The Role of Remote Sensing Feature Extraction in Smart Cities: A Case Study of the Xiangyang Area

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Abstract. This paper takes Xiangyang City, Hubei Province, as an example to explore the role of remote sensing feature extraction technology in smart city construction. The study is based on GF-4 (Gaofen-4) remote sensing imagery. Supervised classification was performed using ENVI software. Features such as vegetation, water bodies, and bare land were extracted through band fusion, standard false-color composition, and the Maximum Likelihood method. Classification accuracy was verified using a confusion matrix. Thematic maps were created using ArcGIS, and land use proportions were calculated (e.g., water bodies accounting for 65.3%). The results indicate that remote sensing technology can efficiently quantify current urban land use, providing precise spatial data support for smart city planning and facilitating optimized resource allocation and sustainable development. Moreover, the approach highlights the potential of integrating multi-source remote sensing with geographic information systems for dynamic urban monitoring. It also emphasizes the scalability of the method for application in other medium-sized Chinese cities. Finally, the findings provide practical guidance for decision-makers seeking to balance ecological protection and urban growth under the framework of smart city development.

Keywords: remote sensing feature extraction; smart city planning; land use classification.

1. Introduction

With rapid economic development and continuous population growth, urban expansion has been accelerated, and cities in China have entered a period of accelerated development. Urbanization and industrialization are inevitable paths for the modernization of human society and necessary trends for economic and social development. They hold significant importance for China in constructing a new development pattern and promoting common prosperity. Since the founding of the People's Republic of China, the urbanization rate has increased from 10.64% in 1949 to 65.22% in 2022, representing the largest-scale urbanization process in human history. This has profoundly impacted and changed the global urbanization landscape, forging a path of urbanization with Chinese characteristics. During the "14th Five-Year Plan" period, China remains in a phase of rapid urbanization, with a continuously growing urban population and steadily improving urbanization quality [1]. The role of urbanization in promoting national economy and social progress has significantly enhanced. However, urban issues such as population (expansion), environmental pollution, resource shortages, and traffic congestion have gradually become major problems restricting urban development in China. Whether from the perspective of ecology, human sustainable development, or economic advancement, establishing a new urban development model is an essential path for China's urban development today. Seizing the pulse of the times and integrating the trends of the new technological revolution with urbanization urgently requires seeking effective comprehensive solutions to urban problems that follow the objective laws of urban development. Hence, smart cities become an inevitable choice.

The essence of a smart city is the efficient allocation of urban resources through data-driven dynamic perception and intelligent decision-making. Surveying, mapping, and geographic information technology, as core tools for spatial data acquisition, analysis, and representation, provide the foundational support for constructing urban digital twins [2]. This paper will discuss and delve into the significant role remote sensing technology plays in promoting road and urban planning within the context of smart citie [3]. First, the paper will explain the results presentation and acquisition methods of GIS in the visual expression of digital information [1, 4]; subsequently, it will demonstrate how to use ENVI software for urban feature extraction, classification, and application of results; finally, the paper aims to provide a reference framework for decision-makers in road construction and urban planning for smart cities, to better promote the development of smart cities and the efficient operation of related work.

2. Methods

2.1. Overview of Xiangyang City and Urban Development Background

The study area is in Xiangyang City, Hubei Province. As a second-tier city in Hubei Province and a vital city on the Yangtze River Economic Belt, on November 26, 2010, the State Council officially approved the renaming of Xiangfan City to Xiangyang City, and Xiangfan City's Xiangyang District was renamed Xiangzhou District of Xiangyang City. After the renaming, the administrative divisions remained unchanged. It currently governs three county-level cities: Zaoyang, Yicheng, and Laohekou; three counties: Nanzhang, Baokang, and Gucheng; and three urban districts: Xiangcheng, Fancheng, and Xiangzhou. It has two national-level development zones (National Xiangyang High-Tech Industrial Development Zone, National Xiangyang Economic and Technological Development Zone) and one provincial-level development zone (Yuliangzhou Economic Development Zone). The total area of the city is 19,700 square kilometers, with a population of 5.8 million. The built-up area of the urban district is 100 square kilometers, with a population of 1.2 million. In September 2003, it was designated as a sub-provincial central city by Hubei Province [5, 6].

