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Research on Road Extraction Method Based on Sustainable Development Goals Satellite-1 Nighttime Light Data

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Abstract: Road information plays a fundamental role in many applications. However, at present, it is difficult to extract road information from the traditional nighttime light images in view of their low spatial and spectral resolutions. To fill the gap in high-resolution nighttime light (NTL) data, the Sustainable Development Goals Satellite-1(SDGSAT-1) developed by the Chinese Academy of Sciences (CAS) was successfully launched on 5 November 2021. With 40 m spatial resolution, NTL data acquired by the Glimmer Imager Usual (GIU) sensor on the SDGSAT-1 provide a new data source for road extraction. To evaluate the ability of SDGSAT-1 NTL data to extract road information, we proposed a new road extraction method named Band Operation and Marker-based Watershed Segmentation Algorithm (BO-MWSA). Comparing with support vector machine (SVM) and optimum threshold (OT) algorithms, the results showed that: (1) the F1 scores of the roads in the test area extracted by SVM, OT, and BO-MWSA were all over 70%, indicating that SDGSAT-1/GIU data could be used as a data source for road extraction. (2) The F1 score of road extraction by BO-MWSA is 84.65%, which is 11.02% and 9.43% higher than those of SVM and OT, respectively. In addition, the F1 scores of BO-MWSA road extraction in Beijing and Wuhan are both more than 84%, indicating that BO-MWSA is an effective method for road extraction using NTL imagery. (3) In road extraction experiments for Lhasa, Beijing, and Wuhan, the results showed that the greater the traffic flow was, the lower the accuracy of the extracted roads became. Therefore, BO-MWSA is an effective method for road extraction using SDGSAT-1 NTL data.

Keywords: nighttime light; Sustainable Development Goals Satellite-1; road extraction; marker-based watershed segmentation algorithm; support vector machines

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1. Introduction

Roads are one of the important components in China's transportation system. Acquiring timely road information plays an important role in urban planning, traffic navigation, digital map updating, and the construction of real-time road traffic information systems [1]. As remote sensing imagery has advantages in macro monitoring, it has become an important tool for road extraction. The traditional road extraction methods using remote sensing images are mostly manual, which are time-consuming and laborious. Therefore, strengthening the research on efficient road extraction methods is of great significance in traffic planning [2–4]. To date, many research studies have been carried out on road extraction using high-resolution multi-spectral remote sensing images [5–10], which can be classified as image classification and image segmentation [10–16]. In image classification, the support vector machine (SVM) performs best [17], while in image segmentation, the marker-based watershed segmentation algorithm (MWSA) has great advantages in morphological extraction [18]. Although these methods have achieved some success in road extraction from high-resolution multi-spectral remote sensing images, the following problems still exist: (1) High cost: high-resolution images are not freely available to the public, causing them not to be suitable for large-scale areas. (2) Redundant information: road information is a small part of high-resolution images, which is generally mixed with buildings, trees, water, and mountains, causing the road extraction to be difficult [19]. Therefore, a new data source suitable for road extraction with lower cost is urgently needed.

Nighttime light (NTL) imagery has the characteristic of detecting weak light on the ground, which is easy to be acquired for long time series without shadows. NTL imagery can also be used to distinguish the surface features at night, which is beneficial to the identification of roads and buildings [20–22]. At present, the main NTL satellites include the Defense Meteorological Satellite Program Operational Linescan System (DMSP/OLS), National Polar Partnership's Visible Infrared Imaging Radiometer Suite (NPP/VIIRS), and Luo Jia 1-01(LJ-1). However, with low spatial resolutions, it is not easy to extract the road accurately from them. On 5 November 2021, with the successful launch of Sustainable Development Goals Satellite-1 (SDGSAT-1) developed by the "Big Earth Data Science Project" of the Chinese Academy of Sciences (CAS), colored NTL images were acquired by the SDGSAT-1 Glimmer Imager Usual (SDGSAT-1/GIU) sensor. With a high spatial resolution (40 m) of RGB bands, the SDGSAT-1 NTL images significantly improved the detection sensitivity, band numbers and light oversaturation, making it possible to extract roads accurately from them. At present, there are few research studies on road extraction using NTL images. Extracting roads by high-resolution NTL images becomes a helpful supplement to road extraction methods and solves the problem of discontinuously extracted roads caused by vegetation shadows on high-resolution remote sensing images in sunlight.

