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Exploring the Effects of Contextual Factors on Residential Land Prices Using an Extended Geographically and Temporally Weighted Regression Model

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Abstract: A spatial and temporal heterogeneity analysis of residential land prices, in general, is crucial for maintaining high-quality economic development. Previous studies have attempted to explain the geographical evolution rule by studying spatial-temporal heterogeneity, but they have neglected the contextual information, such as school district, industrial zone, population density, and job density, associated with residential land prices. Therefore, in this study, we consider contextual factors and propose a revised local regression algorithm called the contextualized geographically and temporally weighted regression (CGTWR), to effectively address spatiotemporal heterogeneity, and to creatively extend the feasibility of importing the contextualization into the GTWR model. The quantitative impact of contextual information on residential land prices was identified in Shijiazhuang (SJZ) city from 1974 to 2021. Empirical analyses demonstrated that school district and industrial zone factors played important roles in residential land prices. Notably, the distance from a residential area to an industrial zone was significantly positively correlated with residential land prices. In addition, a positive relationship between school districts and residential land prices was also observed. Finally, the R^2 value of the CGTWR model was 92%, which was superior to those of ordinary least squares (OLS, 76%), geographically weighted regression (GWR, 85%), contextualized geographically weighted regression (CGWR, 86%), and GTWR (90%) models. These evaluation results indicate that the CGTWR algorithm, which incorporates contextual information and spatiotemporal variation, could provide policy makers with evidence for understanding the nature of varying relationships within a land price dataset in China.

Keywords: residential land prices; spatial and temporal non-stationarity; contextualized geographically and temporally weighted regression; Shijiazhuang

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1. Introduction

A spatial and temporal heterogeneity analysis of residential land prices is considered to be crucial for revealing major issues in real estate market development, understanding effective strategies of economic macro control, and promoting high-quality development of internal economics [1–4]. In the past decades, urbanization in China has undergone rapid development. The urban population increased from 17.16% to 60.60% between 1974 and 2019 according to the China Statistical Yearbook. Along with the expeditious progression of urbanization, countless internal markets have flourished. The housing market is one of the most active markets in China and plays a crucial role in China's economy [5–9]. The average selling price of commercial housing has increased rapidly, especially in heavily populated provinces. By contrast, the per capita disposable income of urban households has increased from 5425 to 42,358 yuan (equivalent to approximately 838.16–6544 USD). The swift growth of residential land prices as compared with the increase in residents' incomes indicates a growing housing affordability problem in China [10–13]. Thus, the spatiotemporal analysis of residential land prices has become a research priority for researchers and policy makers.

Considering the related available research, various models have been developed to explore the spatial and temporal heterogeneity in residential land prices. Geographic information system (GIS)-based approaches, called automated valuation methods (AVMs), are characterized by a powerful theoretical and methodological basis in order to determine more objective property evaluations [14–17]. Multiple criteria are aggregated into a compound criterion by the multi-attribute utility theory (MAUT) for the purpose of evaluating the decisive property characteristics in the real estate market [18,19]. Hybrid data-driven regression models that incorporate a multi-objective genetic algorithm have been proposed to search expressions about maximization of data accuracy and simplification of mathematical functions [20–22]. Furthermore, the geographically weighted regression (GWR) model, which provides distance metrics with specific parameters in the spatial dimensions, was introduced by [23–25]. The mixed geographically weighted regression (MGWR) model has been verified effectively with some parameters fixed globally and others adjusted locally [26,27]. A prominent advancement in residential land price estimations resulted from the geographically and temporally weighted regression (GTWR) approach, proposed by Bo Huang [28]. The GTWR model provides an efficient approach for evaluating mass price temporal non-stationarity in the field of real estate market.

These techniques have made outstanding contributions towards determining the factors such as floor area, building age, and distance to the nearest central business district (CBD) that affect a rapid rise in real estate prices [29–32]. In addition to building structural and locational requirements, contextual attributes, obviously, also affect changes in residential land prices. For instance, two schools are near each other, but one has better educational facilities and resources; the selling prices of houses near these schools would be influenced by the neighborhood-level attribute space [33–36]. Rich Harris [30] proposed a contextualized geographically weighted regression (CGWR) to integrate attribute correlations between neighborhood-level observations and found that it was significant in a real estate context, but temporal information was ignored. Few studies have made efforts to simultaneously consider contextual and spatiotemporal non-stationarity, although there is an obvious need to do so. Our study aimed to fill this gap and to provide a valuable recommendation for the healthy development of a real estate market.

In this study, a new contextualized GTWR algorithm, named the CGTWR, is proposed by reconstructing spatiotemporal weights. In contrast to previous approaches that only consider spatial and temporal non-stationarity or neighborhood information, this approach extends the GTWR and CGWR algorithms, focusing on redesigning the weight function using neighborhood information in attribute space. Moreover, better fitting ability can be gained through optimizing contextual and spatiotemporal factors. Applications of the CGTWR technique could be used for evaluating residential land value to determine a more adequate and objective property value. The CGTWR model could implement an effective way for large-scale estimation of residential land price and supply evidence for policy makers to understand the nature of varying relationships within a house price dataset in China.

The remainder of this paper is organized as follows: In Section 2, we briefly describe the study area, data source, and methods, using the CGTWR approach; in Section 3, we present the case study results with residential land price data using the CGTWR model, and compare the performance of the CGTWR model with global and local models; finally, we present the discussion and conclusions in Sections 4 and 5, respectively.

2. Materials and Methods

2.1. Study Area

The study area included the Chang'an, Qiaoxi, Xinhua, and Yuhua Administrative Districts, located in SJZ city, Hebei Province, covering approximately 408.76 km^2 (from 37°58′2.58″ to 38°10′1.25″ N and from 114°22′4.99″ to 114°42′6.40″ E) and encompassing a population of 2.74 million people (Figure 1). As a central city in the southern part of the Beijing–Tianjin–Hebei Economic Rim, ongoing rapid economic and urbanization development have been taking place in SJZ city. The GDP (gross domestic product) of this city accounted for 16.54% of the province as reported by the Hebei Economic Yearbook in 2019. At the same time, the urbanization rate of the permanent population was 65.05%, making it one of the high-growth zones in China according to the Shijiazhuang Statistical Yearbook. Moreover, the area of urban construction land increased from 425 square kilometers in 2013 to 2194 square kilometers in 2019, and the average selling price of commercialized buildings increased from 4931 yuan (≈763.32 USD) to 10,452 yuan (≈1617.97 USD) per square meter at this stage. Against the background of rapid economic and urbanization development, the question of whether the real estate market in SJZ city can develop orderly and favorably has become a matter of deep anxiety and concern. Meanwhile, this region, over recent decades, has become one of the most seriously environmentally contaminated cities in China. This area had the highest annual average particulate matter (PM2.5) value among major cities of China in 2020 [37–41]. Improving the utilization rate of land and promoting sustainable economic advancement in SJZ city is a critical issue for achieving high-quality development in this region. Therefore, considering the contradictions between human and environmental relationships, we investigated SJZ city to explore the spatiotemporal heterogeneity in the real estate economy with urban development and calculated the characteristic indexes to describe the residential land price factors.