2.2. Remote Sensing Image Data Source and Parameter Description

Urban development and expansion bring a series of issues such as road planning, land use, and environmental protection. Therefore, land use has long been a focus of research. This paper uses remote sensing data to classify and statistically analyze the land use situation in Xiangyang urban area at the image level, conducting statistical analysis of urban and rural land use. The data source used is GF-4 (Gaofen-4) multispectral remote sensing imagery, with data identifier GF4-RIS-528524. Considering weather conditions, temperature, and cloud cover, data from the same period in 2017 and 2024 for the study area were selected. This period is summer in the Central Plains region, characterized by vigorous crop growth, dry weather, high temperatures, and little recent rainfall, resulting in fewer interfering factors for classification. The panchromatic band resolution of GF-4 imagery is 50 meters, and it has undergone radiometric correction and rough geometric correction.

2.3. Auxiliary Data: Administrative Boundary Vector Map

The SHP data for administrative divisions used in the study is 1:250,000 vector data downloaded from the National Fundamental Geographic Information Database. This vector data is in line file WL format [7- 9]. Open ArcGIS Pro, create a new map from the Insert menu bar to connect to the folder and open the data.

3. Technical Pathway for Remote Sensing Feature Extraction and Classification Workflow

3.1. Image Preprocessing

Supervised classification primarily uses visual interpretation. The images underwent band stacking and geometric correction, followed by principal component analysis extraction. Band fusion and standard false-color composition allow for supervised classification using field-collected sample data to establish Regions of Interest (ROIs) for various land types [6].

The preprocessed remote sensing image of Yicheng City obtained after experimental preprocessing is shown below, allowing the experiment to commence (Fig.1).

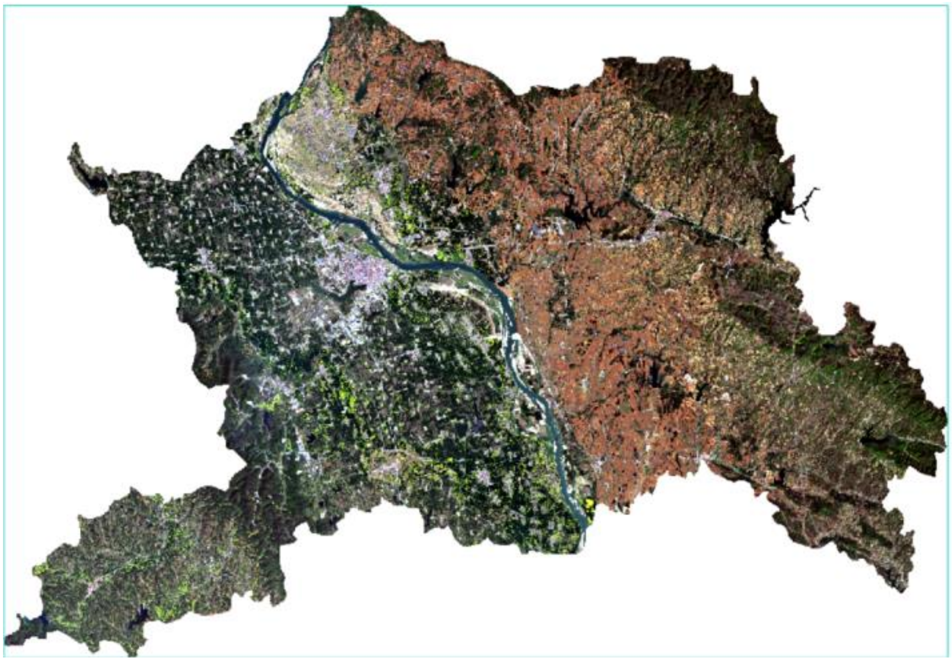

Fig. 1 Remote sensing image of Yicheng City (Photo credit: original)

