RETRACTED ARTICLE: Investigating urban land dynamic change and its spatial determinants in Harbin city, China

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ABSTRACT
Research and analysis of urban growth and its driving factors are crucial to the long-term sustainable development of cities. Based on the multi-temporal Landsat remote sensing data, this paper extracts urban information by interpreting and supervising classification, and makes a dynamic study on the urban expansion of Harbin in different temporal intervals. By analyzing the spatial determinants of urban growth, we deeply understand the process of urban growth, thus providing important help for urban planning and policy formulation. In this paper, four landscape metrics (total area, aggregation index, landscape shape index, and total edge) were selected to characterize the urban landscape characteristics from two spatial scales (2 and 5 km grid sizes), then the spatial regression model was used to explore the relationship between the urban landscape and its spatial determinants. These changes exhibit significant spatial variations and spatial autocorrelation at two spatial scales. Topography and proximity factors have important effects on urban landscape change. These research results may help us to better understand the process and driving factors of urban development, so as to help the underdeveloped cities in northeast China to formulate scientific and reasonable development plans and policies.

Introduction
Urbanization is an important symbol to measure the degree of development and the level of social development of a country or region. At present, about 55% of the world’s population lives in urban areas, the proportion that is expected to increase to 68% by 2050 (United Nations, 2018). The acceleration of urbanization has promoted socioeconomic development and improved the quality of life. The urban population growth has been accompanied by the increasing demand for urban land, the scope of urban land has been expanding, and a large number of undeveloped land around the city has been transformed into urban land, such as cropland and forest. The dynamic process of urbanization has a wide impact on the structure and function of the ecosystem, and has also led to some list of ecological and environmental problems, such as environmental pollution, climate change (Dietzel et al., 2005; Ma et al., 2008). Since the reform and opening up in 1978, China’s economic achievements have attracted the attention of the world. At present, China is experiencing rapid urban development and expansion. China’s urban population increased from 172 million in 1978 to 831 million in 2018, and the urban proportion rose from 17.92% to 59.58% during the same period (China Statistical Yearbook, 2018). Therefore, the rapid urban development and urban environment have been widely concerned. Studying the urban growth pattern and analyzing the factors that affect the urban growth in time and space is the critical to predict the future urban change development and potential environmental impact, thus mitigating the negative impact of urban growth (Peng et al., 2015).

With the development of remote sensing technology and the application of high resolution remote sensing sensor, it provides a cost-effective alternative to ground survey for land use/cover mapping and change analysis. Many scholars use multi-temporal remote sensing image data combined with Geographic Information System (GIS) technologies to study the spatial expansion of urban land (Chen et al., 2016; Tian et al., 2005). They focus on urban spatial expansion patterns and driver factors (McGarigal et al., 2002). The researchers used the landscape metrics to analyze the urban interpretation and analysis of urban spatial structure changes, and some scholars also studied the links between urban growth and population, transportation and policy (Aljou et al., 2013; Yang & Lo, 2003).

The spatial pattern of urban growth will be affected by many factors, including physical factors, socioeconomic factors, neighborhood factors and...
land use policy factors. These factors have spatial autocorrelation with urban growth. Many scholars use the traditional statistical methods such as multiple linear regression, binary linear regression and logical regression to determine the impacts of these factors on urban growth. Because these variables are spatial independent, it is impossible to establish the spatial autocorrelation existing in these variables. Therefore, in the analysis of urban growth, the spatial correlation between influencing factors should be considered.

There are many studies focused on the urban growth and influencing factors of some core big cities in developed areas, including Beijing, Shanghai, Guangzhou, Nanjing. Some scholars choose urban agglomeration as the research object to study the urban spatial expansion and its influencing factors on such a large scale. After 2009, China’s national development strategy has gradually adjusted from the unbalanced development strategy in the early stage of reform and opening up to the balanced development strategy. At present, there are few researches on urban development in underdeveloped areas of Northeast China. Harbin, the core city of Northeast China, is used as the research object, which uses remote sensing and Geographic Information System (GIS) technologies to dynamically monitor the city, describes the urban spatial expansion pattern with landscape metrics, identifies the determinant factors of urban growth through spatial regression analysis, and provides critical references for urban management and planning.

