

Analysis of Regional Transportation Networks and Socioeconomic Spatial Distribution Based on Remote Sensing Image Supervised Classification: A Case Study of Taizhou City

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Abstract: This study investigates the spatial correlation between transportation networks and socioeconomic activities within Taizhou City, utilizing supervised classification of remote sensing imagery and advanced spatial analytical techniques. Based on Landsat 8 imagery, the study classifies the study area into built-up areas, water bodies, and farmland using a neural network algorithm, achieving a classification accuracy of 91.17%. By employing transportation network data and a grid-based approach, the correlation between road length and building area was analyzed, yielding a Pearson correlation coefficient of 0.5388. This indicates a moderate positive correlation between transportation network density and socioeconomic activities. A comparative analysis of satellite images from 2010, 2016, and 2024 demonstrates the significant driving effect of main road construction on commercial development along the route. The study reveals that transportation network optimization not only enhances accessibility but also significantly promotes economic development in surrounding areas.

Keywords: Remote sensing images, supervised classification, transportation network, socioeconomic activities, spatial distribution analysis

1. Introduction

Urban transportation networks are crucial for economic development, directly impacting regional economic vitality and development patterns. A well-structured transportation network facilitates resource flow, information exchange, and personnel movement, reducing transaction costs, expanding market scale, and promoting economic growth. Conversely, inadequate transportation infrastructure can hinder economic development by restricting the movement of production factors and limiting market expansion, ultimately affecting business investment and growth [1].

With the advancement of remote sensing technology, remote sensing imagery has become an increasingly valuable spatial data source in urban studies. Supervised classification of remote sensing imagery facilitates the rapid and efficient acquisition of urban land use data, encompassing roads, buildings, and green spaces, thereby supporting endeavors in urban planning, transportation planning, and economic development research.

This paper is structured as follows: Section 2 introduces general methods for supervised classification of remote sensing images and spatial autocorrelation theory. Sections 3 and 4 describe and analyze the experiment's process and results. Section 5 summarizes the study.

2. Study area overview

Taizhou City is located in central Jiangsu Province, downstream of the Yangtze River, bordering the Yellow Sea to the east, Yangzhou to the south, Nanjing to the west, and Huai'an to the north. As an important prefecture-level city in Jiangsu Province, Taizhou enjoys a favorable geographical location in the core area of the Yangtze River Economic Belt, serving as a key intersection of Jiangsu's economy, transportation, and culture.

Economically, Taizhou is primarily manufacturing-based, with strong foundations in traditional industries such as chemicals, machinery, and shipbuilding. Modern services and high-tech industries have also begun to emerge. In recent years, Taizhou has emphasized industrial transformation and upgrading, promoting emerging industries such as biopharmaceuticals, new energy, and information technology, with a particularly complete industrial chain in chemicals, electronics, and environmental protection.

Taizhou's diverse economic structure, encompassing agriculture, industry, commerce, and services, makes it an ideal case for studying the spatial distribution of socioeconomic activities and the impact of transportation network development on regional economic layout [2].

Moreover, Taizhou has relatively well-documented data availability, with official records on transportation and remote sensing data, providing robust support for supervised classification, transportation network, and socioeconomic spatial analysis.

3. Remote sensing data and supervised classification method

3.1. Remote sensing data overview

This study utilizes Landsat 8 satellite imagery, which provides high-quality Earth observation data with a spatial resolution of 30 meters and multispectral characteristics suitable for urban and regional land cover classification [3]. Landsat 8 is equipped with the Operational Land Imager (OLI) sensor, capturing data across seven spectral bands from visible to thermal infrared, as shown in Table 1.

Table 1: Landsat 8 OLI sensor's seven bands

Band Number	Band Name	Wavelength Range(μm)	Spatial Resolution(m)	Main Usage
1	Coastal/Aerosol (Blue)	0.433 - 0.453	30	Atmospheric and water studies, detecting suspended matter in coastal waters.
2	Blue	0.450 - 0.515	30	Water detection, atmospheric correction, vegetation indices.
3	Green	0.525 - 0.600	30	Water quality monitoring, healthy vegetation identification.
4	Red	0.630 - 0.680	30	Vegetation health monitoring, NDVI calculation.
5	Near Infrared (NIR)	0.845 - 0.885	30	Vegetation cover and moisture analysis.
6	Shortwave Infrared 1 (SWIR1)	1.560 - 1.660	30	Soil and vegetation moisture analysis.
7	Shortwave Infrared 2 (SWIR2)	2.100 - 2.300	30	Fire monitoring, rock and mineral analysis.