3.2. Feature Classification Design and Training Sample Construction

Supervised classification in ENVI uses the ROI Tool to define training samples, meaning Regions of Interest are treated as training samples. Therefore, the process of creating training samples is the process of creating ROIs. First, visual interpretation is performed on the image. The remote sensing image is opened and displayed using an RGB composite of Bands 5, 4, and 3. Then, forest land, grassland, cultivated land, bare land, sandy land, and other land uses are interpreted visually [10]. Currently, for large-scale feature extraction processes, although unsupervised classification methods have a high degree of automation, they require large amounts of training data, and model applicability may be limited under different regions or imaging conditions. These automated methods have certain limitations in application and many shortcomings in distinguishing features. In obtaining detection results, the accuracy of the results is often more critical than automation. To improve result accuracy, reliance on experienced researchers for visual interpretation is still chosen [11]. However, the accuracy of visual interpretation is affected by multiple factors, mainly including the display effect of the remote sensing image, the discriminative power of spectral indices, and the mixed pixel effect at land-water boundaries. Image display enhancement methods affect the display effect, mainly including color composite methods and image stretching methods. During experiments, as many samples as possible should be selected to reduce errors caused by the above factors (Table 1).

Table 1. Band Combinations, Color Characteristics, and Applicability of Different Color Composite Methods

Feature Type	Common Band Combination	Color Characteristics	Applicability
Vegetation	NIR + Red + Green	Vegetation appears bright red (strong NIR reflection), water bodies appear blue-black, soil appears brown or grey	Vegetation coverage survey, crop growth monitoring, forest resource inventory
Water Body	Green + Red + NIR	Clear water appears blue or blue-black, turbid water appears light blue, shoreline vegetation appears red Water resource survey,	water pollution monitoring, lake/river boundary extraction
Urban Building	Green + Red + NIR	Buildings and bare soil appear grey or light brown, vegetation appears red, water bodies appear blue-black	Urban expansion monitoring, construction land identification, urban planning analysis
Soil	Red + Green + Blue	Different soil types appear brown, yellow, grey, etc. (soils high in organic matter are darker, sandy soils lighter)	Soil type classification, soil erosion monitoring, cultivated land quality assessment
Snow	Ice Blue + Green + Red	Snow and ice appear white or light blue (polluted snow/ice appears darker), surrounding vegetation green or red	Snow/ice cover monitoring, glacier change research, snowmelt runoff prediction
Feature Type	Common Band Combination	Color Characteristics	Applicability

Based on the above analysis, it can be found that in standard false-color images, healthy green vegetation and green civilian camouflage nets have relatively similar tones. The reason is that the spectral reflectance relationships of these three features at wavelengths of 0.55 μm (blue), 0.67 μm (green), and 0.88 μm (red) (Red >> Blue > Green) are basically consistent, resulting in similar tones after color composition. Other features are different, thus presenting different colors. Therefore, the key to maximizing the tonal distinction between different features in color images lies in selecting appropriate bands for color composition [12].

3.3. Selection and Execution of Supervised Classification Method

Finally, supervised classification is executed. Depending on the complexity and accuracy requirements, different classifiers are chosen for supervised classification. There are mainly 6 classifiers: 1. Parallelepiped, 2. Minimum Distance, 3. Mahalanobis Distance, 4. Maximum Likelihood (Likelihood Classification) [9], 5. Neural Net Classification, 6. Support Vector Machine Classification. ENVI 4.7 software has two categories with a total of 9 classifiers for supervised classification. Among them, the Maximum Likelihood method is a statistical method based on traditional statistical analysis. Its characteristic is that it requires prior knowledge of the feature categories' characteristics.

Assuming the data follows a normal distribution, it calculates the probability of a pixel belonging to each category and assigns it to the category with the highest probability. This study defined 5 categories for land use classification: vegetation, water body, farmland, residential area, and road. In the main window, click 'Region of Interest' and select the 'ROI Tool' toolbar to define classification names and colors, draw polygons, and select training samples. The Maximum Likelihood classifier was selected, and parameters were changed in the parameter settings interface as needed [13].

Generally using default parameters, after selecting the file output save path, the image was classified and displayed. The image result after Maximum Likelihood classification is obtained. (Note: The original text listing classifiers 5 & 6 here seems misplaced; they are just mentioned as other types).