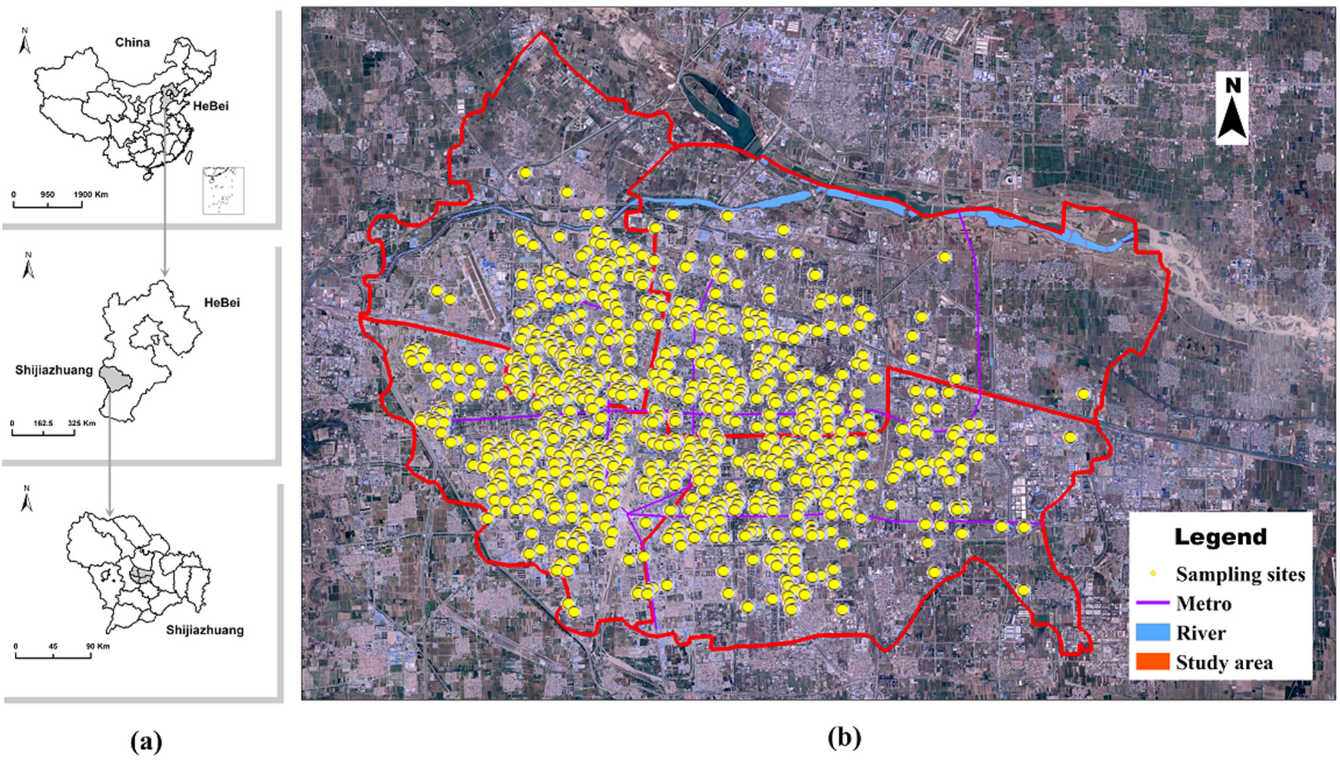

Figure 1. Map of the study area in SJZ city: (**a**) Geographical locations at national, provincial, and city scales; (**b**) Google Earth images, in 2021, at local scales.

2.2. Data Source

According to the hedonic theory [42] and data availability, the dataset consisted of 913 housing data collected from the Anjuke.com website (https://sjz.anjuke.com/, accessed on 25 January 2021). We selected residential land price data with precise geographical locations, including plot ratio (PlOT), number of bathrooms (BATH), floor area (AREA), and age of building (YEAR), as the research objects. The natural logarithm of explanatory variables was used [28,43,44]. The houses in school districts and the population density information were up-to-date and authoritative, and obtained from the Shijiazhuang Education Bureau and China State Statistical Bureau, respectively. The detailed statistical information of the variables in SJZ city is shown in Table 1.

Table 1. The definitions of the dependent and independent variables.

Variables	Abbreviation	Min	Max	Mean	Std.	VIF
Dependent variables						
Residential land prices (CNY)	PRICE	250,000	7,150,000	1,456,421	718,386	—
Structural explanatory variables						
Plot ratio (%)	PlOT	0.400	5.840	2.299	0.880	1.121
Total number of bathrooms	BATH	0.000	3.000	1.200	0.437	2.243
Total floor area (m^2; except basement)	AREA	29.000	282.000	93.223	32.569	3.341
Age of building at time of sale (year, 1974–2021)	YEAR	1.000	48.000	34.434	9.730	1.813
Locational explanatory variables						
Take the logarithm of distance to the nearest transport facility including bus, subway and train station (km)	$LogD_{subway}$	2.732	6.946	5.113	0.603	1.065
Take the logarithm of distance to the nearest central business district (km)	$LogD_{cbd}$	0.657	8.047	5.429	0.885	1.223
Take the logarithm of distance to the nearest central shopping plaza (km)	$LogD_{shopping}$	3.206	8.631	6.423	0.737	1.152
Take the logarithm of distance to the nearest park (km)	$LogD_{park}$	3.046	8.470	6.630	0.644	1.105
Take the logarithm of distance to the nearest river (km)	$LogD_{river}$	3.854	9.000	7.540	0.603	1.101
Neighborhood explanatory variables						
School district housing (Yes: 1, No: 0)	SCHOOL	0	1	0.049	0.216	1.050
Take the logarithm of distance to the nearest factory (km)	$LogD_{factory}$	3.696	7.858	6.365	0.639	1.072
Take the logarithm of population density (people/km^2)	$LogD_{pop}$	2.284	815.783	115.119	106.048	1.194
Take the logarithm of job density (job/km^2)	$LogD_{job}$	0.73	7346.440	135.541	452.350	1.012

Notes: Min, minimum; Max, maximum; Std., standard error; VIF, variance inflation factor.

We applied the non-Euclidean distance (non-ED) metric to locational explanatory variables in order to overcome the inaccurate coefficient estimation of Euclidean distance (ED) measurement and the misinterpreted spatial pattern estimation due to linear measurement [45–47]. Multicollinearity, which can generate misleading regression coefficients and standard errors, refers to the high correlation or mutual correlation between the independent variables in the regression model [48,49]. Thus, to examine the statistical significance and collinearity of variables in the study area (Section 3.2), the variance inflation factor (VIF) was used, the values of which were all less than 4 (much less than 10, which is the typical threshold for concern). The analytical framework of modeling the real estate estimation is shown in Figure 2.

