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Cultivating historical heritage area vitality using urban morphology approach based on big data and machine learning

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ABSTRACT

The conservation of historical heritage can bring social benefits to cities by promoting community economic development and societal creativity. In the early stages of historical heritage conservation, the focus was on the museum-style concept for individual structures. At present, heritage area vitality is often adopted as a general conservation method to increase the vibrancy of such areas. However, it remains unclear whether urban morphological elements suitable for urban areas can be applied to heritage areas. This study uses ridge regression and LightGBM with multi-source big geospatial data to explore whether urban morphological elements that affect the vitality of heritage and urban areas are consistent or have different spatial distributions and daily variations. From a sample of 12 Chinese cities, our analysis shows the following results. First, factors affecting urban vitality differ from those influencing heritage areas. Second, factors influencing urban and heritage areas' vitality have diurnal variations and differ across cities. The overarching contribution of this study is to propose a quantitative and replicable framework for heritage adaptation, combining urban morphology and vitality measures derived from big geospatial data. This study also extends the understanding of forms of heritage areas and provides theoretical support for heritage conservation, urban construction, and economic development.

1. Introduction

In the 20th century, the conservation of historical heritage was a key topic in urban planning, as it is a widely recognized way to promote community economic development and societal creativity (Greffe, 2012; Tyler, Tyler, & Ligibel, 2018). In general, the development of conservation of global historical heritage has two distinct evolution routes. On the one hand, early conservation of historical heritage almost entirely focuses on individual structures, which are often buildings, monuments, and archaeological sites (Whitehand & Gu, 2010). As the concept shifted (Jokilehto, 1998), historical heritage conservation is no longer limited to individual structures and has expanded from single buildings to groups of buildings. Then, the conservation of historic urban landscapes is considered (Ringbeck, 2018). At present, the scope of historical heritage conservation has gradually shifted to the entire historic heritage area (Bandarin & van Oers, 2012). Overall, historical heritage conservation has undergone a paradigm shift from individuals to groups and areas (Ahmad, 2006; Glendinning, 2013). On the other hand, the idea of historic heritage conservation has changed from museum-style conservation to diversified utilization of heritage areas (Wang, 2019). Thus, the concept of heritage adaption was proposed (ICOMOS, A, 1979), which is defined as enhancing the vitality of heritage areas. Heritage adaptation can bring multiple social benefits (Conejos, Langston, & Smith, 2011), adapt to the transformation of modern industrial cities (Plevoets & Sowińska-Heim, 2018), and expedite the development of surrounding communities (Bullen, 2007; Conejos, Langston, & Smith, 2013).

Creating a more vibrant heritage area through planning has not yet been fully discussed, although research on urban planning and urban vitality has emerged (Lan, Gong, Da, & Wen, 2020; Still & Simmonds, 2000; Yang & Pan, 2020). Mounting evidence suggests that urban morphological elements (e.g., ground plan, building pattern, land use

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pattern, etc.) can significantly affect urban vitality (Marcus, 2010; Oliveira, 2013; Wang, 2021; Wu, Ta, Song, Lin, & Chai, 2018; Wu, Ye, Ren, & Du, 2018). However, it remains unclear whether urban morphological elements equally and effectively foster the vitality of historical heritage areas for at least the following three possible reasons.

First, the unique morphological characteristics of heritage areas are significantly different from those of the generally considered vibrant urban areas (Whitehand, Gu, Whitehand, & Zhang, 2011). Heritage areas are often characterized by narrowness, single function, low height, and low density, whereas the opposite is featured in vibrant urban areas. Second, heritage areas are subject to stricter planning control than urban areas, and their original morphological characteristics cannot easily change. Therefore, promoting regional vitality through morphological strategies is more challenging (Ged & Marinos, 2011; Whitehand & Gu, 2007). Finally, the heritage area itself may be relatively inactive. The historical heritage conservation area is usually located in the city's core (Rossi & Tarragó, 1982), where the land value is higher and possibly over-commercialized (Wu, Wang, Zhang, Zhang, & Xia, 2019). Consequently, high land rent may change a community's socioeconomic class and reduce its population density (Jackson, Forest, & Sengupta, 2008). Over-commercialization may also harm tourists and residents (Hwang, 2015). Therefore, it is worth further discussing how to cultivate a vibrant heritage area through the urban morphology approach.

Meanwhile, the emergence of big geospatial data allows for depicting urban morphological elements of heritage areas more precisely (Agapiou et al., 2015; Kitchin, 2014; Saito, Said, & Shinozaki, 2017). The accompanying machine learning technology complements the limitations of traditional statistics in massive data processing reliability reduction and slow calculation (Yang & Pan, 2020). The boom of new data and methods has laid a solid foundation for studying morphological vitality strategies. Therefore, with the help of big geospatial data, this study reshapes the technical ways to measure urban morphology and vitality concerning urban heritage. The morphological approach to the vitality of heritage areas is explored by combining ridge regression and LightGBM. The paper is arranged as follows: Section 2 introduces the research methods. Section 3 describes the study area and data sources. Section 4 presents the analysis of the results. Section 5 discusses the empirical results. The conclusion is summarized in the last section.

2. Analytical framework

A quantitative research approach is proposed to understand the relationships between the urban morphological elements and the vitality of heritage areas at the block level (Fig. 1). The approach contains three essential parts. First, vitality is measured using open-sourced big geospatial data. Second, urban morphology measurements are defined and conducted. Finally, machine learning algorithms are performed to analyze and discuss the differences in elements that affect vitality from multiple perspectives, including heritage and urban areas, daytime and nighttime, and differences across cities.

2.1. Measurement of urban vitality

Vitality can be defined and quantified (Yue et al., 2017). Table 1 lists several commonly used measurements that are generally divided into two theoretical types (Yue, Chen, Zhang, & Liu, 2019): one considers that vitality is a crucial urban factor in expanding the scope of human activities (Lynch, 1984), the richness of urban activities, or the intensity of land use (He et al., 2018; Jin et al., 2017; Zhang et al., 2020); the other is based on Jacobs's diversity measurement to study vitality (Jacobs, 1961), under which framework pedestrian volume is frequently used as a measurement (Sung, Go, & Choi, 2013; Wu, Ta, et al., 2018; Wu, Ye, et al., 2018; Yue et al., 2017).

These methods have their relative merits and drawbacks. Geo-tagged small food facilities are used frequently to characterize urban vitality (Xia, Yeh, & Zhang, 2020; Ye, Li, & Liu, 2018; Yue & Zhu, 2019; Zhang et al., 2020). The spatial distribution of small food facilities is formed by the owner and the crowd (Yue & Zhu, 2019). They are usually located in places with high accessibility, attracting a dense and diverse crowd, directly related to their survival and success (Dawson, 2012). Therefore, the spatial organization of small food facilities reflects the changes in human activities to a large extent (Dong, Ratti, & Zheng, 2019). Using

