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Extraction and Analysis of Mega Cities' Impervious Surface on Pixel-based and Object-oriented Support Vector Machine Classification Technology: A case of Bombay

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ABSTRACT. The object of this paper is to study the impervious surface extraction method using remote sensing imagery and monitor the spatiotemporal changing patterns of mega cities. Megacity Bombay was selected as the interesting area. Firstly, the pixel-based and object-oriented support vector machine (SVM) classification methods were used to acquire the land use/land cover (LULC) products of Bombay in 2010. Consequently, the overall accuracy (OA) and overall Kappa (OK) of the pixel-based method were 94.97% and 0.96 with a running time of 78 minutes, the OA and OK of the object-oriented method were 93.72% and 0.94 with a running time of only 17s. Additionally, OA and OK of the object-oriented method after a post-classification were improved up to 95.8% and 0.94. Then, the dynamic impervious surfaces of Bombay in the period 1973-2015 were extracted and the urbanization pattern of Bombay was analysed. Results told that both the two SVM classification methods could accomplish the impervious surface extraction, but the object-oriented method should be a better choice. Urbanization of Bombay experienced a fast extending during the past 42 years, implying a dramatically urban sprawl of mega cities in the developing countries along the One Belt and One Road (OBOR).

1. Introduction

In today's world, urbanization has become a significant problem of environment in countries and regions on earth, especially in the developing countries. As a typical product of urbanization, mega cities, carrying more than 1,000,000 persons, play a more and more important role in economic development, infrastructure construction and ecological environment response [1]. Meanwhile, mega cities have to face more challenges on the environment protection, resources sustainable utilization as well as people's daily life [2]. There are only 2 mega cities around the world in 1950. According to the UN data in 2014, the number of mega cities had increased from 2 to 29 at an alarming speed over the past 60 years. And it is forecasted that there will be more than 40 megacities along the One Belt and One Road (OBOR) until

2030. Hence, monitoring the urban sprawl of mega cities so as to macroeconomic regulation and control the mega cities development allows of no delay.

Influence of urbanization on environment is mainly from impervious surface. Impervious surface is defined as the entire impermeable surfaces such as buildings, asphalt roads, parking lots, sidewalks and other infrastructural elements of urban areas, and has become a key indicator of urbanization assessment. Monitoring urbanization of mega cities via impervious surface extraction has become a hot topic nowadays. Due to the relatively low cost and is suitable for large area mapping, remote sensing imagery has been widely used in studying urban space distribution since 1970s [3]. And more researchers have been concentrated on urbanization and urban sprawl by impervious surface extraction during the past 20 years [4]. Sun et al. [5] estimated Beijing urban impervious surfaces in 2009 using multilayer perceptron neural network (NLPNN) and SVM classification method. Subsequently, Sun et al. [6] derived impervious surface of Beijing from 1992 to 2009 and investigated the long-term effects of LULC change on surface runoff. Im et al. [7] quantified the urban impervious surface using a synthesis of artificial immune networks, based on the LiDAR nDSM data and WorldView-2 multispectral imagery. Yang and Li [8] extracted Beijing impervious surface in 2003 from QuickBird imagery using linear spectral unmixing models. Nie and Xu [9] quantified the impervious surface of Shanghai, China in 2010 using ETM+ images with the linear spectral mixture analysis (LSMA). Song et al. [10] delineated Washington urban growth in the period 1984-2010 using post per-pixel classification method. Zhang et al. [11] mapped the urban impervious surface of the Pearl River Delta (PRD) using dual- polarimetric SAR data. Amir et al. [12] summarized urban expansion of Kandun Town in Cixi County, Zhejiang Province, China using time series of impervious surface fractions (ISFs). All studies mentioned-above have shown a satisfying result in impervious surface extraction and urban expansion patterns analysis. However, the SVM method was proved to be a relatively simple and typical approach to accomplish LULC classification and urbanization monitoring [13].

