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Regional urban area extraction using DMSP-OLS data and MODIS data

X Y Zhang¹, C Cai ¹ and P J Li ¹

¹ Institute of Remote Sensing and GIS, Peking University, Beijing 100871, P R China

xyzhang58@gmail.com

Abstract. Stable night lights data from Defense Meteorological Satellite Program (DMSP) Operational Line-scan System (OLS) provide a unique proxy for anthropogenic development. This paper proposed two new methods of extracting regional urban extents using DMSP-OLS data, MODIS NDVI data and Land Surface Temperature (LST) data. MODIS NDVI data were used to reduce the over-glow effect, since urban areas generally have lower vegetation index values than the surrounding areas (e.g. agricultural and forest areas). On the other hand, urban areas generally show higher surface temperatures than the surrounding areas. Since urban area is the only class of interest, a one-class classifier, the One-Class Support Vector Machine (OCSVM), was selected as the classifier. The first method is classification of different data combinations for mapping: (1) OLS data and NDVI data, (2) OLS data and LST data, and (3) OLS data, NDVI data and LST data combined. The second one is a morphological reconstruction based method which combines classification results from OLS plus NDVI data and from OLS plus LST data. In the morphological reconstruction based method, the classification result using OLS and NDVI data was used as a mask image, while the classification result using OLS and LST data was used as a marker image. The north China area covering 14 provinces was selected as study area. Classification results from Landsat TM/ETM+ data from selected areas with different development levels were used as reference data to validate the proposed methods. The results show that the proposed methods effectively reduced the over-glow effect caused by DMSP-OLS data and achieved better results compared to the results from the traditional thresholding technique. The combination of all three datasets produces more accurate results than those of using any two datasets. The proposed morphological reconstruction based method achieves the best result in urban extent mapping.

1. Introduction

Regional and global urban extent distribution is a fundamental data source for many applications, such as evaluation of the impact of urbanization on environments and urban management and planning [1-2]. Mapping urban areas at regional and global scales from remote sensing data has considerable significance and has already attracted attention. However, it remains a challenging task [3-6]. Stable night lights data from Defense Meteorological Satellite Program (DMSP) Operational Line-scan System (OLS) provide a unique proxy for anthropogenic development. For mapping urban areas using DMSP-OLS data, the thresholding technique is a common approach, because of its simplicity [7-10]. However, it's difficult to select an appropriate DMSP-OLS threshold value for a large region, especially for the region with different development levels. On the other hand, the use of DMSP-OLS data alone often overestimates urban extents due to over-glow effect [11]. Some studies showed that urban areas generally have lower vegetation index values than their surrounding areas (e.g., agricultural and forest



areas) [12]. Thus, vegetation indices were combined with DMSP-OLS data to reduce the overflow effect and to obtain more accurate results [12-13]. It was also found that Land Surface Temperatures (LST) of urban areas are generally higher than their surrounding areas [14]. However, the LST data have not been used with DMSP-OLS data in mapping urban extent. The objective of this study is to propose new methods of extracting regional urban extents using DMSP-OLS data, MODIS NDVI data and LST data.

2. Study area and data

China has been experiencing rapid urbanization since the 1980s and there is still large economic development discrepancy between different parts of China. Our study area is north China area, covering 14 provinces with different development levels from east to west. In this paper, DMSP-OLS stable night lights data, MODIS NDVI data and LST data were used to map urban areas in a large region.

The DMSP-OLS night lights data used in this study were provided by the National Oceanic and Atmospheric Administration (NOAA)/National Geophysical Data Center (NGDC). The DMSP-OLS images have a DN value range from 0 to 63. Yearly maximum NDVI composite image and yearly maximum LST composite image were used. Table 1 shows a brief description of these remote sensing data. The DMSP-OLS data and MODIS data used in this study, which all were acquired in 2006, were reprojected to Albers Conical Equal Area projection. The DMSP-OLS, MODIS NDVI and MODIS LST images were co-registered and resampled to a 1km pixel size.

Landsat TM/ETM+ images with spatial resolution of 28.5m, which acquired in 2004~2006 and covered the 25 cities, were used to validate the urban extents extracted by the proposed methods. The urban areas were classified by maximum likelihood classifiers based on training samples selected from typical urban area. The classification results were resampled into 1 km urban maps.

Table 1. Description of the data used in this study.