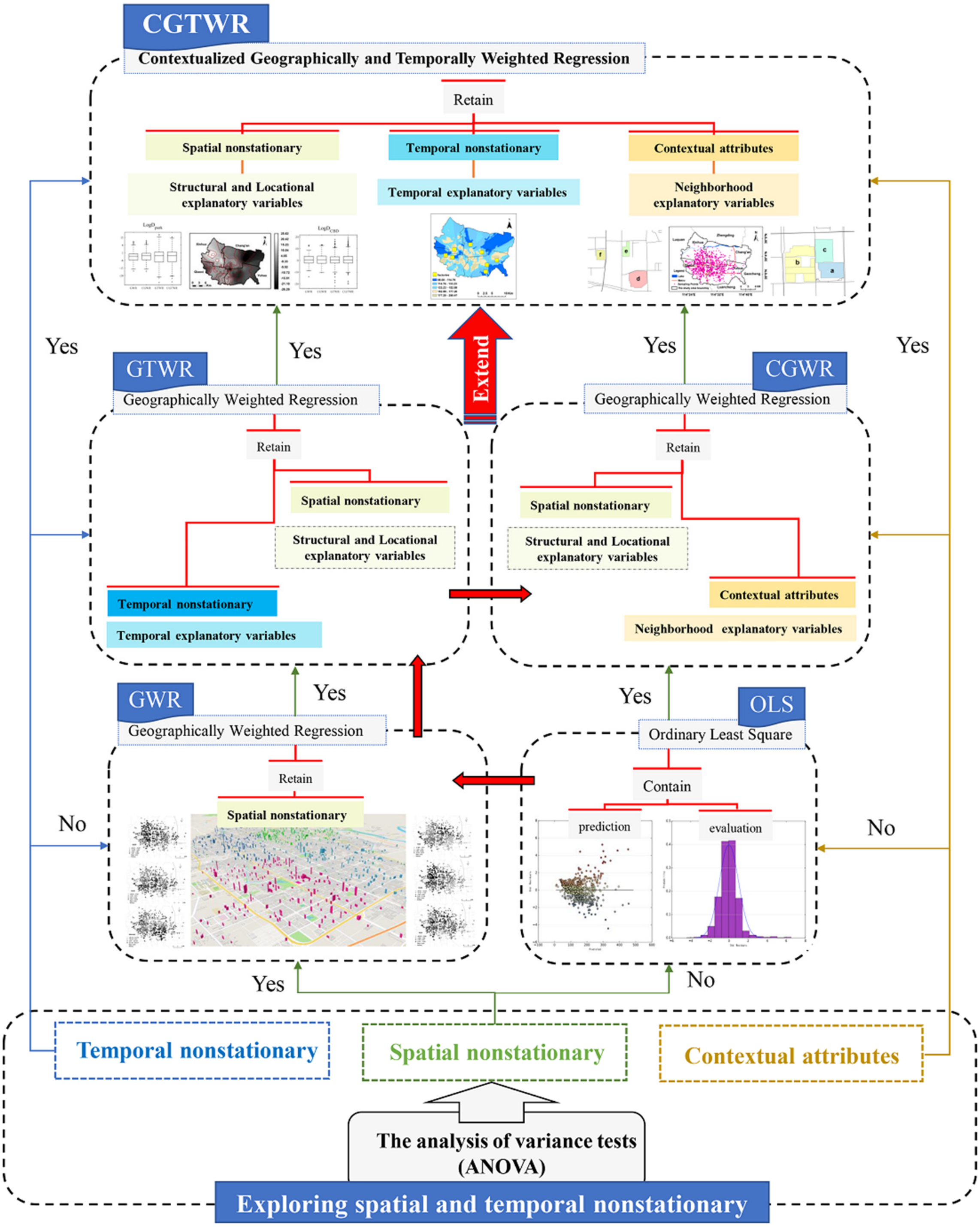

Figure 2. Analytical framework of the modeling methods used.

2.3. Methods

2.3.1. Geographically and Temporally Weighted Regression

The GTWR approach is a spatially and temporally varying local regression model that is extensively used in statistical economic research [28]. It is especially useful for correlation analysis in healthcare, environmental protection, and real estate markets [45,50,51]. The GTWR model is given as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i,\ i = 1, 2, \cdots, n. \tag{1}$$

The local coefficients are derived by the GTWR to manifest spatiotemporal heterogeneity synchronously by importing temporal effects into the GWR [28]. Here, (u_i, v_i, t_i) represents the prescribed coordinate of point i in location (u_i, v_i) at time t_i, $\beta_0(u_i, v_i, t_i)$ represents the intercept value, and $\beta_k(u_i, v_i, t_i)$ expresses a group of values for the figure p of coefficients at sample i. The error obeying a standard normal distribution at random is defined by ε_i, $\varepsilon_i \sim N(0, \sigma^2)$. Random errors at different points are irrelevant, i.e., $\text{Cov}(\varepsilon_i, \varepsilon_j) = 0(i \neq j)$.

The $\hat{\beta}_i$ (regression coefficient) at sample point i can be computed by the least-squares algorithm as:

$$\hat{\beta}_i(u_i, v_i, t_i) = \left(X'W(u_i, v_i, t_i)X\right)^{-1}X'W(u_i, v_i, t_i)y_i. \tag{2}$$

The fitted value $\hat{y}$ is:

$$\hat{y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \cdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} X_1(X'W(u_1, v_1, t_1)X)^{-1}X'W(u_1, v_1, t_1) \\ X_2(X'W(u_2, v_2, t_2)X)^{-1}X'W(u_2, v_2, t_2) \\ \cdots \\ X_n(X'W(u_n, v_n, t_n)X)^{-1}X'W(u_n, v_n, t_n) \end{bmatrix} y. \tag{3}$$

Here, the weighting matrix $W(u_i, v_i, t_i)$ is found to calculate the weight function using distances between the regression point i and the sample points as the variable. In GTWR models, two kernel functions are widely used to determine the weights, namely, fixed and adaptive types [28]. A self-adapting kernel function is applied to achieve an optimal spatial kernel bandwidth for the study area. We use the Gaussian function as the weighting function:

$$W_{ij} = \exp\left(-\frac{d_{ij}^2}{h^2}\right) \tag{4}$$

where h is a non-negative constant called a bandwidth, which decreases as the distance increases between locations i and j.

2.3.2. Extension to GTWR with Neighborhood-Level Similarity

Considering spatial and temporal non-stationarity, spatiotemporal distance, d^{ST}, can be described as follows:

$$d^{ST} = d^S \otimes d^T \tag{5}$$

where $\otimes$ represents different operators, and d^S and d^T stand for the spatial and temporal distance, respectively. Harris [30] proposed a contextualized spatial distance d^{CS} as follows:

$$d^{CS} = d^C \otimes d^S \tag{6}$$

Therefore, the neighborhood information is used in the contextual GTWR approach inspired by Huang [28] and Harris, and a modified contextual and spatiotemporal distance d^{CST} can be given as:

$$d^{CST} = d^C \otimes d^{ST} = d^C \otimes d^S \otimes d^T \tag{7}$$

According to Huang, operator + was adopted, which means that contextual spatiotemporal distance d^{CST} is the linear combination of contextual distance d^C, spatial distance d^S, and temporal distance d^T as follows:

$$(d^{CST})^2 = \varphi^C (d^C)^2 + \varphi^S (d^S)^2 + \varphi^T (d^T)^2 \tag{8}$$

The contextual and spatiotemporal distance d_{ij}^{CST} between regression points (u_I, I, I_i) and (u_j, v_j, t_j) is described as follows:

$$(d_{ij}^{CST})^2 = \varphi^C (d_{ij}^C)^2 + \varphi^S (d_{ij}^S)^2 + \varphi^T (d_{ij}^T)^2 \tag{9}$$

where φ^C, φ^S, and φ^T are scale factors used to counterbalance the contextual, spatial, and temporal effects among d_{ij}^C, d_{ij}^S, and d_{ij}^T.

The contextual distance d_{ij}^C, spatial distance d_{ij}^S and temporal distance d_{ij}^T between regression points (u_i, v_i, t_i) and (u_j, v_j, t_j) can be found as follows:

$$\begin{cases} (d_{ij}^C)^2 = [f(z_i - z_j)]^2 \\ (d_{ij}^S)^2 = (u_i - u_j)^2 + (v_i - v_j)^2 \\ (d_{ij}^T)^2 = (t_i - t_j)^2 \end{cases} . \tag{10}$$

where index score function $f(z_i - z_j)$ is given to estimate the contextual distance in the neighborhood level. The contextual spatiotemporal distance can be described as:

$$\begin{aligned} (d_{ij}^{CST})^2 &= \varphi^C (d_{ij}^C)^2 + \varphi^S (d_{ij}^S)^2 + \varphi^T (d_{ij}^T)^2 \\ &= \varphi^C [f(z_i - z_j)]^2 + \varphi^S \left[(u_i - u_j)^2 + (v_i - v_j)^2\right] + \varphi^T (t_i - t_j)^2 \end{aligned} \tag{11}$$

The contextualized and spatiotemporal kernel function W_{ij}^{CST} can be formulated as:

$$\begin{aligned} W_{ij}^{CST} &= \exp\left\{-\frac{(d_{ij}^{CST})^2}{(b^{CST})^2}\right\} \\ &= \exp\left\{-\frac{\varphi^C (d_{ij}^C)^2 + \varphi^S (d_{ij}^S)^2 + \varphi^T (d_{ij}^T)^2}{(b^{CST})^2}\right\} \\ &= \exp\left\{-\frac{\varphi^C (d_{ij}^C)^2}{(b^{CST})^2}\right\} \times \exp\left\{-\frac{\varphi^S (d_{ij}^S)^2 + \varphi^T (d_{ij}^T)^2}{(b^{CST})^2}\right\} \\ &= \exp\left\{-\varsigma \times [f(z_i - z_j)]^2\right\} \times \exp\left\{-\left(\frac{(d_{ij}^S)^2}{b_S^2} + \frac{(d_{ij}^T)^2}{b_T^2}\right)\right\} \\ &= \exp\left\{-\varsigma \times [f(z_i - z_j)]^2\right\} \times \exp\left\{-\frac{(d_{ij}^S)^2}{h_S^2}\right\} \times \exp\left\{-\frac{(d_{ij}^T)^2}{h_T^2}\right\} \\ &= W_{ij}^C \times W_{ij}^S \times W_{ij}^T \end{aligned} \tag{12}$$

where W_{ij}^C, W_{ij}^S, and W_{ij}^T are contextual, spatial, and temporal kernel functions.

