Urban Classification Based on Sentinel-2 Satellite Data for Slum Identification

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Abstract

Slum settlement detection and mapping is useful for planning, implementing and monitoring urban poverty alleviation programs. However, current methods using traditional surveys cannot meet the demand for the rapid development of urban poverty management. There is an urgent need to develop new methods to overcome the shortcomings of conventional methods. To address this issue, this research applies machine learning (ML), the Support Vector Machine (SVM) and Random Forest (RF), for classifying and identifying slum areas using Sentinel-2 satellite data in Bang Sue district, Bangkok Thailand. The urban classification results show overall accuracy of 70% and 72% for SVM and RF algorithm respectively. The producer's accuracy assessment of slum areas using SVM and RF show 53% and 73% respectively. While in the user aspect, the numbers show 50% and 44% accuracy as a result of applying SVM and RF model respectively. This can offer data-driven decision-makings for urban poverty management. Finally, the application of slum mapping method can improve the credibility of the results and provide a reference for further research and implementation of slum upgrading programs and urban management.

KEYWORDS: TSlum identification, Urban classification, Support vector machine, Random forest, Sentinel-2

1 INTRODUCTION

In the recent decades, people have been moving and settling their lives in urban areas as a result of urbanized growth. This can cause many countries, particularly in developing regions, to face the problem of providing basic services and city infrastructure to meet the people's need (Cohen, 2006; Montgomery, 2008). As a result, the poverty rates of urban population have been increasingly become more challenged, that, in turn, can make an increase in informal settlements, or slums, in city areas (UN Habitat, 2016). The global number of slum populations is approximately estimated to be a billion today, and if no operative tools developed for dealing with the slum expansion, the number could double twice in the year 2030 and thrice by 2050 (United Nations, 2017). This estimate is considered through the paucities of communities including unable to have enough water consumption, inadequate good quality of sanitation and related infrastructure, poor shelters, and unsafe inhabited areas (United Nations, 2017).

The identification and mapping of slums is a very important aspect in many applications (Ansari et al., 2020). The reason of this is that the proliferation of slum settlements is estimated to have negative impacts on both humans and the environment, which are inseparably related. Nevertheless, the circumstances that occur in slums such as living at risks either from natural or manmade catastrophes, or both, and unsuitable land and housing have negative consequences on their everyday lives (Napier, 2007; Shekhar, 2021). This is mostly due to inability of slum residents to protect themselves and also recover from disasters, such as floods, earthquakes and disease outbreak, in comparison with formal settlements (Ebert et al., 2009; Ajibade and McBean, 2014; Solymári et al., 2022). For the purpose, identifying and mapping slum areas may be used for database establishment, from which public and private organizations can share and the work upon. To tackle these issues, this study proposes an urban mapping method using machine learning and Sentinel-2 satellite imagery data for slum identification. In addition, this method shows its performance and then would give a reference for urban slum development programs as well as the guideline for the future research.

2 STUDY AREA AND DATASETS

This study aims to use a remote sensing data source for classifying informal settlements in a Bangkok district in which most slums are located. Thus, Bang Sue district is selected as the study area in this experiment. The selected free satellite data is Sentinel-2 extracted from the Copernicus Open Access Hub. The image processing software used in this study is ArcGIS 10.7.1 from ESRI.