Data source	Product description	Acquisition date	Spatial resolution
DMSP-OLS	Yearly stable nighttime light composite	2006	1km
MODIS NDVI	Yearly maximal NDVI	2006	1km
MODIS LST	Yearly maximal LST	2006	1km
Landsat ETM+	24 images covering 24 cities, bands 1-5 and 7	2004~2006	28.5m

3. Methods

This paper proposed two methods of extracting regional urban extents using multiple remote sensing data. The first method is classification of different data combinations and the second one is a morphological reconstruction based method which combines classification results from different data combinations.

3.1. Urban extent mapping with different data combinations

Three different data combinations were used for mapping urban extents in the first method: (1) DMSP-OLS data and MODIS NDVI data, (2) DMSP-OLS data and MODIS LST data, and (3) DMSP-OLS data, MODIS NDVI data and LST data combined.

Since urban area is the only class of interest in this study, instead of using traditional multi-class classifiers, One-Class Support Vector Machine (OCSVM), a recently developed one-class classifier [15-16], was selected as the classifier. Rather than using training samples of all classes as required by conventional multi-class classifiers, the OCSVM only requires training data from one class (i.e., the target class) and can focus on the class only. It has been successfully used in mapping of a specific land cover types [17-18] and change detection [19].

The OCSVM can be viewed as a special case of the regular two-class SVM where all the training data lie in the first class (i.e., target class), and the origin is taken as the only member of the second class (i.e., outlier class) [16]. The OCSVM first maps input data into a high-dimensional feature space via a

kernel function and then iteratively finds the maximal margin hyperplane, which best separates the training data from the origin [16].

The software LIBSVM (version 2.90) [20] that implements the OCSVM algorithm of Scholkopf et al. (1999) [16] was modified and used in the present study.

3.2. Morphological reconstruction based mapping

It was found that the classification result using OLS data and NDVI data generally shows more accurate extents, while the classification result using OLS data and LST data is more homogeneous inside the extracted urban areas. In order to effectively combine these two classification results, a morphological reconstruction based method is proposed.

Morphological reconstruction is a morphological transformation involving two images. One image, called marker image, is the starting point for the transformation. The other image, called mask image, constrains the transformation. The high points, or peaks, in the marker image specify where processing begins. The peaks spread out, or dilate, while being forced to fit within the mask image. The spreading processing continues until the image values do not change [21].

In this study, the classification result using OLS data and NDVI data was used as the mask image, while the classification result using OLS data and LST data was used as the marker image.

3.3. Validation

In order to validate the effectiveness of different data combinations and the proposed methods, Landsat TM/ETM+ data from selected cities with different development levels were classified to extract urban areas which were then used as reference data.

The locally-optimized thresholding method [12] was applied to DMSP-OLS image to extract urban extent. The obtained results were used as benchmark. In the local-optimized threshold method, an optimal DN threshold was determined for each city by matching the urban areas derived from DMSP-OLS data to Landsat TM/ETM+ classified urban areas as closely as possible.

To quantify the performance of these methods, we performed accuracy assessments using confusion matrix. Two indices, overall accuracy (OA) and Kappa coefficient, were used. The OA and Kappa were calculated from the confusion matrix by comparing DMSP-OLS results and the ETM+ results of each city.

4. Results

The accuracy assessment (Table 2) showed that the combination of OLS data and LST data obtained a relatively low accuracy, compared to other three classification results which produced very similar accuracy (OA and Kappa). From the accuracies of individual classes, it was found that the combination of OLS data and LST data overestimated the urban areas. The combination of three data results was better than the combination of OLS data and NDVI data. The result using morphological reconstruction showed a small increased comparing to the result using local threshold method in most cities.

Figure 1 shows extracted urban areas of the selected 4 cities using different methods and reference data from Landsat TM/ETM+ classification results which was aggregated to generate proportional settlement images at 1 km pixel size.

From figure 1, although the results from local thresholding method (figure 1(c)) are homogeneous, they overestimate the urban extents, compared with reference data from Landsat TM/ETM+ data. The results from combination of OLS data and LST data are also homogeneous, but obviously overestimate the urban extents. The remaining three results look very similar. The results from OLS data and NDVI data show very similar urban extents to the reference data, which indicates that the inclusion of MODIS NDVI data effectively reduces the over glow effect. However, these results are noisy inside the extracted urban areas (e.g., Beijing). The combination of all three datasets by the image classification and the morphological reconstruction based method produced better results. In particular, the combination of all datasets by the morphological reconstruction produces the best results, in terms of both extent and homogeneity.