In order to determine the optimal contextualized and spatiotemporal factor τ, ς, the performance of CGTWR should be measured using criterion:

$$CV(\tau, \varsigma) = \sum_i [y_i - \hat{y}_{\neq i}(\tau, \varsigma)]^2 \tag{13}$$

The pseudo-code of CGTWR is presented in Algorithm 1.

Algorithm 1. Pseudo-code describing the CGTWR model.

Algorithm: CGTWR

INPUT: explanatory variables X
spatiotemporal coordinates (u, v, t)
dependent variable Y
PROCESS:
  Find the optimal spatial bandwidth b_s, golden section search G1:
    for $i \in \{1,\ 2,\ \cdots,\ n\}$ do
      construct the spatial kernel weight W_{ij}^{S} between (u_i, v_i, t_i) and $\left(u_j, v_j, t_j\right)$
      calculate the CV value
    end for
    Achieve the optimal spatial bandwidth b_s
  Find the optimal spatiotemporal factor τ, implement golden section search G2
    Find the optimal contextual factor ς, implement golden section search G3
      for $i \in \{1,\ 2,\ \cdots,\ n\}$ do
        construct the contextual spatiotemporal kernel weight W_{ij}^{CST} between (u_i, v_i, t_i) and $\left(u_j, v_j, t_j\right)$
        calculate the CV value
      end for
    Find the optimal contextual factor ς and spatiotemporal factor τ
Calculate RSS, MSE, AIC, R^2, R_{adj}^2

2.3.3. Model Evaluation of Performance

Statistical indicators were adopted in this study to evaluate the performance of different models on estimating the coefficients. The residual sum of squares (RSS) between the estimated and actual value at each point in the dataset could be normalized by the total variation as follows:

$$RSS = \sum_{i=1}^{n} {\varepsilon_i}^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{14}$$

where y_i and $\hat{y}_i$ denote the estimated and actual values, respectively, in the experimental dataset, and n is the number of observations. Mean square error (MSE) is a standardized variance estimation based on actual and estimated value. The overall estimated coefficient can be measured as follows:

$$MSE = \frac{\sum_{i=1}^{n} (yi - \hat{y}_i)^2}{n} \tag{15}$$

where n, y_i, and $\hat{y}_i$ are defined as in (1). In addition, R^2 can estimate the goodness of fit for different models as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (yi - \hat{y}_i)^2}{\sum_{i=1}^{\mathrm{n}} (yi - \overline{y})^2} \tag{16}$$

when the number of independent variables in the regression model is large, the complex determination coefficient increases gradually, and the degree of interpretation of variables decreases. In order to overcome this shortcoming of the sample determination coefficient, we appropriately adjust R^2 to improve the goodness of fit of the regression equation. The R_{adj}^2 value is given as follows:

$$R_{adj}^2 = 1 - [\frac{n-1}{n - tr(s) - 1}\left(1 - R^2\right)] \tag{17}$$

where R^2 can be computed from Equation (4) and $tr(s)$ is the effective number of parameters.

3. Experimental Results and Comparisons

3.1. Results of the Global Model

Before exploring possible spatiotemporal and contextual variations of residential land price determinants in SJZ city, the global model represents the average relationships between the residential land prices and explanatory factors. Global models generate only one parameter estimate for the residential land price data at all locations, assuming the linkages between this covariate and the dependent variable is stationary over space. In order to acquire a comprehensive understanding of the influences of various factors on residential land price, we list the parameter estimates associated with each covariate in the ordinary least square (OLS) model. The parameter estimates generated by OLS are listed in Table 2, with and without the contextual variables. Those statistically significant values at the 5% level are marked with an asterisk '*'.

Table 2. Parameter estimates for the regression of residential land prices generated by OLS.

	Model 1			Model 2		
Parameter	**Coefficient**	**Std. Error**	***p*-Value**	**Coefficient**	**Std. Error**	***p*-Value**
Intercept	41.803	22.706	0.066 *	9.275	26.108	0.723 *
PlOT	−1.230	1.409	0.383 *	−0.354	1.395	0.800 *
BATH	13.709	4.051	0.001	14.477	3.983	0.000
AREA	1.565	0.066	0.000	1.561	0.066	0.000
$LogD_{subway}$	−2.242	2.019	0.267 *	−1.609	1.987	0.418 *
$LogD_{cbd}$	−3.866	1.436	0.007	−2.160	1.463	0.140 *
$LogD_{shop}$	−7.400	1.678	0.000	−5.002	1.694	0.003
$LogD_{park}$	−2.097	1.926	0.277 *	−1.943	1.911	0.310 *
$LogD_{river}$	−0.647	2.064	0.754 *	−2.090	2.040	0.306 *
YEAR	1.257	0.162	0.000	1.301	0.160	0.000
SCHOOL				0.886	5.486	0.872 *
$LogD_{factory}$				0.271	1.880	0.886 *
$LogD_{POP}$				0.074	0.012	0.000
$LogD_{JOB}$				0.002	0.003	0.610 *
Diagnostic information						
R^2	0.761			0.771		
Adjusted R^2	0.759			0.768		
AICc	15,629.000			15,569.000		
MSE	1246.452			1200.863		

Notes: R^2, R squares; Adjusted R^2, adjusted R squares; AIC, Akaike information criterion; MSE, mean squared error.

As shown in Table 2, the results, in accordance with reducing the mean square error, show that the performance of the OLS model that incorporates the contextual variables (Model 2) is better than that of the OLS model without the contextual variables (Model 1). Notably, there are slight differences between the models. Regarding the linkages between plot ratio and land price, there is a weak association observed in Model 1, and a significantly negative correlation observed in Model 2 (when the contextual variables are included), which is the same as that of $LogD_{river}$. Evaluated as the mean land price and under the two models, residential land price increases significantly with the number of bathrooms.

The effects of $LogD_{park}$ and $LogD_{river}$ are mainly negative on residential land prices in the study area. According to Model 2, with a reduction in distance to the river or park, residential land price will increase. Proximity to $LogD_{cbd}$ and $LogD_{shop}$ exerts a direct effect on residential land prices in Model 2. Reducing the distance to the nearest CBD and shopping mall will increase the residential land price significantly.

The estimated coefficient of SCHOOL has a significant impact on residential land prices within the study area, while the proportion of distance to the nearest factory has a positive impact on residential land prices. Overall, either model approximately explains eight-tenths of the variation in residential land prices, with the inclusion of contextual variables giving a better performance. Therefore, the evaluated residential land prices can be modeled by the selected housing structural attributes, locational explanatory variables, and neighborhood environment variables. The presumed relationships among the housing structural attributes, locational explanatory and neighborhood environment, and residential land prices are supported by the results of the experiments.