3.2. Image preprocessing

In the image processing workflow, Landsat 8 images were first mosaicked and cropped to extract the study area, ensuring data specificity and effectiveness. Radiometric calibration and atmospheric

correction were then applied to eliminate errors from atmospheric effects and sensor inconsistencies. Radiometric calibration ensures consistency between image radiance values and actual surface reflectance, while atmospheric correction removes atmospheric interference, improving the accuracy and reliability of subsequent analysis. Figure 1 displays the final processed image resulting from the analysis.



Figure 1: Preprocessed remote sensing image of Taizhou City

3.3. Supervised classification method

This study employed a neural network algorithm for land cover classification. Neural networks simulate biological neural structures to process information, effectively handling complex, high-dimensional data. The neural network was trained on sample data to learn the characteristics of different land cover types and classify image pixels accordingly into built-up areas, water bodies, and farmland[4].

Compared to traditional classification algorithms such as Support Vector Machines (SVM) and Random Forest (RF), neural networks better capture complex data patterns, particularly in multispectral data with high nonlinearity. Although SVM and RF can also achieve high classification accuracy, they are more computationally intensive and heavily reliant on feature selection.

To evaluate classification accuracy, confusion matrices were used to calculate overall accuracy and the kappa coefficient. The overall accuracy formula is:

$$\text{Overall Accuracy} = \frac{\sum_{i=1}^n M_{ii}}{N} \quad (1)$$

Where M_{ii} represents the diagonal elements of the confusion matrix (correctly classified pixels), and N is the total number of pixels.

The Kappa Coefficient formula is:

$$\kappa = \frac{P_o - P_e}{1 - P_e} \quad (2)$$

Where P_o is the Overall Accuracy, and P_e is the expected accuracy from random classification.

$$P_e = \sum_{i=1}^n \frac{(M_{i+} \cdot M_{+i})}{N^2} \quad (3)$$

M_{i+} and M_{+i} represent the total number of actual and predicted pixels for class i , respectively.

According to the evaluation results, the overall accuracy of this study's classification is 91.17%, indicating that 57,499 pixels were correctly classified, accounting for 91.17% of the total number of pixels. Additionally, the Kappa coefficient is 0.8787, demonstrating a high level of consistency

between the classification results and ground truth data, significantly outperforming random classification results[5].

These accuracy evaluation indicators validate the effectiveness of the neural network method in the supervised classification of remote sensing images, proving its capability to accurately distinguish land cover types such as built-up areas, water bodies, and farmland. This provides a reliable data foundation for subsequent transportation network and socioeconomic activity spatial analysis.

4. Supervised classification results of remote sensing images and regional transportation network analysis

4.1. Transportation network analysis

In the transportation network analysis, the road network data used in this study was not obtained from remote sensing image classification but was downloaded from online sources. Based on the acquired road network data, this study conducts transportation analysis for Taizhou's road network. To deeply analyze the distribution patterns, accessibility, and connectivity of the transportation network, we first established a grid with a 1 km edge length covering the entire city. This grid division allows precise mapping of road length and building area within each grid unit. Specifically, the road length within each grid is obtained from road network data, while the building area is derived from the classified built-up area information[6].