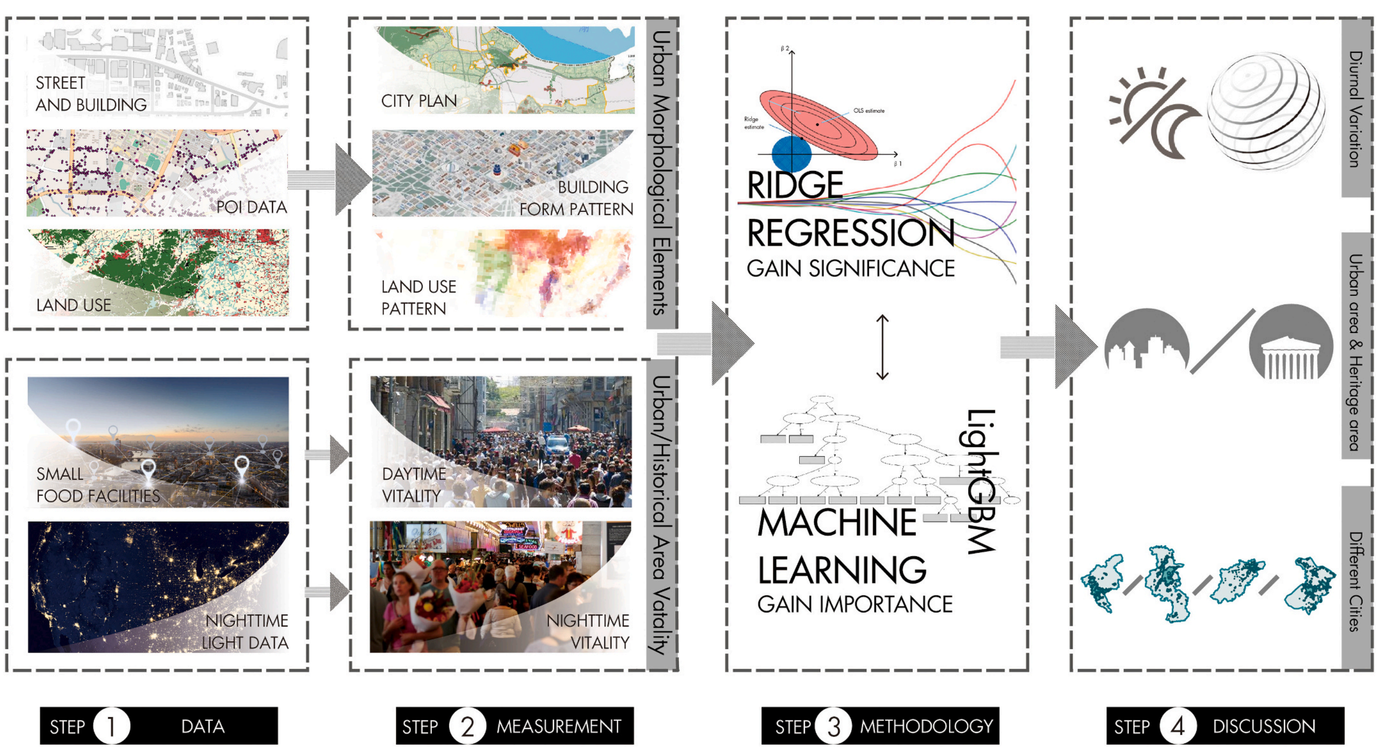

Fig. 1. Analysis approach.

Table 1
Commonly used methods of measuring vitality.

Author (year), study area	Data source & method	Advantages	Disadvantages
Sung, Lee, & Cheon (2015), Seoul, South Korea	Counting the number of pedestrians on the street through a manual survey.	The street vitality each hour can be recorded with high accuracy.	The high cost of data acquisition limits that it can not be used on a macro scale.
Yue et al. (2017), Shenzhen, China	The number of mobile phone users actively recorded by the mobile phone tower provided by a major mobile phone operator in half an hour interval.	The actual usage of cell phones is not required. The dataset has a finer spatial-temporal granularity, can represent the spatial-temporal rhythm.	The dataset is not disclosed to the public and is challenging to obtain.
Li, Wang, Wang, & Wu (2016), Beijing, China	Mobile phone location records provided by Tencent.	There is a large amount of data, and the data is accurate. After inspection, the distribution of mobile location records is positively correlated with the actual distribution of population density.	The socioeconomic characteristics and activity types of users at a specific time and place cannot be identified.
Wang (2021), China	POI data obtained by open API services of Dianping	Data is easy to access and is a powerful way to reflect the urban pattern.	The contribution of each point to vitality is not considered.
Zeng, Wei, & Liu (2020), Shanghai, China	Bike-sharing data provided by bike-sharing operator Mobike.	An understanding of an individual's mobility can be established, especially on the characteristics of travel behavior.	Only departure and arrival areas of sharing bikes can be captured, and the amount of data is low and inaccurate.
Kim (2018), Seoul, South Korea	The density of Wi-Fi access points provided by the government and network operators.	The vitality of virtual space can be measured and compared with that of physical space.	Private Wi-Fi access points are not included. The virtual vitality may show errors for the younger generation and the elderly.
Li, Li, Li, & Long (2020), China; Li, Zhou, & Wang (2018), USA	Check-in and comment data captured by Social Networking Services (SNS) (e.g., Twitter, Foursquare, Flickr, and Weibo.)	An area with more check-in can attract more people and contribute more to urban vitality.	People who do not use SNS, such as the elderly's contribution to urban vitality, are largely ignored.
Kim (2020), Seoul, South Korea	Dedicated dataset for pedestrian traffic provided by SK Telecom.	It helps to overcome the temporal ambiguity of urban vitality studies based on big spatiotemporal data.	Pedestrian traffic data are not free from their inherent biases.
Ye et al. (2018); Zhang et al. (2020); Zheng, Hu, Wang, & Wang (2016), China	Geotagged small food facilities.	The spatial distribution of small food facilities is formed by the owner and the crowd (Yue & Zhu, 2019). Small food facilities are often located in a place where people can easily access, attracting a dense and diverse crowd, directly related to the business's survival and success (Dawson, 2012). Therefore, the spatial organization of small food facilities reflected the changes in human activities to a large extent, representing the intensity of the urban economic activities (Dong et al., 2019).	Small food facilities are representative of only a specific aspect of vitality.
Levin & Duke (2012); Mellander, Lobo, Stolarick, & Matheson (2015), Sweden, Israel, Palestine	Nighttime light images.	Data are relatively accessible and have been regarded as a good indicator of urban expansion and activity.	The image resolution is relatively low and reacts only to vitality at night.

geographical small food facilities to measure urban vitality has two advantages. First, this method is more time-saving and labor-saving than traditional methods, such as manual investigation. Second, geo-tagging has higher accessibility, updatability, and explainability than other big data methods, such as mobile positioning, and can accurately capture the spatial changes in urban vitality (Yue & Zhu, 2019). Therefore, small food facilities can be more effective in symbolizing urban daytime vitality but cannot reflect nighttime vitality.

Daytime and nighttime urban vitality have considerable differences (Xia et al., 2020). Indeed, urban economic activities are reshaped at night. As the most prominent feature of a night city, light is associated with socioeconomic parameters, including economic activity, urbanization, and population density (Wang et al., 2018; Zhang & Seto, 2011). People's social activities usually occur in bright areas at night, whereas dark spots are characterized by low or poor populations (Bennett & Smith, 2017). Therefore, nighttime lights are also regarded as one of those most reliable indicators of nighttime vitality and are widely used to represent human activities and spatial changes (Keola, Andersson, & Hall, 2015; Levin & Duke, 2012; Levin & Zhang, 2017).

Overall, geo-tagged small food facilities and nighttime light data are used to characterize daytime vitality (DV) and nighttime vitality (NV), respectively, in this study. Specifically, kernel density analysis measures the distribution of geo-tagged small food facilities within a 500-m radius. The weights are set according to the number of comments to obtain the average values of different blocks as the DV value. In contrast, the average value of nighttime light data within the block is the NV value.

