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Impact of Mixed Land Use on Housing Prices, Spatial Differentiation and Implications: Empirical Analysis Based on Qingdao

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Abstract

Mixed land use is widely practiced yet needs to be understood regarding its spatially-differentiated patterns and implications over time. This study builds a framework considering both the degree and dominant type, incorporates them into the traditional and geographically weighted hedonic price models, and conducts an empirical analysis in Qingdao, China. We found that: (1) In a global sense, the degree of mixed land use has a significant positive impact on housing prices. The influence of the "commercial-service-dominated" (Bdominate) is negative, and that of the "public-commercial-balanced" (ABdominate) type is worse. (2) When considering spatial autocorrelation, the degree shows a negative effect on average, with the effect of dominant types varying spatially. (3) Following the direction of development sequences, the districts and counties can be categorized into four types. The overall degree of mixed land use decreases while its effect on housing prices increases and decreases, and the negative effects of Bdominate and ABdominate types on housing prices also increase and decrease. The framework for studying mixed land use can be applied in other areas, and the insights on different dominant types and spatial variances are helpful in guiding planning practices.

Keywords Mixed land use · Hedonic price model · Geographically weighted regression · Qingdao

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Introduction

As a planning strategy as opposed to rigid zoning, mixed land use has been widely adopted in various regions of the world (Raman & Roy, 2019). In Europe, mixed land use is commonly viewed as related to the urban renaissance (Stead & Hoppenbrouwer, 2004) and in the US as part of the New Urbanism strategy (Ellis, 2002). Mixed land use reflects the nature of cities (Jacobs, 1961) and has direct influence on the amenities and quality of the neighborhood (Nabil and Abd Eladayem, 2015). However, although mixed land use has received great attention in research and practice, many critical issues remain unresolved. First, the current measurement methods focus on the degree but fail to capture the types and mechanisms of mixed land use (Zhuo et al., 2019). Second, there exists ambiguity about the impact of mixed land use on neighborhood environment as characterized by housing prices. On the one hand, mixed land use can enhance neighborhood vitality and improve living quality (Yue et al., 2017); on the other hand, mixed land use may also bring chaos and undermine the neighborhood quality (Gu et al., 2019; Wo, 2019). Meanwhile, the spatial differentiation of the impact of mixed land use on housing prices hasn't been fully understood (Song & Knaap, 2004; Wu et al., 2018), and the amenities and facilities are often inefficiently allocated in community planning and real estate development (Ghosh, 2017).

This study focuses on the impact of mixed land use on housing prices and selects Qingdao as the case site. Located in the southeast of Shandong Peninsula, Qingdao is a representative new first-tier city with rapid urban expansion and drastic real estate development in past decades (Li et al., 2015). The main research questions include: (1) Does mixed land use have an impact on housing prices? What are the differences between various patterns or types of mixed land use? (2) Are there any spatial variations in the impact of mixed land use on housing prices? What are the characteristics and mechanisms behind it?

The article will be organized as follows. The second part reviews the relevant previous research on the impact of mixed land use on housing prices, with the concepts and research methods covered. The third part presents the case site, data sources, variables, model setting and the theoretical analysis framework. The fourth part analyses and compares the results of the classic ordinary least squares regression (OLS) and geographically weighted regression (GWR). The fifth part discusses the implications of the three dominant types of mixed land use, as well as the four categories based on time and space correspondence with potential policy prescriptions. The sixth part serves as a summary.

Literature review

Mixed land use originated from rethinking "rigid zoning" after World War II (Grant, 2002; Herndon, 2011). There are different scales in studying mixed land use, ranging from a single building, a plot, a block to a district, and even a city (Rowley, 1996).

Horizontal and vertical are the two most important dimensions (Hoppenbrouwer & Louw, 2005). Although mixed land use has become a widely-used regulatory tool for years, there has yet to be a consensus on its potential externality to the neighborhood environment (Van Cao & Cory, 1982; Yang et al., 2021). Some scholars have suggested that mixed land use makes it more convenient to reach various urban facilities (Ye & Zhuang, 2017). It can promote walking, reduce car use (Seong et al., 2021), and help form a safer and more attractive neighborhood with higher housing prices (Ghosh, 2017; Kong et al., 2015). On a smaller scale, however, researchers have noticed some uncertainties. Mixed land use can bring in noise, chaos, and pollution, thus causing safety problems (Song & Knaap, 2004). These may reduce neighborhood attractiveness, negatively affecting housing prices (Wo & Kim, 2022; Matthews & Turnbull, 2007; Wang et al., 2022). At the same time, research have shown that the different patterns of mixed land use may have a diverse impact. For example, a moderate mix of several urban facilities may be preferred rather than introducing some single function in residential neighborhoods (Song & Knaap, 2004). The mix of grocery stores, restaurants, and offices may improve neighborhood safety, but not shopping malls (Sohn, 2016). Plus, the compatibility issues in mixed land uses can be tricky and vary from place to place (Shi et al., 2021). Hence, it is necessary to study the specific patterns of mixed land uses and their impacts in depth.

Hedonic method is essential for studying the impact of various factors on housing prices (Lancaster, 1966; Xiao, 2017). It views each house as a bundle of characteristics and decomposes the market price using regression methods. Architectural characteristics include tenure, area, interior facilities, and decoration (Randeniya et al., 2017). Locational characteristics cover the distance to major roads, city centers, and other vital places or landmarks (Heyman et al., 2018). Neighborhood characteristics mainly refer to the landscape environment and all kinds of facilities in the surrounding area, including mixed land use (Nepal et al., 2020). Previous research have shown that spatial dependence naturally occurs in hedonic models (Wu et al., 2018), with several theoretical mechanisms included. The first one is the spatial proximity effect, where housing prices in one area are more likely to rise if those increase in an adjacent area (Baltagi & Bresson, 2011). The second is spatial error dependence, where omitted variables are spatially interdependent (Anselin and Lozano-Gracia, 2008). Wu et al. (2018) employed several spatial regression models in hedonic studies on housing prices. They found that mixed land use may affect housing prices in complex ways that vary by the specific land-use categories. However, such studies are relatively few and the current case studies are rather limited. More detailed empirical analysis is expected to better understand the regression results and their potential implications, thus disentangling the impact mechanism more deeply.

Therefore, this study aims to improve the existing research in the following aspects. First, we will establish a more comprehensive analytical framework for portraying mixed land use on which empirical studies and discussions are based. Second, a geographically weighted regression model that considers the effects of spatial autocorrelation will be used for more accurate results. Comparisons at different scales will be conducted to carefully explore the spatial variations of the effects of mixed land use on housing prices. This study will further analyze and explore the mechanisms behind spatial variations to propose constructive strategies and complement the relevant theories.

