A Comparative Study of Urban Built-Up Area Change Monitoring by Remote Sensing Images and POI Data—Taking Shenyang as an Example

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Abstract. The urban built-up area change monitoring is important for Urban planning. In this paper, 2016 and 2019 remote sensing images and POI data of Shenyang are selected for monitoring urban built-up area change. First, the remote sensing images and POI data are preprocessed. Second, the urban built-up change area of Shenyang is extracted from remote sensing images by neural network classification. Third, the built-up change area of Shenyang is extracted from POI data by kernel density surfaces. Finally, the similarities and differences are analyzed between the two data in urban built-up area change. Experimental results: the growth trends of built-up areas are same, but the change areas were quite different. The change area is about 404.8 km² with the remote sensing images, and the change area is about 63.3 km² with POI data.

1. Introduction
The urban built-up area change monitoring is important for Urban planning. At present, scholars at home and abroad mainly use supervisory classification or non-supervisory classification methods for studying urban built-up areas change monitoring by traditional remote sensing images. For example, Deng et al. used hyperspectral remote sensing images to extract the boundaries of built-up area [1]; Liang et al. used multispectral remote sensing images to extract urban construction land [2]; Wang used medium resolution remote sensing images to study temporal and spatial urban built-up areas change [3]; Zhang used medium resolution remote sensing images to detect urban built-up areas change in the Nanjing metropolitan area [4]; Fan, He et al. used night light data to monitor construction sites in Wuhan City [5]. Pei et al. monitored urban built-up areas change in Qinzhou region based on medium resolution remote sensing images [6]; Song studied the evolution of urban built-up area expansion patterns in coastal area based on medium resolution remote sensing images [7]; Li et al. processed remote sensing images to automatically extract built-up area based on deep learning [8]; Feng et al. used multi-temporal phase remote sensing data to monitor changes in cities [9]. The above scholars used different remote sensing images such as high resolution, medium resolution, night light and so on, to monitor the urban built-up area through manual, semi-automatic and even automated methods. Although many research results have been achieved, there are some shortcomings, such as the data sources relatively single and the scales are too large.

With the development of the Internet and communication technology, the POI (Point of Interest) data are emerging. POI data are abstracted from real geographical entities (restaurants, medical, schools and other facilities). They are distributed in all corners of the city, the distribution density is positively correlated with the level of urban economic development, very sensitive to economic
changes. POI data have rich properties, strong timeliness, large data volume, fast update, and other characteristics. They were used for the quantitative identification of urban boundaries [10], spatial structure [11], heat island effect [12], functional area identification [13], neighbourhood vitality [14], retail spatial pattern [15], extraction of built-up areas [16], spatial optimization of fire stations [17], urban polycentric identification [18], poverty identification [19], etc. POI data area city cells, the volume changes, spatial distribution changes are closely related to urban economic development.

At present, some scholars use POI data to monitor urban built-up areas. However, the similarities and differences between POI data and traditional remote sensing image data in urban built-up area change monitor have not been discussed [20]. Therefore, this paper uses remote sensing images and POI data to study Shenyang city urban built-up areas change and compares the similarities and differences of result by the two data.

2. Research Framework and Data Processing

2.1. Research Framework

The framework includes three steps (as shown in figure 1): First, the remote sensing images and POI data are preprocessed. Second, the urban built-up change area of Shenyang is extracted from remote sensing images by neural network classification. Third, the built-up change area of Shenyang is extracted from POI data by kernel density surfaces. Finally, the similarities and differences are analyzed between the two data in urban built-up area change.

![Figure 1. Research framework (comparative analysis).](image)

2.2. Study Area and Data Preprocessing

The main urban area of Shenyang City is the study area (shown in figure 2), contains both built-up and unbuilt-up area. The POI data are obtained from the Gaud Navigation Map in August 2016 and July 2019. About 411000 and 446000 pieces of effective data are obtained after data cleaning and duplicate removal. The Landsat8 remote sensing images are obtained from the official USGS website, which are taken in August 2016 and July 2019. Images are used after radiation calibration and atmospheric correction. The 2019 remote sensing and POI data are shown in figure 2.
2.3. Research Method

2.3.1. Extraction Method of Urban Built-Up Area Based on POI Data. The kernel density estimation is a function for estimating the unknown density. The method does not set priori hypotheses for the spatial density distribution of the elements, relies only on the characteristics of the elements themselves for spatial density analysis.