2.2. Measurement of urban morphology

All cities can be conceptualized as formed by urban morphological elements: streets, blocks, and buildings (Oliveira, 2016). Conzen (1960) argues the necessity to combine the morphological aspects of the original theory with land use elements to establish a complete interpretation of urban morphology. There has been a growing popularity of Conzenian approaches on urban morphology (Oliveira, 2019). Conzen extended the concept of urban morphology and pointed out that combining three systematic form complexes, i.e., city planning, building base, and land use, constitutes urban morphology, which provides a valuable concept for quantification in this study.

In Conzenian approaches, the block is used as the research unit to quantify the urban form through big data methods. Measurement details are discussed at length and proven their suitability (Wu et al., 2019; Zhang et al., 2019, 2020). Specifically, the ground plan was composed of three subsets: street system, block pattern, and building base. The 2D and 3D building elements from different spatial dimensions constitute the building form pattern (Zhang et al., 2019). Therefore, we divided the building form pattern into two classes: building 2D form and building 3D form. Land use patterns also have two categories: land use function and intensity. The former represents the heterogeneity of urban morphology and reflects different combinations of land use, while the latter demonstrates the speed and efficiency of land development (Fig. 2, Table 2).

2.3. Empirical strategies

The most frequently used models for exploring the relationship between urban morphology and vitality are linear regressions based on the least-squares method and maximum likelihood estimation (Jin et al., 2017; Long & Huang, 2019; Wang, 2021). Nevertheless, they have two potential issues.

First, due to possible sample limitations and common trends among variables, the dataset may present multicollinearity. In traditional statistical analysis, the neglect of multicollinearity can cause ill-informed conclusions based on the regression (Fan, Rey, & Myint, 2017). Therefore, the variance inflation factor was calculated, and a correlation coefficient was computed to test the multicollinearity among independent variables. The results show the existence of possible multicollinearity, for which penalized regressions are often recommended (see Wang and Vermeulen, 2020 for a detailed discussion regarding the benefits of penalized regressions in urban research). In the family of penalized regression, the commonly used models are the Lasso (least absolute shrinkage and selection operator; Tibshirani, 1996) and ridge regression (Hoerl & Kennard, 1970). They are regularized versions of least squares regression using L1 and L2 penalties on the coefficient vector (Verducci, 2007). However, L1 regularization is better at outputting sparse solutions than L2 regularization. The main reason is the built-in feature selection method of the former (Zeng, Gou, & Deng, 2017). Accordingly, Lasso regression causes some variables in the linear regression, resulting in a coefficient of 0 instead of approaching 0. Thus, Lasso can be used for feature selection. However, feature selection is not necessary to compare and discuss regression results with machine learning in this study. Based on the above discussion, we used ridge regression to identify the main vitality determinants of heritage areas.

Ridge regression is a biased estimation that can effectively solve the multicollinearity problem. The regression coefficient can be more practical and reliable at the cost of information loss and reducing precision (Amico & Currà, 2014; Hoerl & Kennard, 1970; Vinod, 1978). In recent years, ridge regression has been applied in different aspects of urban science, such as urban heat islands (Lan & Zhan, 2017), carbon

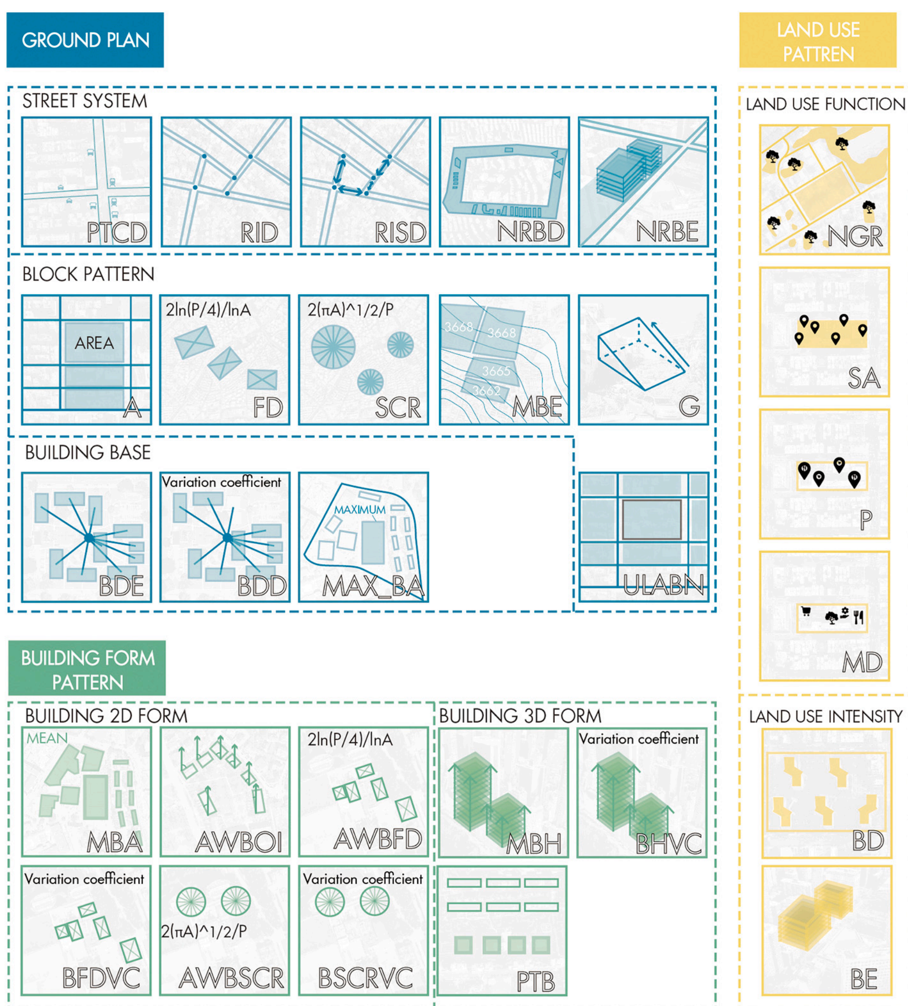

Fig. 2. The framework of urban morphology measurement.

Table 2
Measurement of urban morphology.

Components of urban morphology		Factors	Code
Ground plan	Street system	Public transportation convenience degree	PTCD
		Road intersection quantities	RID
		Road intersection separation distance	RISD
		Near-road building density	NRBD
		Near-road building expandability	NRBE
	Block pattern	Area	A
		Fractal dimension	FD
		Spatial compact ratio	SCR
		The average elevation within the block	MBE
		The average slope within the block	G
		Adjacent Block Number Per Unit Length	ULABN
	Building base	Eccentricity degree of building distribution	BDE
		Dispersion degree of building distribution	BDD
		Max of building area	MAX_BA
Building form pattern	Building 2D form	Mean of building area	MBA
		Building area-weighted orientation index	AWBOI
		Building area-weighted fractal dimension	AWBFD
		Building area-weighted spatial compact ratio	AWBSCR
		Building fractal dimension variation coefficient	BFDVC
		Building spatial compact ratio variation coefficient	BSCRVC
	Building 3D form	Mean of building height	MBH
		Building height variation coefficient	BHVC
		The proportion of the tower building	PTB
Land use pattern	Land use function	Near-block greening rate	NGR
		Green serviceability	SA_GRE
		Industrial serviceability	SA_IND
		Commercial serviceability	SA_COM
		Public serviceability	SA_PUB
		Residential serviceability	SA_RES
		Transportation serviceability	SA_TRA
		The proportion of green service	P_GRE
		The proportion of industrial service	P_IND
		The proportion of commercial service	P_COM
		The proportion of public service	P_PUB
		The proportion of residential service	P_RES
		The proportion of transportation service	P_RES
		Mix degree	MD
	Land use intensity	Building expandability	BE
		Building density	BD