Data sources and study design

Study Area

Qingdao is located south of the Shandong Peninsula, bordering the Yellow Sea to the east and south, Yantai to the northeast, Weifang to the west, and Rizhao to the southwest. It is a typical hilly seaside city with unique urban form and land use patterns influenced by modern planning practices during German and Japanese occupations (Li et al., 2015). Meanwhile, Qingdao is one of the five cities under separate state planning in China, ranking 13th among the 337 prefecture-level cities and municipalities directly under the central government in terms of GDP in 2021. Moreover, the urban construction and the development of the real estate market in Qingdao have been rapid in the past decades, and now they have become relatively stable and mature (Yang et al., 2021). There have already formed different urban areas in Qingdao, including the old city area (Eastern Jiaozhou Bay), the city center area (Northeastern Jiaozhou Bay), the new town area (Western Jiaozhou Bay), and the peripheral town area (Central and Northern part of the city). Therefore, Qingdao can provide sufficient samples for studying how mixed land use can impact housing prices. Using Qingdao as a case study, we can draw conclusions and policy recommendations with universal significance.

The urban expansion in Qingdao follows this direction: "Eastern Jiaozhou Bay—Northeastern Jiaozhou Bay—Western Jiaozhou Bay—Central and Northern part of the city". Urban construction in today's Shinan district (SN) and Shibei district (SB) was formed before the founding of the People's Republic of China. The contiguous expansion between them and the Licang district (LC) took place around the 1950s, and the expansion from Shinan district (SN) to Laoshan district (LS) did not occur until the reform and opening up in the 1980s (Qingdao Municipal Archives, 2002). Huangdao district (HD) was administratively established in 1978, with today's Jiaozhou city (JZ, county-level city), Chengyang district (CY), and Jimo district (JM) assigned to Qingdao at the same time. Pingdu city (PD, county-level city) and Laixi city (LX, county-level city) were added in 1983. However, Qingdao's urban built-up area was still concentrated around today's SN, SB, LC, the southern part of CY, and part of the western area in LS in the early 1990s. The expansion to the middle area of LS and CY did not happen until the first and second ten years of the twenty-first century, respectively (see Fig. 1).

Seven districts and one county-level city (county) are selected in this study, including SN, SB, HD, LS, CY, LC, JM, and JZ. PD and LX are not included due to the independence of planning and financial rights. The eight districts and counties account for around 45% of the total area and 90% of the total GDP,[1] which can reflect the essential characteristics of the land use and real estate development in Qingdao.

[1] The percentages are based on the survey data of land use (2019) and the statistics yearbook (2020).

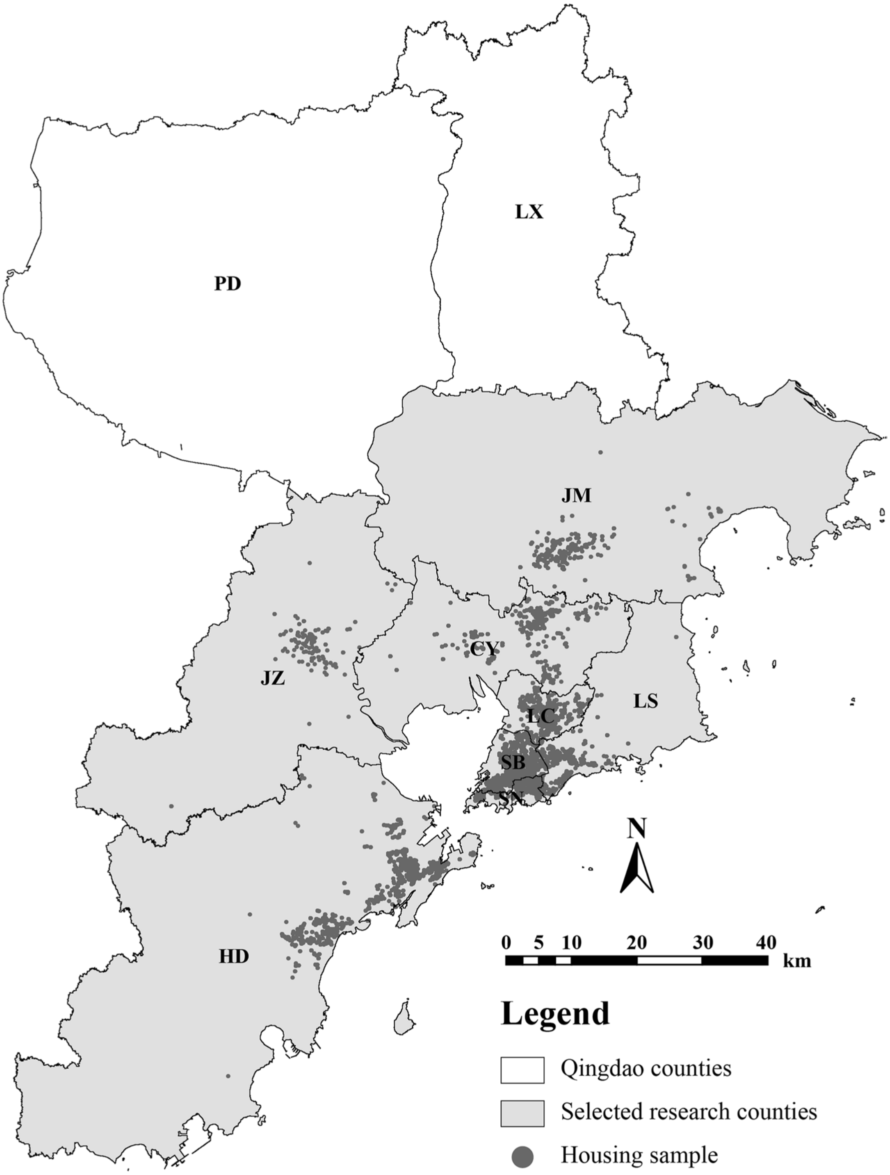


Fig. 1 Study area

Data Pre-processing

This study's spatial data mainly includes the survey data of land use, POI (point of interest) from Gaode Map and road data from Open Street Map,[2] supplemented by relevant planning information from the official website of Qingdao Natural Resource and Planning Bureau. The annual housing transaction data of 2021 is obtained from lianjia.com, and there remain 16,825 transaction samples distributed in 2558 communities and 147 commercial districts after data cleansing. The POI data is further reclassified to be consistent with the land use classification system commonly adopted in China's planning practices. They are divided into public services (A), commercial services (B), transportation services (G), industrial and logistics enterprises (IW), and transportation facilities (S), as detailed in Appendix Table 5.