To accurately extract roads using the SDGSAT-1 NTL images, we proposed a new method named Band Operation and Marker-based Watershed Segmentation Algorithm (BO-MWSA) with the expectation of assisting the government in urban planning and monitoring.

2. Methods

Support vector machines (SVM) classification and optimum thresholding (OT) are the main object extraction methods for NTL data [23].

2.1. Support Vector Machine (SVM)

SVM is a statistical classification method widely used in remote sensing image classification. The method can find the optimal solution between training samples and objective features based on limited information [22]. The basic idea of SVM is to construct an optimal surface according to the training samples, using which the pixel element matrix of the input image is divided into matching and non-matching features.

As shown in Figure 1, the two types of samples with different colors can be separated by a solid line representing the decision surface. Composed of the nearest points to the decision surface, the dashed lines are parallel to the decision surface. Points on the dotted lines are the support vectors when the distance between two classes becomes the maximum.

2.2. Optimum Thresholding (OT)

OT is one of the most commonly used image segmentation methods, whose principle is to divide the image pixels into several categories [24]. Because of its simple implementation, small computation, and stable performance, it has become the most basic and widely used image segmentation algorithm. Based on the NTL image and Open StreetMap (OSM), this paper selects the optimal threshold value to extract roads.

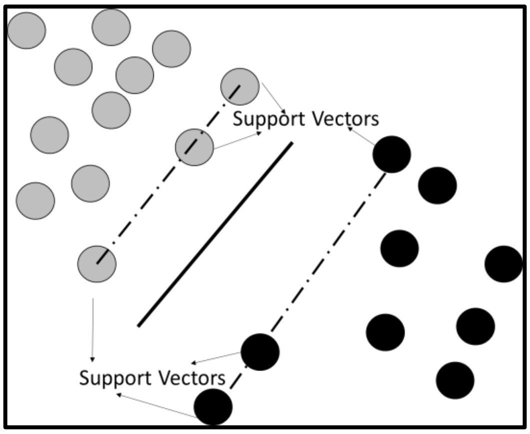

Figure 1. Principle of support vector machine.

2.3. The Improved Extraction Method

2.3.1. Flowchart of the Improved Extraction Method

As shown in Figure 2, based on SDGSAT-1/GIU nighttime light data and OSM road network data, we propose a new road extraction method named Band Operation and Marker-based Watershed Segmentation Algorithm (BO-MWSA), which is mainly divided into three steps: data collection and pre-processing, road-extraction, and accuracy verification. First, the nighttime light data of SDGSAT-1/GIU are acquired, and noise is removed (unstable light sources and stripes are eliminated). According to this, OSM road data is projected on to the same coordinate system. Second, roads are extracted from the nighttime light data according to the selected feature band, band operation, and marker-based watershed segmentation. Finally, the F1 score of the extracted results is calculated according to the referenced OSM roads.

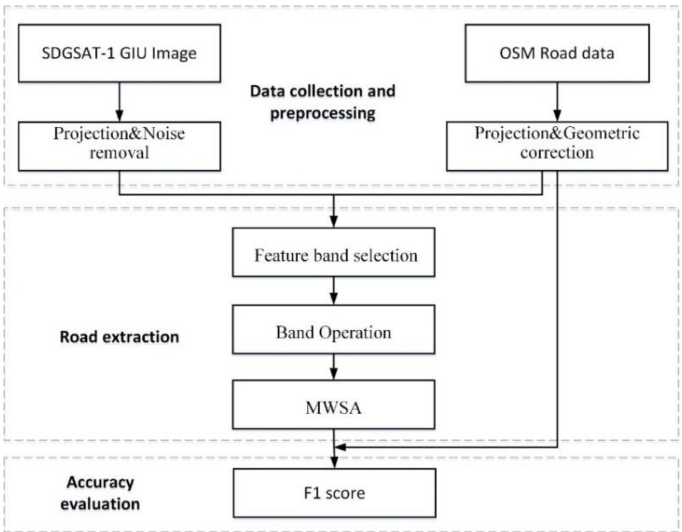

Figure 2. Flowchart of the BO-MWSA method.