dioxide (Xu, Ou, Liu, Liu, & Zhang, 2021), and PM2.5 (Tao, Zhang, Ou, Guo, & Pueppke, 2020). In this study, the ridge regression model is expressed as:

$$Y_i^* = \beta_1^* X_1^* + \beta_2^* X_2^* + \beta_3^* X_3^* + \varepsilon^*$$

where Y_i^* represents the DV and NV of the heritage area, X_1* are ground plan elements, X_2* are building form pattern elements, and X_3* are land use pattern elements. Unlike ordinary least squares, β_i* are standardized parameters of ridge regression, expressed as:

$$\widehat{\beta}(k) = (X'X + kI)^{-1} X'Y$$

where $X'X$ are correlation matrices among independent variables, $X'Y$ are correlation matrices among predicted and independent variables, respectively $\widehat{\beta}(k)$ is the regression coefficient, and k serves as the ridge parameter, reflecting the bias in the regression (García, García, Martín, & Salmerón, 2015; Lan & Zhan, 2017). The reasonable value of k is determined according to the variance inflation factor.

Second, the above studies merely considered the significance value of independent variables in the regression analysis but ignored their importance. Compared with regression models, machine learning algorithms using Classification and Regression Tree (CART) can calculate the importance of variables. Among the many CART algorithms, we used the gradient boosting decision tree (GBDT) in this study for its efficiency, accuracy, and reliability (Georganos et al., 2018; Natekin & Knoll, 2013). With the recent development of big data, GBDT faces new challenges. When the number of samples is large or the feature dimension is high, GBDT requires a trade-off between efficiency and precision. Three efficient methods based on GBDT were developed in recent years, including XGBoost, CatBoost, and LightGBM. These new methods have been successfully applied in industry, academia, and competitive machine learning (Daoud, 2019). Many studies have compared these improved implementations of the gradient boosting framework and showed that LightGBM is the fastest, most accurate, and most robust using the same time budget of hyperparameter optimization (Daoud, 2019; Ke et al., 2017; Machado, Karray, & de Sousa, 2019; Song et al., 2019).

LightGBM (http://github.com/Microsoft/LightGBM) was developed by Microsoft as a faster and higher performance framework that uses less memory and achieves better prediction (Ma et al., 2018). In LightGBM, Microsoft introduced new features, such as leafwise tree growth and histogram-based algorithms (Fig. 3), to solve the efficiency trade-off (Shi, Cheng, & Xue, 2019). LightGBM can be nearly 20 times more efficient than GBDT with the same accuracy (Ke et al., 2017) and is selected as the machine learning framework in this study to obtain the importance of variables.

With the approaches mentioned, the significance of explanatory variables obtained by ridge regression is used to investigate the elements that affect the vitality of heritage areas and then compare and discuss the importance of explanatory variables obtained using LightGBM. Modern cities are all similar, but their heritage areas are bound to have substantial regional differences. Finally, statistics are created for the significance and importance of explanatory variables for each city, and the factors affecting the vitality heritage area in each city are analyzed.

3. Case study

3.1. Study areas

China is chosen for the empirical study due to its long history, creating many famous historical and cultural cities. Like other countries, China has established its legislation on conserving historical heritage under UNESCO principles (Zhu & Goethert, 2010). In most cases, the historical heritage areas in China are full of vitality because of their diverse functions and convenience.

In China, with rapid industrialization and economic growth during the past few decades, the conservation of historical cities and areas has become a challenge to urban development and social progress (Bell, 2014; Zhang, 2012). The National People's Congress passed the Law of the People's Republic of China on the Protection of Cultural Relics in 1982, which clarified the legal status of famous historical and cultural cities as "a city with rich cultural relics, great historical value, and revolutionary significance" (Wang, 2000; Zhang, 2012). Then, in 1986, the State Council of China proposed delimiting "historic preservation zones" (Whitehand & Gu, 2007), which ought to protect real historical remains. The conservation of appearance and improvement of internal conditions in historical preservation zones are advocated to adapt to modern life needs. Simultaneously, the infrastructure should be

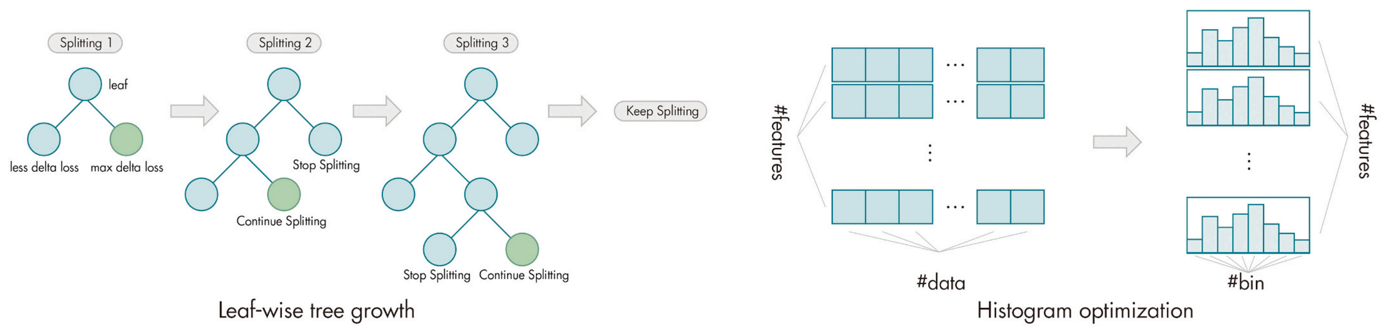

Fig. 3. Improvement of LightGBM.

improved, and a step-by-step approach is necessary to enhance residents' quality of life and activate the vitality of the reserve (Zhao, 2001).

The selected study areas include twelve cities in China, namely, Beijing, Shanghai, Tianjin, Guangzhou, Hangzhou, Wuhan, Chengdu, Nanjing, Qingdao, Shenyang, Changsha, and Suzhou (Fig. 4). These cities were economically developed in history with prosperous historical heritage. Thus, the government recognizes these cities as famous historical and cultural areas and templates for urban development. In the past two decades, zoning plans have been developed for their conservation.

3.2. Data sources

Big data plays a more important role in academic research on human geography with the help of ICT advancement (Lowry & Lowry, 2014; Wu, Ta, et al., 2018; Wu, Ye, et al., 2018). In this study, we adopted data from the following four sources.

3.2.1. Historic preservation zoning data

In addition to the officially released data, finding information on the historical protection zones of 12 cities that have not been formally released online requires much effort. In particular, planning materials related to the historical conservation of cities takes much time. Finally, the data are obtained through multiple resources, including official websites, web portals, newspapers, academic journals, and personal contacts between scholars, planners, and other people involved in landscape planning. These cities have multiple historic preservation plans; in this case, the latest plan was used as the reference (Table 3).

3.2.2. Building and street data

The building and street data come from Amap, one of China's largest online digital map providers. Amap provides a relatively comprehensive database of building boundaries, base area, and building height. The original building footprint data were more than three million in twelve cities, while the road data were more than four million in the whole nation. The basic unit in the analysis is the block (Conzen, 1960). Blocks are essential urban research units and critical elements in urban development and construction and government planning, management, and design (Zhang et al., 2019). A city was divided into blocks through the level-five roads identified by OpenStreetMap (Liu & Long, 2016).

