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The Effect of Flood Risk on Residential Land Prices

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Abstract: Floods are one of the most frequent natural disasters today. Hence, it is highly important to explore the effect of flood risk on residential land prices to promote the rational allocation of land resources and incorporate climate change risk control into territorial spatial planning. This paper takes the primary urban area of Hangzhou as an example, based upon data from 424 residential land plots. With spatial autocorrelation analysis and the Spatial Durbin Model (SDM) approach, the spatial effect of flood risk on residential transaction land price was investigated. The results show that, ceteris paribus, plots with high risk of flooding suffer a price discount of 8.62%. The unique mechanism of the way flood risk affects land prices was discussed further from the perspectives of land ownership and land price systems in China. Furthermore, when the land price in surrounding areas increases one percent, the land price in the area will increase 14.32%. The spatial spillover effects of land price were analyzed with the flood information disclosure system and the stakeholders' considerations in land price comparison. The effect of flooding on residential land prices in Hangzhou is the result of government regulations and market allocations, which are fundamentally different from those of the free market allocations in many western countries. Interestingly, the risk of flooding is capitalized into the price, whether it is determined by government or market pricing. Integrating flood risk into land price determination can help promote the optimal allocation of land resources and minimize depreciation attributable to flood disasters.

Keywords: flood risk; residential land price; Spatial Durbin Model; Hangzhou

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1. Introduction

Floods attributable to climate change have become one of the most frequent natural disasters in cities. In China, the economic losses that accompany flood disasters have also increased over the past several decades [1,2]. Floods are the result of the interaction between human activities and the natural environment, and are closely related to land [3]. On the one hand, land characteristics affect the risk of floods [4,5]; while on the other hand, the floods can seriously affect the efficiency of land use [6,7]. Urbanization has profoundly affected the environment, and cities all over the world are experiencing a wide range of negative effects from climate change. It is well known that the deadliest floods occur mainly in metropolitan centers and tourist areas. Economic development and population growth in these areas have driven the expansion of built-up areas and frequent human interventions within river beds, aggravating urban waterlogging [8,9]. Thus, integrating climate change adaptation and risk management into territorial spatial planning has become a crucial topic for academics and policy makers [10,11].

There is an extensive body of research examining the factors that influence residential land prices. With respect to research methods, in addition to the basic hedonic price model (HPM) [12–14] and geographically weighted regression model (GWR) [15–17], scholars have begun to extend the methodological system of land price research with the help of the Structural Equation Model [18,19], Spatial Lag Model (SLM) [20–22], Spatial Error Model (SEM) [23,24], and Spatial Durbin Model (SDM) [25–27]. As for the factors, many scholars have explored the mechanism of population size, urban planning, land transfer policy, and socioeconomic conditions on land prices from a macro perspective [28–33]. Meanwhile, scholars have revealed the influence mechanism and spatial differences of micro factors, including CBD [34–36], rail transit [37–39], educational resources [40,41], medical facilities [42], green space [43–45], and floor area ratio (FAR) [46,47], from multiple perspectives of location, neighborhood, and plot. Researchers have found that land prices increase to a certain extent when residential land is closer to urban centers or service facilities, and the degree of increase depends upon the facilities' characteristics. The relationship between FAR and land prices is an inverted U-shape. Within a certain threshold, FAR increases land prices, while beyond this threshold, FAR suppresses the land price.

The research on flood disasters' effects on property values in Western countries has achieved rich results, divided primarily into the following three approaches. The first strand is to investigate the effects of potential flood risk based upon the official flood hazard maps published by the government. Most researchers have found that residential property prices in flood-prone areas are generally lower than the prices of the equivalent unexposed properties, and the price discount is typically between 4% and 12% [48–51]. However, some scholars found flood risk to have no effect [52–54] or even found that properties located in flood-prone areas command positive premiums up to 146% due to the water-related positive amenity [55,56]. The second strand analyzes the effects of specific flood events. Researchers largely adopted the difference-in-difference model (DID) or the repeated sales model and have repeatedly found that residential property prices plummet, dropping about 20–32% after a flood event, and the effect disappears gradually within 4–10 years; accordingly, there is no permanent price decline in the aftermath of a flood event [51,57–59]. The newer strand is to investigate the role of residents' climate change beliefs or the governmental information release on residential property values. Some scholars have found that the flood risk will be reflected in the residential property market through the residents' behavioral preferences. For those who believe that floods influence people's lives, their houses will sell at a discount of about 7% compared to houses with the same risk for deniers [60,61]. As for the effect of the posting of the flood risk information, the scholars have argued that the release of flood risk information had a minimal and statistically insignificant effect on residential housing prices [51,62,63].

Some research has focused on the flood hazards' effect on residential land prices. Some scholars have found significant reductions in land values after flood events [64–67], while others found that the residential land prices did not decrease despite flood occurrence [68]. Meanwhile, some scholars investigated the land prices in the flood-prone areas and have found that the land property with a high flood risk tends to have a lower price [64–66]. In terms of the effects of flood risk and flood events, scholars argued that land prices in potential flood-prone zones were higher than that which experienced actual damages [69], and decreased greatly after a flood [65]. The spatial heterogeneity of the effect of flood risk zones on land price has also been explored. These studies have found that the flood effects depend primarily on environmental conditions, especially the distance to water bodies [65,70,71].

Scholars have introduced flood disaster risk into research on residential land grading [72] and land use structure change [73,74] in China. However, only a small number of studies has been conducted on the effect of natural disasters such as floods on land prices. Peng et al. have investigated the role of geological hazards in benchmark residential land prices in Lanzhou [75]. Using a grid land price model and a GWR model, they found that the geological hazard risk will lead to a decrease in land value, and that the effect varies with different land grades and spatial locations. The spatial quantization of the geological hazards correction coefficient contributes to improving the accuracy of land value assessment. In contrast, our analysis focuses on the specific disaster of flooding and how it affects land transaction prices under Chinese policies. Li used a hedonic price model to investigate the relationship between flood intensity and housing prices in Tainan City [76].

Our study focuses more on exploring the spatial effects of integrated flood risk on land prices, i.e., flood risk is measured by a combination of rainfall frequency, depth of accumulated water, impervious cover, and multiple other indicators.

To summarize the existing studies, it has been found that flood events, flood risk, and flood information will affect housing prices and residential land prices. Regarding research methods, most scholars mainly use non-spatial models such as hedonic price models and DID models, or geographically weighted regression (GWR) models to explore the impact of the flooding. However, few explore flood effects from the perspective of spatial correlation of variables. In terms of the location, most studies have analyzed Western cities, while fewer have discussed the flood risk and its spatial effects on residential land prices from the perspective of Chinese cities. Therefore, it is imperative to understand the mechanism of flood risk on residential land prices comprehensively.

This paper takes Hangzhou as an example, based upon residential land data from 2007 to 2020, and uses the spatial Durbin model to measure the spatial effect of flood risk on urban residential land prices. Integrating flood risk into land price determination has important implications for policy makers, developers and urban residents. It also helps to achieve the reasonable spatial allocation of land from the perspective of a sponge city.

The remainder of the paper is organized as follows. Section 2 describes the study area, data sources and methodology. Spatial correlation analysis of residential land prices and the regression results of the model are presented in Section 3. Section 4 discusses the spatial effects of flood risk and Section 5 concludes the paper.

2. Data and Methodology

2.1. Study Area

Hangzhou is the capital and economic, political, and cultural center of Zhejiang Province in China, one of the central cities in the Yangtze River Delta region and an important scenic tourism city (Figure 1). Hangzhou is located in the southeastern coastal region and at the southern end of the Beijing-Hangzhou Grand Canal, with a diverse natural environment. The city spans the Qiantang River and Taihu Lake basins, with well-developed water systems. Hangzhou's total area is 16,850 square kilometers, of which the water area accounts for approximately 8%. Hangzhou has ten municipal districts, two counties, and one county-level city under its jurisdiction. The central districts of Hangzhou (Shangcheng, Xiacheng, Jianggan, Gongshu, Xihu, and Binjiang Districts) are selected as the study area. The polycentric pattern of Hangzhou was formed officially in 2002 when the planning of Hangzhou CBD Qianjiang New Town was established. Hangzhou has transformed gradually from the West Lake Era to the Qiantang River Era. The Wulin Square and the Civic Center are the landmark buildings of Wulin CBD and Qiantang New City CBD, respectively.