The object of this study is to monitor and analyze Megacity Bombay’s urban extent and urbanization patterns. By comparing the efficiency of the pixel-based and object-oriented SVM classification methods operating on Landsat TM of Bombay in 2010, the better method was selected out and applied to extracting the impervious surface of Bombay in the period 1973-2015 from Landsat MSS/TM/ETM+/OLI imagery. This study aims to serve a useful approach for further applications of mega cities’ urbanization planning and sustainable development.

2. Materials and method

2.1 Study area

The study area is Bombay, locating in the western India and covering about 603km^2 (Fig.1). The central latitude and longitude are separately 18°56’N and 72°49’E. Bombay is city of tropical monsoon climate, possessing plenty of moisture and heat, which is suitable for human survival. As the capital and the largest harbor city of India, Bombay has centralized the primary economic, political and cultural activities around the country and experienced rapid urbanization during the past 42 years. According to the UK (2014), population of Bombay was less than 7,000,000 in 1973. In 1985, its population exceeded 10,000,000. Then the number reached about 12,436,000 in 1990. And till 2015, the population of Bombay should be more than 21,000,000, which would be over 3 times of that in 1973. Population growth always results in urban sprawl, so Bombay could be a suitable demo to monitor mega cities’ urbanization patterns.

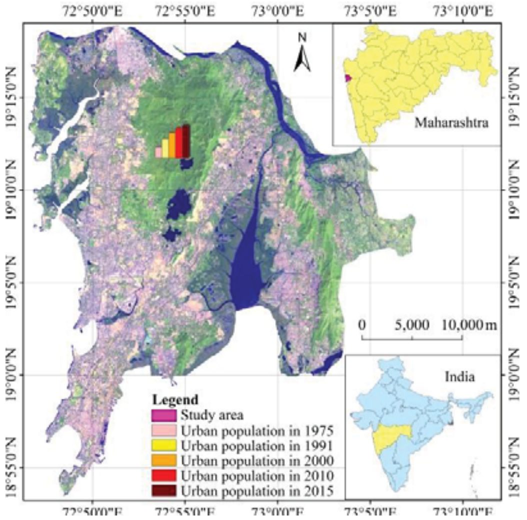


Figure 1. Study area

2.2 Dataset and data preprocessing

The Landsat MSS/TM/ETM+/OLI imagery, acquired in the period 1973-2015, was selected as the study data, due to their low cost, wide coverage and short cycle. Datasets used in the study are all cloudless so as to omit the atmospheric correction [14].

The visible bands, near-infrared (NIR) bands and short wavelength infrared (SWIR) bands were used in this study. During the data preprocessing, the Landsat imagery was resampled to 30m resolution and unified to the Universal Transverse Mercator (UTM) and WGS84 geodetic datum. Additionally, the Normalized Difference Vegetation Index (NDVI) [15], the Soil-adjusted Vegetation Index (SAVI) [16] and the Modified Normalized Difference Water Index (MNDWI) [17] were calculated to participant in the follow-up classification together with the visible, NIR and SWIR bands.