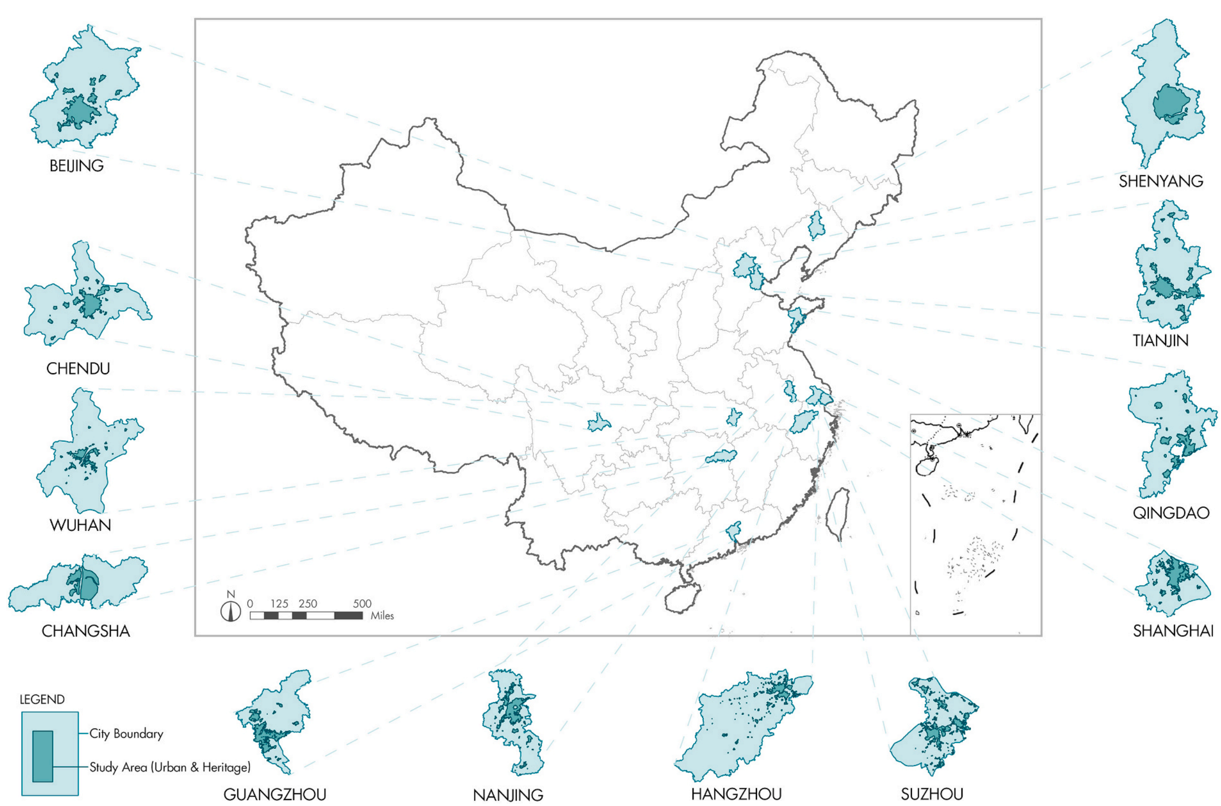

Fig. 4. Research area.

Table 3
Historic preservation planning in twelve cities.

City	Year	Planning policy
Beijing	2002	Beijing's Conservation of Historic-Cultural Cities
	2011	Beijing's Conservation of Historic-Cultural Cities for the 12th Five-Year Plan Period
	2016	Beijing's Conservation of Historic-Cultural Cities for the 13th Five-Year Plan Period
Chengdu	2017	Chengdu's Conservation of Historic-Cultural Cities
Guangzhou	2015	Guangzhou's Conservation of Historic-Cultural Cities
Nanjing	2019	Nanjing's Conservation of Historic-Cultural Cities
Hangzhou	2003	Hangzhou's Conservation of Historic-Cultural Cities
Qingdao	2015	Qingdao's Conservation of Historic-Cultural Cities
Shanghai	2015	Regulations on the Conservation of Historical and Cultural Areas and Historical Buildings in Shanghai
	2017	City Comprehensive Planning of Shanghai (Conservation of Historic-Cultural Cities)
	2019	Shanghai's Conservation of Historic-Cultural Cities
Shenyang	2011	City Comprehensive Planning of Shenyang (Conservation of Historic-Cultural Cities)
	2019	Shenyang's Conservation of Historic-Cultural Cities(Recent Construction Plan)
Suzhou	2013	Suzhou's Conservation of Historic-Cultural Cities
	2020	Suzhou's Conservation of Historic-Cultural Cities
Tianjin	2013	Tianjin's Conservation of Historic-Cultural Cities, Town, and Village
	2019	Tianjin's Conservation of Historic-Cultural Cities
Wuhan	2010	Wuhan's Conservation of Historic-Cultural Cities and Historic Cultural streets in Main Urban Areas
Changsha	2012	Changsha's Conservation of Historic-Cultural Cities
Chongqing	2015	Chongqing's Conservation of Historic-Cultural Cities

Finally, there are 102,865 blocks in all the cities within the study area.

3.2.3. *Point of interest (POI) data*

POI data are obtained from Baidu Map. As the largest search engine in China, Baidu perhaps provides the most up-to-date information on POIs via its Baidu Map product. Specifically, POI data were first acquired in January 2016 using JavaScript from the Baidu Map open interface and divided into 19 categories, including shopping, hotels, food, and attractions. More than seven million POI data points were obtained in the twelve cities. POI data reflect life, work, communication, and other residential activities (He et al., 2018) and thus have been widely used in daily life and scientific research (Wu, Ta, et al., 2018; Wu, Ye, et al., 2018).

3.2.4. *Land use data*

We obtained land use data from the official data provided by the Bureau of Natural Resources of each city. Most of the data were from the second national land survey from 2007 to 2009 (Liu, Liu, & Qi, 2015). This survey investigates urban construction land use and determines each urban land boundary, scope, quantity, and usage. We used these data to verify the effectiveness of the POI data.

4. Results

4.1. *Model performance*

After excluding blocks with incomplete data, the valid blocks in urban areas within 12 cities are 45,206, containing 3532 valid heritage area blocks. The influence of urban morphological elements on the vitality of heritage areas is verified using ridge regression. The DV and NV coefficients of determination are 0.446 and 0.683, suggesting that ridge regression explains NV better than DV. Simultaneously, the model passed the F-test, revealing a significant effect at the confidence interval of 99%.

As too many statistically significant factors contribute to vitality, it is not easy to demonstrate their importance directly. Therefore, LightGBM is applied to determine the importance of these factors. In training, tree and boosting parameters are adjusted to achieve the best predictive effect, keeping the coefficient of determination as large as possible and the residuals as small as possible while maintaining regularization. Table 4 shows the optimal parameters after adjustment. The coefficients of determination are then used to assess the model performance. The coefficients of determination associated with DV and NV are 0.703 and 0.875, respectively.

4.2. *Factors affecting the vitality of heritage and urban areas*

Fig. 5 illustrates the significance of the 39 factors in predicting the vitality of heritage and urban areas. The results demonstrate that most urban morphological elements show a significant influence on heritage areas. Street accessibility indicators (RID and PTCD), block patterns, land use, and building form are among the elements that affect the vitality of heritage areas. Compared with the DV, more elements show significance for NV.