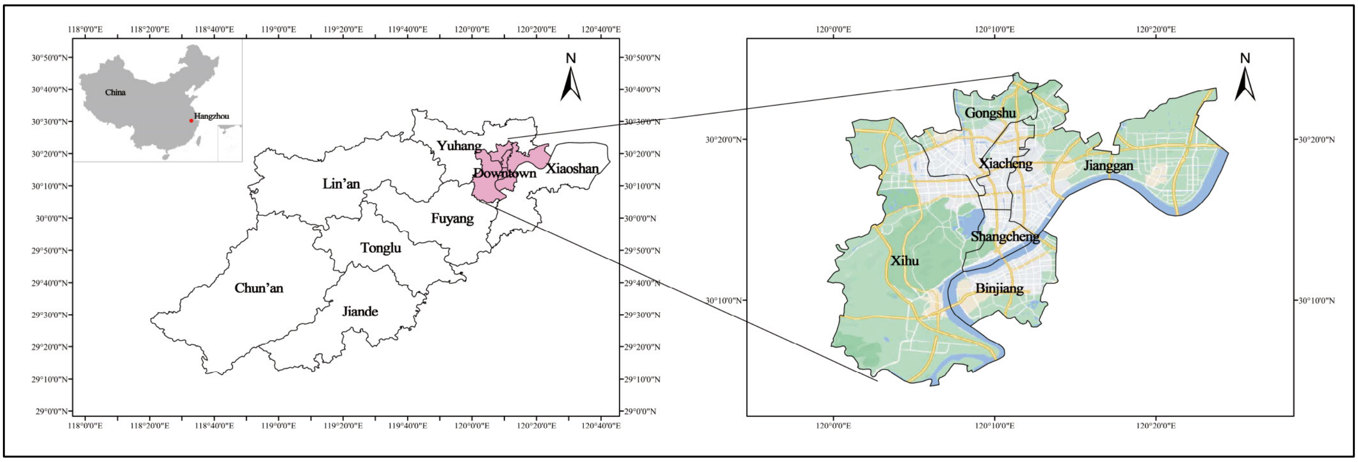


Figure 1. The study area.

Hangzhou has always been at the forefront of land policy reform, and the bidding, auction, and listing system has brought new vitality to the land market. It has been 30 years since the first state-owned land was sold in 1992. After years of development, the land market has become mature and standardized with numerous open market transaction cases [77].

2.2. Data

To ensure the land market's stable development, the government began to issue a series of macro-control measures in 2007 to control the overheated market [77], so the year of 2007 was chosen as the starting point of the study. In early 2021, the urban area of Hangzhou underwent zoning adjustments, and thus, to ensure the regional correspondence of the data, the study period was from January 2007 to December 2020.

The transaction price data of residential land originated from the China Land Market Network, and sales data from 447 residential land plots were obtained. Because of the large time span of the land transaction data selected, land market indicators change over time. The land prices need to be adjusted by correction coefficients. According to the *Urban Land Valuation Regulations*, only the date adjustment is required because regional and individual factors are included as control variables in the model. The residential land price index applied for the date adjustment in the study is derived from the China Land Price Information Service Platform, and the land prices are revised uniformly to December 2020. Finally, 424 samples from 2007 to 2020 are obtained after data collation and cleaning (Figure 2).

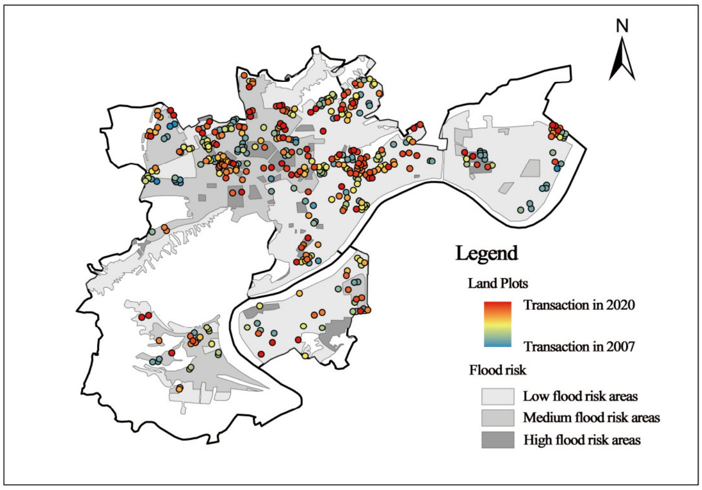


Figure 2. The locations of the residential land transaction samples.

The flood risk data adopt the flooding risk assessment map in the "*Hangzhou Sponge City Special Plan*" compiled jointly by the Hangzhou Municipal Planning Bureau and Hangzhou Urban Planning and Design Institute in 2017. The map applies index system evaluation and scenario simulation methods to assess flood risk based upon topography, geological structure, soil properties, meteorological conditions, hydrological conditions, and other indicators. The risk classification takes into account elevation, depth of accumulated water, waterlogged area, impervious cover, damage and injury, and the presence of important public facilities, etc. Hangzhou is divided into high-, medium-, low-, and no-risk areas (Figure 3).

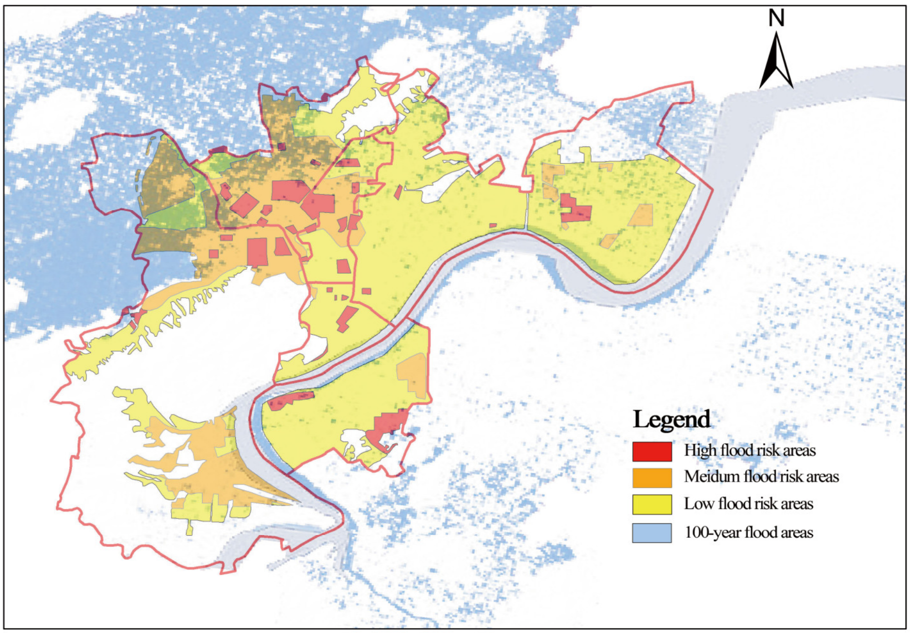


Figure 3. Flooding risk map.

2.3. Methodology

2.3.1. Spatial Autocorrelation Analysis

If land prices between units are spatially correlated, using non-spatial hedonic price models may lead to biased estimation. Therefore, it is necessary to test the variables' spatial correlation before launching the spatial econometric studies to determine whether the dependent variable is suitable for the spatial econometric model. This study introduces the global and local Moran's Index in Exploratory Spatial Data Analysis (ESDA) to explore the spatial characteristics of residential land prices in Hangzhou from different dimensions.

1. Global Spatial Autocorrelation

Using the global Moran's I to describe the distribution of residential land prices overall and judging whether residential land prices cluster in space are the premise of spatial econometric analysis. The specific expression is as follows:

$$I_G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \tag{1}$$

In the formula, $S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2$, $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, x_i and x_j are the observed values of points i and j, n is the number of samples, and w_{ij} is the spatial weight matrix. We select the inverse distance weight matrix according to the first law of geography. The Moran's I has a range of [−1, 1]. If it is greater than 0, residential land prices exhibit a positive spatial correlation, which indicates that there is a high degree of clustering. The larger the absolute value, the more significant the spatial correlation. If the index is near 0, it indicates a random distribution of land prices.

2. Local Spatial Autocorrelation

Compared to the global Moran's I, the local Moran's Index can observe the regional spatial clustering trend and dispersion characteristics of residential land prices further. The calculation formula is as follows:

$$I_i = \frac{(x_i-\bar{x})\sum_{j\neq i}^{n} w_{ij}(x_j-\bar{x})}{S^2}, \tag{2}$$

If the local Moran's I is greater than 0, it indicates that the point *i* with high (low) land price is surrounded by other high (low) land prices; if it is less than 0, it indicates that the point *i* with high (low) land price is surrounded by other low (high) land prices.