Study Design

Measuring Mixed Land Use

There are two major ideas of measuring mixed land use. One is from a quantitative and typological perspective (Bordoloi et al., 2013; Kong et al., 2015), and the other is to introduce the distance factor (Abdullahi et al., 2015; Wu et al., 2018). The former mainly applies various diversity indices represented by Shannon entropy (Comer & Greene, 2015). The latter mainly considers accessibility or proximity (Zheng et al., 2016). This study employs the information entropy (Shannon entropy) to quantify the degree of mixed land use, since it is the most fundamental, concise and widely used method on which many other indices are based (Zheng et al., 2019). Moreover, the equilibrium index is defined using the ratio of the actual information entropy to the maximum entropy, enabling the comparison of the measurement results between different locations (Chen & Liu, 2001). The formula of the equilibrium index is as follows.

$$J_i = \frac{-\sum_{j=1}^{K}(p_{ij})\ln(p_{ij})}{lnK} \tag{1}$$

where p_{ij} refers to the proportion of the area of a certain type of land use (j) to the total area, or that of the number of a certain type of POI (j) to the whole number within a certain range of the surrounding are for each sample i. K refers to the total number of the types for land use or POI. Since POI is more related to urban function and can better reveal the situation of mixed land use from a vertical perspective. The regression model as control will mainly use the raw POI data. For each sample point, we calculate the equilibrium index using land use and POI data, the total number of land use and POI types, and the number of POI within a radius of 1000 m. This specific radius is decided to best represent the scale of mixed situations (Wu et al., 2022;

[2] The data of land use is investigated around December 2019, POI data is obtained in October 2021 and the OSM data is obtained in August 2021.

Table 1 The component matrix of constructing the aggregated mix index (*ZScore*)

	Original Variable Name		Factor 1	Factor 2
1	Equilibrium index based on current land use data	*DLMix*	-0.190	0.883
2	Total number of land use types	*DLKind*	-0.711	0.441
3	Equilibrium index based on POI data	*POIMix*	0.715	0.404
4	Total number of POI types	*POIKind*	0.931	0.168
5	Total number of POI	*POINum*	0.820	0.044

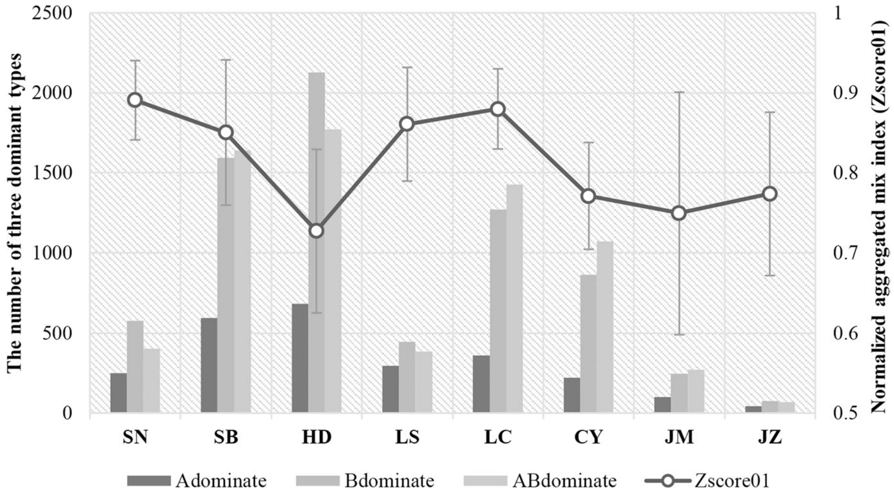


Fig. 2 Indicators related to mixed land use among districts and counties

Zhang & Zhao, 2017). Two main factors are extracted using principal component analysis (PCA, see Table 1), and the aggregated mix index (*ZScore*) is then constructed using the formula below:

$$ZScore_i = \lambda_1 Factor1_i + \lambda_2 Factor2_i \tag{2}$$

This study also builds a variable of the dominant types of mixed land use using the raw data of land use and POI types. Those with absolute dominance of land for public service facilities or POI of public services in its surrounding area are classified into the "public-service-dominated" (Adominate) type, the same for the "commercial-service-dominated" (Bdominate) type. Those with a similar area or number are classified into the "public-commercial-balanced" (ABdominate) type. As Fig. 2 shows, districts and counties in the eastern and northeastern regions of Jiaozhou Bay, namely SN, LC, LS, SB, are among the top group regarding the degree of mixed land use. In contrast, the newly developed HD in the western region of Jiaozhou Bay, CY, JM, and JZ in the northern region has a relatively lower degree of mixed land use with a more discrete distribution. HD has the largest sample size, followed by the districts around the northeastern region of Jiaozhou Bay like SB, LC, and CY. JM and JZ may be the least active in terms of housing transaction activities. The number of Bdominate type exceeds that of Adominate for all districts and counties, and the differences between them are the biggest in the northeastern region of Jiaozhou Bay, indicating that the commercial-services-oriented development used to dominate in a certain period. There may gradually emerge a growing number of the ABdominate type as well.

Classic Hedonic Price Model

The housing prices in this study are the actual transaction prices recorded on the website. A hedonic price model is built as follows controlling architectural characteristics, location characteristics, neighborhood characteristics, and transaction characteristics and examining the influence of the mixed land use. The regression units in the classic hedonic price models are the transaction samples.

$$lnP = \alpha + \beta_j A_j + \gamma_j L_j + \delta_j N_j + \theta_j MLU_j + \rho_j D_j + \mu_j F_j + \varepsilon \tag{3}$$

Some variables are eliminated considering their contribution to the model and the significance level of the estimated coefficients. The final variables selected are listed in Table 2. *A* indicates variables of architectural characteristics, including the number of bedrooms, living halls, and restrooms (*NoR*, *NoH* and *NoT*) that characterize the structure of the house, the use of the house (*houseuse*), the decoration (*intedesign*), the condition of the heating system (*heatcon*), and the main orientation (*orientcon*). *L* indicates variables of location characteristics, including the distance to the district or county center (*dtqxzx*) and the dummy variable constructed based on this (*far*). *N* indicates variables of neighborhood characteristics, including the availability of an elevator (*elevator*), the year of construction (*buildtime*) and the dummy variable constructed correspondingly (*builddacade*). *D* indicates variables of transaction characteristics, mainly the number of price adjustments (*NoPA*). *MLU* indicates variables of the characteristics of mixed land use, including the aggregated mix index (*ZScore*) and its normalized version (*ZScore*01), the dominant type (*DomiType*), and the raw data of the number of each type of POI for a comparison between different models. *DomiType* are split into three zero–one dummy variables which includes whether it is an Adominate type, a Bdominate type and an ABdominate type. All models in the following analysis only include *Bdominate* and *ABdominate* to avoid collinearity problems.

Geographically Weighted Regression Model

The classic hedonic model is based on the least square algorithm (OLS), which implicitly assumes spatial homogeneity and that the estimated coefficients are equal across sample points. However, if the attributes of each sample point are spatially autocorrelated, the average estimated results may not be able to measure the differential effects. Therefore, this study develops a geographically weighted regression model of hedonic price as follows. Due to the model setting and arithmetic