2.3.2. Feature Band Selection

For objects with different spectral characteristics, making full use of the spectral features is beneficial to improve the accuracy of their classification. However, the traditional NTL data only has a single band and cannot distinguish well between the spectral information of different ground objects. With 40 m spatial resolution, three bands of the SDGSAT-1 NTL data effectively highlight the difference between roads and other objects.

The spectra of the road, buildings, and background are shown in Figure 3. From this, we can see that roads and buildings are significantly different in band 2 and band 3. Thus, the distinction between roads and buildings can be improved by the operation on band 2 and band 3.

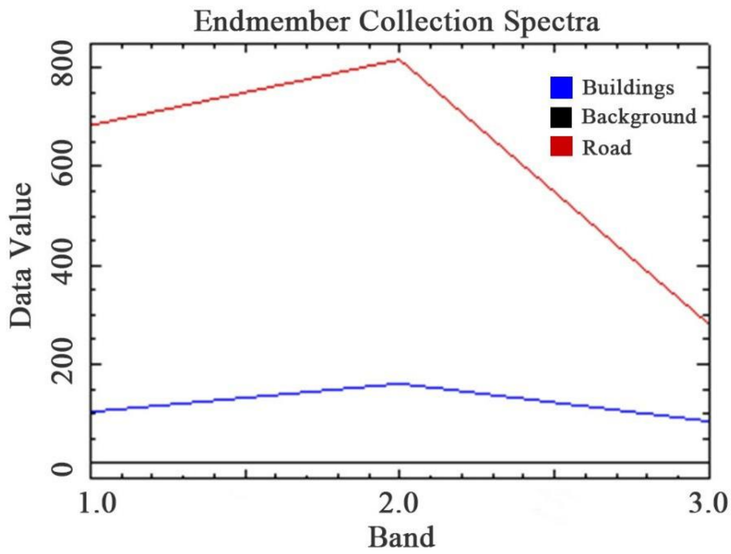

Figure 3. Spectral characteristic curves of ground surface objects.

2.3.3. Band Operation

The essence of band operation is to perform a mathematical operation on the pixel value corresponding to each pixel. Based on the characteristics of spectral curves of ground objects, the RGB bands of SDGSAT-1/GIU data are calculated to enhance roads as follows.

$$\text{Band}_{\text{road}} = \text{Band}_2 - \text{Band}_3, \tag{1}$$

in which $\text{Band}_{\text{road}}$ is the result of the band operation enhancing roads, Band_2 is the green band of NTL, and Band_3 is the blue band of NTL.

2.3.4. Marker-Based Watershed Segmentation Algorithm (MWSA)

The watershed segmentation algorithm [25] is a commonly used image segmentation method in mathematical morphology. However, traditional watershed segmentation methods present certain problems, such as over-segmentation and noise sensitivity [26]. The MWSA performs noise reduction on the foreground and background markers, which significantly reduces the image segmentation error and thus segments the images more accurately [27]. Based on topological theory, pixels of NTL images are regarded as the terrain surfaces, and the DN value of each pixel represents elevation. Different regions are labeled as "catchment basin." The boundary of the catchment basin is determined by adjusting the level for image segmentation, and then the roads are extracted from the image.