2.3.2. Spatial Weight Matrix

The spatial weight matrix reflects the degree of correlation and dependence between spatial units. The spatial weight matrix used commonly is a matrix constructed based upon geographical location, such as the adjacency matrix and geographic distance weight matrix, which can express the correlation between spatial units intuitively. In this paper, a geographic distance weight matrix is constructed based upon the reciprocal of the distance calculated by each plot's latitude and longitude, which indicates that the closer the distance between the blocks, the greater their mutual influence. When the distance exceeds a certain threshold, the degree of influence drops to 0. The matrix is expressed explicitly as follows, with w_{ij} being the spatial linkage between observation *i* and *j*, and d_{ij} being the distance between *i* and *j*.

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}} \ d_{ij} \leq d \\ 0 \ d_{ij} > d \end{cases}, \tag{3}$$

2.3.3. Spatial Econometric Model

According to existing research on the factors of residential land price, the econometric or spatial econometric models include the hedonic price [12–14], GWR [15–17], structural equation [18,19], spatial autoregressive [20–22], spatial Durbin models [25–27] and so on. As a spatial econometric model to measure the spatial correlation effect, the spatial Durbin Model is the general model of the spatial lag model and the spatial error model, which includes spatially lagged dependent variables and spatially lagged explanatory variables. Unlike the GWR model, the spatial Durbin model can explain spatial interaction, which refers to the spatial effect between variables. Therefore, this study uses the spatial Durbin model to explore flood risk's spatial effect on residential land prices.

The spatial Durbin model considers the explanatory variables' spatial lag term and the explained variable's lag term comprehensively. Its mathematical expression is:

$$Y = \beta_0 + \varphi W X_i + \rho W Y + \beta_1 X_i + \varepsilon \tag{4}$$

where Y is the dependent variable matrix, and X_i represents the selected factor matrix, W is the spatial weight matrix used to measure the spatial lag attribute, and ε is the random error term vector whose elements follow $\varepsilon \sim (0, \sigma^2 I_n)$.

When φ equals 0, the model is converted to a spatial lag model. When $\varphi = -\rho\beta_1$, the spatial error model is carried out. This illustrates that the spatial Durbin model can be simplified into the spatial lag model or spatial error model by imposing certain constraints on it. The spatial Durbin model can capture the spatial spillovers generated from different sources, which is more extensive and explanatory.

Typically, the spatial Durbin model is regressed by the maximum likelihood method. In addition to the goodness-of-fit test (R^2) and log-likelihood (LL) test, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) can also be applied to determine whether there is a spatial spillover effect.

3. Results

3.1. The Residential Land Market Analysis

According to land market management policies, Hangzhou has used listings and biddings for residential land since 1992, and the residential land price shows a continuous upward trend during the study period (Figure 4). The HP filtering method is applied to the unit price of residential land to separate the trend and the random fluctuation element of the average unit price of residential land including land for commercial housing and affordable housing. Using the HP filtering method, the residential land market can be divided into approximately three periods, stage I (2007–2011), stage II (2012–2016), and stage III (2017–2020).

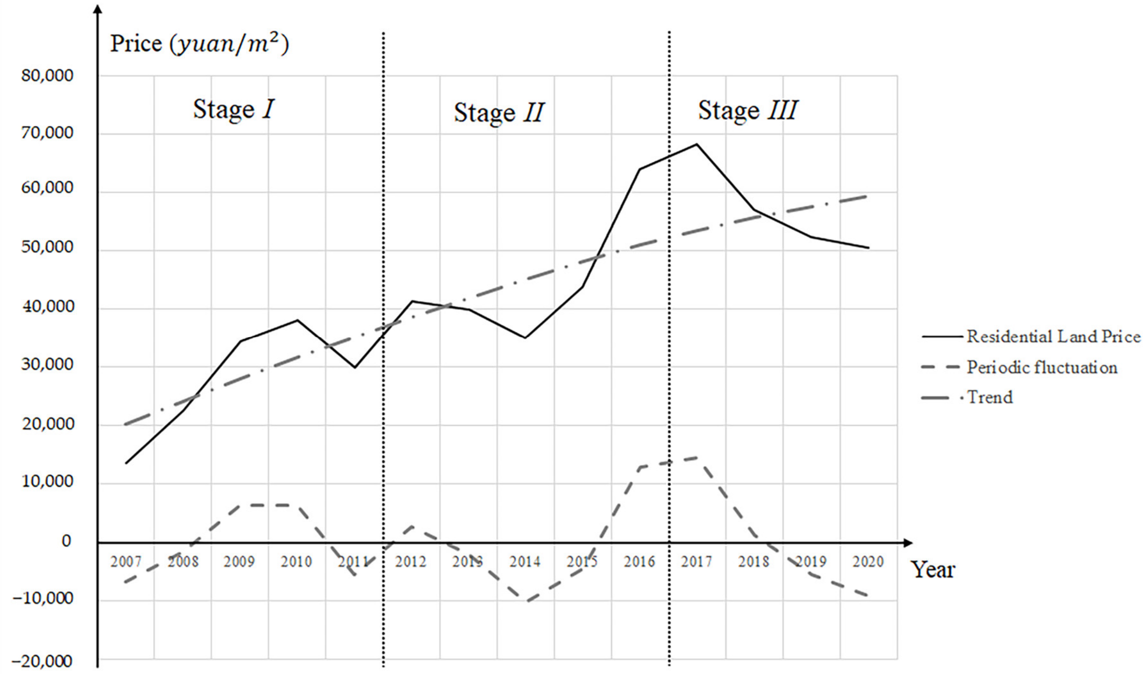
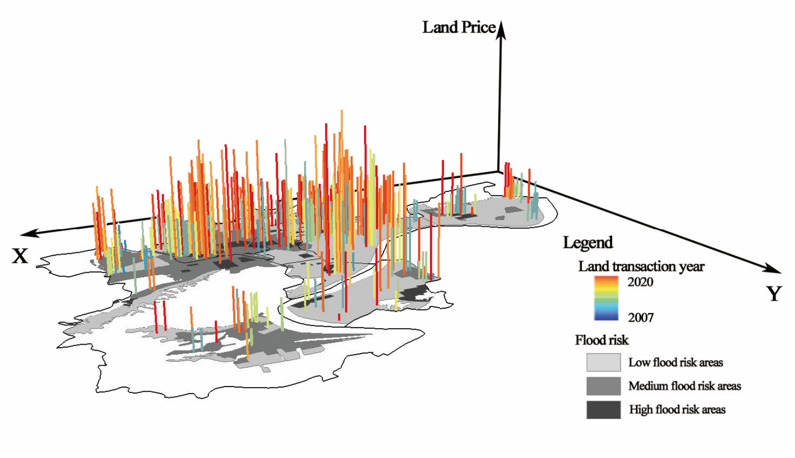


Figure 4. The HP filtering map of residential transaction land prices in Hangzhou from 2007 to 2020.

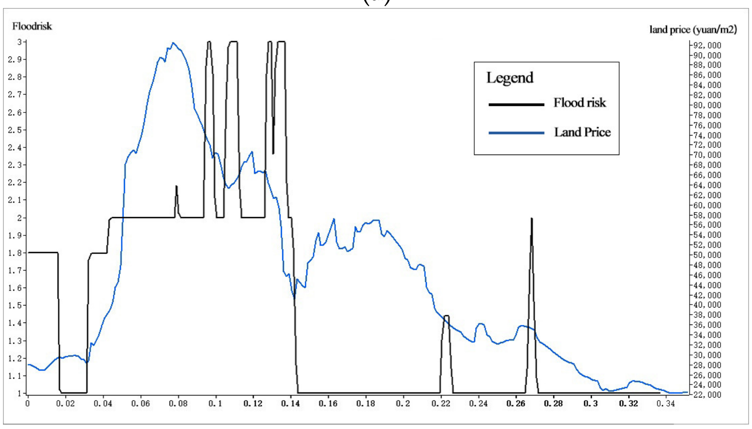
After the slight climax in the land market in 2007, the land market policy was inclined to tighten regulation, and the land market fell into the doldrums. In 2009, the government introduced a four trillion yuan stimulus policy, and the market rebounded. Then, in 2011, after the government introduced the *Notice on Promoting the Stable and Healthy Development of the Real Estate Market*, the land market stabilized. The periodic component of land price fluctuated above and below 0 from 2012 to 2016. To achieve stable housing price expectations, the land market was in an oscillation of tightening-relaxing, yet land prices continued to rise. Furthermore, since 2017, Hangzhou has upgraded and tightened a series of land market control policies, such as the *Renting and Purchasing Policy*, *Setting Ceiling Prices for Houses and Land*, *Bidding for Free Construction Areas*, and other measures to control the land transfer strictly with the hope that these policies will play a role in stabilizing market expectations.