Table 2 Description of control and intervention variables

Type	Variable Name		Meanings
Architectural Features (A)	*NoR*	Number of bedrooms	
	NoH	Number of living rooms	
	NoT	Number of bathrooms	
	houseuse	Use of house	0 = common residential, 1 = commercial residential, 2 = other
	intedesign	Furnishing situation	0 = no, 1 = simple, 2 = furnished, 3 = other
	heatcon	Heating situation	0 = central, 1 = self, some missing
	orientcon	Main orientation	0 = south, 1 = east, 2 = north, 3 = west
	residential	Common residential or not	0 = other, 1 = common residential (*houseuse* = 0)
	commerresi	Commercial residential or not	0 = other, 1 = commercial residential (*houseuse* = 1)
	*design*0	No decoration or not	0 = other, 1 = no decoration (*intedesign* = 0)
	*design*1	Simple decoration or not	0 = other, 1 = simple decoration (*intedesign* = 1)
	*design*2	Well-furnished or not	0 = other, 1 = furnished (*intedesign* = 2)
Location Feature (L)	*dtqxzx*	Distance to county center	Distance to the geometric center of the construction land in the county where the sample is located (km)
	far	Far in the county or not	0 = near, 1 = far (*dtqxzx* > *average*, county-based)
Neighborhood Features (N)	*elevator*	With an elevator or not	0 = no, 1 = yes, some missing
	buildtime	Time of construction	
	builddecade	Decade of construction	0 = before 1990, 1 = 1991–2000, 2 = 2001–2010, 3 = 2011–2015, 4 = after 2016, some missing

Table 2 (continued)

Type	Variable Name		Meanings
Dealing Features (D)	*NoPA*	Number of price adjustments	
Mixed land use Features (MLU) (Intervening Variables)	*ZScore*	Aggregated mix index	Aggregated index of mixed land use using principal component analysis method (PCA)
	*ZScore*01	Normalized *ZScore*	
	DomiType	Dominant type of mixed land use	0 = other, 1 = public-service-dominated, 2 = commercial-service-dominated, 3 = public-commercial-balanced
	POI_A	Number of POI-A	Number of public services POI within 1000
	POI_B	Number of POI-B	Number of commercial services POI within 1000
	POI_G	Number of POI-G	Number of green and open space POI within 1000
	POI_IW	Number of POI-A	Number of industrial and logistics POI within 1000
	POI_S	Number of POI-S	Number of transportation facilities POI within 1000
	Adominate	"Public-service-dominated" type or not	0 = other, 1 = public-service-dominated (*DomiType* = 1)
	Bdominate	"Commercial-service-dominated" type or not	0 = other, 1 = commercial-service-dominated (*DomiType* = 2)
	ABdominate	"Public-commercial-balanced" type or not	0 = other, 1 = public-commercial-balanced (*DomiType* = 3)

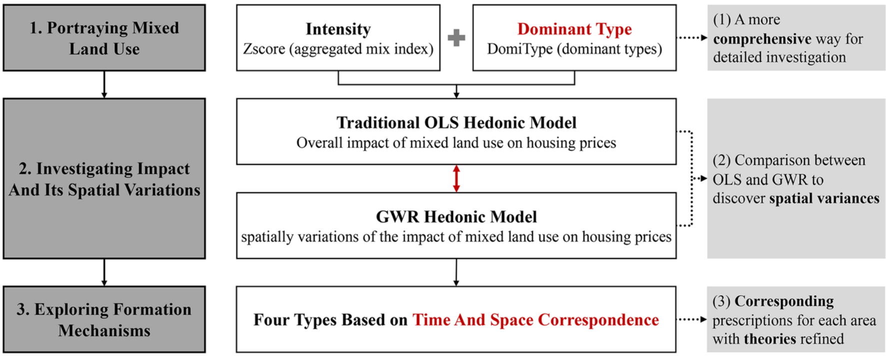


Fig. 3 This study's theoretical analysis framework

limitation of the GWR model (Li et al., 2019), this study refers to Shen et al. (2020) and selects the communities as the basic regression unit whose data have been aggregated to represent each of them.

$$lnP_i = \beta_0\left(\mu_i, v_i\right) + \beta_1\left(\mu_i, v_i\right)x_{i1} + \beta_2\left(\mu_i, v_i\right)x_{i2} + \cdots + \beta_n\left(\mu_i, v_i\right)x_{in} + \varepsilon_i \quad (4)$$

where $\left(\mu_i, v_i\right)$ is the geographic location for each sample point in the projection coordinates system. $\left(x_{i1}, x_{i2}, \ldots, x_{in}\right)$ includes all the control and intervening variables selected in this study. $(\beta_1\left(\mu_i, v_i\right), \beta_2\left(\mu_i, v_i\right), \ldots, \beta_n\left(\mu_i, v_i\right))$ are the estimated coefficient, the formula as follows:

$$\hat{\beta}(\mu_i, v_i) = \left[X^T W\left(\mu_i, v_i\right)X\right]^{-1} X^T W(\mu_i, v_i)Y \quad (5)$$

where $W\left(\mu_i, v_i\right)$ is the spatial weight matrix, W_{ij} is the spatial weight of sample point i to sample point j that is calculated using a Gaussian function:

$$W_{ij} = e^{-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2} \quad (6)$$

where d_{ij} is the distance between sample point i and sample point j, b is the most adaptive bandwidth obtained using AICc criterion.

The control and intervening variables in the classic OLS hedonic model are modified or regenerated to accommodate the new regression unit. Specifically, *NoR*, *NoH*, *NoT*, *buildtime* and *NoPA* are aggregated by the mean value, with *heatcon* and *orientcon* taking the percentage. The variables *houseuse* and *intedesign* are split into multiple zero–one dummy variables, aggregated by taking the percentage, and partly removed considering the collinearity problem.

Theoretical Analysis Framework

The following theoretical analysis framework is developed to respond to the research questions (see Fig. 3). First, compared to most previous studies dealing with the degree of mixed land use, we will also focus on the various dominant types. By introducing them into the regression models, we will discuss the potential implications regarding how mixed land use under different dominant functions could heterogeneously impact housing prices. Second, studies have already been tackling with spatial autocorrelation factors (Shen et al., 2020; Wu et al., 2018). We will compare the traditional OLS with GWR models at different scales to reveal the spatial variations of the impact in a more detailed way. Furthermore, we will explore the mechanisms behind the impact and its spatial variations considering the urban expansion sequence and provide corresponding policy recommendations, which will contribute to understanding how mixed land use is developed theoretically from a life cycle perspective.

Research results

The Overall Impact of Mixed Land Use on Housing Prices

Several models are built and the regression results are shown in Table 3. There are only control variables in model 1, the aggregated mix index added in model 2, and the dominant types further added in model 3. Model 4 adds the number of POIs based on model 1 and forms a comparison with model 2 and model 3. Model 5 and model 6 consider the fixed effects of the districts and the commercial circles based on model 3. Model 4 does not perform as well as the former model 2 and model 3 in terms of the goodness of fit and the significance levels of the estimated coefficients, indicating that indicators related to mixed land use have better explanatory power for housing transaction prices. All these models can pass the collinearity tests.

In general, most control and intervening variables have a significant impact on the housing transaction prices, and the positive and negative signs of the estimated coefficients are mainly consistent with common sense (Li and Brown, 1980; Chau and Chin, 2003; Xiao, 2017). With other variables controlled, more bedrooms, living rooms, and bathrooms may lead to higher prices (at the 99% confidence level). This holds the same when it comes to the non-shared ownership compared to the shared ownership, the common residential to the commercial residential, the well-furnished to the rough, the south or east oriented compared to the north or west oriented, the elevator-equipped to their counterparts, those closer to district center it belongs to, and those with lower times of price adjustment. These findings are consistent with most previous studies. For example, Lu (2018) found that a south-facing orientation was associated on average with a 14% premium in property value in Shanghai. Duan et al. (2021) discovered that the distance to downtown could have mediation effect on housing prices through urban facilities. The times of price adjustments may reveal the potential impact from the market stability (Xiao, 2017).