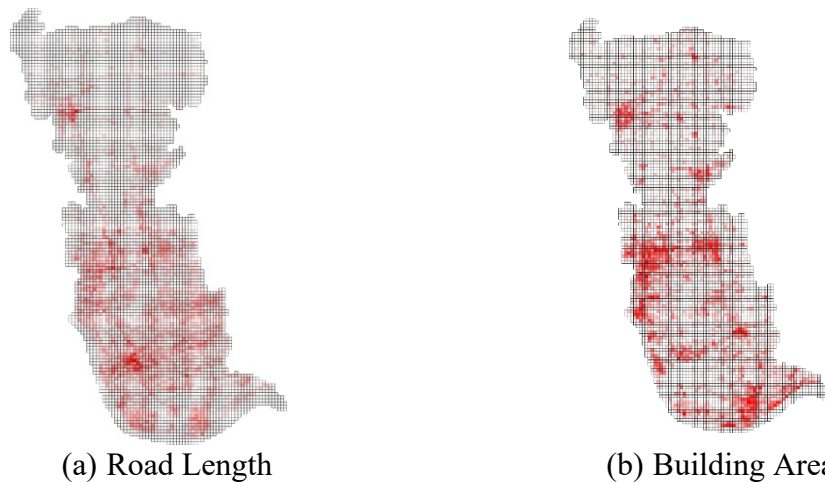


Figure 2: Distribution of road length and building area within 1km grids in Taizhou

In analyzing the distribution pattern of the transportation network, Taizhou's road network exhibits a high degree of concentration around the urban center and surrounding areas. The central urban area has a higher road density, forming a dense transportation network, whereas areas farther from the city center have a sparser road network. Accessibility analysis reveals that the connectivity between Taizhou's central area and its peripheral regions is relatively strong. However, some areas farther from the center may have poor accessibility, which could impact economic and social development in those regions.

4.2. Relationship between transportation networks and socioeconomic activities

Transportation networks and socioeconomic activities are closely linked spatially. To explore their mutual influence, this study employs spatial analysis methods and uses Pearson Correlation Analysis to calculate the relationship between road length and building area within each 1 km grid unit.

Specifically, we mapped each grid unit's road length and building area into corresponding Shapefile fields and calculated their spatial correlation using the Pearson correlation coefficient[7].

The Pearson correlation coefficient is calculated as follows:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (4)$$

where:

r is the Pearson correlation coefficient;

x_i and y_i represent the road length and building area of the i -th grid unit, respectively;

$\bar{x}$ and $\bar{y}$ are the average values of road length and building area;

n is the total number of grid units.

Through correlation analysis, the results indicate a strong positive correlation between Taizhou's road network density and building area. The Pearson correlation coefficient is 0.5388, suggesting a moderate positive correlation between road network density and urban expansion. This result highlights the promoting effect of a dense transportation network on urban construction activities. In the central urban area, road network density is closely related to the expansion of built-up areas, whereas in the outskirts, the road network density is relatively low, resulting in uneven spatial distribution of construction activities.

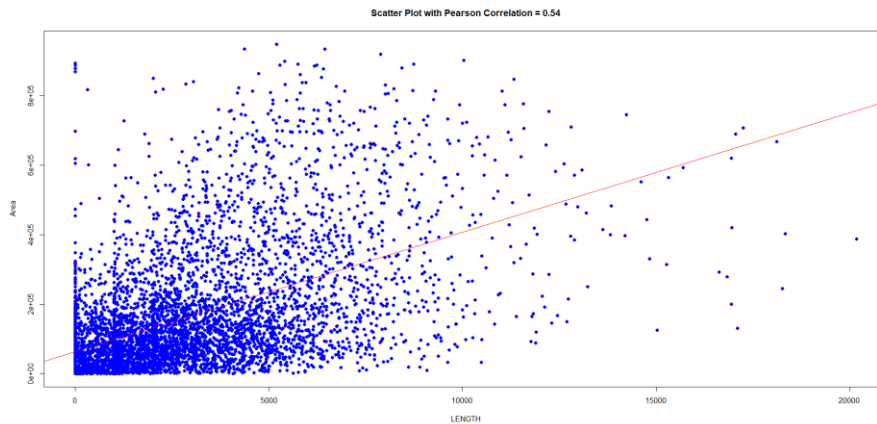


Figure 3: Pearson correlation analysis results

4.3. Case study and empirical results

The construction and improvement of transportation networks significantly impact the distribution and development of regional socioeconomic activities. To further analyze this effect, this study selects a large commercial complex in Taizhou as a case study. By comparing satellite images from 2010, 2016, and 2024, we explore the development process of major roads and their driving effect on commercial layouts.