3.2. Statistic Description and Visualization

The descriptive statistics of land prices in different risk zones (Table 1) show that most of the land transaction records are in low-risk and medium-risk zones, while the highest mean/medium price is in high-risk zone. To visualize the result of flood risk, ArcScene 10.2 was applied to construct a 3D map and a sectional view of residential land price and flood risk (Figure 5). Land transaction prices are depicted in dark blue to dark red. The solid black line in the sectional view shows the flood risk curve from the west to east, and the solid blue line shows the interpolated land price curve.



(**a**)



(**b**)

Figure 5. (**a**) Spatial 3D map of land price and flood risk, where the xy plane is the flood risk; (**b**) Sectional view of residential land price and flood risk, where the solid black line shows the flood risk curve from the west to east and the solid blue line shows the interpolated land price curve.

Table 1. The descriptive statistics of residential land prices in different risk zones.

Land Price (Yuan/m^2)	No Risk	Low Risk	Medium Risk	High Risk
Mean	30,798.00	46,162.46	42,999.00	58,285.49
Medium	25,225.67	37,165.00	37,039.08	52,151.19
Minimum	6919.61	3684.00	5722.49	9902.75
Maximum	70,005.28	155,106.07	121,882.66	124,973.00
Std. Deviation	19,866.95	29,400.28	24,907.68	29,011.68
Std. Error	4235.65	1942.82	2151.70	4645.59
Obs.	22	229	134	39

3.3. Spatial Autocorrelation Analysis

3.3.1. Global Spatial Autocorrelation

Using the inverse distance spatial weight matrix in ArcGIS 10.2, this paper measures the global Moran's I of residential land prices in the main urban area of Hangzhou. Table 2 illustrates that the global Moran's I of residential land prices within the selected periods are all positive and pass the significance test, indicating positive spatial autocorrelation. Therefore, the non-spatial econometric model should be extended to a cross-sectional model that includes spatial effects, and the spatial econometric model is considered appropriate for this study.

Table 2. Global Moran's I for residential land price.

Stages	Global Moran's Index	*p*-Value
2007–2011	0.373427	0.0000
2012–2016	0.582483	0.0000
2017–2020	0.132190	0.0026
All data	0.294169	0.0000

3.3.2. Local Spatial Autocorrelation

Furthermore, to clarify the local spatial autocorrelation and spatial clustering characteristics of residential land prices within the study area, the Moran scatterplot and LISA cluster map of land prices are also drawn in the paper. As shown in Figure 6, 312 points are clustered in the first and third quadrants of the coordinate system, indicating that approximately 73.6% of the 424 land plots show a positive autocorrelation regionally. As the LISA cluster map shows (Figure 7), the significantly High-High clustering areas (i.e., hot spots) are located primarily around Hangzhou Civic Center and Wulin Square. In contrast, the Low-Low clustering areas (i.e., cold spots) are located primarily in the southern part of Xihu District and the northern and eastern parts of Binjiang District, far from the city centers. The dependent variable, land price, has significant spatial clustering characteristics and presents uneven spatial heterogeneity.

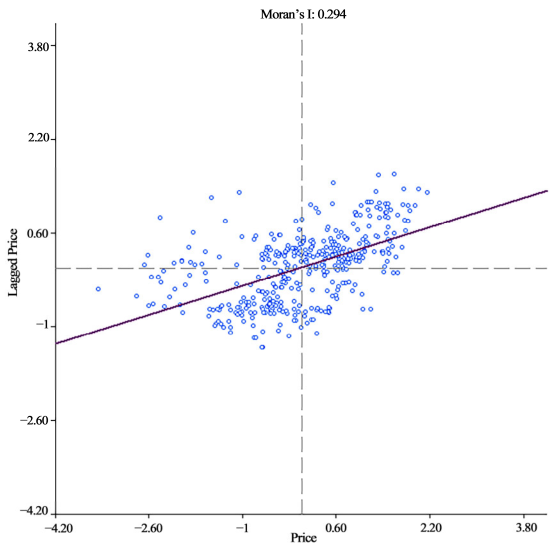


Figure 6. Lisa Scatter Plot Frame. The blue circles represent the correlations between the land price and its spatial lag, while the purple line refers to the linear fit of the scatter plot, the slope of which is the global Moran's index.

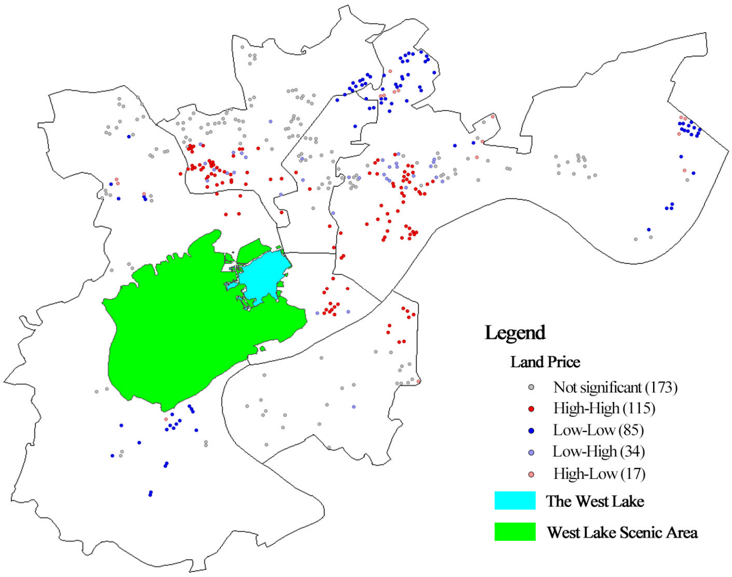


Figure 7. Lisa Cluster Map.

3.4. Model Specification

3.4.1. Variable Selection

The existing research has found that a combination of different factors determines the land price, which can be divided primarily into macro and micro factors [78,79]. There exists a variety of macro factors that determine the difference in land prices between cities, such as population size, land policy, and the level of economic development. Micro factors can be divided primarily into the plot, location, and neighborhood factors. According to previous research, variables at the location, neighborhood and plot levels were selected. Initially, seventeen variables were selected in the study (Table 3). According to the correlation test of the variables, it was found that the correlation coefficient between the distance to Wulin Square and the distance to the nearest 3A hospital exceeded 0.5, which is a high correlation. The reason for this is that the 3A hospitals in Hangzhou are distributed mainly around Wulin Square, and the distance to Hangzhou Wulin Square was excluded. Finally, the sixteen specific variables are detailed in Table 3.

Table 3. Selected variables and definitions.

	Definition	Variables
Location Factor	Linear distance to Hangzhou Civic Center	CBD
Neighborhood Factors	Distance to the nearest planning subway	PMETRO
	Distance to the nearest constructed subway	JMETRO
	The number of bus stops within 500 m	BUS
	Distance to the nearest primary school	PRIM
	Distance to the nearest high school	HIGH
	Distance to the nearest 3A hospital [1]	HOSP
	Distance to the nearest park	PARK
Plot Factors	Whether the land is used for affordable housing, if yes, then 1; otherwise, 0	AFFOR
	Whether it is a mixed-use land, if yes, then 1; otherwise, 0	MIX
	The sold area of the land	AREA
	Whether the land is sold by bidding, if yes, then 1; otherwise, 0	BID
	The upper limit of the planning floor area ratio	FAR
Research Factor	Flood hazard risk, low risk is 1, medium risk is 2, high risk is 3, and no risk is 0	FLOOD
Time	Whether the land was sold between 2007 and 2011, if yes, then 1; otherwise, 0	T1
	Whether the land was sold between 2012 and 2016, if yes, then 1; otherwise, 0	T2

[1] In China, hospitals are classified into three tiers and nine levels. 3A is the highest level of hospital.

3.4.2. Spatial Econometric Model Test

This study draws largely on Anselin's process of determining appropriate spatial econometric modeling [80,81]. First, the Ordinary Least Squares (OLS) regression is required, and the residuals obtained are subjected to the Lagrange Multiplier Test (LM). The LM test contains two indicators, LM-Error and LM-Lag. If neither indicator is significant, the model without spatial effects is chosen as the final model. The spatial error model is selected if the LM-Error is significant, while the spatial lag model is chosen if the LM-Lag is significant. If both indicators are significant, Anselin proposed the Robust Lagrange Multiplier Test (RLM). The RLM test contains two indicators, RLM-Error and RLM-Lag. The spatial error model is selected if the RLM-Error indicator is significant. The spatial lag model is chosen if the RLM-Lag indicator is significant. The spatial Durbin model is preferred if both are significant.

As shown in Table 4, LM-lag, LM-error, and RLM-lag are significant at the 5% confidence level, while RLM-error fails the significance test. According to Anselin's judgment criteria, the spatial lag model (SLM) is more appropriate, indicating that the land prices have a spatial correlation of substantiality but not of interference.