Study area

Harbin (125°42’E~130°10E; 44°04’N~46°40’N), located in the northeast of Northeast China Plain and the south of Heilongjiang Province, which is the capital city of Heilongjiang Province (Figure 1). It is the national important manufacturing base in the north of Northeast China, are the core cities of Harbin-Changchun megalopolis. Harbin has four distinct seasons, long winter and short summer. It belongs to the middle temperate continental monsoon climate, with an average annual precipitation of 569.1 mm, mainly concentrated in June-September. Harbin has a total area of about 53,840 square kilometers (9 municipal districts, 7 counties and 2 county-level cities), of which the municipal area covers an area of 10,198 square kilometers and a total population of 9.5 million. In this paper, Songbei District, Hulan District, Daoli District, Daowai District, Nangang District, Xiangfang District, Pingfang District, Shuangcheng District and Acheng District area of Harbin City were selected as the study area to study the land use change in this area from 1995 to 2018.

Data and methods

Data acquisition and collection

In order to study the urban land change and its spatial determinants from 1995 to 2018, this study used Landsat Thematic Mapper (TM) images acquired on 1995, 2000, 2005, 2015 and 2018 (Path: 129, Row: 28)
In addition to the satellite imagery, we collected ancillary datasets which were collected from Harbin Bureau of Natural Resources and Planning to assist land use/cover classification and the urban land change mapping. These data include 1:1000 scale topographic map, administrative region boundary and census data on population, social economy from 1995 to 2018.

Image processing of remote sensing

Urban land is composed of construction land, cultivated land, forest, water and bare land, which are interpreted and classified from Landsat TM/OLI images by combining the supervised maximum likelihood classifier and manual interpretation in ENVI 5.3 software. In the study, 150 training samples are randomly selected for each image to supervise and classify, and ensure that all the land-cover types can be adequately represented according to the training samples. A total of more than 1000 classification samples, which were selected by field survey in 2018, to assess the accuracy of classification (Tan et al., 2014).

The overall accuracy and the Kappa coefficient of each land-cover map were above 85% and 0.72%, respectively, which indicates that the classifications could satisfactorily represent the real landscape (Janssen & Van der Wel, 1994).

Before classification, all images were corrected by atmospheric correction, the spectral characteristics was standardized, and then geometric correction was performed to rectified each image to the same coordinate projection. Firstly, geometric correction of 2018 image data was performed based on topographic map, and then, the image was registered based on the 2018 image to ensure that all the images have the same projection. The root mean square error (RMSE) of geometric rectification was limited to within 0.5 pixels (15 m).

After classification, the classification results of remote sensing interpretation are statistically analyzed by using the spatial analysis of ArcGIS 10.2 software, and the data needed in this paper are obtained.

Quantifying urban expansion patterns

We used the average urban expansion rate to assess urban growth in the study area from 1995 to 2018.

\[
K = \frac{U_i - U_j}{U_j} \cdot \frac{1}{T} \cdot 100\% \tag{1}
\]

where \(T\) is the time period, and \(U_j\) and \(U_i\) are the areas of urban land at the beginning and end of this period, respectively.

In the study of urban growth, the landscape metrics is a very important quantitative index, which can quantitatively describe the urban spatial expansion pattern. Botequilha Leitao and Ahern (2002) proposes a core(sub) set of metrics, identified through literature reviews, which the urban landscape changes can be analyzed and understood, so as to solve the problem of urban planning. We elected five landscape metrics, i.e. total area (TA), total edge (TE), landscape shape index (LSI) and aggregation index (AI) (Table 2) to characterize the urban growth patterns. All the landscape metrics were calculated for urban areas of 5 years, respectively, in FRAGSTATS 4.2 (McGarigal et al., 2012 ; Sun et al., 2013) at different landscape block scales. The block sizes of 2 and 5 km were selected as the units for the landscape metrics analysis because it retains more information of the landscape pattern, and it avoids the noise which the smaller pixel size captured (Su et al., 2011; Zhang et al., 2013). Each of the changes in the urban landscape metrics at each spatiotemporal scale was normalized and standardized.