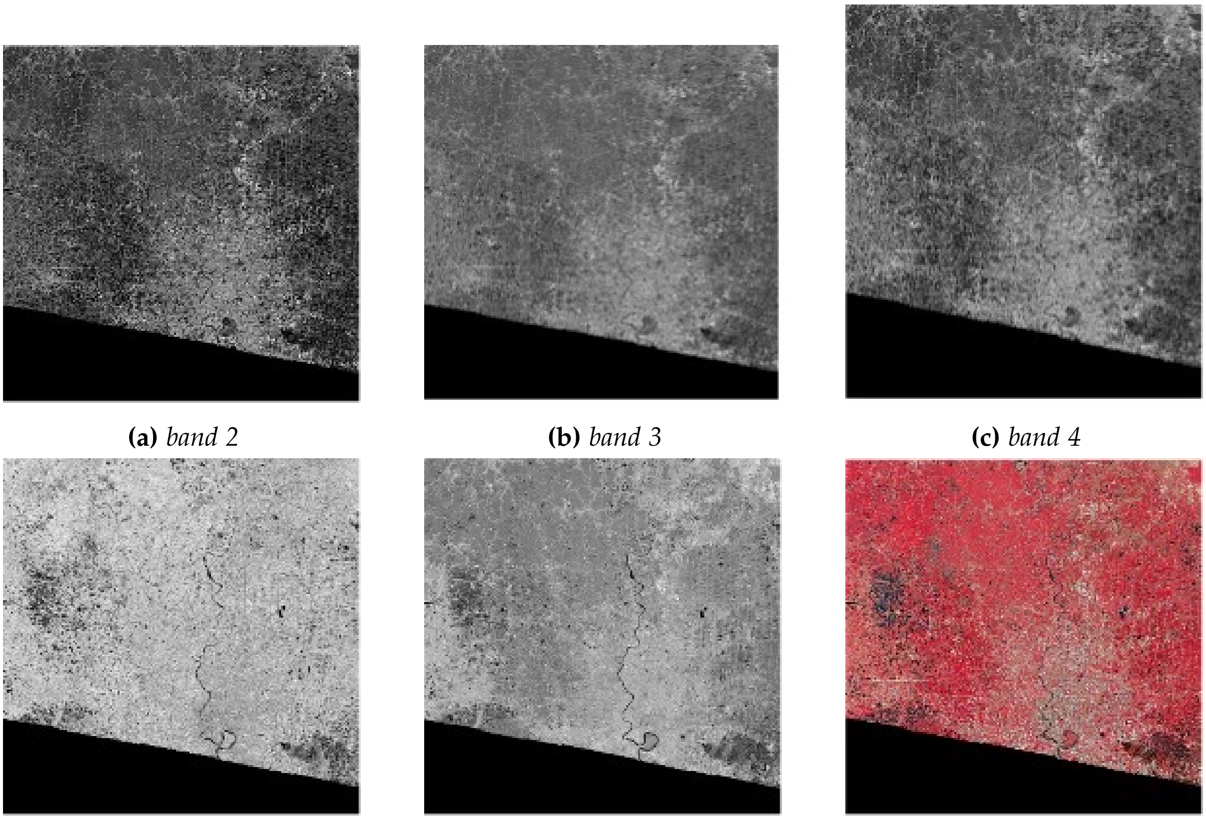
2.1 Study area of Bangkok

Bangkok is the Thailand's capital city, and it is also the most populated city in the country. Like in several other areas, this urbanisation has led to more settlements as slum communities, affecting the city's structure and society. Bangkok population in 2020 was counted around 10.7 million people (15% of Thailand population). Approximately 20% of Bangkok population lived in informal settlements that lack essential services and there is a risk of being affected by floods and other threats, including a lack of good quality housing for low and middle-income people. Nevertheless, funding for affordable housing and expanding housing financing options for the urban poor remains limited. The main issues that lead to population growth in this area are natural growth (e.g. birth rate), legal and illegal immigration from other countries and internal migration from urban areas.

2.2 Sentinel-2 datasets

The Sentinel-2 Multispectral Instrument (MSI) consists of two satellites surveying the globe at the spatial resolution of 10 m, 20 m and 60 m. The spatial resolution of 10 m is the highest among all free-to-use satellite products. Additional, special characteristic feature of the Sentinel-2 data is the presence of three red border bands that can capture the intense reflections of plants in the near-infrared portion of the electromagnetic spectrum (EMS).

The criteria for selecting satellite images is that the image data must not contain major obstacles; in other words, the area of interest should have little or no clouds and mist. As such, ten bands of a Sentinel-2A scene captured in 2021: July 05 (see Figure 1) were used in this analysis. The satellite dataset was selected and downloaded from the Copernicus Open Access Hub (`https://scihub.copernicus.eu/`) on 10 August 2021. The datasets provided



(a) *band 2* **(b)** *band 3* **(c)** *band 4*

(d) *band 8* **(e)** *band 11* **(f)** *Composite bands*

Figure 1: *Multi-bands of the Sentinel-2A imagery used in this study*

from the Copernicus Open Access Hub basically are in Level-1C processing format, which means that geometric and radiometric correction have been done already, but not atmospherically corrected. Several spectral bands including red, blue, green, red edge, near infrared, and short-wave infrared portions of the electromagnetic spectrum were chosen for urban classification in this study (see Table 1).