Table 4. LM Test for spatial econometric model.

Indicators	Statistic	p-Value
LM-Error	10.747	0.001
RLM-error	0.350	0.554
LM-lag	15.897	0.000
RLM-lag	5.500	0.019

Since the LM test can only diagnose and select between the spatial lag model and the spatial error model, it is easy to miss a more appropriate model in the end. The likelihood ratio (LR) test can generally be used to test whether the spatial Durbin model can degenerate into SLM or SEM. In this paper, only the spatial lag term of the flood hazard risk is considered because the model has already contained plenty of dependent variables. The LR test statistic conducted by Stata shows that the original hypothesis is rejected at a 5% confidence level, so the SDM model should be chosen (Table 5).

Table 5. LR Test for spatial econometric model.

H_0	Statistic	p-Value
$\rho = 0$, (SDM can degenerate into OLS)	4.5957	0.032
$\varphi = 0$, (SDM can degenerate into SLM)	22.3770	0.000

3.4.3. Model Estimation

The OLS and SDM models were carried out in Stata SE 15, and Table 6 shows the regression results. Model 1 is the OLS model, while Models 2 and 3 are spatial lag models and SDM with the spatial lag terms for the dependent and independent variables, respectively. The R^2 of Models 2 and 3 has increased compared to Model 1, indicating that the spatial lag model/SDM is a better fit. The log-likelihood values of Model 3 with the spatial lag terms of the dependent and independent variables are also larger, indicating that Model 3 explains the residential land prices in the study area better than Model 2.

Table 6. Estimation results of the spatial Durbin model.

Variable	Model 1	Model 2	Model 3
FLOOD	0.0496 * (0.0279)	0.0214 (0.0278)	−0.0862 ** (0.0354)
CBD	−0.3963 *** (0.0437)	−0.2719 *** (0.0534)	−0.4026 *** (0.0596)
PMETRO	−0.0140 (0.0242)	−0.0053 (0.0233)	0.0099 (0.0230)
JMETRO	−0.1206 *** (0.0249)	−0.1056 *** (0.0243)	−0.0721 *** (0.0247)
BUS	−0.0696 ** (0.0332)	−0.0515 (0.0323)	−0.0397 (0.0316)
PRIM	0.0320 (0.0273)	0.0224 (0.0264)	0.0175 (0.0258)
HIGH	0.0157 (0.0320)	0.0204 (0.0308)	0.0570 (0.0310)
HOSP	−0.1422 *** (0.0287)	−0.1289 *** (0.0278)	−0.1105 *** (0.0274)
PARK	0.0153 (0.0250)	0.0178 (0.0240)	0.0226 (0.0234)
AFFOR	−1.8673 *** (0.0929)	−1.8820 *** (0.0893)	−1.9118 *** (0.0875)
MIX	−0.4304 *** (0.1163)	−0.4260 *** (0.1118)	−0.4145 *** (0.1092)
AREA	−0.0295 *** (0.0075)	−0.0253 *** (0.0073)	−0.0234 *** (0.0071)
BID	0.1709 (0.1316)	0.1249 (0.1270)	0.1275 (0.1241)
FAR	0.7954 *** (0.0949)	0.7177 *** (0.0935)	0.6994 *** (0.0915)
T1	−0.6501 *** (0.0485)	−0.6466 *** (0.0466)	−0.6587 *** (0.0456)
T2	−0.4923 *** (0.0448)	−0.4998 *** (0.0430)	−0.5017 *** (0.0420)
W * FLOOD			0.2644 *** (0.0559)
_cons	15.7222 *** (0.5140)	11.8674 *** (1.1337)	13.1074 *** (1.1608)
ρ		0.2395 *** (0.0634)	0.1432 ** (0.0668)
R^2	0.7242	0.7268	0.7445
Adj R^2	0.7134	0.7167	0.7345
Log-L		−148.6326	−137.6672

Note: *, **, *** refer to coefficients that are significant at 10%, 5%, and 1% levels of significance, respectively. Standard errors are in parentheses.

The variables that have a significant negative effect on residential land value at the 95% confidence level are Flood hazard risk (FLOOD), the distance to the Civic Center (CBD), distance to the completed subway station (JMETRO), distance to the nearest 3A hospital (HOSP), whether it is land for affordable housing (AFFOR), whether it is mixed residential land (MIX), land area (AREA), and time control variables (T1, T2). These control variables' coefficients on residential land price are all consistent with expectations.

The estimated coefficient of flood hazard risk (FLOOD) is negatively and statistically significant at the 5% significance level, which indicates that as the flood risk where the plot is located increases by one unit, the price of residential land will decrease by approximately 8.62%. The negative coefficients for the location factor (CBD) and neighborhood factors (JMETRO, HOSP) indicate that the land price will increase when the plot is closer to the CBD or neighborhood amenities. Among the location factors, the CBD plays an undeniable role in increasing residential land prices. With respect to the neighborhood factors, the medical and traffic conditions have a more significant positive effect on the residential land price, which are important factors that developers consider when acquiring land. Furthermore, developers prefer plots around built subway stations over planned ones. According to the estimated coefficients of other control variables in Model 3, it is found that the upper limit of the FAR has a positive effect on residential land prices at the 99% confidence level. The plot ratio's effect on land price is consistent with the results of related studies. The higher the plot ratio within a specific reasonable range, the higher the land price. The negative effect of affordable housing land and mixed residential land indicates that the land value of these two residential land types will be lower than the value of commercial housing. As both are dummy variables, the prices of the three types of residential land can be ranked from highest to lowest based upon the coefficients: commercial housing land; mixed residential land, and affordable housing land. The coefficient of the land area indicates that the larger the plot size, the lower the unit price of residential land. The coefficients of the time-control variables indicate that residential land prices have been increasing over time. Land prices showed an overall upward trend during the study period, consistent with the analysis derived by the HP filtering method in the previous section.

Some factors had the same effect as expected, but others were not consistent with previous research, such as educational resources (PRIM, HIGH), transit accessibility (BUS), and park accessibility (PARK) in neighborhood characteristics. Because the urban area of Hangzhou is rich in educational resources, bus stops, and parks, the service facilities are highly accessible to most of the land plots. The difference in accessibility is not significant. Therefore, the effect of these neighborhood variables is not significant. In addition, the distance to the planned subway station (PMETRO) and whether it is a bid-offer (BID) are not significant at the 90% confidence level.

The spatial-lag parameter is ρ, whose value is 0.1432 and statistically significant at the 5% significance level. The positive coefficient (ρ) implies that values of land price are positively related to values of land price in adjacent areas. When the land prices in surrounding areas increase by 1%, the land price in the area will increase 14.32%. The land price in the neighboring regions will have a positive spatial spillover effect on the region, which shows a convergence effect of land prices between neighboring regions. Meanwhile, the spatial lag term of flood risk (W * FLOOD) shows a positive value at the 1% level of significance, indicating that the land price in one location is positively related to the flood risks in other locations.

4. Discussion

Climate change affects the world's trillion-dollar real estate market, and these effects are gradually being felt more profoundly. Although China is also one of the countries with the most meteorological disasters in the world, looking back at the major meteorological disasters in the past 10 years, it seems that Hangzhou's housing prices have not been affected by floods, and the effects of flooding have not been capitalized into land values. As shown in Table 2, the high-risk zone has the highest mean/medium transaction price, and flood risk may not be the most important consideration in land transaction for governments and developers.

One reason for this phenomenon is that the flood control facilities are believed to be effective in preventing floods. Since 1997, Hangzhou has promoted the 100-year flood standard after typhoon No. 11 which caused huge losses. In 2017, Hangzhou proposed "sponge city" planning and started to enhance the use of rainwater to alleviate waterlogging through initiatives including green roofs, pervious pavement, rain gardens, and bioswales based on the Low-Impact-Development (LID) concept. Alternative and innovative financial mechanisms such as PPP are used to expand the sources of funding for flood control [82]. *The Urban Flood Control and Drainage Planning* revised in 2018 pointed out that the future flood control standard of the main urban area of Hangzhou will be raised from 100-year to 300-year. On both sides of some rivers, the government has combined levees with public services, such as highways and hiking paths, and made them more aesthetically pleasing to enhance the flood control function and give residents a space to rest. However, as global warming increases the frequency and intensity of floods, the traditional approach to flood management may not reduce or prevent all the detrimental effects of flood waters. Flooding will lead to more disasters, loss of life and economic loss. It affects the residents' immediate interests.