2.3 Methodology

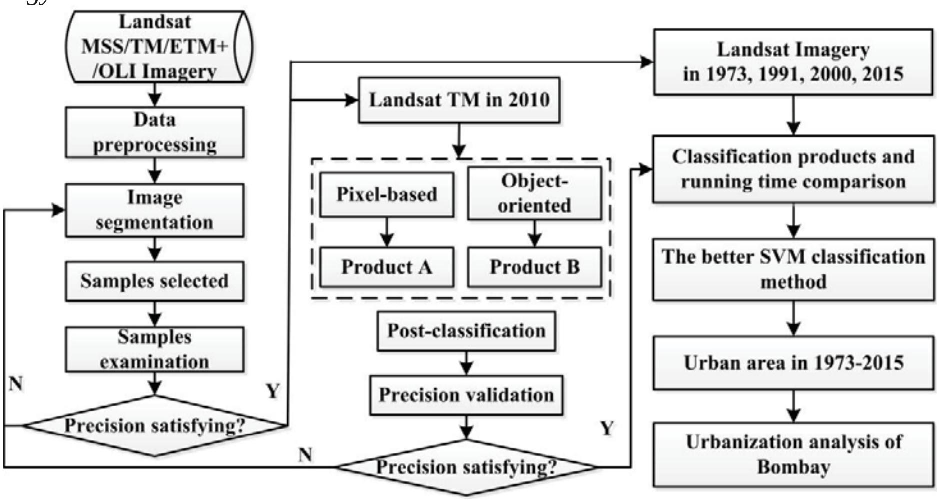


Figure 2. The detailed study framework

Fig.2 was the detailed study framework. Firstly, the data preprocessing was executed and LULC samples were selected. Secondly, the pixel-based and object-oriented SVM classification methods were compared using the Landsat TM imagery of Bombay in 2010. Thirdly, images in the period 1973-2015 were classified using the better method. At last, the urbanization pattern of Bombay was analyzed.

The concept of the SVM derived from a nonparametric machine learning methodology based on Vapnik's [18] structural risk minimization (SRM) principle, aiming to map data into a high-dimensional space and trying to find the optimal hyperplane of different classes. The theory of SVM has been extensively described in the literature by Burges [19] and Brown et al [20]. Therefore, the paper will only describe the basic concepts about image segmentation, the pixel-basic and the object-oriented method.

Table 1. Image segmentation parameters of Bombay

Parameters	MSS	TM	ETM+	OLI
Scale	5	5	10	35
Shape	2	1	2	1
Compactness	0.8	0.9	0.8	0.9

The multiresolution segmentation is a semi-automatic process before the SVM classification. Users defined segmental scale, shape and compactness parameters manually and the Landsat imagery was divided into different objects named "image samples". The scale parameter directly defines size of the image samples, it shouldn't be too large or small because a suitable image sample should only contain one LULC type. Usually, the scale of Landsat MSS/TM/ETM+ and HJ-1 CCD imagery is less than the Landsat OLI imagery, due to their diffident bit numbers. The shape parameter defines the weight the shape criterion should have. The higher its value, the lower the influence of color feather on image samples. And the compactness parameter defines the weight of the compactness criterion. The higher the value, the more compact image objects may be. According to plenty of experiments, the three parameters of Landsat imagery for Bombay are set in table 1.

During the SVM classification, the same training samples were used in the pixel-based and the object-oriented methods. The pixel-based classification implemented supervised classification, using maximum likelihood algorithm, according to the spectrum and geometrical characteristics of each pixel. Each pixel is an individual to participant in the classification. So each pixel was classified to the most similar class. However, the basic unit in the object-oriented classification is not pixels but image samples. Each image sample is composed of multiple pixels. Pixels of the same image sample share similar size, shape, spectrum, texture, context and geometrical characteristics. During the object-oriented classification, pixels of the same image sample are classified into the same class due to their common features.

3. Results and discussion

3.1 Comparison of the pixel-based and object-oriented SVM classification methods

The Landsat TM imagery of Bombay in 2010 was classified using the pixel-based and object-oriented methods in this study. In Fig. 3, the red represents impervious surface, the buff represents bare soil, the green represents vegetation and the blue represents water area. At a first glance, it is difficult to find out any differences between the two results. However, differences indeed existed. The lower-left corner gives the enlarged views near 18°9'11"N, 72°9'8"E. It proves that the pixel-based SVM classification method has a better ability in classification, especially for impervious surface and bare soil.

The Landsat TM imagery of Bombay in 2010 is classified into impervious surface, bare soil, vegetation and water in the classification product. In order to compare the two methods' precision, 199 random Points of each class were selected. By the cross-validating with google earth images as reference, the accuracy and running time of the two classification methods were calculated (Table 2).