3.2. Results of the Local Model

As compared with other GWR-based models, the most significant improvement of the CGTWR model is that it allows the parameter estimates to vary over spatiotemporal location, and produces individual optimal bandwidths for the contextual relationships between the response variable and each predictor variable. It allows the spatial variation of different processes to be modeled at different spatial scales. The units of position and time measurement are actually different. In this study, non-ED metrics were cited in meters and time in years.

The rate of regression weight attenuation near a given point (u, v, t) is determined by the bandwidth in the CGTWR model. One critical issue is the election of spatiotemporal and contextual bandwidth (B, t, ς) to obtain reliable estimates of coefficients [28,30,52]. The parameter ς was introduced to offset or reconcile the various spatiotemporal units. Before constructing contextual weighting matrices, these units were unified by computing the spatial and temporal distance. The cross-validation method has been proven to be an effective method for finding ways to eliminate standard errors and deviations [34]. The validation procedure was used in this study to acquire a suitable parameter value in terms of fitting accuracy, with the optimal bandwidth found to be B = 2221, τ = 80,118, and ς = 216,407 (Figure 3).

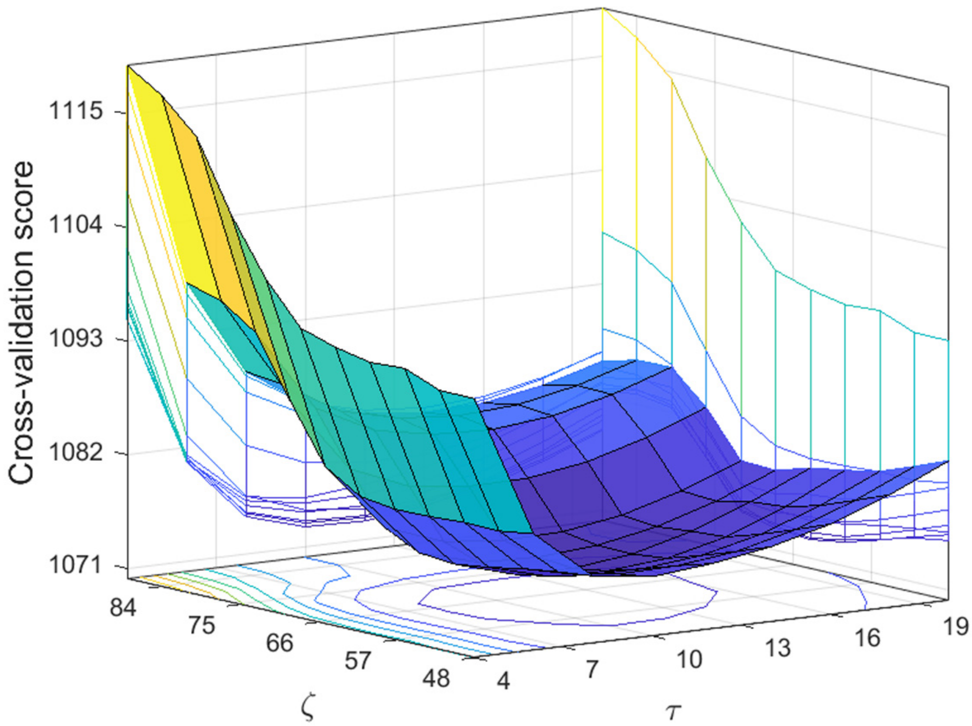

Figure 3. The selection of parameters in the CGTWR model.

The analysis of variance (ANOVA) test [18,53] was adopted to test the significance of the sum of squares from comparisons of the OLS, GWR, CGWR, GTWR, and CGTWR models in Table 3. The residual sum of squares for these models and the improvement of GWR-based models are shown in the first column. The degrees of freedom for each model are listed in the second column. The mean square results of the respective degree of freedom are given in the third column. The F statistic and its corresponding significance level are shown in the fourth and fifth columns, respectively.

Table 3. ANOVA comparisons among the OLS, GWR, CGWR, GTWR and CGTWR models.

Source of Variation	RSS	DF	MS	*p* Value	F Value
OLS residuals	3,511,506.98	8.00	438,938.37	330.59	0.00
GWR residuals	719,819.36	762.08	944.54	48.75	0.00
CGWR residuals	649,167.14	743.47	873.16	33.15	0.00
GTWR residuals	467,541.40	639.07	731.60	10.58	0.00
CGTWR residuals	399,451.12	628.03	636.04	9.05	0.00
CGWR/GWR improvement	0.10%	0.02%	0.08%	-	-
GTWR/GWR improvement	0.35%	0.16%	0.23%	-	-
CGTWR/GWR improvement	0.45%	0.18%	0.33%	-	-

Notes: The statistically significant values at the 5% level; RSS, residual sum of squares; DF, degrees of freedom; MS, mean squared error.

The statistics from the ANOVA tests in Table 3 show that there is significant spatiotemporal non-stationarity in SJZ city. Therefore, local models are more suitable for analyzing the dataset in this study area. As compared with the global OLS model, the GWR, CGWR, and GTWR models reduce the residual sum of squares values from 3,511,506.98 to 719,819.36, 649,167.14, and 467,541.40, respectively, and the CGTWR model generates a considerably lower RSS of 399,451.12. In addition, the MS of the CGTWR model (636.04) is far less than the global model (438,938.37), GWR model (944.54), CGWR model (873.16), and GTWR model (731.60). The CGTWR model with context information is superior to the OLS, GWR, CGWR and GTWR models as evidenced by a lower RSS and MS.

Unlike global models, local models achieve individual parameter estimates at each location. Summaries of local parameter estimates are generated by GWR, CGWR, GTWR, and CGTWR. The minimum (Min), lower quartile (LQ), median (Med), upper quartile (UQ), and maximum (Max) are presented in Tables 4–7, respectively. The R^2, adjusted R^2, and AIC statistic are also listed.

Table 4. The distribution of the localized coefficient estimates for the GWR model (B = 2221).

GWR							
Variables	**Min**	**LQ**	**Med**	**UQ**	**Max**	***p* Value**	**F Value**
Intercept	−290.876	−96.802	−24.21	51.612	339.021	0.002	9.565
PlOT	−9.598	−0.04	1.314	2.829	22.548	0.837 *	0.042
BATH	−13.122	1.791	10.722	15.785	81.652	0.030	4.698
AREA	0.708	1.709	1.839	2.014	2.228	0.000	1853.778
$LogD_{subway}$	−32.905	−1.794	0.402	4.44	10.283	0.198 *	1.654
$LogD_{CBD}$	−13.98	−2.302	0.592	3.367	12.842	0.000	13.615
$LogD_{shopping}$	−15.826	−5.851	−2.732	0.056	11.407	0.000	30.087
$LogD_{park}$	−32.278	−9.683	−0.566	6.217	30.315	0.140 *	2.173
$LogD_{river}$	−25.14	−5.951	0.255	4.901	34.554	0.783 *	0.076
R^2	0.85						
Adjusted R^2	0.85						
AICc	15,322.34						

Table 5. The distribution of the localized coefficient estimates for the CGWR model (B = 2221 and ς = 216,407).

CGWR							
Variables	**Min**	**LQ**	**Med**	**UQ**	**Max**	***p* Value**	**F Value**
Intercept	−312.335	−99.96	−22.323	55.574	494	0.001	10.617
PlOT	−9.873	0.201	1.601	3.256	23.549	0.828 *	0.047
BATH	−23.376	0.714	10.495	15.823	84.373	0.022	5.215
AREA	0.861	1.683	1.803	1.967	2.344	0.000	2057.813
$LogD_{subway}$	−35.519	−1.845	0.568	4.734	10.219	0.175 *	1.837
$LogD_{CBD}$	−10.572	−2.538	0.697	3.527	13.229	0.000	15.114
$LogD_{shopping}$	−15.877	−5.428	−2.492	0.425	11.962	0.000	33.399
$LogD_{park}$	−40.692	−9.599	−1.199	5.704	28.474	0.120 *	2.412
$LogD_{river}$	−29.566	−6.019	0.542	5.254	37.039	0.772 *	0.084
R^2	0.86						
Adjusted R^2	0.86						
AICc	15,259.77						

Table 6. The distribution of the localized coefficient estimates for the GTWR model (B = 2221 and τ = 80,118).