The kernel density method is to estimate the change in the density distribution of the surrounding elements by distance decay for other elements within a certain range (search radius) from a certain element (POI data point) in space, in order to obtain the spatial density surface of that element. Elemental kernel density values are obtained by spatial superposition of surfaces of different densities. The formula is as follows:

$$f(\chi) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{r} K \left( \frac{X - X_i}{r} \right)$$

where the kernel density value for any point $\chi$ in space, $r$ is search radius, $X - X_i$ is the distance between point $X_i$ and centre point $X$, $n$ is the number of elements at any point $X$ (distance $\leq r$) in distance space, $k(X)$ is the spatial weight function.

2.3.2. Extraction Method of Urban Built-Up Area Based on Remote Sensing Data. The kernel density estimation is a function for estimating the unknown density. The method does not set priori hypotheses for the spatial density distribution of the elements, relies only on the characteristics of the elements themselves for spatial density analysis.

In this paper, extract urban built-up areas by Neural Net Classification to process remote sensing data. NNC is a classification method that simulates decision making by human brain neurons and is suitable for handling non-linear problems. Its core formula is as follows:

$$h_j = \int \left( \sum_{i=1}^{m} \omega_{ij}x_i \right) - \theta_i$$
where the parameters \( x_i \) and \( x_j \) are the values of the neuronal nodes of the previous layer i and j, \( \theta_j \) and \( \theta_k \) are the thresholds of the implicit nodes and output points in the formula, \( \omega_{ij} \) and \( \omega_{kj} \) are the connection weights between the nodes of the implicit layer j and the nodes of the output layer k, \( h_j \) is the sample information of the input layer i nodes, \( y_k \) is the sample information of input layer k.

3. Experimental Analysis

3.1. Monitoring Change in Urban Built-Up Areas Basing on Remote Sensing Images

The kappa coefficients of 0.89 and 0.90 for the extraction of the urban built-up area of Shenyang city are obtained by neural network classification method with remote sensing images, which can meet the accuracy requirement. The urban built-up area of Shenyang is in a state of expansion from 16 to 19 years (the red part in the figure represents the expansion area from 16 to 19 years). The total area of change is calculated to be approximately 404.8 km² (as shown in figure 3).

![Figure 3](image)

**Figure 3.** The results of urban built-up areas change based on remote sensing images.

3.2. Monitoring Change in Urban Built-Up Areas Based on POI Data

The POI data are computed by the kernel density method for obtaining the spatially distributed density surface of the POI data, where the search radius \( r=1200 \text{m} \). The results are got (shown in figure 4) after processing by the natural break point method (divided into eight classes).

The densities distribution of the 2016 and 2019 year POI data are shown in figure 4. Results of urban change monitoring results are shown in figure 5. It is found that the density distribution of the POI data showed a density increase from 16 to 19 years (the red part of the figure represents the expansion area from 16 to 19 years), and the change area in density surface is about 63.3 km².

3.3. Comparative Analysis of Test Results

From the above experimental results, the monitoring results by remote sensing images and POI data show the areas increase trends are same, but areas change amounts are different. According to the characteristics of the two types of data, remote sensing images can be used to monitor the changes of surface features(such as arable land, water bodies, built-up areas, etc.) from a macroscopic perspective, and the monitoring results have no obvious economic attributes; POI data are closely related to the level of regional economic development, reflecting the economic development of the city from a
microscopic perspective, and its monitoring results have obvious economic attributes. The results can reflect the changes in the level of economic development of built-up areas using POI data, while the results by remote sensing image data do not have obvious economic properties, but can reflect the development changes of urban built-up areas in a comprehensive and objective.

(a) Density of spatial distribution of POI data in 2016

(b) Density of spatial distribution of POI data in 2019

**Figure 4.** POI data density surface map.

Figure 5. Results of urban change monitoring results based on POI data.

4. Discussion and Conclusion

This paper studies the differences and similarities in urban change monitoring based on traditional remote sensing images and POI data. The following results were achieved: first, the results of the experiment show that the increase changes trend of Shenyang urban built-up areas are same with two types of data; second, the increase change quantities of Shenyang urban built-up areas extracted from the two types of data were quite different. The change area was about 404.8 km² with the remote sensing images, and the change area was about 63.3 km² with POI data.

Although the paper analyses the similarities and differences between remote sensing images and POI data for monitoring changes in urban built-up areas, there are also shortcomings: the relationship between the two data cannot be analyzed in depth; the samples of the experiment were too less; and the quantitative analysis was lacking. In the future, it is proposed to use more experimental samples for the study and to use quantitative research methods to further analyse the relationship between the two data and their application in monitoring changes in urban built-up areas.
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