### Table 1. List of the Landsat Thematic Mapper(TM) scenes used.

| Acquisition data | Sensor_ID | Sun elevation (°) | Sun azimuth(°) | Atmospheric correction | Path/row | Scene RMSE |
|------------------|-----------|-------------------|----------------|------------------------|----------|------------|
| 22 September 1995 | TM        | 36.84             | 139.42         | Yes                    | 117/28   | 0.358      |
| 29 September 1995| TM        | 34.61             | 141.48         | Yes                    | 118/28   | 0.198      |
| 29 September 1995| TM        | 35.54             | 140.40         | Yes                    | 118/29   | 0.185      |
| 18 August 2000   | TM        | 50.87             | 139.40         | Yes                    | 117/28   | 0.231      |
| 25 August 2000   | TM        | 48.90             | 140.08         | Yes                    | 117/29   | 0.143      |
| 26 September 2000| TM        | 38.96             | 151.71         | Yes                    | 118/28   | 0.122      |
| 29 June 2005     | TM        | 60.93             | 134.05         | Yes                    | 117/28   | 0.182      |
| 8 August 2005    | TM        | 45.81             | 149.47         | Yes                    | 118/28   | 0.191      |
| 8 September 2005 | TM        | 46.87             | 148.14         | Yes                    | 118/29   | 0.149      |
| 11 June 2010     | TM        | 61.63             | 137.05         | Yes                    | 117/28   | 0.220      |
| 1 May 2010       | TM        | 54.75             | 145.15         | Yes                    | 118/28   | 0.345      |
| 22 September 2010| TM        | 42.52             | 153.04         | Yes                    | 118/29   | 0.201      |
| 24 May 2015      | OLI_TIRS  | 60.78             | 144.21         | Yes                    | 117/28   | 0.286      |
| 16 June 2015     | OLI_TIRS  | 62.75             | 140.09         | Yes                    | 118/29   | 0.295      |
| 16 June 2015     | OLI_TIRS  | 63.63             | 137.51         | Yes                    | 118/29   | 0.345      |
| 1 June 2018      | OLI_TIRS  | 61.85             | 142.43         | Yes                    | 118/29   | 0.201      |
| 24 June 2018     | OLI_TIRS  | 62.59             | 139.11         | Yes                    | 118/28   | 0.286      |
| 24 June 2018     | OLI_TIRS  | 63.45             | 136.51         | Yes                    | 118/29   | 0.295      |
Identifying geographic determinants

Identify the spatial determinants factors of urban growth

Urban growth is a very complex process, which is affected by many factors, such as socioeconomic development, natural ecological environment and so on. Through the review of the relevant literature, it may be summarized that the driving factors of urban land use spatial change include natural ecological environment, socioeconomic development, neighborhood factors and related planning and policies. Natural ecological environment is an important material basis for urban development. Topography, distribution of natural resources, distance to lakes and rivers can affect the growth rate and expansion direction of the city. For example, the city will develop to a flat area, and the area close to the water source will also be selected when choosing the place of residence. Therefore, slope, elevation and distance to river are considered to be important factors of urban growth. Socioeconomic development factors include distance to socioeconomic center, distance to road, population, gross national product (GDP). Neighborhood effects mean that a non-urban cell is surrounded by more urban land, it is more likely to be converted into urban land. Urban planning and land-use policy and other related policies will play a certain role in the development direction of urban construction. In the process of this study, it is necessary to study the spatial determinant of urban growth under different scales, population, GDP, neighborhood factors and urban planning and related land-use policy data are always based on administrative units, and thus cannot be calculated based on block units, can not be regression analysis.

Spatial autocorrelation

Spatial autocorrelation can be regarded as a scale of reaction agglomeration. In urban research, a certain variable of urban spatial data is aggregated in space, which means that in a certain region, this variable has autocorrelation among each regional unit, but the autocorrelation of spatial data does not conform to the assumption of conventional regression method, such as ordinary least squares (OLS) (Gao & Li, 2011). Global Moran’s I proposed by Moran in 1950 is the most commonly used spatial autocorrelation statistical test in univariate map patterns (Tiefelsdorf, 2002). It is used to reflect the similarity between each regional unit and the adjacent regional unit in the whole study area, and it is the estimated value of the coefficient of spatial autocorrelation regression equation, and its value range can only be between −1 and 1. Greater than 0 indicates positive correlation, and a value close to 1 indicates that similar attributes are gathered together; less than 0 indicates negative correlation, and a value close to −1 indicates that the attributes are aggregated together with different attributes; if the value is close to 0, the attributes are randomly distributed, or there is no spatial autocorrelation (Moran, 1950). In this study, we used Global Moran’s I to describe the degree of spatial dependence of the urban growth pattern changes. Moran’s I has the following form:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} W_{ij} (x_i - \bar{x}) (x_j - \bar{x})}{s^2 \sum_{i=1}^{n} \sum_{j=1}^{m} W_{ij}}$$

(2)

where $x_i$ is the value at point i, $x_j$ is the value at point i’s neighbor j, $W_{ij}$ is a coefficient, n is the number of points, and $s^2$ is the variance of x value with a mean of
The coefficient $W_{ij}$ is the weight for measuring spatial autocorrelation.

