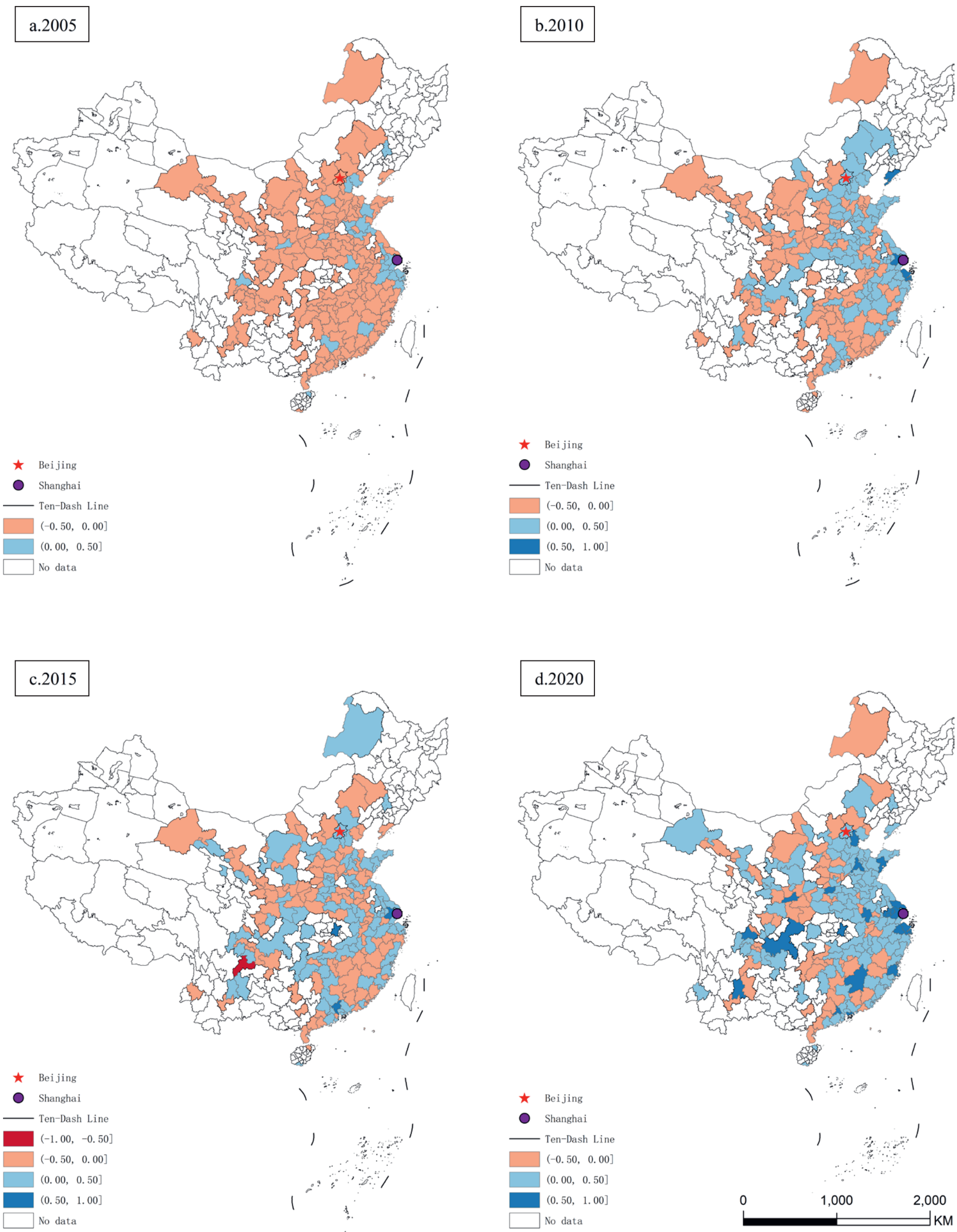

Fig. 7 – Spatiotemporal heterogeneity of land finance's Impact on urban expansion