2.3.5. Accuracy Verification

The F1 score is used to evaluate the model, and is defined as the harmonic mean value of precision and recall [18]. In this paper, the corrected OSM road network data is used as the reference data to verify the accuracy of the road extraction method as follows:

$$\text{precision} = \text{a}_{\text{overlap}}/\text{a}_{\text{computed}}, \tag{2}$$

$$\text{Recall} = \text{a}_{\text{overlap}}/\text{a}_{\text{comparative}}, \tag{3}$$

$$\text{F1 score} = 2 \times (\text{precision} \times \text{recall})/(\text{precision} + \text{recal}) \tag{4}$$

in which $a_{overlap}$ is the area of the overlap between the extracted results and the reference data; $a_{computed}$ is the total area of extracted results; and $a_{comparative}$ is the total area of reference data.

3. Experiment

3.1. Study Area

To verify the effectiveness of BO-MWSA, the Chengguan District of Lhasa was selected as the test area. As shown in Figure 4a, with the geographic coordinates of 91°03′~91°18′E, 29°30′~29°48′N, it is located in the downstream Tibetan Plateau hinterland Lhasa River, whose total area is 520.51 km^2. Driven by the development of the western region and the Belt and Road Initiative, Chengguan District is the center of the Tibet Autonomous Region, and is representative of a medium-sized city with rapid development in western China [28]. The road extraction of Lhasa city is helpful in understanding its development.

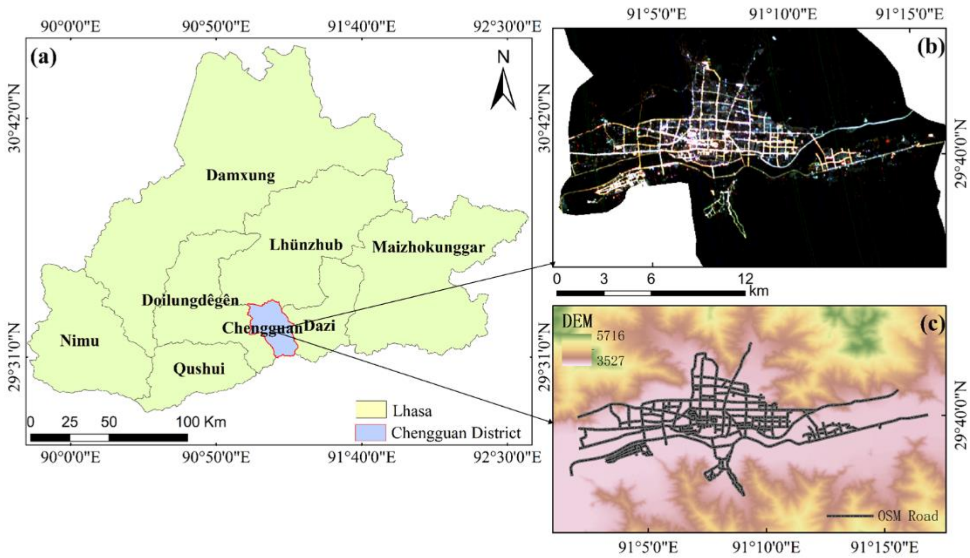

Figure 4. Location map of the test area: (**a**) location of test area, (**b**) SDGSAT-1 nighttime light data, and (**c**) OSM road network data.

3.2. Data

Research data mainly include SDGDSAT-1/GIU data (Figure 4b) and Open StreetMap (OSM) road network data (Figure 4c) from April 2022. SDGDSAT-1/GIU data is acquired from the International Research Center of Big Data for Sustainable Development Goals, with a spatial resolution of 40 m. OSM road network is a global open-source map (https://www.openstreetmap.org/ (accessed on 10 June 2022)), which has been widely used worldwide [29,30]. We acquired the OSM network data for Lhasa City Chengguan District on 14 June 2022 and confirmed its reliability using high-resolution remote sensing data, such as Quickbird.We then selected the checked OSM road network data as the reference data to evaluate the accuracy of the proposed method.

NTL data and OSM road network data are matched by geometric corrections with the WGS_1984_UTM_zone_46N projection. To evaluate the accuracy of extracted roads, the OSM road network data in vector was converted into raster with a spatial resolution of 40 m.