In general, the performance of the proposed methods was comparable with that of the local-optimized threshold method. Since the optimized thresholds for cities were generated one-by-one according to Landsat TM/ETM+ classification results, this method relies on the acquisition of high-resolution data of cities investigated, which involves massive and tedious classification. The new methods are more efficient and easier for extracting urban extent with comparable accuracy.

Table 2. Accuracy assessments of different methods of extracting urban areas by city.

City	Local-optimized threshold		DMSP-OLS and MODIS LST		DMSP-OLS and MODIS NDVI		DMSP-OLS, MODIS NDVI and LST		DMSP-OLS, MODIS NDVI and LST by the Morphological reconstruction method	
	OA	Kappa	OA	Kappa	OA	Kappa	OA	Kappa	OA	Kappa
Beijing	0.95	0.69	0.90	0.54	0.96	0.72	0.96	0.72	0.96	0.72
Harbin	0.95	0.67	0.86	0.45	0.95	0.67	0.95	0.67	0.95	0.67
Zhengzhou	0.93	0.62	0.87	0.51	0.93	0.60	0.93	0.60	0.93	0.60
Shijiazhuang	0.95	0.71	0.88	0.54	0.96	0.74	0.96	0.74	0.96	0.74
Xi'an	0.88	0.67	0.56	0.25	0.80	0.55	0.82	0.59	0.74	0.42
Baoding	0.93	0.55	0.91	0.52	0.94	0.55	0.94	0.55	0.94	0.55
Cangzhou	0.92	0.60	0.89	0.54	0.93	0.60	0.93	0.61	0.93	0.60
Handan	0.94	0.77	0.87	0.63	0.93	0.71	0.93	0.71	0.93	0.71
Hengshui	0.96	0.53	0.96	0.50	0.97	0.46	0.97	0.46	0.97	0.46
Anyang	0.91	0.75	0.79	0.54	0.89	0.66	0.89	0.70	0.89	0.66
Kaifeng	0.93	0.65	0.92	0.68	0.93	0.64	0.93	0.64	0.93	0.64
Xinxiang	0.89	0.61	0.76	0.43	0.89	0.63	0.89	0.63	0.89	0.63
Xuchang	0.93	0.69	0.86	0.57	0.94	0.69	0.94	0.69	0.94	0.69
Huhehaote	0.89	0.54	0.72	0.33	0.81	0.45	0.80	0.44	0.81	0.45
Jinan	0.94	0.67	0.80	0.38	0.92	0.63	0.92	0.62	0.92	0.62
Lanzhou	0.96	0.69	0.86	0.40	0.86	0.39	0.86	0.40	0.86	0.39
Fushun	0.90	0.55	0.86	0.54	0.92	0.58	0.92	0.59	0.92	0.58
Shenyang	0.89	0.66	0.85	0.62	0.90	0.66	0.90	0.66	0.90	0.67
Zibo	0.93	0.52	0.83	0.36	0.93	0.51	0.93	0.51	0.93	0.51
Taiyuan	0.90	0.54	0.89	0.62	0.90	0.55	0.90	0.56	0.90	0.56
Xianyang	0.82	0.50	0.66	0.36	0.82	0.50	0.82	0.51	0.82	0.50
Tianjin	0.92	0.59	0.87	0.54	0.92	0.54	0.92	0.55	0.92	0.55
Wulumuqi	0.97	0.61	0.93	0.40	0.94	0.50	0.94	0.50	0.94	0.50
Xining	0.99	0.44	0.98	0.39	0.99	0.44	0.99	0.44	0.99	0.44
Changchun	0.88	0.59	0.86	0.57	0.88	0.59	0.88	0.60	0.88	0.59

5. Conclusion

This paper proposed two new methods of extracting regional urban extents using DMSP-OLS data, MODIS NDVI data and LST data. The result shows that the inclusion of MODIS NDVI data and LST data provide complementary information to overcome the overglow effect of DMSP-OLS data. The combination of all three datasets produces more accurate results than those of using any two datasets. The proposed morphological reconstruction based method achieves the best results in urban extent mapping.