3.4. Accuracy Verification and Confusion Matrix Analysis

However, accuracy cannot be guaranteed based on a single image, so another set of ROI images is taken for verification. A certain sampling method is used to obtain validation data, which is compared with the remote sensing classification result map to generate a confusion matrix. The form of the confusion matrix is shown in the table below. The confusion matrix can present accuracy in a quantitative manner [8]. The final classification result map was drawn using ArcMap software. When exporting the classification results to mapping software, the corresponding classification results are not directly visible. It is necessary to use the attribute transformation symbol system, use 'Unique Values' to add all values. If the category colors on the loaded map differ from the aforementioned classification results, manual color adjustment can be done without affecting the classification outcome. To make the map clear and understandable, it is also necessary to add four elements: scale bar, north arrow, legend, and graticule (latitude/longitude grid). Meanwhile, corresponding format adjustments can be made according to the map size, making the result map more complete and aesthetically pleasing (Fig. 2).

Finally, the results obtained by the above classification methods are preliminary and generally difficult to meet the final application purpose. Therefore, the acquired classification results require further processing to achieve the desired classification outcome. These processes are called post-classification processing. They mainly include: changing classification colors, small patch processing, post-classification statistics, conversion of classification results to vectors, and other operations. The effect after filtering analysis is as follows:

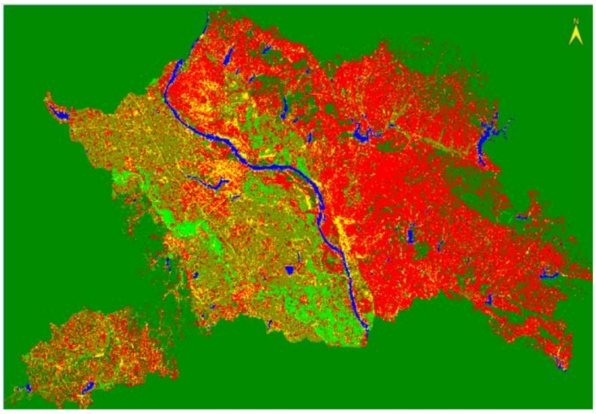

Fig. 2 Final Remote Sensing Classification Result Map of Xiangyang City after Post-Classification Processing (Photo credit:Original)

4. Results

4.1. Production of Classification Results Map and Feature Distribution Identification

Based on the thematic map above, the area and relevant proportions of various buildings, vegetation, water bodies, buildings, and soil were calculated. Before calculating the area of each patch, the relevant data must be projected. To make the area size of each feature more accurate, when adding a field in the attribute table, the double-precision type was selected, retaining three decimal places. The 'Calculate Geometry' method was used to calculate the area of each patch. Each patch represents a feature type. Then, the areas of patches belonging to the same type were summarized to obtain the total area of that feature type, in square meters. Finally, the total area of that feature type was divided by the total area of the entire region to obtain the corresponding proportion of that type in this region. The results are shown in the table below. The total area of the region is 19,700 square kilometers. This shows the land use situation of non-construction land in the area, providing strong support for future urban planning and land management [14].

4.2. Feature Area Calculation and Proportion Statistics

This study statistically analyzed the land use types and their proportions in Xiangyang City based on remote sensing classification results. The findings indicate that water bodies account for the largest proportion at 65.3%, reflecting the region’s typical water resource characteristics. Forest land makes up 9.1%, while grassland and cultivated land each account for 5.7%. Bare land has the smallest share at only 4.9%. Overall, the distribution of land use types shows significant variation. Large water bodies play a crucial role in maintaining the regional ecological environment and supporting sustainable urban development, while the presence of grassland, forest land, and cultivated land highlights the diversity and multifunctionality of the ecosystem (Table 2).

Table 2. Land Use Classification Results and Proportions in Xiangyang City

Land Type	Numerical Ratio (Numerator / Denominator)	Percentage Proportion	Land Type
Water Body	401 / 614	65.3%	Water Body
Bare Land	30 / 614	4.9%	Bare Land
Forest Land	56 / 614	9.1%	Forest Land
Grassland	35 / 614	5.7%	Grassland
Cultivated Land	35 / 614	5.7%	Cultivated Land

4.3. Potential Application of Results in Smart City Planning

In the process of Xiangyang's smart city planning, feature extraction technology,relying on its powerful data acquisition and analysis capabilities, provides multi-dimensional support for urban development, assisting the city in embarking on a new journey towards high-quality development.

In terms of urban expansion detection and construction land planning management, feature extraction from satellite images of different periods can clearly show the trajectory of urban expansion. For example, over the past five years, construction land in a certain area of Xiangyang has continued to increase. Using feature extraction technology for analysis revealed that some newly added land had unreasonable layouts. Based on this information, the planning department adjusted land use plans, prioritizing new construction land quotas for key industrial parks and livelihood projects, avoiding disorderly expansion, and achieving efficient allocation of land resources.

