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A SVM-based method to extract urban areas from DMSP-OLS and SPOT VGT data

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ABSTRACT

Mapping urban areas at regional and global scales has become an urgent task because of the increasing pressures from rapid urbanization and associated environmental problems. Satellite imaging of stable anthropogenic lights from DMSP-OLS provides an accurate, economical, and straightforward way to map the global distribution of urban areas. To address problems in the thresholding methods that use empirical strategies or manual trial-and-error procedures, we proposed a support vector machine (SVM)-based region-growing algorithm to semi-automatically extract urban areas from DMSP-OLS and SPOT NDVI data. Several simple criteria were used to select SVM training sets of urban and non-urban pixels, and an iterative classification and training procedure was adopted to identify the urban pixels through region growing. The new method was validated using the extents of 25 Chinese cities, as classified by Landsat ETM+ images, and then compared with two common thresholding methods. The results showed that the SVM-based algorithm could not only achieve comparable results to the local-optimized threshold method, but also avoid its tedious trial-and-error procedure, suggesting that the new method is an easy and simple alternative for extracting urban extent from DMSP-OLS and SPOT NDVI data.

1. Introduction

Urban areas cover a small fraction of Earth's surface but exert a disproportionate influence on their surroundings in terms of mass, energy, and resource fluxes. Driven by economic development and population increase, rapid urbanization is altering land use and cover and further affecting biodiversity, hydrosystems, biogeochemical cycles, and climate, both locally and globally (Foley et al., 2005; Grimm et al., 2008). For the sustainable management of urban areas and evaluation of the impacts of urbanization on environments, scientists and governments increasingly need to monitor the spatial extents of urban areas. Remote sensing techniques, which provide large spatial and frequent temporal cover, have a high potential to meet these needs.

It is possible to map urban areas at different scales with different remotely sensed data. High or medium spatial resolution images (e.g., IKONOS, Quickbird, Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper plus (ETM+), SPOT/High Resolution Visible (HRV)) have been widely employed on urban land use classification for individual cities. At regional or even global scales, the Defense Meteorological Satellite Program (DMSP)'s Operational Line-scan System (OLS) of nighttime images (city lights or stable lights) has been demonstrated to be an effective and economical data source for mapping urban areas or human settlements (e.g.,Elvidge et al., 1997, 1999, 2001; Imhoff et al., 1997a; Henderson et al., 2003; Milesi et al., 2003a; Sutton, 2003; Gallo et al., 2004; Lu et al., 2008) and for estimating demographic and socioeconomic parameters (e.g., Welch, 1980; Sutton et al., 1997, 2001; Lo, 2001, 2002). For the mapping of urban areas or human settlements from DMSP-OLS data, the thresholding technique is mostly used, because of its simplicity (e.g., Imhoff et al., 1997a,b; Henderson et al., 2003; Milesi et al., 2003b). However, existing studies have revealed that this technique is problematic, especially when compared across cities at different levels of development. It was reported that a single threshold not only significantly overestimated urban areas in larger-scale cities due to the blooming effect, but also omitted a large number of cities with lower development levels (Henderson et al., 2003; Small et al., 2005). With the recognition of this problem, significant efforts have been made to develop multiple thresholds based on the development level of cities (e.g.,Imhoff et al., 1997a; Owen et al., 1998; Sutton et al., 2001; Lawrence et al., 2002; Henderson et al., 2003). However, the existing threshold values are still empirical or subjective, without effective validation in other areas. There are currently no general guidelines for the selection of threshold values according to development level of cities. In addition, selection of optimal thresholds is a complex and time-consuming process that largely limits its application in practice. These problems can result in a large uncertainty in urban area mapping based on DMSP-OLS data at the regional scale. Consequently, we attempted to develop a semi-automatic method based on support vector machine (SVM) classifiers for the applications of the DMSP-OLS data in mapping urban areas or human settlements. The new method could avoid the threshold related problems by assuming urban area

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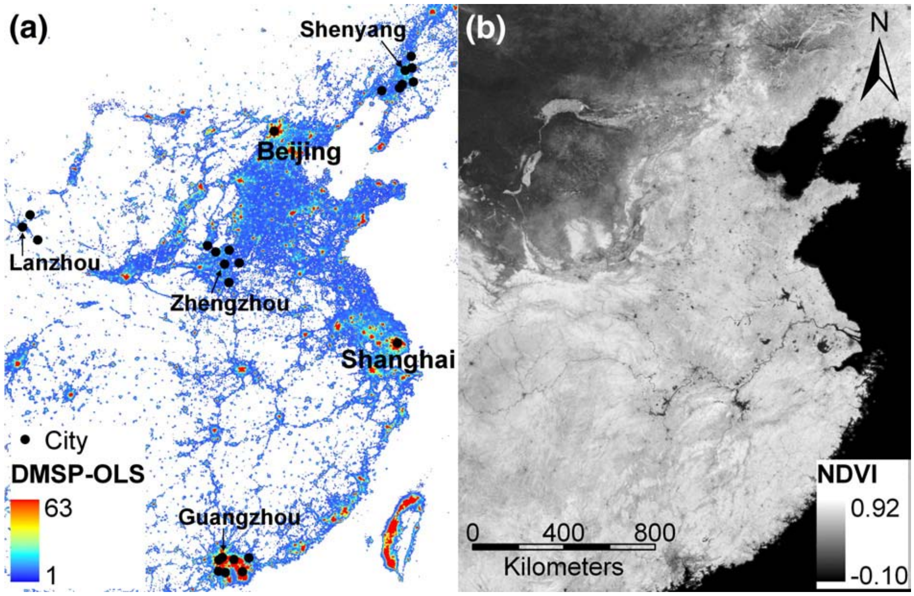