3.3. Comparison of Extracted Results

The outputs of street extraction of BO-MWSA, OT, and SVM are bitmaps, and shown in Figure 5.

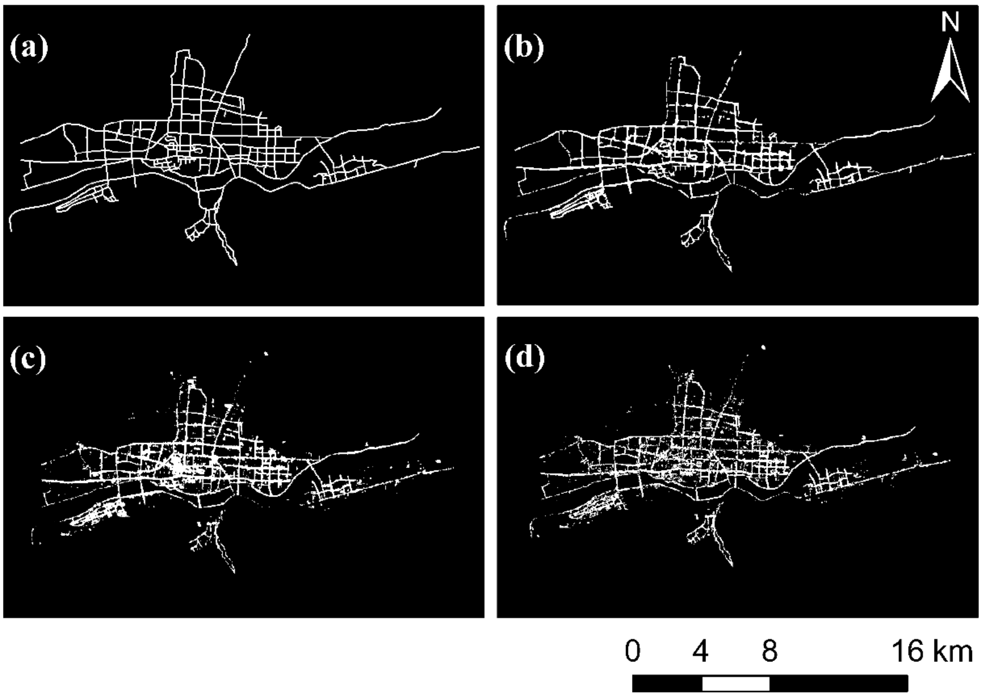

Figure 5. Extracted roads of Chengguan District from (**a**) OSM road network data, (**b**) BO-MWSA, (**c**) OT, and (**d**) SVM.

As shown in Figure 5, the extracted roads by BO-MWSA (Figure 5b) are the most consistent with the reference road network (Figure 5a), with fewer fragmentations and lower overflow than OT (Figure 5c) and SVM (Figure 5d).

To compare the road extraction results of the three methods, we selected three typical local areas (railway station, busy street, and residential area), which are shown in Figure 6. Road 1 is located in Lhasa Railway Station with a heavy traffic flow. Road 2 is located in the Potala Palace, and Road 3 is Jiangsu Avenue, representing a residential area. Road 1 and Road 2 are located in the densely built-up area. The comparison of the extraction results of the three roads shows that the roads extracted by BO-MWSA are more consistent with the reference road network than those extracted by OT or SVM. Road 1 and Road 2 extracted by OT have a serious overflow phenomenon, and the two roads extracted by SVM have significant plaque fragmentation. For the road extraction results of Road 3, the three methods can all extract a complete road; however, the BO-MWSA performs the best. Comparing the extraction results of the three roads, OT and SVM perform poorly in areas with busy and complex roads, although better in areas with simpler roads. Meanwhile, Bo-MWSA has achieved greater success for all three roads extraction.