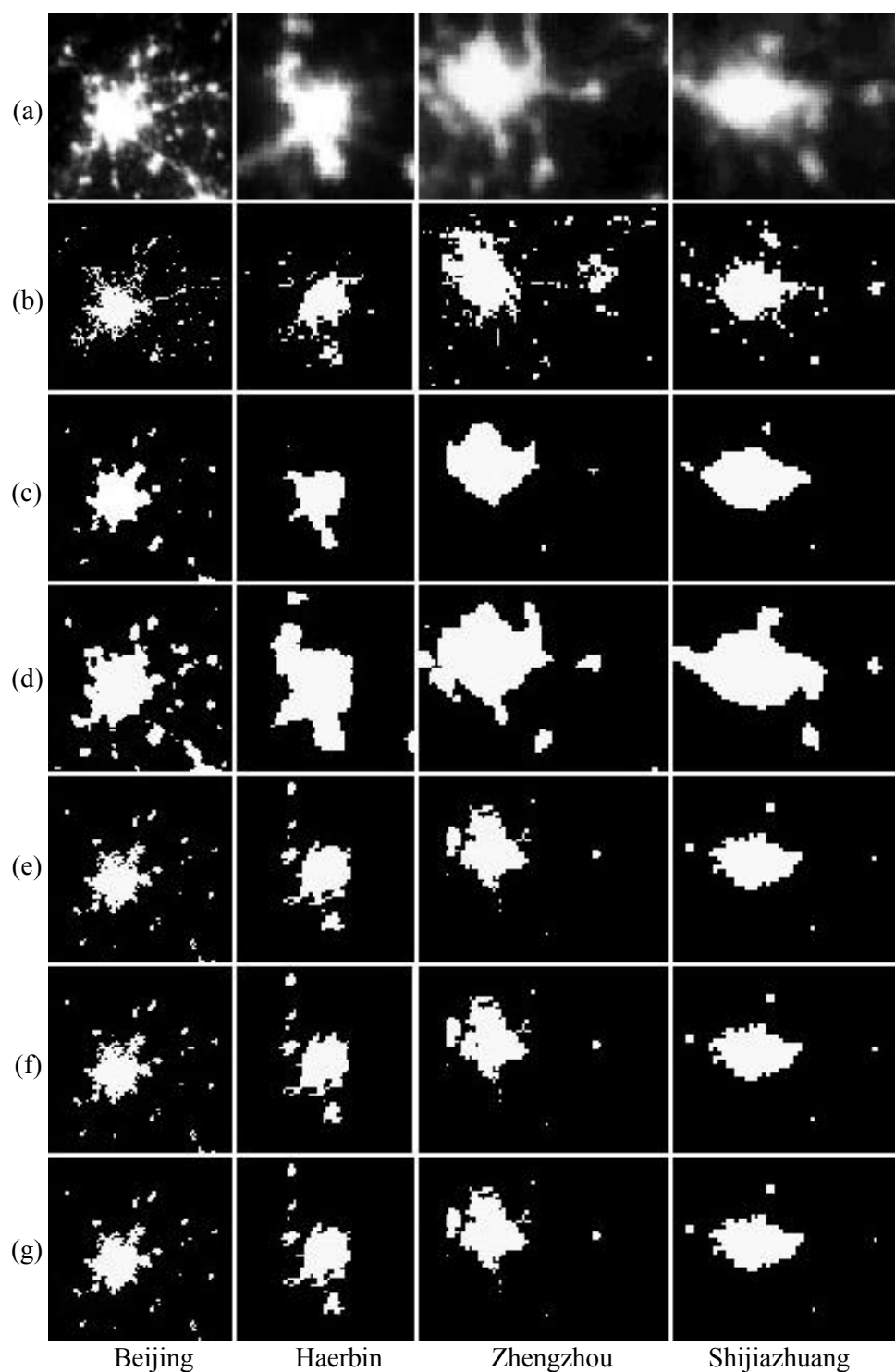


Figure 1. Urban area extraction results: (a) DMSP-OLS images of selected cities, (b) the urban extents from Landsat ETM+ classification, (c) local-optimized threshold method, (d) result with combination of DMSP-OLS and MODIS LST data, (e) result with combination of DMSP-OLS and MODIS NDVI data, (f) result with the combination of DMSP-OLS, MODIS NDVI and LST data, (g) result with the combination of DMSP-OLS, MODIS NDVI and LST data by morphological reconstruction.

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