The age of construction may have a relatively complex impact on housing prices. Most estimated coefficients are negative but insignificant in models without considering the fixed effect, but they turned significantly positive in model 5 and model 6. The absolute values of the coefficients increase as the house age decreases, with the largest leap happening between the 1991–2000 and 2001–2010 groups. This phenomenon may be related to the potential deficiencies in construction standards

Table 3 Main model results of global classic OLS regression (sample as the unit)

Dependent:*ln HP_total*	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
NoR	0.237***	0.242***	0.241***	0.239***	0.262***	0.269***
	(43.16)	(45.71)	(45.66)	(43.52)	(66.15)	(78.91)
NoH	0.149***	0.153***	0.152***	0.148***	0.147***	0.126***
	(22.99)	(24.44)	(24.51)	(22.89)	(31.37)	(31.1)
NoT	0.259***	0.259***	0.260***	0.258***	0.201***	0.153***
	(26.86)	(28.00)	(28.13)	(26.84)	(28.80)	(25.04)
tenure 0. non-shared						
1.tenure	-0.057***	-0.042***	-0.040***	-0.057***	0.007	0.013**
	(-6.93)	(-5.26)	(-5.03)	(-6.90)	(1.20)	(2.60)
houseuse 0. common						
1. commercial	-0.615***	-0.643***	-0.653***	-0.610***	-0.711***	-0.765***
	(-23.38)	(-25.39)	(-25.88)	(-23.25)	(-37.52)	(-46.16)
2. other	0.159*	0.212***	0.224***	0.163*	0.286***	0.373***
	(2.45)	(3.39)	(3.60)	(2.51)	(6.13)	(9.18)
intedesign 0.no						
1. simple	0.061***	0.023	0.023	0.061***	0.006	-0.008
	(4.44)	(1.74)	(1.74)	(4.42)	(0.57)	(-0.91)
2. furnished	0.175***	0.132***	0.131***	0.172***	0.091***	0.059***
	(13.69)	(10.73)	(10.64)	(13.56)	(9.87)	(7.37)
3. other	0.088***	0.059***	0.059***	0.087***	0.055***	0.038***
	(5.85)	(4.10)	(4.13)	(5.83)	(5.13)	(4.12)
heatcon 0. self						
1. central	0.185***	0.189***	0.188***	0.193***	0.106***	0.125***
	(8.35)	(8.85)	(8.88)	(8.72)	(6.61)	(8.82)
orient 0. north/west						
1. south/east	0.173***	0.160***	0.155***	0.174***	0.152***	0.159***
	(10.16)	(9.77)	(9.49)	(10.27)	(12.4)	(15.20)
dtqxzxkm	-0.020***	-0.008***	-0.008***	-0.020***	0.013***	-0.002
	(-36.67)	(-12.68)	(-13.49)	(-36.59)	(20.35)	(-1.22)
elevator 0. no						
1. yes	0.195***	0.195***	0.195***	0.200***	0.086***	0.082***
	(19.57)	(20.3)	(20.40)	(20.09)	(11.85)	(12.71)
builddecade 0. before 1990						
1. 1991–2000	-0.011	-0.033	-0.034	-0.010	0.147***	0.168***
	(-0.62)	(-1.90)	(-1.95)	(-0.55)	(10.91)	(13.66)
2. 2001–2010	0.073***	0.091***	0.090***	0.073***	0.411***	0.435***
	(3.84)	(4.97)	(4.98)	(3.86)	(28.38)	(32.52)
3. 2011–2015	-0.069***	-0.020	-0.016	-0.071***	0.455***	0.511***
	(-3.42)	(-1.01)	(-0.82)	(-3.50)	(28.77)	(35.37)
4. in and after 2016	-0.149***	-0.057**	-0.051*	-0.148***	0.430***	0.524***
	(-7.03)	(-2.76)	(-2.50)	(-6.98)	(25.9)	(34.57)
NoPA	-0.012***	-0.010***	-0.010***	-0.012***	-0.007***	-0.004***

Table 3 (continued)

Dependent:*ln HP_total*	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(-14.49)	(-13.21)	(-13.27)	(-14.57)	(-11.15)	(-7.93)
ZScore01		1.33***	1.330***		0.826***	0.248***
		(34.13)	(34.15)		(26.67)	(5.94)
Bdominate			-0.043***		0.007	0.007
			(-4.81)		(1.04)	(1.10)
ABdominate			-0.092***		-0.009	-0.005
			(-10.39)		(-1.35)	(-0.81)
POI_A				0.0001*		
				(2.40)		
POI_B				-0.0002***		
				(-6.52)		
POI_G				-0.001**		
				(-3.27)		
POI_IW				-0.0007***		
				(-4.85)		
POI_S				0.001***		
				(6.62)		
Constant	3.668***	2.474***	2.543***	3.660***	2.564***	3.156***
	(104.47)	(50.85)	(51.72)	(103.52)	(67.16)	(68.74)
N	14,628	14,628	14,628	14,628	14,628	14,618
Adjusted R^2	0.4774	0.5160	0.5200	0.4803	0.7308	0.8065

This table reports marginal effects. Robust standard errors are reported in parentheses. *, **and***denote statistically significant at the 10%, 5% and 1% levels, respectively

and the relatively poorer maintenance of the houses built before 2000. This result is consistent with the findings in other Chinese cities like Beijing and Hangzhou (Xiao et al., 2019; Zhang & Dong, 2018). In model 5, houses built in and after 2016 show slightly lower transaction prices than those built between 2011–2015 with other variables controlled, which may be related to an increase in the proportion of affordable housing more recently (Dong et al., 2017).

Regarding the dominant type, model 3 shows that being in the ABdominate type may significantly decrease the housing transaction prices by about 9.2% compared to their counterparts. This lower inclination in statistics remains the same in model 5 and 6, indicating that the current "public-commercial-balanced" type across Qingdao are having negative effects on housing prices. Being in the Bdominate type can also significantly decrease the housing transaction prices by about 4.3% compared to their counterparts, while the average impact turns to be insignificantly positive when considering the fixed effects in model 5 and 6. These estimated results suggest that the "public-service-dominated" type of mixed land use may be the most preferred in the current real estate market of Qingdao.

Spatial Variations of The Impact of Mixed Land Use

The above classic OLS models reveal a positive effect of mixed land use on housing transaction prices at the global level. However, the regression coefficients of each major indicator change after the inclusion of fixed effects, suggesting that the spatial factors may play a great role. The transaction-sample-level data are aggregated using the community as the regression unit, and a community-based geographically weighted regression (GWR) model is established. The main regression results are shown in Table 4.