In 2010, the satellite image shows that the road network in this area was still in its early stages, with low traffic connectivity. Commercial activities were relatively scattered, and farmland dominated the surroundings, lacking a clear economic center.

By 2016, the image indicates that roads had been expanded, connecting more surrounding areas and gradually improving transportation conditions. Concurrently, there was a marked transformation in land use patterns, witnessing a shift from agricultural to construction land in certain areas, which gave rise to the development of small-scale commercial and service establishments. This shift

underscores the substantial impact of road expansion on enhancing the development potential along the corridor, thereby establishing a precursor for future expansive economic ventures.

In 2024, the major road was fully completed and officially opened to traffic. The image reveals that this road greatly improved regional accessibility, driving the construction and opening of the commercial complex. The development density of surrounding land significantly increased, with the commercial complex becoming the regional business core, forming a strong spatial connection with the major road. The surrounding area's building density and commercial layout also saw substantial enhancement, further reflecting the direct impact of transportation infrastructure on the spatial distribution of economic activities[8].

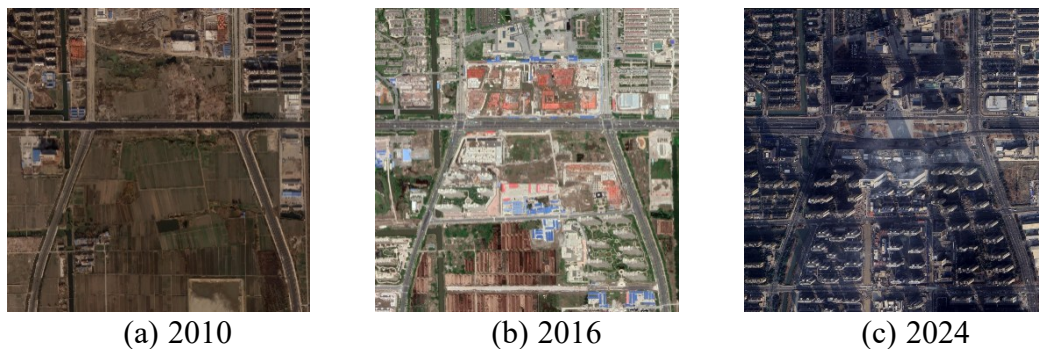


Figure 4: Spatiotemporal evolution of a large commercial complex and major road construction in Taizhou

This case clearly demonstrates how the gradual improvement of the transportation network, from initial planning to full-scale construction, has driven commercial development and land use changes along its route. The construction of main roads not only enhances regional accessibility but also significantly promotes the concentration and prosperity of economic activities, highlighting the crucial regulatory role of transportation infrastructure in the spatial distribution of socioeconomic factors.

5. Conclusion

This study utilizes supervised classification of remote sensing images of Taizhou, combined with spatial distribution analysis of regional transportation networks and socioeconomic activities, to reveal the profound impact of transportation infrastructure on urban economic activity layouts. The findings indicate that the construction and optimization of transportation networks not only alter the spatial distribution of land use but also significantly enhance regional accessibility and economic vitality. Through supervised classification, we successfully categorized the study area into built-up areas, water bodies, and farmland, and analyzed the coupling relationship between transportation networks and socioeconomic activities. Particularly in the case study, satellite images from three different periods clearly illustrate the driving effect of major road construction on commercial activities along the route. Furthermore, Pearson correlation analysis corroborates a substantial positive relationship between transportation networks and socioeconomic activities, yielding a correlation coefficient of 0.5388. This finding underscores the pivotal role of transportation infrastructure in fostering socioeconomic development.

Despite these findings, this study has limitations, including potential inaccuracies in supervised classification due to sample data quality, reliance on static data for analyzing transportation and socioeconomic ties, and the lack of broader regional validation. Future research should optimize classification methods, incorporate dynamic models, and expand the scope to different regions for

general impact validation. Advanced remote sensing and spatial analysis will enhance urban planning and decision-making with ongoing technological progress.

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