The spatial lag and spatial error models are used to explore the relationship between urban growth patterns and their spatial determinants (Anselin et al., 2006). The spatial lag model which considers spatial lag dependency can be expressed as follows:

$$y_i = \lambda \sum w_{ij} y_j + x_i' \gamma + \mu_i + \varepsilon_i$$

where $i$ represents the spatial units, $y_i$ represents the dependent variable (landscape metric changes) of $i$; $\lambda$ is the spatial autoregressive coefficient; $W_{ij}$ is a matrix containing weights that describe the spatial relationships of all the spatial units; $x_i$ is the vector of observed parameters of unit $i$; $\gamma$ is the matrix of explanatory variables; $\varepsilon_i$ is an independently and randomly distributed error term for observation $i$; and $\mu_i$ denotes a specific spatial effect.

The spatial error model which incorporates spatial error dependency can be expressed as follows:

$$\sigma_i = \lambda \sum w_{ij} \sigma_j + \varepsilon_i$$

$$y_i = x_i' \gamma + \mu_i + \sigma_i$$

where $\sigma_i$ represents the spatially autocorrelated error term, and $\lambda$ is the spatial autocorrelation coefficient.

### Result

**Spatiotemporal variations of urban land expansion**

During the whole study period, the urban area of the region nearly doubled, and TA increased from 519.11 km² in 1995 to 1005.59 km² in 2018 (Table 3). Table 4 shows the urban area and the growth rate in each period. The average annual expansion of urban area is about 21.151 km², with an average growth rate of 4.07%, of which T2 (2000–2005) has the largest growth rate of 7.48% in this stage. We can see from the Table 4 that the urban area in T2 shows a large rapid growth, T3 shows a significant downward trend and T4 returns to normal growth level, which is determined by the law of urban spatial development. Urban growth not only refers to the expansion of spatial scope, but also the internal elements and organizational structure should be coordinated with urban space, so there will be a slowdown in urban spatial expansion. Figure 2 shows the urban land interpretation of the 1995–2018 satellite image, and Figure 3 shows the urban expansion pattern in five time intervals. TA, TE and LSI index showed a rapid growth trend in the whole study time span, and the change value of AI was not more stable, indicating that urban expansion led to urban edge growth, and urban landscape was more dominant and unstable.

Spatial autocorrelations of urban landscape pattern changes

The global Moran’s I values of the selected landscape metrics at different spatial scales are illustrated in Figures 4 and 5, respectively. They are all greater than zero, but the values are not high, which indicates that there is a general positive spatial autocorrelation but not high correlation in the urban landscape changes in the whole study time; The global Moran’s I change trend is consistent at the 2 and 5 km scales, but the values are different, such as the global Moran’s I values of LSI at 5 km scale are all higher than that at 2 km scale in each time period, indicating that the re-analysis of urban landscape change needs to consider the scale effect of spatial autocorrelation. In each of the five periods studied, the global Moran’s I value of LSI and TA are large in the early stage and small in the later stage, which indicates that the urban expansion is the whole regional growth in the early stage and the local growth in the later stage. The increasing global Moran’s I value of TE indicates that the urban development of the study area has been in the extended state.

**Spatial determinants of urban growth**

The spatial determinants of urban landscape patterns obtained from spatial regression are shown in Tables 5 and 6. The results show that the $R^2$ values for the changes in TA, TE and LSI are greater than 0.5 at two spatial scales. This indicates that these models have a good fit, and the variation of these spatial indices can be explained by these two models. The $R^2$ value of the AI index change less than 0.25 cannot be explained by these two models. For the independent variables of the spatial model, the distance to river, distance to county road, and distance to city centers are not the primary factor, and do not affect the urban spatial expansion, while the slope and elevation affect the urban spatial expansion, which are related to almost all landscape metrics.
Spatial determinants of urban growth

Topographic factors are the important influencing factors of urban spatial expansion, and the influence of natural environment on urban distribution, urban spatial expansion direction and macroscopic pattern is significant (Ma & Xu, 2010). Slope is a determinant of urban growth, and more influence than that of elevation in the change of urban landscape pattern. Previous studies (Henry et al., 2001; Ma & Xu, 2010) have shown that urban construction mainly focuses on areas with gentle slope, low topography and better natural conditions, and elevation has a negative impact on urban development and shape changes. The higher elevation slope area will increase the cost of urban construction compared with the lower elevation area, from the study area in the surface environment, southeast and southwest are mostly hilly and mountainous, which restricts the development of the city, while the middle and north are plain, so the urban space is mainly concentrated in this direction.