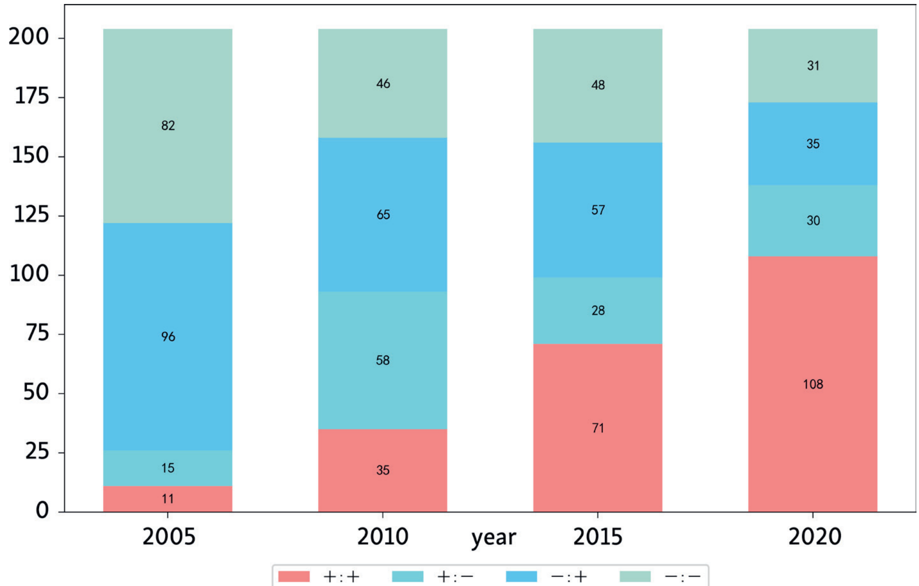

Fig. 8 – Proportion of different types of spatial Interaction effects

trend intensified. For example, land finance in Zhaotong, Yunnan significantly weakened local urban expansion. In 2020, 67.65% of prefecture-level cities saw land finance exerting positive impacts on urban expansion. High-positive-value regions were concentrated in second-tier cities such as Foshan, Jinan, Xi'an, and Wuhan, reflecting that land finance is an important factor for urban expansion in late-developing cities.

On this basis, combined with the basic principles of moderation effects (Cohen et al. 2013; James, Brett 1984), the interaction terms between land finance and the GeoShapley values of spatial characteristics were analyzed, as shown in Figure 8. It can be seen from Figure 8 that in 2005, spatial interactions mainly alleviated the negative inhibition of land finance on urban expansion (47.06%), while by 2020, spatial interactions mainly strengthened the positive effects (52.94%). In other words, the main role of spatial interactions shifted from alleviating negative impacts to strengthening positive impacts. Meanwhile, the proportion of positive spatial interaction terms across all cities increased from 52.45% in 2005 to 70.10% in 2020, indicating that spatially positive correlation areas expanded continuously.

5. Discussion

5.1. The effectiveness of GeoXAI and its integrated application with traditional econometric models

This study integrates XGBoost with GeoShapley, representing a novel GeoXAI framework. Applying this framework to analyze the relationship between land finance and urban expansion in China's prefecture-level cities is both effective and necessary. On one hand, the model evaluation indicators of this study ($MAE = 0.447$, $RMSE = 0.658$, $R^2 = 0.766$) significantly outperform the traditional spatial panel regression model (Tong et al. 2023), and are basically on par with other studies using this method (Foroutan, Hu, Li 2025). This indicates that the model has strong explanatory power in analyzing the relationship between land finance and urban expansion in China's prefecture-level cities. On the other hand, as previously mentioned, the spatial econometric models commonly used in previous studies are fundamentally modeling methods based on linear assumptions, which are not applicable when exploring non-linear relationships. Although existing studies have attempted to solve this dilemma by introducing machine learning, they still only treat location features as separate features and do not consider the impact of spatial interaction effects in the modeling process. Therefore, this study chooses to introduce a novel GeoXAI framework, which effectively solves the above problems and realizes the effective estimation of non-linear effects and spatiotemporal heterogeneity.

In addition, we further draw on the idea of Qiu et al. (2025) to plot the fitted curve of GeoShapley value of the land finance through generalized additive model, which not only realizes the visual presentation of the nonlinear effect, but also identifies the tipping points of the nonlinear relationship with the help of the semiparametric model, maximizing the potential of GeoXAI in identifying nonlinear relationships. In addition, considering that spatial interaction effects need to be analyzed with direct effects, this study introduces the basic principle of moderation effects and explores the role of spatial features in the baseline relationship. In summary, this study effectively estimates the nonlinearity and spatiotemporal heterogeneity of the relationship between land finance and urban expansion in China's prefecture-level cities by integrating the GeoXAI with traditional econometric models.