3.4. Accuracy Verification

As shown in Table 1, F1 scores of BO-MWSA, OT, and SVM are 84.65%, 75.22%, and 73.63%, respectively. The results show that the F1 scores of the three methods are all over 70%, indicating that SDGSAT-1/GIU NTL data can be used as a data source for road extraction. Furthermore, the F1 score of BO-MWSA is 11.02% and 9.43% higher than those of OT and SVM, respectively, and the quality of road extraction results is best. In general, the light of the road at night is brighter than that of buildings, while the light of buildings is higher than that of the road in a densely built-up area, resulting in misclassification of road extraction.

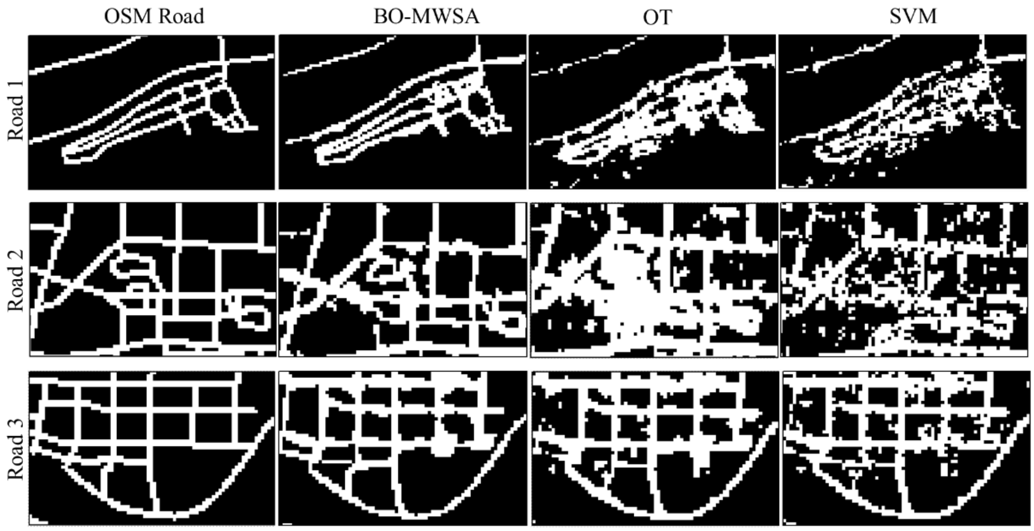

Figure 6. Comparison of road extraction results. Road 1 is located in Lhasa Railway Station with large traffic flow in the city; Road 2 is located in the Potala Palace; and Road 3 is Jiangsu Avenue, representing a residential area.

Table 1. F1 scores of BO-MWSA, SVM, and OT.

Method	Overlap (km^2)	Computed (km^2)	Comparative (km^2)	F1 Score
BO-MWSA	16.59	18.50	20.69	84.65%
SVM	15.41	21.19	20.69	73.63%
OT	16.64	23.57	20.69	75.22%

4. Discussion

NTL is a new remote sensing data that has been widely used in research on social economy. In addition, the primary NTL data used in previous studies were DMSP/OLS and NPP/VIIRS, with low resolutions of 1000 m and 700 m, respectively. Therefore, they can only be used to solve macro problems, such as economic development and population. However, obtaining high-resolution NTL data is expensive and challenging. Therefore, there are as yet fewer studies on high-resolution nighttime light images. The SDGSAT-1 NTL data has the characteristics of high resolution, multi-band, and free availability, and can provide more benefits for micro-urban research studies, such as urban traffic evaluation. Furthermore, there have been few studies on road extraction using NTL data. This research uses SDGSAT-1 nighttime light data to explore the possibility of road extraction methods, filling the gap of road extraction with NTL data.