Most estimated coefficients of the control variables are still significant in community-based models. The mean values of the coefficients in the community-based GWR model are mostly in agreement with the community-based OLS and sample-based OLS results. For the control variables, "whether it is simply decorated or not" has a positive but insignificant effect in the OLS model, yet shows an averagely negative effect in the GWR model. For the intervening variables, the effect of aggregated mix index on housing prices is averagely negative in the GWR model, which is opposite to the previous OLS models. Previous research considering

Table 4 Overall results of the plot-based OLS and GWR models (community as the unit)

	Model 7 (OLS)		Model 8 (GWR)	
	β	t	mean	sd
NoR	0.243***	11.527	0.305	0.086
NoH	0.237***	11.313	0.192	0.083
NoT	0.309***	14.83	0.136	0.117
tenure	-0.022	-1.536	0.014	0.035
commerresi	-0.117***	-7.408	-0.17	0.075
design1	0.011	0.558	-0.019	0.055
design2	0.153***	8.05	0.059	0.066
heatcon	0.065***	4.446	0.01	0.057
orientcon	0.06***	3.936	0.061	0.079
dtqxzxkm	-0.071***	-4.244	0.011	0.569
elevator	0.227***	11.482	0.083	0.076
buildtime	-0.186***	-8.13	0.24	0.144
NoBargain	-0.064***	-4.466	-0.046	0.06
Zscore01	0.204***	11.526	-0.053	0.302
Bdominate	-0.007	-0.333	-0.003	0.06
ABdominate	-0.03	-1.406	-0.01	0.051
Intercept	-0.000	0	0.223	0.709
RSS	1010.827		226.979	
Adjusted R^2	0.549		0.878	
AICc	4626.349		2179.019	
Reduced AICc			2447.33	

*, **and***denote statistically significant at the 10%, 5% and 1% levels, respectively

spatial autocorrelation showed the same negative effect of mixed land use on housing prices (Wu et al., 2018), indicating that the impact may vary enormously by location. The estimated coefficients for *Bdominate* and *ABdominate* are not significant. However, their positive and negative signs in community-based OLS and GWR remain mostly the same as in the previous models. That is, with all other factors controlled, being in the Bdominate and ABdominate negatively impact housing prices, and the negative effect of ABdominate is more pronounced. Public service facilities may be most preferred in the real estate market in Qingdao, since the influence of Adominate type should be positive compared to the counterparts. A satisfactory public-commercial-balanced type of mixed land use can be challenging to reach.

The spatial distributions of the coefficients and the corresponding p-value of the intervening variables are further examined (see Fig. 4). For the aggregated mix index, the confidence level is generally high, with positive and high values mainly in the coastal areas of HD, SN, and LC. Negative and low values are mainly distributed in the eastern and northern regions around the Jiaozhou Bay, indicating that the mixed land use here may have a negative effect due to the chaos and disorder. For the dominant type, the confidence levels of the influences of Bdominate on housing prices are mostly significant overall, while those of ABdominate decreases slightly. Specifically, the high values of the estimated coefficients for Bdominate are mainly distributed in SB, LC, part of CY, JM, and HD, with the low values mainly in SN. For the ABdominate type, the high values of the estimated coefficients are basically located in SN and LS, part of LC, CY, and HD. The low values are mainly in the junction area of SN and SB. The places with negative values may be in a less efficient state in terms of mixed land use.

Comparative Analysis of OLS and GWR Based on Districts

There are apparent spatial–temporal differences in the process of urban expansion in Qingdao. The geographically weighted regression has revealed the diverse characteristics among "Eastern Jiaozhou Bay—Northeastern Jiaozhou Bay—Western Jiaozhou Bay—Central and Northern part of the city", which corresponds to the time sequences of urban construction. Therefore, the results of the classic OLS (by districts and counties) and the community-based GWR model are further compared by aggregating the results to districts and counties (see Fig. 5). The dashed horizontal line is the global classic OLS result conducted to each district and county based on model 3. The solid gray line reports the mean and standard deviation of the GWR results in each district and county. The darker the color of the label, the higher the confidence level in the classic OLS model is.

The aggregated results of the GWR models differ from that of OLS, which means that the estimates without considering spatial autocorrelation may be biased. For the aggregated mix index, the coefficients of LC, SB, and HD in OLS models are significantly positive, close to or even higher than the global result. Those of CY and JM are significantly positive but lower than the global result. Those of JZ are