Water resource management and ecological redline delineation also rely on feature extraction technology. With this technology, surface water bodies such as rivers and lakes can be accurately extracted, enabling real-time understanding of water resource distribution and dynamic changes. In the ecological redline delineation work, Xiangyang referred to the feature extraction results and, combined with ecological protection needs, designated a certain wetland and its surrounding area as an ecological redline zone, strictly limiting development activities, effectively protecting the ecological environment, and maintaining the balance and stability of the ecosystem.

Feature extraction plays an important role in supporting road and transportation network expansion. By extracting road information and combining it with big data on traffic flow, traffic congestion nodes and bottleneck road sections can be accurately analyzed. A main road in Xiangyang experienced a sharp increase in traffic pressure due to rapid commercial development in the surrounding area. After analysis using feature extraction technology, the relevant departments added lanes at suitable locations and optimized the micro-circulation system of the surrounding roads, significantly improving the traffic efficiency of that road section, effectively alleviating traffic congestion, and providing convenience for citizens' travel.

Feature extraction technology permeates multiple key areas of Xiangyang's smart city planning, from land use to ecological protection, to traffic optimization, providing powerful data support and decision-making basis for the sustainable development of the city, with huge application potential.

5. Discussion

Remote sensing technology,leveraging its macro, dynamic, and efficient characteristics, provides key support for urban governance but still faces multiple challenges in practical application.

Its core advantage is reflected in the value of multi-temporal remote sensing data for urban dynamic monitoring. For example, by comparing high-resolution remote sensing images of Xiangyang from 2018 and 2023, dynamic changes such as urban construction land expansion and changes in water body area can be accurately captured. This kind of monitoring can timely detect issues such as illegal land occupation and unauthorized construction, providing real-time basis for urban planning adjustments and land resource control, avoiding the limited coverage and low efficiency of traditional manual inspections.

At the technical level, the applicability and accuracy differences of different classifiers directly affect governance effectiveness. For instance, the Maximum Likelihood classifier is simple to operate and suitable for scenarios with distinct spectral features, such as extracting urban main roads, but it can easily confuse shadows and green spaces in densely built areas. While the Support Vector Machine classifier has higher accuracy (extraction accuracy for complex features can reach over 85%) and can distinguish between old residential areas and new housing, it requires more data and has higher computational costs. Governance needs to select appropriate classifiers based on targets (e.g., water body monitoring, building extraction), balancing accuracy and efficiency.

However, there are application bottlenecks for remote sensing extraction results in urban decision-making. On one hand, there is a "disconnect" between technology and operational needs. For example, traffic flow heat maps extracted from remote sensing need to be integrated with urban traffic management system data to guide traffic light timing, but data interfaces between some city departments are not interconnected, making it difficult to implement the data. On the other hand, there is a "time lag" in the extraction results. After acquisition, satellite remote sensing data requires 1-2 weeks of processing, making it difficult to timely support emergency decision-making (such as real-time assessment of urban waterlogging after heavy rain), limiting its immediate value in dynamic governance.

6. Conclusion

High-resolution remote sensing imagery combined with ENVI and ArcGIS platforms, utilizing ENVI's spectral analysis and image preprocessing functions alongside ArcGIS's spatial data management and visualization advantages, enables refined feature classification and urban land use identification, providing a precise spatial information foundation for urban governance.

Building on this, remote sensing technology, with its macro and dynamic monitoring capabilities, provides fundamental spatial data support for smart city construction. Whether it's optimizing land use layout in urban planning or analyzing congestion nodes in traffic governance, decision-making、scientificity can be enhanced based on its data, thereby promoting the improvement of intelligent urban governance levels.

In the future, to further unleash the value of remote sensing technology, follow-up research can expand in multiple directions: First, deepen dynamic monitoring to shorten data processing cycles to meet emergency decision-making needs. Second, strengthen multi-source data fusion to break down data barriers with urban management systems. Third, explore the integration of deep learning classifiers to improve feature classification accuracy in complex scenarios, thereby better serving the long-term development of smart cities.

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