The other reason is that geographical data often displays spatial autocorrelation, which can drive spurious correlations or biased estimates. As Table 6 shows, when the model does not include spatial effects, as shown in Model 1, the estimated coefficient of flood hazard risk (FLOOD) is positively and statistically significant, indicating that a plot's higher flood risk contributes to higher land prices. However, after including the spatial lag term of the flood risk and land price, as shown in Model 3, the coefficient of FLOOD becomes negative instead. The nonspatial Model 1 estimated by conventional regression procedures is not reliable representation; while the SDM model can identify the presence of disturbance variables that are spatially autocorrelated.

The results of this study show that other things being equal, plots with high risk of flooding suffer a price discount, and the values of land price are positively related to flood risk in adjacent locations. These are similar findings to previous studies, but for different reasons. These effects of flood risk on land price can be analyzed with China's land ownership and price system. The state ownership of urban land in China is distinguishable from private landownership in the West. Differences in property rights and land price systems may lead to different interpretations of the results. China traditionally does not have a market-based land and property transfer system. In 1978, the land-use rights reform separated the land-use rights from land ownership. In the late 1980s, land benchmark price (LBP) was formed to serve as a reference point for land sales. The LBP method and later the comparison method have become the two most popular land price assessment approaches. According to the *Regulations for Gradation and Classification on Urban Land* issued in 2001 and revised since then, as the supply side of the land market, the government considers flood hazards and other natural factors that affect land use or construction activities in the land classification. The determination of the LBP for urban construction land is based upon land use type and many other factors. For example, plots with higher flood risk have relatively lower benchmark land prices, other things being equal. Therefore, the effect of flooding risk on land price can be explained, as the government considers the flooding conditions when determining the LBP.

Furthermore, the spatial spillover effects of land price can be analyzed with the flood information disclosure system and the stakeholders' considerations in land price comparison. The developers need to survey the surrounding environment to determine the appropriate expected land transaction price before acquiring the land. However, the governments did not publish flood hazard risk maps, and developers and residents had few ways to obtain information about flood risk. They could make decisions based only upon the government's real-time flood warnings and the surrounding plots' actual situation. Developers and residents have unequal information and status in the entire process, so they can make land and house purchasing decisions based upon relevant public information and comparisons. A large number of empirical analyses have found that an individual's risk management decision is related closely to the resources he has at present and his knowledge of risks and risk management strategies [83]. Due to the limited information and less risk awareness of flooding, in the process of land buying and selling, the price determinations mainly rely on the method of market comparison. Therefore, land prices showed a higher spillover effect within regions with similar land market characteristics.

The impact of flood risk on land prices and the spatial spillover effect of land prices in Hangzhou may be similar to that of related research in Western countries; however, the mechanisms of the two are completely different. In Hangzhou, the government pricing of the benchmark land price and the market pricing of the developers' comparison both play an important role in the determination of land prices. In western countries, the market is the most important determinant of the price of land. Interestingly, the risk of flooding is capitalized into the price, whether it is determined by government or market pricing.

5. Conclusions

Extensive evidence on the effect of flooding on residential land prices in the US and Europe exists but little such evidence in China. Using SDM model, this study analyzes the spatial correlation between the flood risk and the residential land prices from 2007 to 2020 in Hangzhou's main urban area. It shows a significant spatial interaction between the flood hazard risk and land prices. The empirical insights delivered by the SDM model are as follows: (1) The residential land price has a positive spatial autocorrelation; (2) Various factors' influence on residential land price differs significantly; (3) Flood hazard risk will have an adverse effect on a plot's land price, while surrounding plots' high risk of flooding will increase the plot's land price. (4) The unique mechanism of the way flood risk affects land prices was discussed further from the perspectives of land ownership and land price systems in China. The LBP issued by the local government considers flooding, making the benchmark price lower for plots with higher flood risk, with other things being equal. (5) The spatial spillover effects of land price can be analyzed with the flood information disclosure system and the stakeholders' considerations in land price comparison. (6) The effect of flooding on residential land prices in Hangzhou is the result of government regulations and market allocations, which is fundamentally different from those of the free market allocations in many western countries. However, the capitalization of floods in land prices has been achieved, whether it is via government pricing or market pricing.

From the perspective of urban planning, spatial allocation should consider the risk of flooding. For the policy makers, it is necessary to include the flood risk in land transaction price determination and to compile a flood hazard risk map, particularly for residential land transactions. The information on flood risk should be released publicly and transparently to protect developers and residents' right to know the land plots' flooding status. According to the flood risk, the government should reasonably determine the development intensity of residential land and regulate the behavior of residential land transfer in high-risk areas. In view of the built-up residential land construction in high-risk areas, flood control projects that minimize the flood risk effect on residential land, such as green roofs and rain gardens, should be provided in urban renewal and transformation.

In drawing conclusions based on this work, a couple of limitations should be considered. With respect to the indicators of flood risk, it uses a dummy variable to measure the flood hazard risk so that the flood risk is constant in the region, which is an abstraction of the reality. With respect to the effect of flood risk on land price, the developers' or residents' views on flood risk have not been considered, which may be an additional explaining factor.

In future research, developers' or residents' views should be obtained through interviews. Furthermore, additional natural hazards and geological disasters may be included in the dataset. In addition, the dataset analyzed consists of residential land prices in Hangzhou, and we suggest expanding the related research to other cities in China.

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References

1. Wang, Y.-J.; Gao, C.; Zhai, J.-Q.; Li, X.-C.; Su, B.-D.; Hartmann, H. Spatio-temporal changes of exposure and vulnerability to floods in China. *Adv. Clim. Chang. Res.* **2014**, *5*, 197–205, https://doi.org/10.1016/j.accre.2015.03.002.
2. Guo, Y.; Wu, Y.; Wen, B.; Huang, W.; Ju, K.; Gao, Y.; Li, S. Floods in China, COVID-19, and climate change. *Lancet Planet. Health* **2020**, *4*, e443–e444.
3. Zhou, M.; Feng, X.; Liu, K.; Zhang, C.; Xie, L.; Wu, X. An Alternative Risk Assessment Model of Urban Waterlogging: A Case Study of Ningbo City. *Sustainability* **2021**, *13*, 826, https://doi.org/10.3390/su13020826.
4. Szwagrzyk, M.; Kaim, D.; Price, B.; Wypych, A.; Grabska, E.; Kozak, J. Impact of forecasted land use changes on flood risk in the Polish Carpathians. *Nat. Hazards* **2018**, *94*, 227–240, https://doi.org/10.1007/s11069-018-3384-y.
5. Rahman, M.; Ningsheng, C.; Mahmud, G.I.; Islam, M.; Pourghasemi, H.R.; Ahmad, H.; Habumugisha, J.M.; Washakh, R.M.A.; Alam, M.; Liu, E.; et al. Flooding and its relationship with land cover change, population growth, and road density. *Geosci. Front.* **2021**, *12*, 101224, https://doi.org/10.1016/j.gsf.2021.101224.
6. Asumadu-Sarkodie, S.; Rufangura, P.; Jayaweera, M.P.C.; Owusu, P.A. Situational analysis of flood and drought in Rwanda. International, *J. Sci. Eng. Res.* **2015**, *6*, 1960–1970.
7. Salihu, M.D.; Shabu, T. Using geographic information system to evaluate land use and land cover affected by flooding in Adamawa State, Nigeria. *J. Disaster Risk Stud.* **2019**, *11*, 1–11.
8. Chatzichristaki, C.; Stefanidis, S.; Stefanidis, P.; Stathis, D. Analysis of the flash flood in Rhodes Island (South Greece) on 22 November 2013. *Silva Balc.* **2015**, *16*, 76–86.
9. Diakakis, M. Characteristics of Infrastructure and Surrounding Geo-Environmental Circumstances Involved in Fatal Incidents Caused by Flash Flooding: Evidence from Greece. *Water* **2022**, *14*, 746, https://doi.org/10.3390/w14050746.
10. Thoidou, E. Spatial Planning and Climate Adaptation: Challenges of Land Protection in a Peri-Urban Area of the Mediterranean City of Thessaloniki. *Sustainability* **2021**, *13*, 4456, https://doi.org/10.3390/su13084456.
11. Wu, Z. Integrating adaptation to climate change into territorial spatial planning: Progress, dilemma and strategy. *Clim. Change Res.* **2021**, *17*, 559–569.
12. Sasaki, M.; Yamamoto, K. Hedonic Price Function for Residential Area Focusing on the Reasons for Residential Preferences in Japanese Metropolitan Areas. *J. Risk Financ. Manag.* **2018**, *11*, 39, https://doi.org/10.3390/jrfm11030039.
13. Berawi, M.A.; Suwartha, N.; Kurnia, K.; Gunawan, G.; Miraj, P.; Berawi, A.R.B. Forecasting the Land Value around Commuter Rail Stations using Hedonic Price Modeling. *Int. J. Technol.* **2018**, *9*, 1329, https://doi.org/10.14716/ijtech.v9i7.2589.
14. Džupka, P.; Gróf, M. The influence of the new cultural infrastructure on residential property prices. *Evidence from Košice ECoC* 2013. *Cities* **2021**, *110*, 103047, https://doi.org/10.1016/j.cities.2020.103047.
15. Nilsson, P. Natural amenities in urban space—A geographically weighted regression approach. *Landsc. Urban Plan.* **2014**, *121*, 45–54.
16. Liu, H.; Meng, Y.; Ma, J. Spatial Distribution of Influence Factors of Residential Land Price in Cangzhou City Based on GWR Model. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *332*, 022032, https://doi.org/10.1088/1755-1315/332/2/022032.
17. Chai, Z.; Yang, Y.; Zhao, Y.; Fu, Y.; Hao, L. Exploring the Effects of Contextual Factors on Residential Land Prices Using an Extended Geographically and Temporally Weighted Regression Model. *Land* **2021**, *10*, 1148, https://doi.org/10.3390/land10111148.
18. Wu, W.; Liu, Z.; Zhang, W. Determinants of Residential Land Price: Structure Equation Model Analysis Using Land-leasing Parcel Data in Beijing. *Acta Geogr. Sin.* **2010**, *65*, 676–684.
19. Prasetyo, K.A.; Swasito, A.P.; Safitra, D.A. Identification of Factors Influencing Land Value for State's Assets Mass Appraisal Purposes: Evidence from Indonesia. *Plan. Malays.* **2021**, *19*, 37-47. https://doi.org/10.21837/pm.v19i17.985.
20. Netusil, N.R. Urban environmental amenities and property values: Does ownership matter? *Land Use Policy* **2013**, *31*, 371–377.
21. Bongjoon, K.; Taeyoung, K. A Study on Estimation of Land Value Using Spatial Statistics: Focusing on Real Transaction Land Prices in Korea. *Sustainability* **2016**, *8*, 543–549.
22. Cui, N.; Feng, C.; Song, Y. Spatial pattern of residential land parcels and determinants of residential land price in Beijing since 2004. *Acta Geogr. Sin.* **2017**, *72*, 1049–1062.
23. Grimes, A.; Liang, Y. Spatial Determinants of Land Prices: Does Auckland's Metropolitan Urban Limit Have an Effect? *Appl. Spat. Anal. Policy* **2009**, *2*, 23–45.