Rivers can affect the urban landscape in many aspects, in the process of urban development, the residence, factories generally choose to be close to the water source for construction, rivers, lakes can provide a good environment for urban development and convenient transportation. With economic development, urban growth is highly dependent on transportation, and rivers have less advantages in transportation than road traffic. The river traffic function in this study area is weak, so the urban growth is

Figure 2. Urban expansion in Harbin from 1995 to 2018.
not correlated with the distance to rivers (Shu et al., 2014).

Many socioeconomic resources, such as hospitals, shopping malls, schools and other infrastructure, are concentrated in urban centers, and the farther away from the city center, the less they are distributed (Li et al., 2013; Li et al., 2013). In our study, it is found that the distance to the city center has a negative correlation with urban expansion and the closer the non-urban land to the city center, the easier it is to convert to the city. With the development of urban center and surrounding area, the agglomeration effect of urban center is gradually weakened. At present, the agglomeration effect of urban centers in the study area is still obvious.
In the process of urban development, the development of road network plays a great role in the transformation of non-urban areas into urban processes. Our research shows that different levels of roads have different effects on urban landscape change. The higher the road grade, the greater the impact on urban expansion, the national roads have the strongest influence on urban expansion, followed by provincial roads, railways and roads in intercity transport is an important part of the impact on the urban landscape.

Urban planning and policy elements

Urban growth is influenced by many complex factors, and in the course of research, we find that urban development is influenced not only by natural geographical factors, but also by relevant urban planning and economic development policies. As a major government intervention, the government uses urban planning and land use policy means to control and guide the direction of urban development, infrastructure construction. In the past two decades, the urban landscape of Harbin has become fragmented and irregular, which poses a certain threat to the surrounding basic farmland and ecological environment, and needs to balance the relationship between urban development and the environment. The government should assess the influence of geographical and socioeconomic factors on urban growth in the past, and then make different, concrete and scientific plans according to the evaluation results to ensure the reasonable and orderly development of the city. However, Institutional policy is a macro factor, this study does not quantitatively estimate the influence of the institutional background on urban growth in the study area, its effects could not be accurately calculated at grid scale, and needs further in-depth study.

Conclusion

In this study, we first examined urban land expansion in Harbin in 1995–2018 and then explored the relationship between urban growth and spatial determinants from two different spatial scales in regression models. Based on multi-temporal remote sensing image data, we dynamically monitor urban growth. We found that the urban land in the study area doubled from 519.11 to 1005.59 km² between 1995 and 2018. The average annual expansion of urban area is about 21.151 km², with an average growth
Table 5. The coefficients of the spatial regression between urban landscape changes and geographic determinants at the 5 km scale (n = 951).