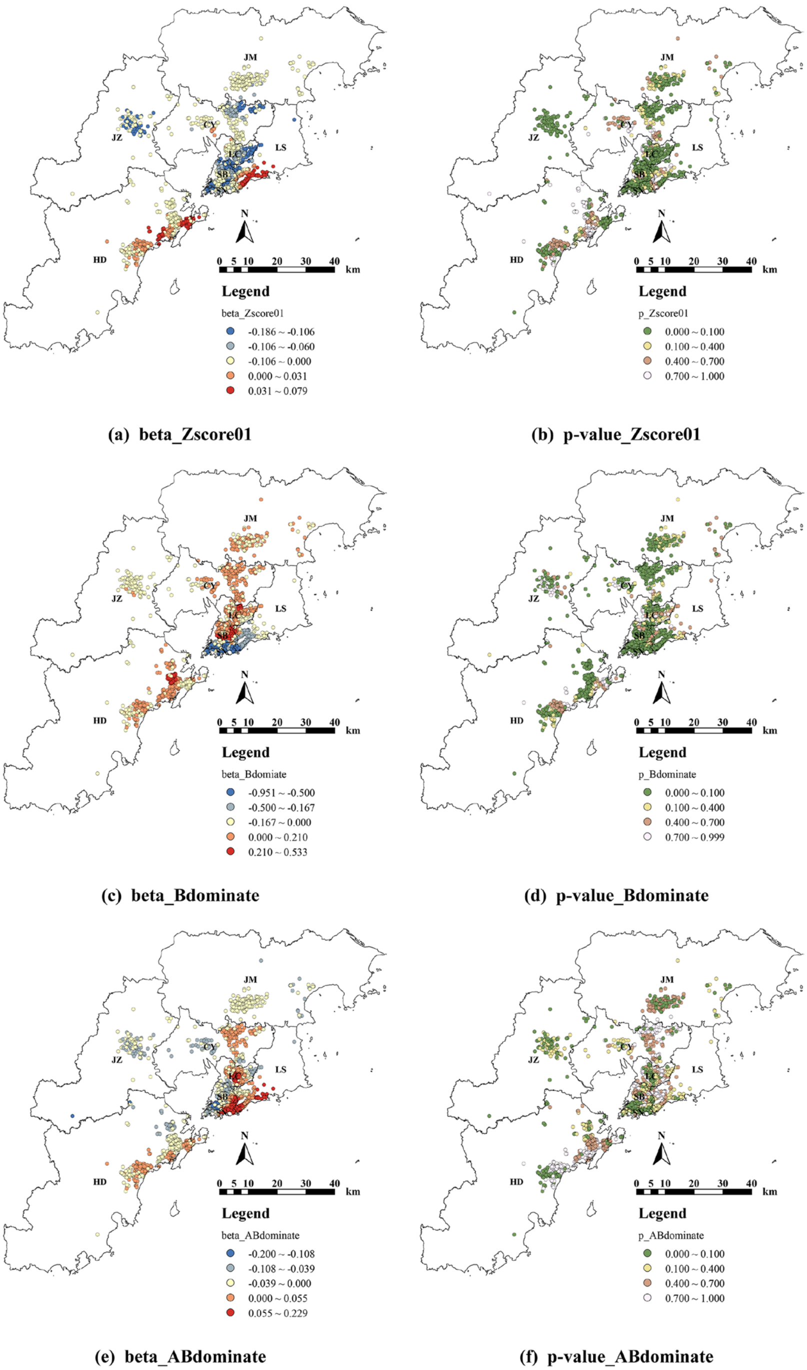
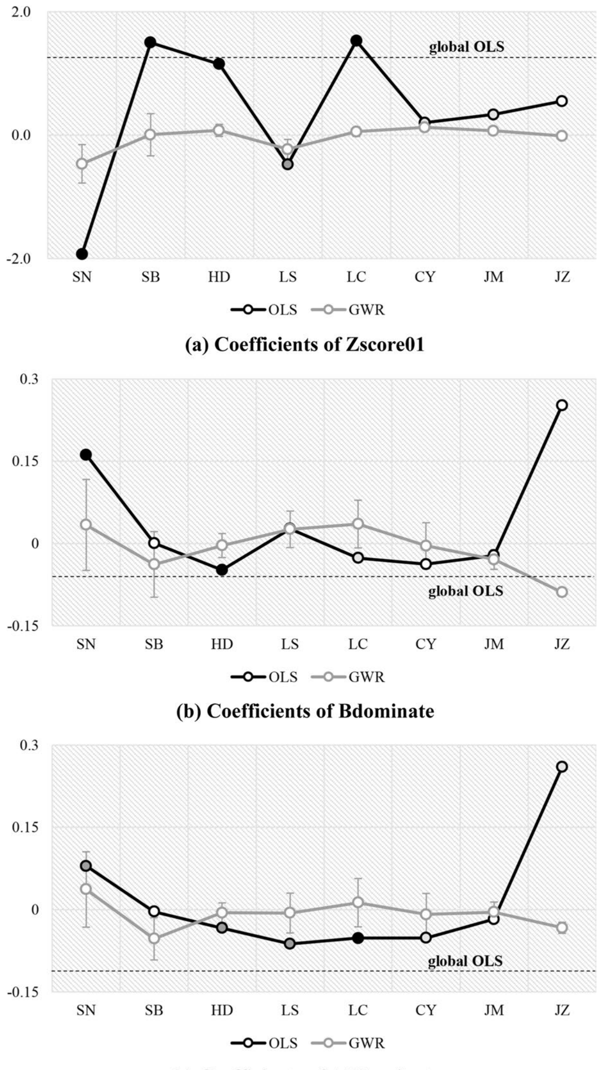


Fig. 4 Spatial distribution of the coefficients and p-values of the main indicators in the geographically weighted hedonic price model

Fig. 5 Statistical results of the results of OLS and GWR by districts and counties



insignificantly positive, probably due to the relatively small sample size. The aggregated mix index negatively affects the housing prices in SN and LS, suggesting that the higher degree of mixed land use here may have brought chaos instead of positive influences. The GWR model shows that the aggregated mix index also has a negative effect on housing prices in SN, SB, and LS. The average value of the coefficients in HD, LC, CY, and JM are generally smaller than those in OLS models. These all indicate that mixed land use may have a worse effect on housing prices when considering spatial autocorrelation. The contrast is particularly pronounced in the central part of the city, suggesting that the negative effect of mixed land use on housing prices here may be largely neglected.

For the dominant type, the estimated results in the OLS models are higher than the global one in almost all districts and counties, and the GWR results are generally consistent with the OLS models. The coefficients of the Bdominate type are generally higher than those of the ABdominate. The differences between districts and counties brought by the Bdominate type are also more pronounced than the ABdominate. Generally, being in the Bdominate type or the ABdominate type has a more positive effect in the core and old areas of Qingdao, like SN. While in the central parts like SB, LS, HD, LC, and CY, Bdominate and ABdominate are having negative effects on housing prices in an unstable yet prominent way. More imbalances may exist in the northern outlying areas since the estimated coefficients show opposite signs in OLS and GWR models.

Discussion

Three Dominant Types in Qingdao

Both the sample-based OLS model and the community-based GWR model reveal that mixed land use of different dominant types has different effects on housing prices. The mixed land use of the public-service-dominated type may positively impact housing prices compared to the counterparts, while the commercial-service-dominated type negatively impacts housing prices, and the public-commercial-balanced type has an even worse effect.

The mixed land use dominated by public service facilities can bring in more convenience and order, thus promoting the living qualities of the corresponding neighborhood and pushing up the housing prices (Van Cao & Cory, 1982). However, the mixed land use with commercial facilities may have distinctly two sides. The comparison between districts and counties shows that the adverse effects of Bdominate are not as strong and pronounced as in the global OLS regressions. In contrast, the negative effect of ABdominate type is more widespread and undeniable. For example, both Bdominate and ABdominate positively affect housing prices only in SN district, the most central part of the city. Though the public-commercial-balanced type of mixed land use has gained popularity in some newly developed areas in recent years, they need to be sustainably rooted to be truly effective. They may bring in more chaos and conflicts. For example, it is common that medical institutions like clinics or hospitals are mixed with fragmented commercial services nearby. And the resulting neighborhood environment turns out to be less welcomed in the real estate market, which is also found in Beijing (Wu et al., 2018). When huge cultural facilities like exhibition halls are mixed with small commercial buildings, the neighborhood tends to be significantly less convenient, consistent with the study by Matthews and Turnbill (2007). They found that the mixed land use with commercial facilities had a more positive effect in highly connected grid-based communities but a negative effect in poorly connected communities. These two specific models of the public-commercial-balanced type are common not only in Qingdao, but also in many large and small cities.

There seems to be a subtle balance between order and convenience, as is manifested by comparing the different patterns of mixed land use. For Qingdao, the positive contribution of order to housing prices is more apparent though not that widespread, and the commercial-service-dominated mix still needs to resolve the chaos that comes along. And an ideal ABdominate type may be difficult to achieve.