GTWR							
Variables	**Min**	**LQ**	**Med**	**UQ**	**Max**	***p* Value**	**F Value**
Intercept	−318.933	−65.66	2.642	58.118	425.358	0.000	14.726
PlOT	−29.568	−1.91	0.656	3.453	16.852	0.799 *	0.065
BATH	−46.788	−2.679	13.601	25.134	130.518	0.007	7.233
AREA	0.097	1.281	1.536	1.795	2.942	0.000	2854.048
$LogD_{subway}$	−37.534	−3.034	0.256	4.219	37.555	0.110 *	2.547
$LogD_{CBD}$	−21.974	−2.255	0.487	3.009	17.697	0.000	20.962
$LogD_{shopping}$	−26.48	−7.494	−2.819	1.75	17.629	0.000	46.322
$LogD_{park}$	−40.117	−7.183	−0.943	5.64	40.797	0.067 *	3.345
$LogD_{river}$	−36.415	−6.041	0.166	5.166	80.012	0.733 *	0.116
R^2	0.90						
Adjusted R^2	0.90						
AICc	15,225.56						

Table 7. The distribution of the localized coefficient estimates for the CGTWR model (B = 2221, τ = 80,118, and ς = 216,407).

CGTWR							
Variables	**Min**	**LQ**	**Med**	**UQ**	**Max**	***p* Value**	**F Value**
Intercept	−455.092	−68.178	2.916	55.817	381.896	0.000	17.255
PlOT	−28.392	−1.726	0.867	3.814	17.659	0.782 *	0.076
BATH	−47.745	−2.163	14.292	26.304	135.756	0.004	8.476
AREA	0.005	1.272	1.508	1.763	2.914	0.000	3344.251
$LogD_{subway}$	−37.153	−2.961	0.367	4.271	34.581	0.084 *	2.985
$LogD_{CBD}$	−20.187	−2.329	0.683	3.361	19.615	0.000	24.562
$LogD_{shopping}$	−25.717	−7.126	−2.644	1.77	15.428	0.000	54.278
$LogD_{park}$	−44.432	−7.276	−1.445	5.509	57.899	0.052 *	3.920
$LogD_{river}$	−37.176	−6.12	0.396	5.129	82.746	0.712 *	0.136
R^2	0.92						
Adjusted R^2	0.91						
AICc	15,179.84						

Tables 4–7 provide the detailed statistical comparisons. The AIC value of the models decreased from 15,322.34 in the GWR model, to 15,259.77 in the CGWR model, 15,225.56 in the GTWR model, and 15,179.84 in the CGTWR model. By comparing the R^2 values, the CGWR model significantly improved the R^2 value to 0.86, indicating that adding contextual variables to the analysis by adjusting the geographical weights matrix outperformed the GWR model. Moreover, the CGTWR model, which considered contextual information, yielded a 92% improvement over the GTWR model. Thus, it should be noted that the CGTWR model, using the sample data, could effectively address spatiotemporal heterogeneity, and could creatively extend the feasibility of importing the contextualization into the GTWR model.

The abundant information generated by local models presents a challenge for displaying the results. Since the CGTWR model is more effective than the GTWR model and CGTWR achieves a similar performance to CGWR, we only focused on the local estimates of CGTWR. CGTWR generates local parameter estimates that reflect possible spatiotemporal and contextual heterogeneity in the processes affecting residential land price. The CGTWR model's performance and its spatiotemporal non-stationarity were explored visually by mapping the local coefficient estimates of the variables. Figure 4a–h presents the spatial pattern of the CGTWR model estimated coefficients.

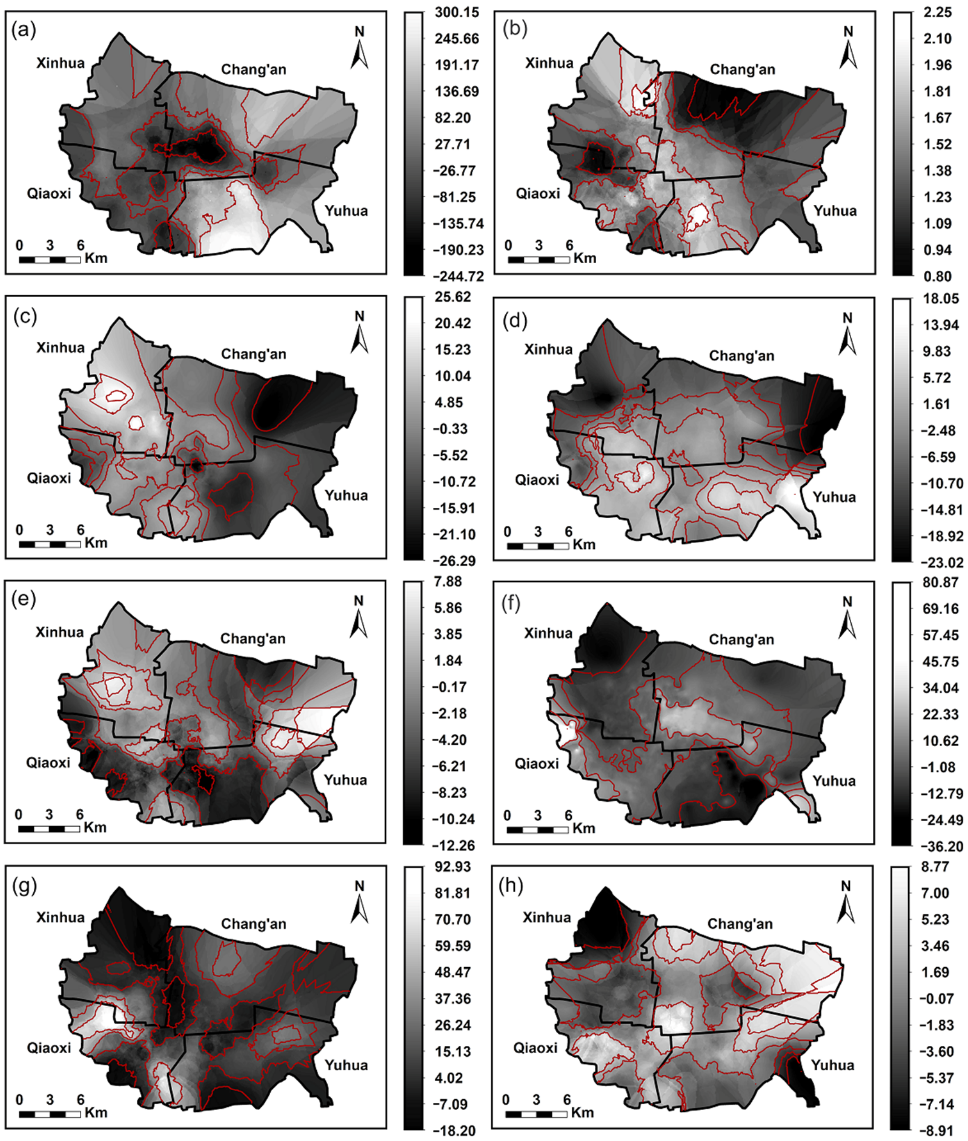

Figure 4. Spatial mapping for: (**a**) coefficients of intercept; (**b**) total floor area; (**c**) proximity of the nearest park; (**d**) proximity of the nearest transport facility; (**e**) proximity of the nearest central shopping plaza; (**f**) proximity of the nearest river; (**g**) total number of bathrooms; (**h**) proximity of the nearest central business district, by contextualized geographically and temporally weighted regression modeling.