Table 2. Accuracy of pixel-based and object-oriented SVM classification methods

	a. Pixel-based SVM Classification Method						
		Impervious surface	Bare Soil	Vegetation	Water	Total	UA(%)
Classified Data	ISA	187	7	4	1	199	93.97
	BS	8	187	2	2	199	93.97
	Veg	2	13	183	1	199	91.96
	Water	0	0	0	199	199	100.00
	Total	197	207	189	203	796	
	PA(%)	94.92	90.34	96.83	98.03		
	OA(%)	94.97					
	OK	0.96					
	Time	78minutes					

	b. Object-oriented SVM Classification Method						
		Impervious surface	Bare Soil	Vegetation	Water	Total	UA(%)
Classified Data	ISA	184	13	2	0	199	92.46
	BS	11	184	1	3	199	92.46
	Veg	5	13	179	2	199	89.95
	Water	0	0	0	199	199	100.00
	Total	200	210	182	204	796	
	PA(%)	92.00	87.62	98.35	97.55		
	OA(%)	93.72					
	OK	0.94					
	Time	25seconds					

ISA: the impervious surface area; BS: the bare soil; Veg: the vegetation; PA: the producer's accuracy; UA: the user's accuracy; OA: the overall accuracy; OK: the overall kappa coefficient

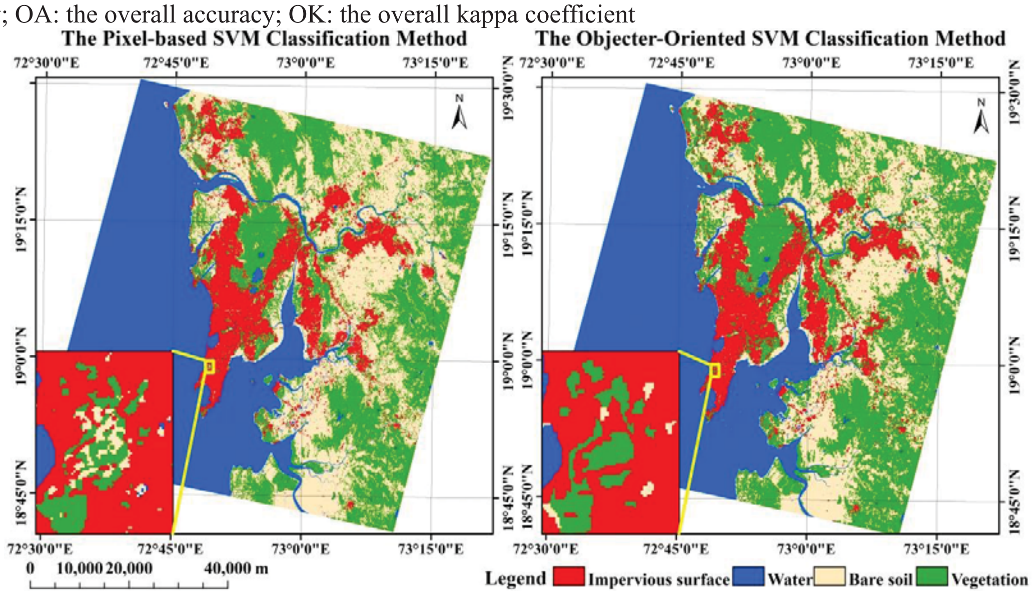


Figure 3. Results of pixel-based and object-oriented SVM classification methods

The overall accuracy (OA) and overall Kappa (OK) of the pixel-based SVM classification method were 94.97% and 0.96, the OA and OK of the object-oriented SVM classification method were 93.72% and 0.94. Both the two methods could acquire a satisfying result, but the precision of the pixel-based SVM classification method was a little higher. However, table 2 also gives the running time, the pixel-based SVM classification method needs 78 minutes but the object-oriented SVM classification method just needs 17s. In comparison, the object-oriented SVM classification method along with post-classification process should be a better choice.