|       | TA        | TE        | LSI       | AI        |
|-------|-----------|-----------|-----------|-----------|
|       | t1 ^  a   | t2 ^  a   | t3 ^  a   | t4 ^  a   | t5 ^  a   | t1 ^  a   | t2 ^  a   | t3 ^  a   | t4 ^  a   | t5 ^  a   | t1 ^  a   | t2 ^  a   | t3 ^  a   | t4 ^  a   | t5 ^  a   | t1 ^  a   | t2 ^  a   | t3 ^  a   | t4 ^  a   | t5 ^  a   |
| Cons  | 53.033    | 210.038   | 40.639    | 170.439   | 212.188   | 1014.890  | 2006.410  | 1418.250  | 2866.110  | 1227.570  | 1.394     | 1.669     | 1.042     | 2.601     | 1.118     | 4.009     | 2.500     | 4.695     | 2.124     | 3.068     |
| Ele   | −0.115    | −0.175    | 0.110     | 0.018     | −0.172    | −1.257    | 0.700     | 3.591     | 2.657     | −4.127    | −0.002    | −0.001    | 0.002     | −0.001    | 0.002     | −0.001    | 0.002     | 0.002     | 0.002     |
| Slope | 5.943     | 3.836     | −3.850    | 2.502     | 8.745     | 101.560   | −74.186   | −161.271  | 21.774    | 226.195   | 0.032     | −0.024    | −0.044    | 0.023     | 0.010     | 0.026     | 0.012     | −0.147    | 0.009     | 0.006     |
| Dis_G | −0.002    | −0.003    | −0.004    | −0.002    | −0.029    | −0.097    | −0.074    | −0.064    | −0.042    |          | 0.026     | 0.012     | −0.147    | 0.009     | 0.006     |          |          |          |          |          |
| Dis_C | −0.008    | 0.019     | 0.007     | −0.002    | −0.024    |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
| Dis_X | −0.001    | −0.001    | 0.000     |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
| Dis_CE| −0.016    | −0.034    | −0.012    | −0.017    | −0.019    |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
| Dis_R | −0.021    | −0.037    | −0.014    | −0.020    | −0.021    |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
| Dis_CE| −0.004    | 0.011     | 0.012     | −0.017    | 0.016     |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
| W/lam | 0.387     | 0.390     | 0.233     | 0.366     | 0.403     | 0.061     | −0.002   | 0.103     | 0.082     | 0.175     | 0.458     | 0.352     | 0.514     | 0.445     | 0.371     | 0.137     | 0.174     | 0.335     | 0.005     | 0.092     |
| R²    | 0.68**    | 0.68**    | 0.46**    | 0.45**    | 0.51**    | 0.51**    | 0.42**   | 0.43**    | 0.56**    | 0.76**    | 0.64**    | 0.78**    | 0.79**    | 0.66**    | 0.15**    | 0.24**    | 0.21**    | 0.22**    | 0.22**    |

**Significant at the 99% confidence level.

Abbreviation: total area (TA), landscape shape index (LSI), total edge (TE), aggregation index (AI), constant (Cons), distance to city centers (Dis_CE), distance to county roads (Dis_C), distance to national roads (Dis_G), distance to provincial roads (Dis_X), distance to rivers (Dis_CE), Elevation (Ele), Wy of spatial lag model (W), lambda of spatial error model (lam).

aSpatial lag models.
bSpatial error models.
Table 6. The coefficients of the spatial regression between urban landscape changes and geographic determinants at the 2 km scale (n = 5492).

|        | TA     | LSI    | AI     |
|--------|--------|--------|--------|
|        | t1a    | t2a    | t3a    | t4a    | t5a    | t1a    | t2a    | t3a    | t4a    | t5a    | t1a    | t2a    | t3a    | t4a    | t5a    |
| Cons   | 67.707 | 49.222 | 12.632 | 42.270 | 90.353 | 317.031| 222.279| 156.462| 137.088| 235.788| 1.827  | 1.913  | 1.250  | 1.546  | 1.671  |
| Ele    | −0.052 | −0.019 | 0.004  | −0.098 | −0.181 | 0.083  | 0.121  | −0.172 | −0.001 | 0.001  | 0.002  | 0.002  | 0.002  | 0.002  |
| Slope  | 2.187  | 0.135  | −0.944 | −1.373 | 4.793  | 5.602  | −1.846 | −5.075 | −3.063 | 6.250  | 0.010  | 0.019  | 0.022  | 0.008  | 0.002  |
| Dis_G  | −0.002 | −0.001 | −0.002 | −0.005 | −0.005 | −0.001 | −0.001 | −0.001 | −0.001 | 0.001  | 0.001  | 0.001  | 0.001  | 0.001  |
| Dis_C  | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | 0.001  | 0.001  | 0.001  | 0.001  | 0.001  |
| Dis_X  | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | 0.001  | 0.001  | 0.001  | 0.001  | 0.001  |
| Dis_R  | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | 0.001  | 0.001  | 0.001  | 0.001  | 0.001  |
| Dis_CE | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  | 0.004  |
| W/lam  | 0.116  | 0.170  | 0.174  | 0.098  | 0.116  | 0.170  | 0.098  | 0.116  | 0.170  | 0.098  | 0.116  | 0.170  | 0.098  | 0.116  |
| R²     | 0.53** | 0.52** | 0.50** | 0.52** | 0.54** | 0.42** | 0.52** | 0.52** | 0.52** | 0.52** | 0.55** | 0.62** | 0.66** | 0.72** |