Specifically, among the three urban morphological element groups, land use patterns mainly promote the vitality of heritage areas through serviceability elements, which have a greater impact than urban planning and building patterns, mainly in the daytime. Street accessibility indicators and areas have significant positive effects on DV and NV. Most of the building form pattern elements do not show significance. Only the building 3D form elements (MBH, BHVC, and PTB) show significant positive effects on NV. The impact of the land use function on vitality has apparent diurnal variation, which is consistent with previous research (Xia et al., 2020). Serviceability elements significantly affect the DV but are insignificant or less significant on NV. In addition, P_PUB and P_IND significantly reduce the vitality of heritage areas throughout the day, while P_TRA and P_GRE significantly promote NV.

Fig. 6 identifies the importance of the 39 explanatory variables in predicting the vitality of both urban and heritage areas. Comparing Figs. 5 and 6, factors with high importance do not necessarily show significance. The significance and importance of urban morphological elements are more consistent in the daytime than at night. Among those significant elements, street accessible indicators and block pattern elements (A and G) have higher importance during the daytime. In contrast, street accessibility indicators, ULBAN, and P_COM have higher importance at night. Regarding diurnal variation, ground plan elements (PTCD, FD, ULABN, and MBE) have a more critical impact on DV. In contrast, A, MBH, and NGR have a more substantial effect on NV.

4.3. *Vitality across different cities*

Fig. 7 shows the vitality across different cities. The DV and NV distinctly differ across cities. For instance, Shanghai and Guangzhou have higher DV, whereas Tianjin and Shenyang have greater NV. In terms of day–night differences, the DV in 11 cities except Changsha is higher than that in the urban areas (DV_UR). In contrast, the NV in 10 cities except Changsha and Beijing is higher than that in urban areas (NV_UR). Fig. 7 also shows that Suzhou has the most considerable

Table 4
Optimal parameters of LightGBM.

Parameter	Description	DV	NV
num_leaves	Maximum tree leaves	45	81
learning_rate	Boosting learning rate	0.05	0.05
max_depth	Limit the max depth for the tree model	8	8
feature_fraction	The proportion of randomly selected features in each iteration	0.63	0.8
reg_alpha	L1 regularization term on weights	0	0
reg_lambda	L2 regularization term on weights	0	0
min_child_samples	The minimum number of samples contained in a leaf	18	20
min_child_weight	The minimum sum of instance weights needed in a leaf	0.001	0.001
n_estimators	Number of boosted trees to fit	498	867

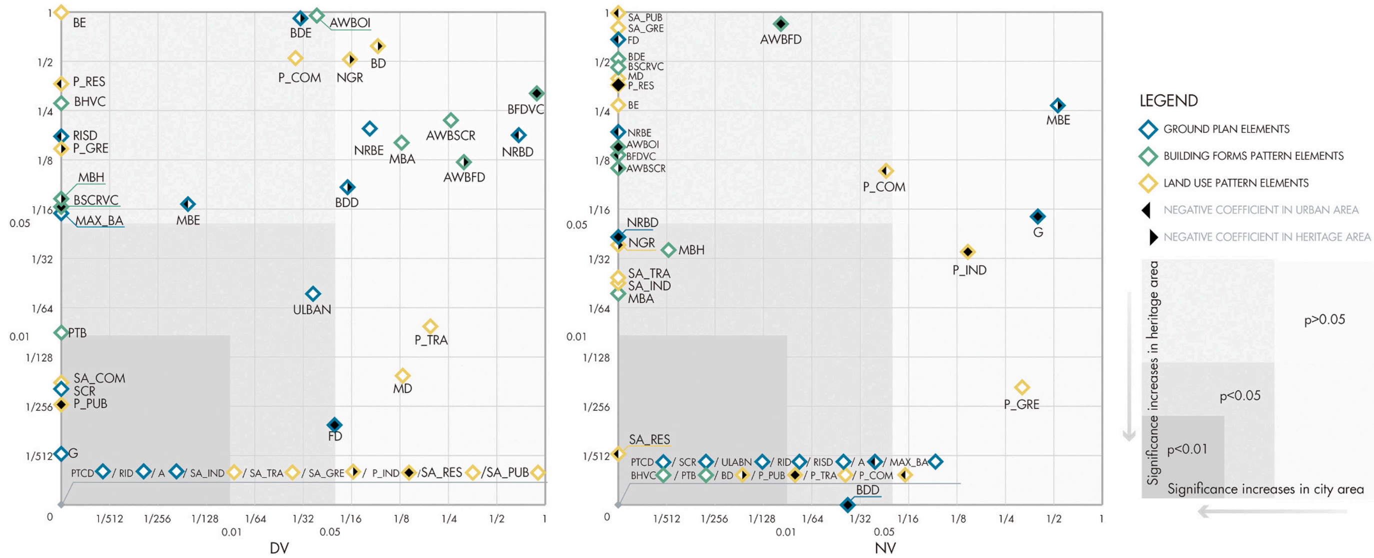

Fig. 5. Significance of explanatory variables.

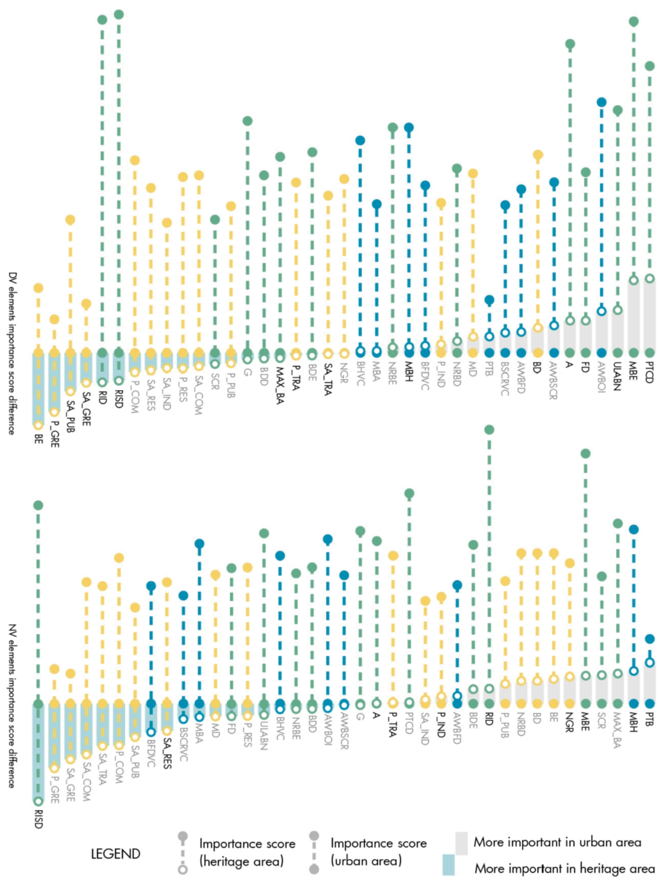

Fig. 6. Importance of explanatory variables.

difference between DV and NV, possibly due to its reputation as a famous tourist city with extensive and remarkable heritage areas (Tang & Cheung, 2020) that attract more tourists during the daytime. In contrast, Tianjin is inactive in the daytime but overly active at nighttime. Unlike Suzhou, Tianjin's historical development has determined its unique urban style that integrates east and west (Biao, Xiao-meng, & Ming-yong, 2012). Its heritage areas can bring different rich experiences to tourists to increase their activities.