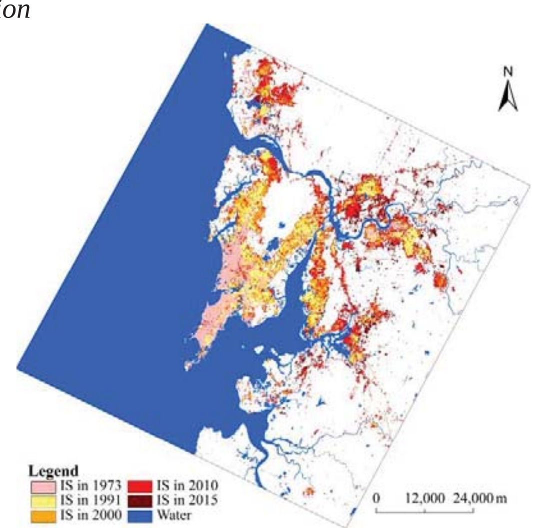
3.2 Accuracy validation

The impervious surface of Megacity Bombay in the period 1973-2015 was extracted using the object-oriented SVM classification method. By the same validation techniques as table 2, the accuracy of the five classification products was estimated. Table 3 showed the user's accuracy (UA), producer's accuracy (PA), OA and OK of impervious surface in the period 1973-2015. According to Table 3, UA are all above 79.00%, OA are all above 88.91%, OK are all above 0.80, and PA in the period 1973-2010 are all above 89.24%. Year 2015 doesn't show a satisfying result due to none Landsat OLI images of good quality were found. The main problem is the impervious surface and bare soil share similar spectral signature in the used OLI image. However, the precision in 2015 was still better than that in 1973 because OLI images often possessed of more bands and better definition than MSS images. In short, the accuracy proved that the object-oriented SVM classification and post-classification method is able to acquire impervious surface of mega cities and analysis of Bombay urbanization was feasible.

Table 3. Accuracy of impervious surface in the period 1973-2015

Year	UA(%)	PA(%)	OA(%)	OK
1973	69.20	72.24	88.91	0.87
1991	88.00	97.24	93.51	0.91
2000	90.50	94.00	93.12	0.92
2010	93.10	97.42	95.80	0.94
2015	79.00	40.72	93.70	0.80

3.3 Analysis of urban expansion



IS: the impervious surface

Figure 4. The urban sprawl of Bombay in the period 1973-2015

Fig.4 shows the impervious surface's dynamic changes of Bombay in the period 1973-2015. It is obvious that the impervious surface experienced tremendous changes during the past 42 years. The biggest change occurred in the period 1973-1991. There was only limited impervious surface in 1973, and it mostly located along the coast and the main river channel. However, quantities of small towns appeared in the period 1973-1999. They just used less than 3 decades to develop into large cities. Until 2015, areas of impervious surface had expanded about five times with 1973 as baseline. The basic expansion pattern was from coastal areas to inland. And impervious surface in the inland area showed a concentric expansion pattern.

According to the urbanization pattern of Bombay, it could be speculated that expansions of mega cities along the OBOR were analogous to Bombay. The urban sprawl direction is from the coastal areas to the inland. And it's mainly "concentric expansion pattern" in the inland area. Additionally, there are also a large number of satellite town generated.

4. Conclusions

Using the Landsat MSS/TM/ETM+/OLI imagery, this study accomplished two tasks.

1) Based on the Landsat TM imagery of Bombay in 2010, the pixel-based and object-oriented SVM classification methods were available to extract impervious surface and analyze urbanization of mega cities. According to the classification products and running time, the object-oriented SVM classification method was suggested to be more efficient.

2) Using the object-oriented SVM classification method, the impervious surface of Megacity Bombay in the period 1973-2015 was delineated out. And the urbanization process of Bombay was analyzed.

This study explored an effective method to monitor and analyze mega cities' urbanization patterns. Analysis about Bombay was a helpful reference for other mega cities in the developing countries along the OBOR. The study findings provided scientific theory basis for relevant departments to regulate new type of urbanization, preserve the ecological environment, develop the economy and ensure supplies in the future.

However, there are still several weaknesses in the study. 1) The study dataset are 30m moderate resolution remote sensing images, which inevitably lead to errors in the classification products. 2) Impervious surface and bare soil share the same spectral signature, bringing mix-classification problems.

Aiming to provide more and better references for mega cities' sustainable development, the high resolution remote sensing images should be used to the impervious surface extraction, and urbanization patterns of more mega cities will be monitored and analyzed in the next study.