**Significant at the 99% confidence level.
Abbreviation: total area (TA), landscape shape index (LSI), total edge (TE), aggregation index (AI), constant (Cons), distance to city centers (Dis_CE), distance to county roads (Dis_C), distance to national roads (Dis_G), distance to provincial roads (Dis_X), distance to rivers (Dis_R), Elevation (Ele), W of spatial lag model (W), lambda of spatial error model (lam).
aSpatial lag models.
bSpatial error models.
rate of 4.07%. The rate of urban land expansion, however, had slowed down considerably after 2005. The Moran’s I calculation indicated that there is a general spatial positive spatial autocorrelation in urban growth changes on these two scales. The Moran’s I change trend is consistent at the 2 and 5 km scales. In the regression results, the topography and proximity factors have influence on the change of urban landscape, and there are different at different time and space scales. Among these variables, The Moran’s I of slope, elevation, distance to the national highway and the provincial road is relatively high, so these variables have a large correlation with urban landscape changes, while the Moran’s I calculated by the distance to river, distance to city center and the distance to the railway parameters are smaller or tends to 0, so they have little or no correlation with urban landscape changes. That means the impact of these variables is not considered in urban landscape change studies.

There are several limitations in the research process: Firstly, the TM image of several time periods is selected to obtain the information of urban spatial expansion, for the long-term data analysis is needed to study the mechanism and determinants of urban spatial expansion, the data is insufficient, research on urban spatial development requires more high-resolution, wider coverage and longer continuous observation time, supported by more detailed supporting socio-economic data; Secondly, the process of urban space expansion is very complex, and there are many influential factors. In this study, only terrain and adjacent geographical determinants were analyzed, and other factors that could not be quantified, including economy, population and policy, were not analyzed. In the future urban research, integrated terrain, adjacent geographical determinants and various socio-economic factors together, can more comprehensive analysis of urban spatial problems; there are defects in visual interpretation of TM image, because of the problem of image resolution and manual identification, the pixel level information cannot be obtained, but the information is lost. Based on image data, how to extract urban spatial information efficiently and accurately is an important research direction in the future; finally, only two spatial scales are analyzed in the research process, and more scales are needed to study it. The above limitations will be considered in our future studies of urbanization in Harbin.

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References

Aljoufie, M., Brussel, M., Zuidegoest, M., & van Maarseveen, M. (2013). Urban growth and transport infrastructure interaction in Jeddah between 1980 and 2007. International Journal of Applied Earth Observation and Geoinformation, 21, 493–505. https://doi.org/10.1016/j.jag.2012.07.006

Anselin, L., Syabri, I., & Kho, Y. (2006). Geoda: an introduction to spatial data analysis. Geographical Analysis, 38(1), 5–22. https://doi.org/10.1111/j.0016-7363.2005.00671.x

Botequilha Leitão, A., & Ahern, J. (2002). Applying landscape ecological concepts and metrics in sustainable landscape planning. Landscape and Urban Planning, 59(2), 65-93. https://doi.org/10.1016/S0169-2046(02)00005-1

China Statistical Yearbook (2018), National Bureau of Statistics. http://www.stats.gov.cn/tjsj/ndsj/2018/indexen.htm

Chen, Y., Chang, K.-T., Han, F., Karacsonyi, D., & Qian, Q. (2016). Investigating urbanization and its spatial determinants in the central districts of Guangzhou, China. Habitat International, 51, 59–69. https://doi.org/10.1016/j.habitint.2015.10.013

Dietzel, C., Herold, M., Hemphill, J. J., & Clarke, K. C. (2005). Spatio-temporal dynamics in California’s central valley: Empirical links to urban theory. International Journal Of Geographical Information Science, 19(1), 175-195.

Gao, J., & Li, S. (2011). Detecting spatially non-stationary and scale-dependent relationships between urban landscape fragmentation and related factors using geographically weighted regression. Applied Geography, 31(1), 292–302. https://doi.org/10.1016/j.apgeog.2010.06.003

Henry, M. S., Schmitt, B., & Piguet, V. (2001). Spatial econometric models for simultaneous systems: Application to rural community growth in France. International Regional Science Review, 24(2), 171–193. https://doi.org/10.1177/016001701761013169

Janssen, L. L., & Van der Wel, F. J. (1994). Accuracy assessment of satellite derived land-cover data: A review. Photogrammetric Engineering and Remote Sensing, 60, 419–426. https://www.researchgate.net/publication/40208382_Accuracy_assessment_of_satellite_derived_land-cover_data_A_review/citation/download

Li, X., Zhou, W., & Ouyang, Z. (2013). “Forty years of urban expansion in Beijing: What is the relative importance of physical, socioeconomic, and neighborhood factors? Applied Geography, 38, 1–10. https://doi.org/10.1016/j.apgeog.2012.11.004