5.2. Theoretical contributions

In response to the ongoing debate in the existing literature regarding the relationship between land finance and urban expansion, this study validates the driving effect of land finance on urban expansion over an extended period using a large sample panel dataset. More importantly, it further uncovers the nonlinearity and spatial dynamics between the two, which helps clarify the underlying logic of how land finance translates into urban expansion. land finance is not a conventional on-budget revenue; rather, it is a financing model centered on land transfer and land mortgage. As in other emerging economies, most of its value-added gains are channeled into public infrastructure investment (Peterson 2009). Driven by fiscal incentives, local governments, which serve as the core suppliers in the primary land market, attract capital inflows by supplying industrial land at low prices while obtaining substantial extra-budgetary revenues by leasing commercial and residential land at high prices. This financing model directly results in a situation where, in practice, urban spatial expansion in China typically precedes population agglomeration. At the same time, under fiscal incentives, the impact of land finance on urban expansion is not static or linear; it exhibits dynamic temporal nonlinearity and spatial heterogeneity that are subject to market cycles and regional economic conditions. These findings extend the theoretical boundaries of land finance as a form of spatial intervention by local governments.

Furthermore, this study provides an important reference for land capitalization practices in rapidly urbanizing countries. The uniqueness of the Chinese model lies in the coupling of public land ownership and fiscal decentralization, which enables local governments to capture land value increments for decades to come in the form of one-time land conveyance fees, thereby providing adequate funding for infrastructure construction during rapid urbanization. Although China's institutional context is distinctive, the inherent logic of urban expansion under fiscal incentives holds significant theoretical insights for rapidly urbanizing countries. In such rapidly urbanizing regions as India and Latin America, local governments similarly face enormous infrastructure investment gaps (Jain 2023, Smolka 2013). This study offers a land capitalization approach under fiscal incentives, which not only helps advance the capitalization of land in a public ownership economy but also helps bridge local fiscal gaps and promote urban infrastructure investment.

5.3. The interpretation of the results

During the research period, both land finance and urban expansion exhibited steady growth, accompanied by widening regional disparities. The root cause lies in the well-documented interurban economic inequality in China (Hou, Gao 2025). Within the centralized tax system, local governments face uniform fiscal pressure, leading them to rely on land finance as the most effective revenue tool (Tong et al. 2022). This transforms economic inequality into land finance inequality.

Subsequently, unequal land finance provides varying degrees of impetus to cities' urban expansion, further reinforcing urban expansion inequality caused by economic inequality.

Using the two-way fixed effects model, this study finds that, on average, a 1% increase in land finance leads to a 0.091% rise in urban expansion, which is like the results of Tong et al. (2022) and again confirms the positive direct effect of land finance on urban expansion. Moreover, based on GeoXAI, this study finds that land finance's contribution to the predictive model ranks seventh among all variables, accounting for 6.3%, offering new evidence of land finance's relative importance in explaining urban expansion. Additionally, by fitting GeoShapley value with generalized additive model, this study identifies the tipping points in the non-linear relationship between land finance and urban expansion. This extends the previous "threshold interpretation" (Li et al. 2021, Zhang et al. 2023) and once again confirms the complex non-linear relationship between land finance and urban expansion.

Regarding spatiotemporal heterogeneity, this study finds that land finance's impact on urban expansion has evolved from negative to positive with an increasing effect during the research period. High-value areas are concentrated in second-tier cities and are gradually spreading from the coastal to the inland. This reflects that China's urbanization has reached a turning point (Bai, Shi 2025). Studies show that between 2010 and 2020, the growth of urban population and housing in first-tier cities gradually saturated, while second-tier cities experienced rapid growth (Shi et al. 2025). That is, the new round of land-based urbanization may be led by late-developing cities. Although coastal urban agglomerations were larger in scale at the baseline and maintained relatively high annual growth rates compared to inland ones (Hu et al. 2024), with the advancement of China's regional coordinated development policy, the traditional urbanization pattern is changing at an unprecedented speed.