24. Conway, D.; Li, C.Q.; Wolch, J.; Kahle, C.; Jerrett, M. A Spatial Autocorrelation Approach for Examining the Effects of Urban Greenspace on Residential Property Values. *J. Real Estate Financ. Econ.* **2010**, *41*, 150–169, https://doi.org/10.1007/s11146-008-9159-6.
25. Hui, E.C.; Liang, C. Spatial spillover effect of urban landscape views on property price. *Appl. Geogr.* **2016**, *72*, 26–35, https://doi.org/10.1016/j.apgeog.2016.05.006.
26. Zhong, H.; Li, W. Rail transit investment and property values: An old tale retold. *Transp. Policy* **2016**, *51*, 33–48, https://doi.org/10.1016/j.tranpol.2016.05.007.
27. Glumac, B.; Herrera-Gomez, M.; Licheron, J. A hedonic urban land price index. *Land Use Policy* **2019**, *81*, 802–812, https://doi.org/10.1016/j.landusepol.2018.11.032.
28. Chan, H.L.; Woo, K.Y. Studying the Dynamic Relationships between Residential Property Prices, Stock Prices, and GDP: Lessons from Hong Kong. *J. Hous. Res.* **2013**, *22*, 75–89, https://doi.org/10.1080/10835547.2013.12092068.
29. Ball, M.; Cigdem, M.; Taylor, E.; Wood, G. Urban Growth Boundaries and their Impact on Land Prices. *Environ. Plan. A Econ. Space* **2014**, *46*, 3010–3026, https://doi.org/10.1068/a130110p.
30. Bao, S.; Lu, L. Impact of planning-guided spatial evolvement on temporal-spatial evolution of land price: Taking Hefei as an example. *Acta Geogr. Sin.* **2015**, *70*, 906–918.
31. Yang, S.; Hu, S.; Li, W.; Zhang, C.; Torres, J.A. Spatiotemporal Effects of Main Impact Factors on Residential Land Price in Major Cities of China. *Sustainability* **2017**, *9*, 2050, https://doi.org/10.3390/su9112050.
32. Codosero Rodas, J.M.; Naranjo Gómez, J. M.; Castanho, R. A.; Cabezas, J. Land Valuation Sustainable Model of Urban Planning Development: A Case Study in Badajoz, Spain. *Sustainability* **2018**, *10*, 1–18.
33. Jalali, D.; MacDonald, H.; Fini, A.A.F.; Shi, S. Effects of planning regulations on housing and land markets: A system dynamics modeling approach. *Cities* **2022**, *126*. https://doi.org/10.1016/j.cities.2022.103670.
34. Rakhmatulloh, A.R.; Buchori, I.; Pradoto, W.; Riyanto, B.; Winarendri, J. What is The Role of Land Value in The Urban Corridor? *IOP Conf. Ser. Earth Environ. Sci.* **2018**, *123*, 012–033.
35. Zhang, P.; Hu, S.; Qu, S. Research on the Non-homogeneous Diffusion Law of Urban Center on Spatial Distribution of Land Price. *Geogr. Geo-Inf. Sci.* **2018**, *34*, 79–86.
36. Huang, D.; Yang, X.; Liu, Z.; Zhao, X.; Kong, F. The Dynamic Impacts of Employment Subcenters on Residential Land Price in Transitional China: An Examination of the Beijing Metropolitan Area. *Sustainability* **2020**, *10*, 1016, https://doi.org/10.3390/su10041016.
37. Cervero, R.; Kang, C.D. Bus rapid transit impacts on land uses and land values in Seoul, Korea. *Transp. Policy* **2011**, *18*, 102–116, https://doi.org/10.1016/j.tranpol.2010.06.005.
38. Li, L. A Research on Evaluation of Land Value for Comprehensive Development of Intercity Rapid Rail Transit Station based on the Hedonic Price Model (HPM). *Railw. Transp. Econ.* **2019**, *41*, 1–7+13.
39. Malaitham, S.; Fukuda, A.; Vichiensan, V.; Wasuntarasook, V. Hedonic pricing model of assessed and market land values: A case study in Bangkok metropolitan area, Thailand. *Case Stud. Transp. Policy* **2018**, *8*, 153–162, https://doi.org/10.1016/j.cstp.2018.09.008.
40. Zhou, Y.; Wang, Y. Research on How the Educational Resources and Educational Policy have Affected Urban Residential Land Price: Evidence from Beijing Land Market. *J. Renmin Univ. China* **2015**, *29*, 79–89.
41. Lee, Y.S. School districting and the origins of residential land price inequality. *J. Hous. Econ.* **2015**, *28*, 1–17, https://doi.org/10.1016/j.jhe.2014.12.002.
42. Peng, T.-C.; Chiang, Y.-H. The non-linearity of hospitals' proximity on property prices: Experiences from Taipei, Taiwan. *J. Prop. Res.* **2015**, *32*, 341–361, https://doi.org/10.1080/09599916.2015.1089923.
43. McCord, J.; McCord, M.; McCluskey, W.; Davis, P.; McIlhatton, D.; Haran, M. Effect of public green space on residential property values in Belfast metropolitan area. *J. Financ. Manag. Prop. Constr.* **2014**, *19*, 117–137, https://doi.org/10.1108/jfmpc-04-2013-0008.
44. Wu, J.; Wang, M.; Li, W.; Peng, J.; Huang, L. Impact of Urban Green Space on Residential Housing Prices: Case Study in Shenzhen. *J. Urban Plan. Dev.* **2015**, *141*, https://doi.org/10.1061/(asce)up.1943–5444.0000241.
45. Huo, X.; Gong, Y.; Zhang, S.; Hou, H.; Wang, F. The Estimation of Urban Park Spillover Value from the Perspective of the Willingness to Pay: Based on the Characteristic Price Analysis of the Land Market in Xuzhou. *Ecol. Econ.* **2020**, *36*, 77–84.
46. Moon, B. The effect of FAR (floor area ratio) regulations on land values: The case of New York. *Pap. Reg. Sci.* **2019**, *98*, 2343–2354, https://doi.org/10.1111/pirs.12421.
47. Zhang, L.; Li, S.; Nong, H. Measuring Land-use Regulation and Its Effect on Residential Land Price. *China Econ. Stud.* **2020**, *321*, 104-121.
48. Bernstein, A.; Gustafson, M.T.; Lewis, R. Disaster on the horizon: The price effect of sea level rise. *J. Financ. Econ.* **2019**, *134*, 253–272, https://doi.org/10.1016/j.jfineco.2019.03.013.
49. Harrison, D.; Smersh, G.T.; Schwartz, A. Environmental Determinants of Housing Prices: The Impact of Flood Zone Status. *J. Real Estate Res.* **2001**, *21*, 3–20, https://doi.org/10.1080/10835547.2001.12091045.
50. Zhang, L. Flood hazards impact on neighborhood house prices: A spatial quantile regression analysis. *Reg. Sci. Urban Econ.* **2016**, *60*, 12–19, https://doi.org/10.1016/j.regsciurbeco.2016.06.005.
51. Rajapaksa, D.; Wilson, C.; Managi, S.; Hoang, V.-N.; Lee, B. Flood Risk Information, Actual Floods and Property Values: A Quasi-Experimental Analysis. *Econ. Rec.* **2016**, *92*, 52–67, https://doi.org/10.1111/1475-4932.12257.