NTL only detects the surface information under nighttime light, which can effectively solve the discontinuous extraction of roads caused by tree shadows and shrubs in multi-spectral remote sensing images in sunlight. However, multi-spectral remote sensing data have higher spatial resolutions and more bands than nighttime light data. At present, road extraction methods based on multi-spectral remote sensing data mainly include SVM, threshold segmentation, and deep learning, with an extraction accuracy of 70–90% [14,31]. In the Chengguan district of Lhasa, F1 scores of the three road extraction methods based on SDGSAT-1 NTL data are all over 70%, and the F1 score of BO-MWSA is 84.65%, indicating that it is an effective method for road extraction using NTL data. To verify the universality of the method, we selected the areas within the 5th Ring Road of Beijing and the areas within the 3rd Ring Road of Wuhan for demonstration. Beijing is the central city in North China and China's capital, while Wuhan is a major city in central China. The results showed that the F1 scores of extracted roads by the proposed method in these two cities were 85.21% and 84.64%, respectively. Therefore, the F1 scores of the road extraction method in the three cities are more than 84%, which prove that the road extraction method proposed in this paper can be used in different regions based on SDGSAT-1 nighttime light imagery.

The road information in multi-spectral remote sensing images is easily affected by the shadows of trees and shrubs, reducing road interpretation accuracy. NTL only detects surface information under nighttime light, which can effectively solve this problem. In addition, in road extraction experiments of Lhasa, Wuhan, and Beijing, we also found that the greater the traffic flow was, the lower the accuracy of these three methods became. This phenomenon is similar to the conclusion drawn from the research on extracting roads by LJ-1 NTL data [32].

However, some challenges still exist in extracting road networks, which need to be further addressed. Since the NTL data can only detect the road information with light, they are only applicable to urban roads with light and have a low extraction accuracy in rural roads with weak light intensity. Furthermore, the light intensity of busy streets with large traffic volumes is high, and the overflow phenomenon is relatively serious, making it challenging to extract roads by NTL data alone. These limitations have impacts on extracting roads from NTL data. To solve these challenges, road extraction methods combining high-resolution multi-spectral remote sensing images in sunlight with nighttime light images are the key direction of future research.

5. Conclusions

This paper discusses the potential use of SDGSAT-1/GIU data in urban road extraction, which provides a new data source for urban planning. The main conclusions can be drawn as follows.

(1) SDGSAT-1/GIU data can be used as one of the data sources for urban road extraction. Based on NTL data, this paper uses SVM, OT, and BO-MWSA to extract roads in the study area, and the results showed that F1 scores of the three methods were all over 70%, indicating that SDG-SAT-1/GIU data could be used as a data source for road extraction.

(2) BO-MWSA is an efficient road extraction method. The F1 score of road extraction by BO-MWSA is 84.65%, which is 11.02% and 9.43% higher than those of SVM and OT, respectively. The F1 scores of BO-MWSA road extraction in Beijing and Wuhan are more than 84%, indicating that BO-MWSA is an effective method for road extraction using NTL image.

(3) In road extraction experiments for Lhasa, Beijing, and Wuhan, the results showed that the heavier the traffic flow was, the lower the accuracy of the extracted roads became.

In the future, we will use this method to carry out more research on multiple cities.

Author Contributions: All authors contributed in a substantial way to the manuscript. Conceptualization, D.C. and Q.W.; methodology, D.C.; software, D.C., J.Y. and W.X.; validation, D.C. and Q.W.; formal analysis, D.C.; investigation, D.C., J.Y. and W.X.; resources, D.C.; data curation, D.C. and Q.W.; writing—original draft, D.C.; writing—review and editing, D.C. and Q.W.; visualization, D.C.; supervision, Q.W.; funding acquisition, Q.W. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

Abbreviation	Explanation
SDGSAT-1	Sustainable Development Goals Satellite-1
CAS	Chinese Academy of Sciences
NTL	Nighttime light
GIU	Glimmer Imager Usual
BO-MWSA	Band Operation and Marker-based Watershed Segmentation Algorithm
SVM	Support vector machine
OT	Optimum thresholding
MWSA	Marker-based watershed segmentation algorithm
DMSP/OLS	Defense Meteorological Satellite Program Operational Linescan System
NPP/VIIRS	National Polar Partnership's Visible Infrared Imaging Radiometer Suite
LJ-1	Luo Jia 1-01
OSM	Open StreetMap

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