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References

[1] Aguilar A G, Ward P and Smith C B 2003 Globalization, regional development, and mega-city expansion in Latin America: Analyzing Mexico City's peri-urban hinterland *Cities*. **20** 3-21

[2] Esch T, Taubenbock H, Felbier A, Heldens W, Wiesner M and Dech S 2012 Monioring of Global Urbanization-time series analyses for maga cities based on optical and SAR data *EORSA*. 21-25

[3] Zhang L and Weng Q H 2016 Annual dynamics of imperious surface in the Pearl River Delta, China from 1988 to 2013, using time series Landsat imagery *ISPRS*. **113** 86-96

[4] Guo H D, Yang H N, Sun Z C, Li X W and Wang C Z 2014 Synergistic use of optical and PolSAR imagery for urban impervious surface estimation *Photogramm. Eng. Remote Sens*. **80** 91-102

[5] Sun Z C, Guo H D, Li X W，Liu L L and Du X P 2011 Estimating urban ISAs from Landsat-5 TM images using multilayer perceptron neural network and support vector machine J *J. Appl. Remote Sens.* **5** 053501

[6] Sun Z C, Li X W, Fu W X, Li Y K and Tang D S 2014 Long-term effects of land use/land cover change on surface runoff in urban areas of Beijing, China *J. Appl. Remote Sens.* **8** 084596

[7] Im J, Lu Z Y and Rhee J 2012 Impervious surface quantification using a synthesis of artificial immune networks and decision/regression trees from multi-sensor data *Remote Sens. Environ.* **117** 102-113

[8] Yang J and Li P J 2015 Impervious surface extraction in urban areas from high spatial resolution imagery using linear spectral unmixing *Remote Sens. Appl. Soc. Environ*. **1** 61-71

[9] Nie Q and Xu J H 2015 Understanding the effects of the ISAs pattern on land surface temperature in an urban area *Front. Earth Sci*. **9** 276-285

[10] Song X P, Sexton J O, Huang C Q, Channan S and Townshend J R 2016 Characterizing the magnitude, timing and duration of urban growth from time series of Landsat-based estimates of impervious cover *Remote Sens. Environ.* **175** 1-13

[11] Zhang H S, Lin H, Li Y, Zhang Y Z and Fang C Y 2016 Mapping urban impervious surface with dual-polarimetric SAR data: An improved method *Landscape Urban Plan.* **151** 55-63

[12] Shahtahmassebi A R, Song J, Zheng Q, Blackburn G A, Wang K, Huang L Y, Pan Y, Moore N, Shahtahmassebi G, Haghighi R S and Deng J S 2016 Remote sensing of impervious surface growth: A framework for quantifying urban expansion and re-densification mechanisms *Int. J. Appl. Earth Obs*. **46** 94-112

[13] Gong P, Wang J, Yu L, Zhao Y, Zhao Y, Liang L, Niu Z, Huang Z, Fu H and Liu S 2013 Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data *Int. J. Remote Sens*. **34** 2607-2654

[14] Taubenbock H, Esch T, Felbier A, Wiesner M, Roth A and Dech S 2012 Monitoring urbanization in mega cities from space *Remote Sens. Environ.* **117** 162-176

[15] Townshend J R G and Justice C O 1986 Analysis of the dynamics of African vegetation using the Normalized Difference Vegetation Index *INT. J. Remote Sens.* **7** 1435-1445

[16] Baret G 1991 Potentials and limits of vegetation indices for LAI and APAR assessment *Remote Sens. Environ.* **35** 161-173

[17] Xu H Q 2005 A study on information extraction of water body with the Modified Normalized Difference Water Index (MNDWI) *J. Remote Sens*. **9** 589-595

[18] Vapnik V N 1997 The nature of stature of statistical learning theory *Neural Networks*. **8** 1564-1564

[19] Burges C J C 1998 A tutorial on support vector machines for pattern recognition *Data Min. Knowl. Discov.* **2** 121-167

[20] Brown M, Lewis H G and Gunn S R 2000 Routear spectural mixture models and support vector machines for remote sensing *Geosci. Remote Sens*. **38** 2346-1360