Li, Y., Yansui, L., Long, H., & Wang, J. (2013). Local responses to macro development policies and their effects on rural system in China’s mountainous regions: The case of Shuanghe Village in Sichuan Province. Journal of Mountain Science, 10(4), 588–608. https://doi.org/10.1007/s11629-013-2544-5

Ma, R., Gu, C., Pu, Y., & Ma, X. (2008). Mining the urban sprawl pattern: a case study on sunan, china. Sensors (Basel), 8(10), 6371-6395. https://doi.org/10.3390/s8106371

Ma, Y., & Xu, R. (2010). Remote sensing monitoring and driving force analysis of urban expansion in Guangzhou City, China. Habitat International, 34(2), 228–235. https://doi.org/10.1016/j.habitint.2009.09.007

Meganigal, K., Cushman, S., Neel, M., & Ene, E. (2012). FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps, 2012. Available online: http://www.umass.edu/landeco/research/fragstats/fragstats.html

McGarigal, K., Cushman, S. A., Neel, M., & Ene, E. (2002). Fragsats: Spatial pattern analysis program for categorical maps.
Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37(1/2), 17–23. https://doi.org/10.1093/biomet/37.1-2.17

Peng, W., Wang, G., Zhou, J., Zhao, J., & Yang, C. (2015). Studies on the temporal and spatial variations of urban expansion in Chengdu, western China, from 1978 to 2010. *Sustainable Cities and Society*, 17, 141–150. https://doi.org/10.1016/j.scs.2015.03.004

Powell, R. L., Matzke, N., de Souza, C., Clark, M., Numata, I., Hess, L. L., & Roberts, D. A. (2004). Sources of error in accuracy assessment of thematic land-cover maps in the Brazilian Amazon. *Remote Sensing of Environment*, 90(2), 221–234. https://doi.org/10.1016/j.rse.2003.12.007

Shu, B., Zhang, H., Li, Y., Qu, Y., & Chen, L. (2014). Spatiotemporal variation analysis of driving forces of urban land spatial expansion using logistic regression: A case study of port towns in Taicang City, China. *Habitat International*, 43, 181–190. https://doi.org/10.1016/j.habitatint.2014.02.004

Su, S., Jiang, Z., Zhang, Q., & Zhang, Y. (2011). Transformation of agricultural landscapes under rapid urbanization: A threat to sustainability in Hang-Jia-Hu region, China. *Applied Geography*, 31(2), 439–449. https://doi.org/10.1016/j.apgeog.2010.10.008

Sun, C., Wu, Z.-F., Lv, Z.-Q., Yao, N., & Wei, J.-B. (2013). Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, 21, 409–417. https://doi.org/10.1016/j.jag.2011.12.012

Tan, R., Liu, Y., Liu, Y., He, Q., Ming, L., & Tang, S. (2014). Urban growth and its determinants across the Wuhan urban agglomeration, central China. *Habitat International*, 44, 268–281. https://doi.org/10.1016/j.habitatint.2014.07.005

Tian, G., Liu, J., Xie, Y., Yang, Z., Zhuang, D., & Niu, Z. (2005). Analysis of spatio-temporal dynamic pattern and driving forces of urban land in China in 1990s using TM images and GIS. *Cities*, 22(2005), 400–410. https://doi.org/10.1016/j.cities.2005.05.009

Tiefelsdorf, M. (2002). The saddlepoint approximation of Moran’s I’s and local Moran’s I’s reference distributions and their numerical evaluation. *Geographical Analysis*, 34(3), 187–206. https://doi.org/10.1111/j.1538-4632.2002.tb01084.x

United Nations. (2018). *World urbanization prospects: 2018 revision of world urbanization prospects*. https://www.un.org/development/desa/publications/2018-revision-of-world-urbanization-prospects.html

Yang, X., & Lo, C. P. (2003). Modelling urban growth and landscape changes in the Atlanta metropolitan area. *International Journal of Geographical Information Science*, 17(5), 463–488. https://doi.org/10.1080/1365881031000086965

Zhang, Z., Su, S., Xiao, R., Jiang, D., & Wu, J. (2013). Identifying determinants of urban growth from a multi-scale perspective: A case study of the urban agglomeration around Hangzhou Bay, China. *Applied Geography*, 45, 193–202. https://doi.org/10.1016/j.apgeog.2013.09.013