Four Types in Time and Space Correspondence

According to the analysis above, the eight districts and counties in Qingdao can be divided into four types, which correspond to the development sequences along “Eastern Jiaozhou Bay (old city area) —Northeastern Jiaozhou Bay (city center area) —Western Jiaozhou Bay (new town area) —Central and Northern part of the city (peripheral town area)”. The first one is Shinan (SN) and Laoshan (LS) in the eastern part of Jiaozhou Bay. They are developed early, have a relatively higher degree of mixed land use, and belong to the “old city area”. The high aggregated mix index here has a negative impact on the housing prices, but being in the Bdominate type shows significantly positive impact. The second is Shibei (SB), Licang (LC), and Chengyang (CY). They are in the northern and eastern part of Jiaozhou Bay, developed earlier and belonging to the “city center area”. The degree of mixed land use here is relatively high, but being in the Bdominate or ABdominate type is not that preferrable, suggesting that the construction activities continue to fill in and some development modes are not playing the facilitating role in the real estate market. The third is Huangdao (HD), the “new town area” in the western part of Jiaozhou Bay, where the past few decades have witnessed rapid progress in urban construction and the flourishment of the real estate market. The degree of mixed land use here is relatively low, positively impacting housing prices, but being in the Bdominate and ABdominate type have significant negative impacts. The fourth is Jimo (JM) and Jiaozhou (JZ), the “peripheral town area” in the central and northern part of the city. The degree of mixed land use is low, and there is an insignificantly positive effect on the housing prices, the impact of the different dominant types having more imbalance and uncertainties.

There are some hidden logics behind. For the “old city area” which has already entered the renewal phase, mixed land use may bring more chaos and negatively impact the housing prices, and this phenomenon has been found in other cities and areas either (Majewska et al., 2020). For the “city center area” that is still at the stage of growth, mixed land use may contribute to the increase of housing prices, especially for the “public-service-dominated” (Adominate) type. For the “new town area” that has been expanding in a drastically rapid speed in recent times, the degree of mixed land use may also have a significantly positive impact similar to the “city center area”. But the mechanism behind can be different, as Wang et al. (2010) pointed out that housing prices in new town area will be generally higher due to policy factors that cannot be easily stripped out in the model. For the “peripheral town area” that is relatively independent to the far center area, the impact of mixed-land-use-related indicators on housing prices is limited, probably because these areas are still in the early stage of construction infill, and the land development here can sometimes encounter obstacles due to the land ownership problems (Tong et al., 2018).

These four types can be linked to the different stages in the time course or life cycle of urban construction. The inversed gradient pattern of "Central and Northern part of the city—Western Jiaozhou Bay—Northeastern Jiaozhou Bay—Eastern Jiaozhou Bay" can be corresponded to the development stage of mixed land use which is the "budding period—accelerating period—stable period—mature period", similar to the life cycle of a plot's development (Lotteau et al., 2015). There may be more uncertainties in the budding period. Mixed land use positively affects housing prices in the accelerating or stable period. While the negative effects may occur due to the chaos and disorder in the mature stage. This corresponding feature in time and space may be widespread since mixed land use does manifest itself in different ways in the central and peripheral urban areas (Shi & Yang, 2015).

Policy Implications and Further Research Topics

The three dominant types of mixed land use and the four types in time and space correspondence may reflect some natural law of construction expansion in terms of the evolution of the planning logic. Several policy implications are as follows.

First, mixed land use should be paid more attention due to its compounded and changing externalities. Research and practice should focus more on the mechanisms behind, especially from the dynamic perspective of development stages. Second, different patterns or dominant types of mixed land use may perform differently despite their common function. In Qingdao, mixed land use of "public-service-dominated" type may prevail over other types with differences between the older and newer areas, requiring further investigation at smaller scales. Third, there may exist a subtle balance between homogeneity and the mixture of functions (Song & Knaap, 2004). For example, recent real estate development projects should think more about the effective mix of urban functions rather than some single function or simple repetition. However, the renewal or regeneration projects in old city areas should be cautious about the potential adverse effects like chaos. Since mixed land-use projects can take a long time and their returns uncertain, interventions should involve operations, maintenance, and institution building other than physical facilities (Grant, 2002).

Conclusion

In summary, this study establishes a framework for analyzing mixed land use that covers both the degree and the dominant type of mixed land use and incorporates them into the hedonic models. We use Qingdao as the case site and find that: First, the mixed land use related indicators have better explanatory power on housing prices than simply including the raw data of facilities. In a global sense, the degree of mixed land use has a significantly positive impact. While the "commercial-service-dominated" (Bdominate) type and "public-commercial-balanced" (ABdominate) type impose negative effects. Second, when considering spatial autocorrelation, the degree of mixed land use negatively affects housing prices on average. The effects of the different dominant types vary from space to space. It remains the same that the Bdominate type generally has a negative effect, and the ABdominate type is the least satisfactory in most areas. Third, the direction of urban construction in Qingdao can be summarized as “Eastern Jiaozhou Bay (old city area) —Northeastern Jiaozhou Bay (city center area) —Western Jiaozhou Bay (new town area) —Central and Northern part of the city (peripheral town area)”. Following this direction, the degree of mixed land use decreases, and its effect on housing prices increases and decreases to below zero. The negative effects of Bdominate and ABdominate type on housing prices also increase and decrease. The eight districts and counties can be divided into four types corresponding to the time sequences of urban construction, and policy implications should be given separately.

There are several innovative contributions. First, this study combines POI data with land use data and establishes a methodological system for portraying mixed land use that focuses on both degree and dominant type. The measurement results are further introduced into a hedonic model that considers spatial autocorrelation. This is an improvement to the traditional research methods. Second, this study compares the results of traditional OLS and GWR models at different scales and explores the spatially-differentiated characteristics of the impact of mixed land use on housing prices. This provides insights for current research in better understanding the regression results and the potential implications. We also analyze the laws and formation mechanisms inherent in the spatial variations from a life cycle perspective and provide corresponding policy prescriptions. This forms a dialogue between the real world and the normative world and enhances the mixed land use theory.

The analytical framework and the model structure established in this study are promising to be applied to other related studies. However, several points could still be improved: First of all, the sample acquisition is limited by the data source, and the spatial distribution may be biased somewhere. Second, due to the model setting and arithmetic limitation, we are using the aggregated version of the transaction samples with communities as basic units in geographically weighted regressions, which is harmless yet requires improvement. Hopefully, this can be resolved with the advancement of models and the computing power in the future. Moreover, though hard to strip, policies may have had a prominent influence on the Chinese real estate market in recent years. Geographic factors like the coastline and natural hills may also play important factors. These should be considered more cautiously in future studies.

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Appendix

Table 5 Qingdao POI reclassification criteria

Class I	Class II	Class III
A public service	04 public cultural facilities	0401 schools
		0402 research institutes
		0403 public culture facilities like museums, etc
		0404 training agencies
		0405 media agencies
	06 sports facilities	
	07 medical health service	0701 hospitals
		0702 clinics
		0703 drugstores
	08 government agencies	0801 township level and below
		0802 above township level
B commercial service	01 food service	
	02 shopping and entertainment	0201 shopping service
		0202 entertainment facilities
	03 other commercial service	0301 life service
		0302 telecommunications and post offices
		0303 accommodation service
		0304 car service
	09 financial service	
	11 commercial housing	
G green and open space	05 green and open space	0501 parks and squares
		0502 tourist sites
IW industrial firms	10 industrial firms	
S transportation service	12 transportation service	1201 bus stops
		1202 subway stations
		1203 parking lots
		1204 railway stations
		1205 bus stations
		1206 fueling stations
		1207 ticket offices

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Data Availability The data used in this study is available upon request.

Declarations

Conflict of interest The authors claim that they have no conflict of interest.

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