5. Discussion

5.1. Are factors affecting the vitality of heritage areas consistent with those of urban areas?

For comparison with heritage areas, data for urban areas are obtained using the method described in Section 2.3. Table 5 shows the coefficients of determination. Fig. 5 shows that the elements affecting the vitality of heritage and urban areas are almost the same and differ by only a few elements, consistent with previous theoretical research (Sung & Lee, 2015; Ye et al., 2018; Zeng, Song, He, & Shen, 2018). However, the results unexpectedly indicate that the land use pattern has the greatest impact on the vitality of heritage areas among the three urban morphological element groups. However, according to Zhang et al. (2020), the ground plan has a greater effect on urban vitality, mainly through street accessibility indicators. The reason for the difference is possibly twofold. First, land use and urban vitality at the block level have a mismatched distribution (Xia et al., 2020). Land use can more easily affect the vitality of heritage areas. More substantial serviceability can enhance the block function of a heritage area (Zumelzu & Barrientos-Trinanes, 2019) and increase crowd attraction, promoting vitality. Second, heritage areas are usually subject to stricter planning control by the government (Whitehand & Gu, 2007). Buildings and streets have strikingly different forms from urban areas (Bandarin & van Oers, 2012). Consequently, the impact of the ground plan and building form patterns on the vitality of the heritage area is relatively weak.

In addition, this empirical study finds that several urban morphological elements only influence the vitality of heritage areas. During the daytime, P_TRA and MD do not guarantee urban vitality but are generally considered significant contributors in the existing literature (Hachem, 2016; Sharifi, 2019). The reason is that intensive urban land does not promote urban vitality (Xia et al., 2020). Blocks with a high mix degree and a high proportion of traffic attract more nonlocal populations (Mouratidis & Poortinga, 2020) and inhibit local social bonds (Wood, Frank, & Giles-Corti, 2010). The green space indicators (P_GRE, SA_GRE, and NGR) are not guarantees of NV_UR. Possible reasons include the constraints of service hours and safety concerns in urban areas, where the vitality of public service facilities and parks declines at night (Schwanen, van Aalst, Brands, & Timan, 2012). At night, people tend to gather in certain bright places in urban areas, such as commercial centers, bars, karaoke, and restaurants, which are the main venues for Chinese nightlife (Zhang et al., 2020) rather than green spaces. Nevertheless, people visit heritage areas for their architectural, social,

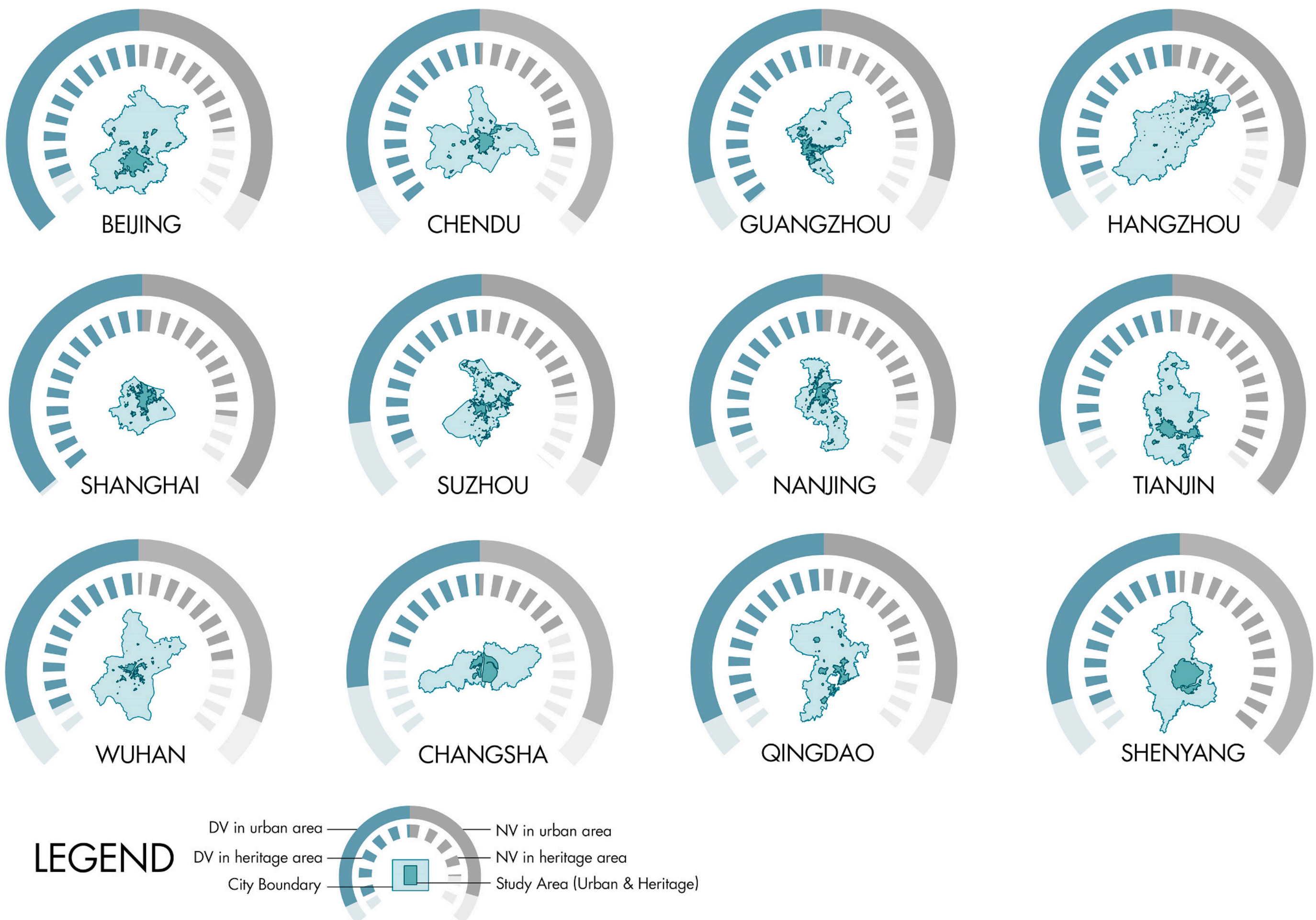

Fig. 7. The vitality of heritage and urban area in 12 cities.

Table 5
Comparison of prediction performance.

	DV_UR	DV	NV_UR	NV
k -value of ridge regression	0.206	0.206	0.196	0.196
R^2-value of ridge regression	0.449	0.486	0.446	0.683
R^2-value of LightGBM	0.534	0.703	0.661	0.875

cultural, and historical value (Latham, 2016) and thus tend to participate in large-scale activities in heritage green spaces at night.

5.2. Are factors affecting the vitality of heritage areas consistent among different cities?

This study obtains significant results of urban morphological elements of different cities. Fig. 8 shows that the results are similar to previous research, where all urban morphological features only affect the vitality of the heritage area at specific times in specific cities (Zhang et al., 2020). In particular, several elements can effectively affect the vitality of heritage areas in most cities. For example, street accessibility and traffic-related indicators (P_TRA and SA_TRA) also have a substantial effect on vitality in multiple cities, which means that convenient transportation and high accessibility attract people and improve the vitality of heritage areas in most cities, in line with public expectations and previous theoretical research (Xia et al., 2020; Zhang et al., 2020).

Factors affecting the vitality of heritage areas also have a specific relationship with city size. As the city progresses in development, more urban morphological elements can affect the vitality of its heritage area. For instance, 3D building pattern elements only affect the vitality of the heritage areas of first-tier cities in China, such as Beijing and Shanghai, but have little or no impact on other cities; the possible reason is that Beijing and Shanghai heritage areas have more enormous proportions of renovated architectural sites than in other cities (Chen, Judd, & Hawken, 2016; Zheng, 2017). In the master and conservation plan of historical-cultural cities in Beijing and Shanghai, controlling the building height in heritage areas is explicitly stated (Wang, 2009). The possibility that differences in the amount of data between cities may lead to such results has been ruled out. The number of blocks in different cities in this study only varies slightly and not to the extent that the results can be influenced.