Fig. 1. Study area and data: (a) DMSP-OLS image in 2000 and 25 selected cities, (b) SPOT VGT NDVI (MVC of April–September 2000).

mapping as an urban and non-urban classification problem. Here, a SVM classifier was adopted because it was a non-parametric classifier, which works well for two-class classification with a small number of training samples. To validate the flexibility and robustness of the new method, a case study was carried out for Chinese cities with different development levels.

2. Study area and data

Chinese cities were selected for the case study because China has been experiencing rapid urbanization since the 1980s, and there are still large economic development discrepancies. Twenty-five cities (Fig. 1a) were selected around Beijing, Shanghai, Guangzhou, Zhengzhou, Lanzhou, and Shenyang with different development levels. In 2000, the populations of these 25 cities varied from less than 70,000 (Dingxi) to over 9 million (Shanghai), and the per capita gross domestic product (GDP) spanned from less than 8000 RMB (or 1200 USD) for Dingxi to over 150,000 RBM (or 22,000 USD) for Shenzhen (Bureau of Statistics of China, 2001).

A brief description of remotely sensed data is shown in Table 1. The DMSP-OLS nighttime light data used in this study were provided by the National Oceanic and Atmospheric Administration (NOAA)/ National Geophysical Data Center (NGDC). The data include the lights from cities and settlements with persistent lighting and ephemeral events such as fires are discarded (Elvidge et al., 1997, 1999, 2001). The data were recorded as 6-bit digital numbers (DN) ranging from 0 (background) to 63 (saturated) by averaging DN values of stable light images for the whole year. In this study we used the DMSP-OLS data with compositing period of 2000. We also used normalized difference vegetation index (NDVI) data to reduce the blooming effect (Lu et al., 2008). The SPOT VGT NDVI global 10-day composite product (Hagolle et al., 2004) from April to September 2000 (growing season) was acquired and processed by maximum value composition (MVC, Holben, 1986) to create a yearly maximal NDVI image. The DMSP-OLS and SPOT NDVI images were co-registered and resampled to a 1 km spatial resolution (Fig. 1). Finally, we used 6 Landsat ETM+ images in total with spatial resolution of 28.5 m, which were acquired in 1999–2000 and covered the 25 cities, to validate the urban extents extracted by OLS and NDVI data. The urban areas were produced by maximum likelihood classifiers based on training data extracted from typical urban area. It was difficult to distinguish urban and suburban by using Landsat ETM+ data if pixels covered by buildings and roads don't matter whether they belonged to urban or suburban. Consequently, the supervised classification produced the urban map including both urban and some suburban. The aggregation procedure was employed to aggregate 28.5-m classification results to 1 km urban maps, in which some smaller suburban areas were eliminated. Considering the spatial resolution difference between Landsat ETM+ and DMSP data, the ETM+ results were accurate enough to be used as reference maps for validation.

3. Methods

We developed a SVM-based region-growing algorithm to semi-automatically distinguish urban pixels from the non-urban background. The SVM is a non-parametric method based on the statistical learning theory (Vapnik, 2000). The advantage of the SVM-based classifier over traditional ones is that it solves learning problems better when only a small number of training samples is available (Mantero et al., 2005). The basic idea of SVM is to classify the input vectors into two classes using a hyperplane with the maximal margin, which is derived by solving the following constrained quadratic programming problem:

$$\begin{aligned}&\text{Maximize } W(\alpha) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K\left(x_i, x_j\right)\\ &\text{Subject to } \left\{\sum_{i=1}^{n}\alpha_i y_i = 0 \text{ and } 0 \le \alpha_i \le T \text{ for } i = 1, 2, \dots n\right\}\end{aligned}, \quad (1)$$

where $x_i \in R_d$ are the training sample vectors, $y_i \in \{-1, +1\}$ the corresponding class label, and $K(u, v)$ the kernel function. Vapnik (2000) gave three types of SVMs (seeVapnik, 2000 for details). In this study, the radial basis function (RBF) was selected as the kernel

Table 1
Description of the data used in this study.

Data source	Product description	Date of acquisition	Spatial resolution
DMSP-OLS	Yearly stable nighttime light composite	2000	1 km
SPOT NDVI	Yearly maximal NDVI by MVC	Apr–Sep 2000	1 km
Landsat ETM+	Six images covering 5 cities, bands 1–5 and 7	1999–2000	28.5 m