Moreover, the results of spatial interaction analysis show that spatially positive correlation areas expanded continuously, indirectly proving the initial effectiveness of the regional coordinated development policy. From a temporal perspective, the role of spatial interaction has gradually shifted from mitigating negative effects to reinforcing positive ones. This result needs to be discussed against the macro background of China's land marketization reform since the 21st century. Market-oriented reforms in transition economies are usually top-down and incremental, and China's land marketization reform is no exception. In the early stage of land marketization reform, due to limited market mechanisms and strict government control (Chen et al. 2024, Liu et al. 2016), land finance's driving role for urban expansion was hard to exert, and spatial dominance mainly served to mitigate negative effects. As local governments' dependence on land finance increased and the land transfer market matured (Fan, Qiu, Sun 2020), urban expansion began to shift from disorderly expansion to systematic development. At this point, spatial dominance played a more significant role in reinforcing positive effects.

5.4. Policy implications

The following policy implications emerge from the research findings: Firstly, implement zoned regulation to tackle the widening regional disparity. On the one hand, in the eastern coastal regions, exploring the piloting of property taxes could be considered as a potential measure to cool down the real estate market. This would pressure local governments to reduce their reliance on land based fiscal revenues. Also, machine learning algorithms and big data platforms can strengthen satellite remote sensing monitoring. Based on this monitoring, the approval of land supply indicators for fast-expanding cities should be strictly scrutinized or restricted. On the other hand, in the central and western inland regions, the land revenue reliance rate and land use efficiency indicators should be gradually incorporated into the cadre promotion assessment system. This would drive restrictions on inefficient land development. Additionally, transit-oriented-development based integrated urban and industrial development model projects should be created to provide a replicable and referenceable approach for effective urban expansion.

Secondly, establish a polycentric collaborative governance network to address the spatiotemporal shift. In mature city clusters such as the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei regions, a cross regional trading mechanism for construction land indicators should be explored. Meanwhile, an assessment system for policies on regulating the surplus indicators of urban-rural construction land readjustment should be established. This would coordinate the allocation of land resources across cities within the cluster. Also, fostering a "provincial capital-sub regional center" dual core structure could be beneficial in inland regions. Collaborative efforts in building regional core industrial parks and high-speed rail hubs would curb the inefficient expansion of secondary cities and guide the formation of locally distinctive intensive land use models.

Finally, coordinate the complex system through targeted policies at key nodes. Specifically, when the land revenue reliance degree or expansion rate of a city reaches a certain threshold, targeted intervention measures might be warranted. These could include requiring a certain proportion of rental housing, strictly limiting the supply of commercial land at the urban fringe, and increasing the plot ratio of industrial land. Furthermore, third party assessments of intervention policies should be introduced to dynamically update the key threshold parameters annually.

5.5. Limitations

This study also has some limitations: first, the independent and dependent variables in this study are derived from statistical yearbook data, which can ensure the authenticity and accuracy of the data, but there is also the problem of too much missing data, and future research can be verified by using multiple sources of data such as NPP–VIIRS nighttime lighting data and LandScan population data. Second, although this study used generalized additive model to plot the fitting curves based on the XGBoost-GeoShapley model, it only analyzed the nonlinear relationship between land finance and urban expansion, and future studies can consider further exploring the conditional nonlinear relationship under different variable scenarios. Third, this study used data at the prefecture-level city level, so the sample size is small and may not be able to maximize the advantages of the GeoXAI framework, and future research can further refine to the county level to enhance model effectiveness and explanatory power.

6. Conclusions

Using the panel data of 204 prefecture-level cities in China for the years 2005, 2010, 2015, and 2020, we integrated GeoXAI with traditional econometric models. This approach enabled us to investigate the spatiotemporal characteristics of land finance and urban expansion, as well as the nonlinear relationship and spatiotemporal dynamics between them. The results indicate that in terms of temporal evolution, both land finance and urban expansion in China's prefecture-level cities have shown sustained growth, accompanied by an expansion of regional disparities. Furthermore, a 1% increase in land finance leads to a 0.091% increase in urban expansion. land finance's contribution to explaining the urban expansion model is 6.3%, and there is a complex nonlinear relationship between the two. Through the visualization of GeoShapley values, it is revealed that the impact of land finance on urban expansion has transitioned from negative to positive and continues to strengthen. High-positive-effects are concentrated in second-tier cities and are spreading from the coastal to the inland. Additionally, the spatially positive correlation areas expanded continuously, and spatial interactions have shifted from mitigating negative impacts to reinforcing positive ones. Based on these findings, we propose several policy insights, including implementing zoned regulation to address widening regional disparities, establishing a polycentric collaborative governance network to tackle spatiotemporal shifts, and coordinating complex systems through targeted policies at key nodes.

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