Table 1: *Description of Sentinel-2A bands used in this study*

Band	Spectral region	Spatial resolution (m)	S2A	
			CW (nm)	Bandwidth (nm)
2	Blue	10	496.6	98
3	Green	10	560.0	45
4	Red	10	664.5	38
8	Near Infrared	10	835.1	145
11	Shortwave Infrared	20	1613.7	143

3 RESEARCH METHODOLOGY

In this study, for Sentinel-2A image classification, Support Vector Machine (SVM) and Random Forest (RF) approach are applied and processed in ArcGIS 10.7.1, and taken into account in terms of overall accuracy for image classification. In this section, the overall methodology described here is twofold: image classification and accuracy assessment.

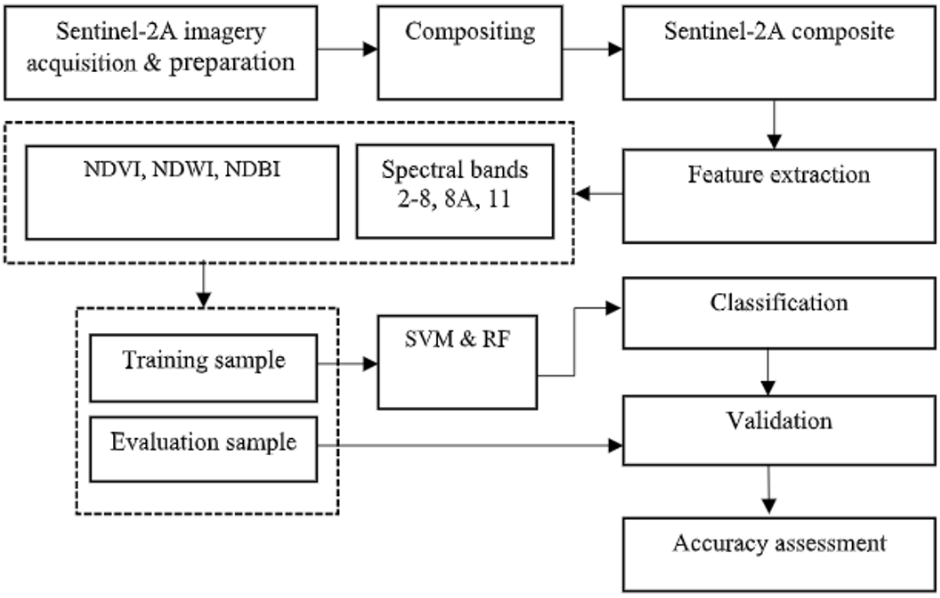


Figure 2: *Research methodology*

3.1 Image classification

Training data are crucial components in supervised classification that requires a number of training data samples. The study design (see Figure 2) involves satellite data acquisition and preparation, image composite, feature selection, training sample selection, classification, and accuracy assessment. In the first step, the selected tile of the Sentinel-2A was downloaded and clipped according to the study area (see Figure 3).

In the experiment, remote sensing indices including normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and normalized difference build-up index (NDBI) are applied to consist the process of feature extraction. In the study area, nine feature classes shown in table 2 were extracted to be used as training samples. Afterward, the SVM and the RF models were selected and used for urban classification.

The SVM is a cutting-edge-machine-learning method established based on statistical learning model and the concept of structural risk minimization (Cortes and Vapnik, 1995). The SVM shows the characteristics of high accuracy, quick speed of calculation, and good generalization capacity, which is extensively applied in both urban and non-urban classification mapping (Zhang et al., 2015). On the other hand, the RF concept is an integrated learning algorithm developed by Breiman in 2001. The RF can generate the variation of classification trees and enhance the capability of a single of classification tree or regression tree by return-