6. Conclusion

The main research questions in this study are the differences in urban morphological elements affecting the vitality of urban areas and heritage areas across cities. With empirical evidence from twelve Chinese cities, the following conclusions can be drawn. First, factors that affect the vitality of heritage areas differ from those that affect the vitality of urban areas. However, some common factors are found that significantly affect both heritage areas and urban areas. Among the three groups of urban morphological elements, the land use pattern group has a more substantial impact on heritage areas than the ground plan and building form pattern. In addition, land use is mainly influenced by various service capabilities. The building form pattern has little influence on the vitality of heritage areas, mainly through the building's 3D patterns. The urban morphological elements that affect DV and NV considerably

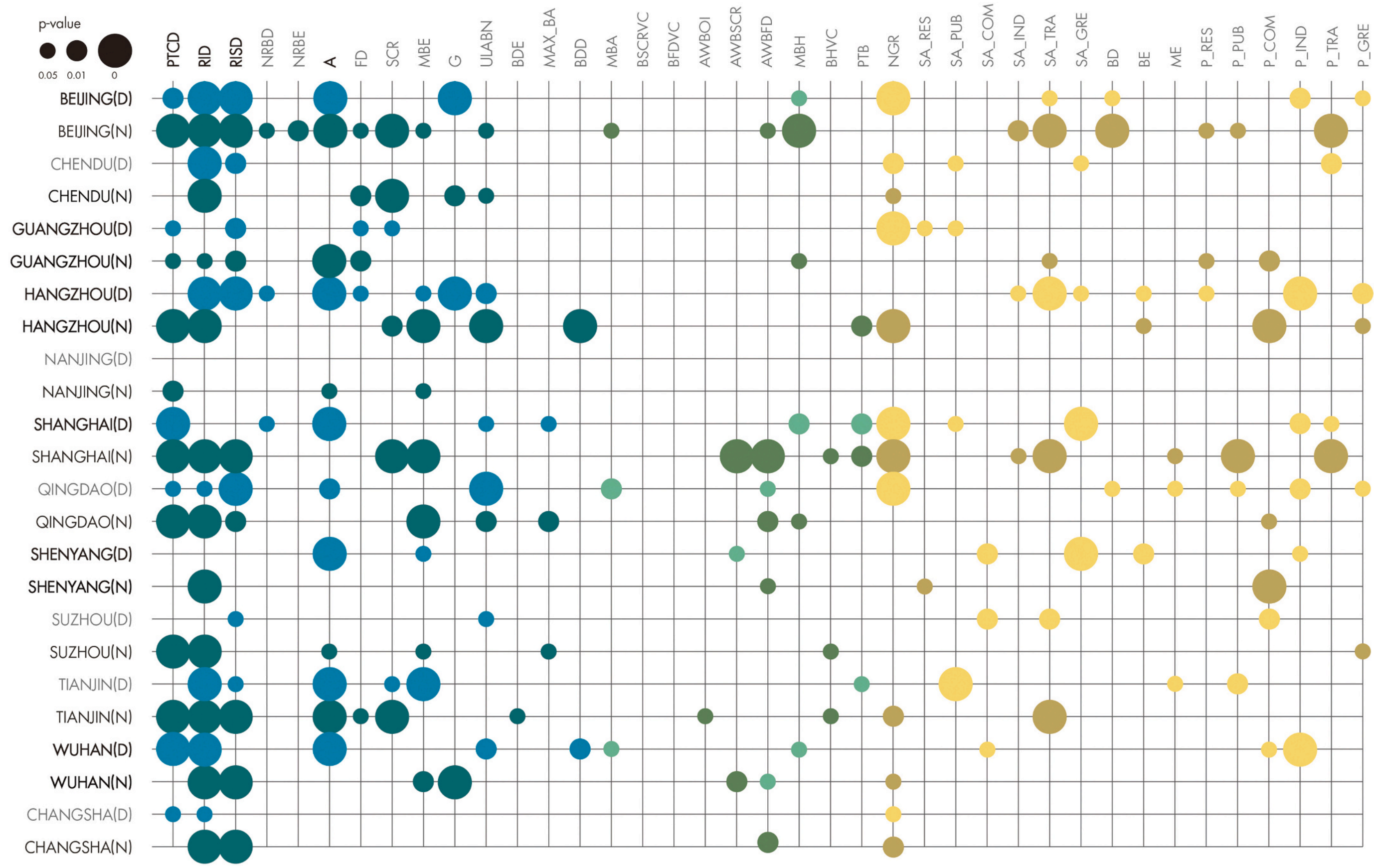

Fig. 8. Significance of urban morphological elements in 12 cities.

differ. Second, the elements that affect the vitality of heritage areas vary across cities. The number of elements affecting heritage areas has a specific relationship with city size, and more urban morphological elements affect the vitality of heritage areas in more developed cities.

The overarching contribution of this study is a proposal of a path of urban morphology for heritage adaptation. Various elements of urban morphology and vitality are quantitatively measured by big geospatial data. The differences in urban morphological elements affecting the vitality of urban and heritage areas, spatial changes, and diurnal changes are empirically analyzed. This path evaluates the significance of urban morphological elements to vitality and assesses their importance through a multidimensional perspective. This study can also help understand the forms of heritage areas and provide theoretical support for heritage conservation, urban construction, and economic development in China. After establishing the institution of historic city conservation in mainland China in 1982, the scope of conservation has gradually extended from single buildings to historical blocks, and the conservation of urban material spaces has expanded to nonmaterial elements. The government strictly protects the physical environment of heritage areas but has implemented relatively few policies and practices to promote social life.

Moreover, large-scale exploration of heritage adaptation only began in the 2010s. For example, the Conservation of Historic-Cultural Cities in Shanghai addresses the relationship between conservation and adaptive reuse. Thus, the relationship between the physical environment and social life and the conservation of the street form, block scale, environment, and ground paving is confirmed. However, these explorations are based on empirical judgments. The management and control of the heritage area are often carried out following the current technical guidelines for management, and at most, several modifications can be made. In essence, the overall view, data, and theoretical support for Chinese heritage adaptation policy are lacking. This study can fill these gaps from the general urban morphology perspective and implement policy recommendations to activate heritage areas from a new perspective. For example, we argue that improving green land and transportation serviceability may enhance the vitality of most heritage areas. In the future, regulatory guidelines on greening should be introduced for heritage areas. A series of small but flexible greening measures should also be implemented in heritage areas to enhance the vitality of the area while maintaining historical features.

Finally, this study encounters certain limitations. Vitality is an abstract and complex concept resulting from dimensions including society, economy, and culture. As such, measurements using small food facilities and night light data may lead to incomplete results, but these are only one dimension of proxies. Therefore, the study results may be biased or possibly vary due to the data characteristics. Furthermore, the data collected are not from the same year, and the POI data cannot demonstrate the temporal dimension. However, this study is the first to analyze the factors affecting the vitality of heritage areas on the block scale. It compares with those in the urban area. In the future, this study can be used as evidence to provide references for planning and construction to improve the vitality of heritage areas and revitalize cities.

Author statement

Jiayu WU: Conceptualization, Writing - original draft; Writing - review & editing, Project administration.

Yutian LU: Writing - original draft; Writing - review & editing; Data curation; Formal analysis; Methodology.

Hei GAO: Data curation.

Mingshu WANG: Writing - original draft; Writing - review & editing.

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