52. Cupal, M. Flood Risk as a Price-setting Factor in the Market Value of Real Property. *Procedia Econ. Financ.* **2015**, *23*, 658–664, https://doi.org/10.1016/s2212-5671(15)00447-5.
53. Murfin, J.; Spiegel, M. Is the Risk of Sea Level Rise Capitalized in Residential Real Estate? *Rev. Financ. Stud.* **2020**, *33*, 1217–1255.
54. Bin, O.; Landry, C.E. Changes in implicit flood risk premiums: Empirical evidence from the housing market. *J. Environ. Econ. Manag.* **2013**, *65*, 361–376, https://doi.org/10.1016/j.jeem.2012.12.002.
55. Atreya, A.; Czajkowski, J. Graduated Flood Risks and Property Prices in Galveston County. *Real Estate Econ.* **2019**, *47*, 807–844, https://doi.org/10.1111/1540-6229.12163.
56. Bin, O.; Kruse, J.B. Real Estate Market Response to Coastal Flood Hazards. *Nat. Hazards Rev.* **2006**, *7*, 137–144, https://doi.org/10.1061/(asce)1527-6988(2006)7:4(137).
57. Atreya, A.; Ferreira, S.; Kriesel, W. Forgetting the Flood? An Analysis of the Flood Risk Discount over Time. *Land Econ.* **2013**, *89*, 577–596, https://doi.org/10.3368/le.89.4.577.
58. Beltrán, A.; Maddison, D.; Elliott, R. The impact of flooding on property prices: A repeat-sales approach. *J. Environ. Econ. Manag.* **2019**, *95*, 62–86, https://doi.org/10.1016/j.jeem.2019.02.006.
59. Rajapaksa, D.; Zhu, M.; Lee, B.; Hoang, V.-N.; Wilson, C.; Managi, S. The impact of flood dynamics on property values. *Land Use Policy* **2017**, *69*, 317–325, https://doi.org/10.1016/j.landusepol.2017.08.038.
60. Baldauf, M.; Garlappi, L.; Yannelis, C. Does Climate Change Affect Real Estate Prices? Only If You Believe In It. *Rev. Financ. Stud.* **2020**, *33*, 1256–1295, https://doi.org/10.1093/rfs/hhz073.
61. Bakkensen, L.; Barrage, L. Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics. *Rev. Financ. Stud.* **2021**, *35*, 3666–3709.
62. Hsieh, L.-H.C. Is it the flood, or the disclosure? An inquiry to the impact of flood risk on residential housing prices. *Land Use Policy* **2021**, *106*, 105443, https://doi.org/10.1016/j.landusepol.2021.105443.
63. Filippova, O.; Nguyen, C.; Noy, I.; Rehm, M. Who Cares? Future Sea Level Rise and House Prices. *Land Econ.* **2020**, *96*, 207–224, https://doi.org/10.3368/le.96.2.207.
64. Ismail, N.H.; Karim, M.Z.A.; Basri, B.H. Flood and Land Property Values. *Asian Soc. Sci.* **2016**, *12*, 84, https://doi.org/10.5539/ass.v12n5p84.
65. Dudzińska, M.; Prus, B.; Cellmer, R.; Bacior, S.; Kocur-Bera, K.; Klimach, A.; Trystuła, A. The Impact of Flood Risk on the Activity of the Residential Land Market in a Polish Cultural Heritage Town. *Sustainability* **2020**, *12*, 10098, https://doi.org/10.3390/su122310098.
66. Zhai, G.; Fukuzono, T.; Ikeda, S. Effect of flooding on megalopolitan land prices: A case study of the 2000 Tokai flood in Japan. *J. Nat. Disaster Sci.* **2003**, *25*, 23–36.
67. Saptutyningsih, E.; Suryanto, S. Hedonic price approach of flood effect on agricultural land. *Econ. J. Emerg. Mark.* **2011**, *25*, 87–96.
68. Sawada, Y.; Nakata, H.; Sekiguchi, K.; Okuyama, Y. Land and Real Estate Price Sensitivity to a Disaster: Evidence from the 2011 Thai Floods. *Econ. Bull.* **2018**, *38*, 89–97.
69. Hatori, K.; Inoue, R. Impact of flood experiences and risk on land prices infrequently-flooded areas: A case study on Nagoya City. *J. Jpn. Soc. Civ. Eng.* **2020**, *76*, I_703–I_708.
70. Kawai, C.; Nakai, F.; Hideshima, E. Heterogeneity of Causal Effects of Designating Tsunami Inundation Zone on Land Price. In Proceedings of the 2021 IEEE 10th Global Conference on Consumer Electronics (GCCE), Kyoto, Japan, 12–15 October 2021; pp. 113–114, https://doi.org/10.1109/gcce53005.2021.9621954.
71. Murakami, D.; Yoshida, T.; Seya, H.; Griffith, D.A.; Yamagata, Y. A Moran coefficient-based mixed effects approach to investigate spatially varying relationships. *Spat. Stat.* **2017**, *19*, 68–89, https://doi.org/10.1016/j.spasta.2016.12.001.
72. Chen, C. Study on Land Grading and Benchmark Price in Ruichang City. Ph.D. Thesis, Jiangxi Agricultural University, Jiangxi, China, 2018.
73. Shan, X.; Yin, J.; Wang, J. Risk assessment of shanghai extreme flooding under the land use change scenario. *Nat. Hazards* **2022**, *110*, 1039–1060, https://doi.org/ 10.1007/s11069-021-04978-1.
74. Shen, L.; Wen, T.; Shi, P.; Qu, S.; Zhao, L.; Li, Q. Responses of extreme hydrologic events to future land use change in the upper reaches of Huaihe River. *Water Resour. Hydropower Eng.* **2021**, *53*, 95–107.
75. Peng, J.; Wu, Q.; Qiang, C. Influence of Geological Hazard on the Benchmark Land Price of Urban Residential Land and Its Correction Coefficient Appraisal: A Case Study in Lanzhou City. *China Land Sci.* **2016**, *30*, 73–81.
76. LI, Y.-W. *The Impact of Flooding Potential on Housing Price: A Case Study of Tainan City; Department of Business Administration*; Southern Taiwan University of Science and Technology: Tainan City, Taiwan, 2019.
77. Shen, J. *Research on the Spatial and Temporal Evolution of Residential Land Price in Hangzhou and Its Influencing Factors*; Zhejiang University of Technology: Zhejiang, China, 2020.
78. Liu, Y.; Fan, H. Study on Micro-Influencing Factors of Changsha New Residential Land Prices. *J. Urban Stud.* **2016**, *37*, 11–14.
79. Zhou, G. *The Micro Factors and Empirical Research on Urban Land Price*; Economic Science Press: New York, NY, USA, 2005.
80. Anselin, L. *Exploring Spatial Data with GeoDaTM: A Workbook. Center for Spatially Integrated Social Science*; Center for Spatially Integrated Social Science: Urbana, IL, USA, 2005; pp. 165-223.
81. Mueller, J.; Loomis, J. Spatial Dependence in Hedonic Property Models: Do Different Corrections for Spatial Dependence Result in Economically Significant Differences in Estimated Implicit Prices? *J. Agric. Resour. Econ.* **2008**, *33*, 42459.

82. Li, L.; Collins, A.M.; Cheshmehzangi, A.; Chan, F.K.S. Identifying enablers and barriers to the implementation of the Green Infrastructure for urban flood management: A comparative analysis of the UK and China. *Urban For. Urban Green.* **2020**, *54*, 126770, https://doi.org/10.1016/j.ufug.2020.126770.
83. Zhang, F.; Gu, B.; Peng, Y.; Yuan, T. Analysis of Knowledge Map of Disaster Risk Perception. *Saf. Environ. Eng.* **2019**, *26*, 32–37.