The results suggest that AREA is positively correlated with residential land prices, as shown in Table 7. In other words, the larger the living area is, the higher the residential land price is (Figure 4b). The effects of $\mathrm{LogD_{park}}$ changes from positive in the northwest to negative in the southeast. This is reasonable since the Xinhua district is located in three parks, i.e., Xiushui Park, Yulin Park, and Qiushi Park, which increases coefficient values on parks (Figure 4c). The spatial variation of $\mathrm{LogD_{subway}}$ in the CGTWR model varies from high in the inner zone near metro lines to low in the external zones over this study area (Figure 4d). This is consistent with the distribution of the Shijiazhuang Metro Lines 1, 2, and 3.

4. Discussion and Policy Implications

4.1. The Performance of the Model in Exploring Spatiotemporal Heterogeneity

The aim of exploring spatiotemporal heterogeneity of residential land prices was to provide appropriate guidance to strengthen classified regulation and control of the real estate market. Furthermore, we should take measures to protect the environment from further deterioration under the rapid acceleration of urbanization. In this study, we develop the CGTWR method, which extends the definition of proximity to include geographical location, temporal information, and contextual attributes by incorporating contextual attribution into the GTWR weights matrix. Furthermore, the method focuses on the construction of a spatiotemporal and contextual weights matrix for a hierarchical dataset as opposed to a spatiotemporal matrix. In other words, the CGTWR gives the greatest weight to points that are both proximate and situated in the same or similar neighborhood types by adjusting the spatiotemporal weights.

The results from Tables 3–7 justify considering the added complexity of the CGTWR model; it still performs better than the OLS, GWR, CGWR, and GTWR models. By incorporating contextual information in the GTWR, there are substantial benefits. The GWR, CGWR, GTWR, and CGTWR models reduce the residual sum of squares by 79.5%, 81.5%, 86.7% and 88.6%, respectively, as compared with a global ordinary least squares model. More importantly, the CGWR and CGTWR significantly improve the R^2 values to 0.86 and 0.92, respectively, indicating that models considering contextual information outperform GWR and GTWR models. In addition, the R^2 values between the GTWR and CGTWR modles, taking into consideration temporal variation, yield 90% and 92% improvement, respectively, over the GWR and CGWR models. The CGTWR model using sample data effectively addresses spatiotemporal heterogeneity, and creatively extends the feasibility of importing the contextualization into the GTWR model.

Some limitations still remain in our analysis and further research is needed. There were only 913 housing data available. Inadequate information can be expected to influence the model's performance. Further investigation of the performance of the CGTWR model with more effective data would be worthwhile. Furthermore, the simple weighting system based on a linear combination of spatiotemporal and contextual distances was used. In addition, we used a simple weighted system based on a linear combination of space time and context distance. In order to produce better results, more effective weightings need to be designed. Although the contextual variables are used within the weight's matrix, no estimate of the effect of each contextual variable upon the response variable was determined. The contextual variables adjust the weights matrix but, aside from this, have no explanatory or predictive role within the model. We are devoted to developing this model into free software to assist with understanding the trends of residential land price and the patterns of urban expansion.

4.2. The Impact Factors of Policy Driven by Residential Land Prices

The results of our analyses indicate that contextual explanatory variables including school district, proximity to industrial zone, population density, and job density all have an impact on residential land prices. Notably, we further distinguished linkages between school district and industrial zone factors and residential land prices under the influence of Chinese policy. From the perspective of educational reform, the policy of district correspondence enrolment was first adopted in 1986 [54,55]. The purpose was to ensure equal access to public education resources, and to improve the fairness of the admission process. Residential areas were divided into designated school districts corresponding to nearby public primary and junior middle schools, and it was specified that children living in neighborhoods of school districts were required to enroll in the corresponding schools [56–58]. However, houses in school districts have gradually become a manifestation of capitalization for public goods, i.e., the precious popularity of school district housing in China, where the quality of public schools is higher [59,60].

Under the strict enforcement policy, Chinese parents are willing to pay higher prices for residential land so that their children can enroll in schools with higher quality teaching. The average price of residential land in school districts over the study area was 1,711,954.55 yuan (≈264,325.78 USD), which was 14.64% higher than the average values of all house types (Table 1). It is worth noting that a school may serve several communities, where the residential land prices decrease with increasing distance to the school. This is likely to be caused by school quality, where higher quality schools result in significantly higher residential land prices than other schools. The two popular schools in Figure 4 were selected to be typical cases that all had high-quality and expensive homes in their district. Linyin Dayuan is a house in the Hezuolu Primary School District, which has a price 34.18% higher than the residential land prices at Zhongxiu Garden just across the road. The housing within the foreign language school district, Fuqiang Power District, is 35.42% higher than the residential land prices of Qingyuan District, while the structure of the houses is similar, and the distance between the houses is relatively close. Figure 5 clearly shows the capitalization effect of public-school quality on residential land prices in urban areas through the visual distribution of residential land prices.

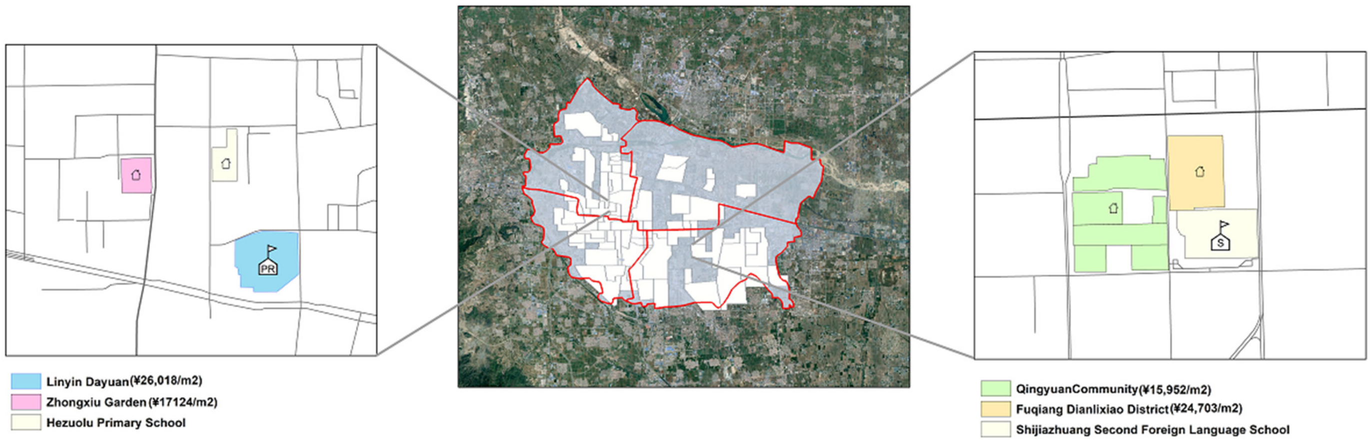

Figure 5. Special samples illustrating the residential land prices of school districts.

From the perspective of industrial reform, SJZ city was viewed as a major construction project during China's First Five-Year Plan in 1953 [61,62]; numerous factories including textile, chemical, pharmaceutical, steel, and machinery factories were set up with the support of national policies. Under the implementation of the Reform and Opening up Policy, the city's rate of GDP increment was approximately 71.66% from 1953 to 1984 according to the Shijiazhuang Industry and Information Bureau. The quantity of enterprise has expanded rapidly, and the business scale has enlarged continuously with diversified product features [38,63,64]. SJZ city has become a crucial industrial town in China over the last several decades due to its industrial system with reasonable layout, complete structure, and strong comprehensive strength. However, the problem of environmental pollution in this city has become increasingly prominent, and has begun to cause negative effects for some factories with the development of urban construction and the economy framework [65,66]. In 2018, the municipal government issued policies to relocate and transform polluting industrial enterprises in the main urban areas. If these enterprises fail to complete the relocation as planned, they will be forced to close down in accordance with the regulations and law.

Under the series of policies on industrial land allocation, many industrial factories have gradually moved out of the four main urban areas. The remainder is mainly divided into seven factories including chemical, steel, paint, machinery, food, electrochemical, and pharmaceutical factories. However, some factories also cause water and air pollution from industrial solid waste due to their inadequate management, for example, the iron and steel plant located in the east of the Chang'an District creates industrial dust that has a deleterious effect on the surrounding environment and the sound of the factory operation has seriously affected the work and lives of nearby residents (Figure 6b). The chlorine leakage accident that occurred in the electrochemical plant, resulted in dozens of losses in the surrounding vegetable fields acres (Figure 6g). Furthermore, the first food factory was exposed because a nearby dweller could smell something peculiar in the well water due to leakage of a benzene distillate storage tank in the factory (Figure 6h). Therefore, the distance to factories is the main factor affecting residential land prices. However, regarding industrial zone factors, there is a positive correlation between $\mathrm{LogD_{factory}}$ and residential land prices, since the coefficients of $\mathrm{LogD_{factory}}$ were positive. The closer the houses are to the factory, the more sensitive the house values are to these attributes, that is to say, the same amount of change in these attributes (ceteris paribus) will bring a larger change in house values for houses located near the factory as compared with those located farther away.

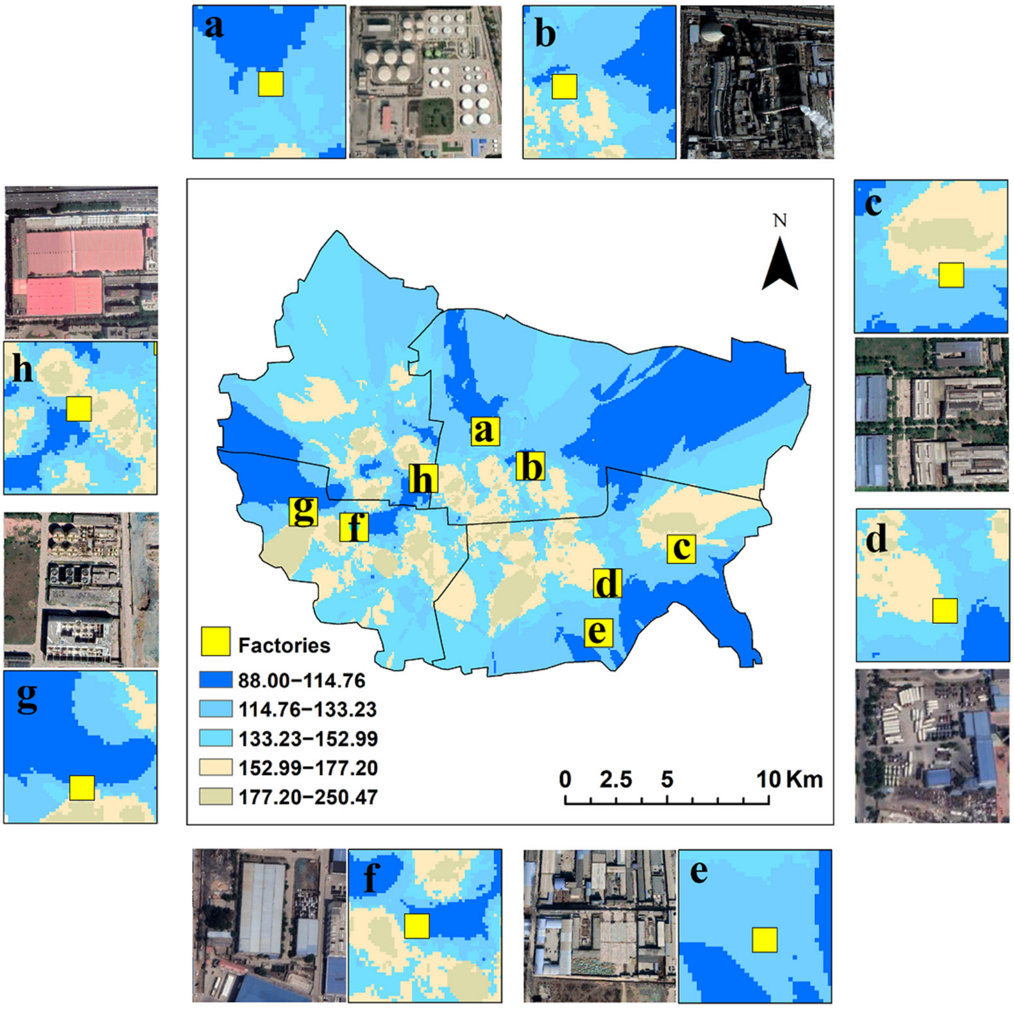

Figure 6. Examples of factories: (**a**) Chemical factory; (**b**) steel factory; (**c**) pharmaceutical factory; (**d**) building materials factory; (**e**) machinery factory; (**f**) paint factory; (**g**) electrochemical plant; (**h**) food factory.

5. Conclusions

In this study, the contextualized geographically and temporally weighted regression (CGTWR) model was outlined and applied to a case study of residential land price values in SJZ city, China. The analysis revealed that global and local regression models were customized to explain some types of phenomena: the OLS model adapts to global uniform variation, the GWR model accommodates single spatial heterogeneity, the CGWR model contributes to the effect of contextual attributes, and the GTWR model applies to spatiotemporal non-stationarity. The CGTWR model upgraded the spatiotemporal kernel to a context-adjustable kernel and completed the neighborhood-level information for the GTWR model.

The GWR-based models (GWR, CGWR, GTWR and CGTWR) all provided significant improvements in terms of R^2 and AIC measures as compared with the OLS model. The empirical results suggest that the traditional distance weights matrix of GTWR with a measure of contextual difference in CGTWR appears to be justified since the residual sum of squares is significantly reduced and the contextual and spatiotemporal non-stationarity are considered. Moreover, we applied the non-ED metric to locational explanatory variables in order to overcome the inaccurate coefficient estimation of Euclidean distance (ED) measurement and the misinterpreted spatial pattern in estimation due to linear measurement. The CGTWR model using sample data could effectively address spatiotemporal heterogeneity, and could creatively explore the feasibility of importing the contextualization into the GTWR model.

Meanwhile, the empirical research proves that floor area, building age, transport facility, school district, and proximity to an industrial zone all have significant effects on residential land prices in SJZ city. Notably, the relationships between school district and industrial zone factors and real estate were analyzed under the influence of Chinese policy. With the continuous development of economy and technology, Chinese parents have attached significant importance to their children's education and are willing to pay higher prices for residential land so that their children can enroll in better schools. Houses in school districts have gradually become a manifestation of capitalization for public goods, i.e., the precious popularity of school district housing in China, where the quality of public schools is higher. Several social problems may arise due to the high price of housing in school districts, such as unfair educational opportunities, social stratification, and speculative trading. The government should carry out institutional reform to ensure adequate educational funds, equalize access to public educational resources, and enhance fairness in the enrollment process.

Furthermore, under the rapid urbanization process, the problem of environmental pollution in SJZ city has become increasingly prominent, and has begun to manifest as negative effects of some factories on the contextual environment. The experimental results show that there is a positive correlation between $LogD_{factory}$ and residential land price, that is, the closer the distance to the factory, the lower the residential land price. The government could consider rationally adjusting the industrial structure, comprehensively planning urban construction, and rationally arranging industrial distribution. Overall, the CGTWR model provides a supplementary effective methodology for large-scale estimation of residential land price and supplies evidence for policy makers to understand the nature of varying relationships within a house price dataset in China.

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