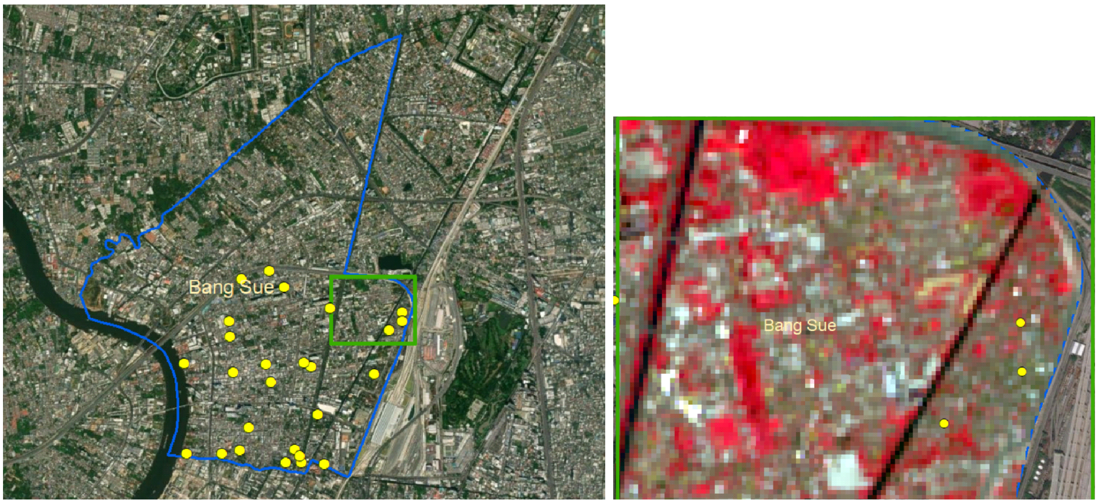


Figure 3: *Natural and the composite of the Sentinel-2A imagery of the study area*

Table 2: *Description of the 10 Sentinel-2A bands used in this analysis*

No.	Class name	Symbology
1	Slum	
2	Road	
3	High rise building	
4	Low rise building	
5	Urban residence	
6	Tree	
7	Water	
8	Turf	
9	Bare soil	

ing sampling and randomly altering the mixture of predictive variables in the establishment of different threes

As a result of applying SVM and RF in this study, all area categories were classified in the form of map. The result maps of using SVM and RF are shown in Figure 4 and 5 respectively, the classification of the study area for both algorithms show a fair overall accuracy performance. However, the overall accuracy of slum settlement using RF is relatively high in comparison with that using SVM. The detail of the accuracy assessment is discussed in the next sections.

3.2 Accuracy assessment

The accuracy of algorithm was evaluated using a number of metrics derived from a confusion matrix. This includes overall accuracy (OA), producer's accuracy (PA), and user's accuracy (UA) as calculated in the following equations.

OA formula:

Overall accuracy = Total number of correctly classified pixels (Diagonal)Total number of

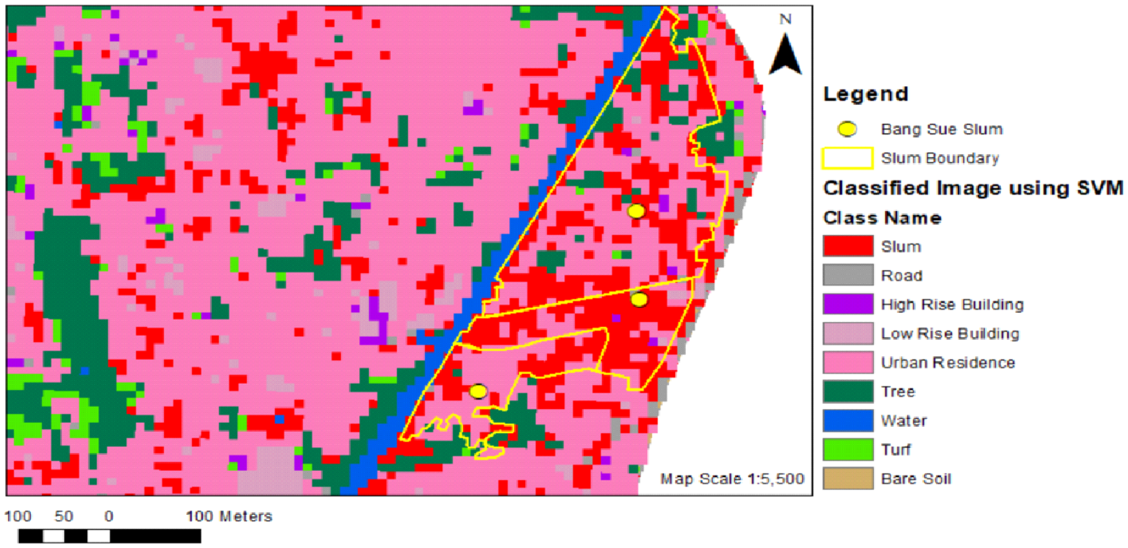


Figure 4: *The mapping result using SVM classifier*

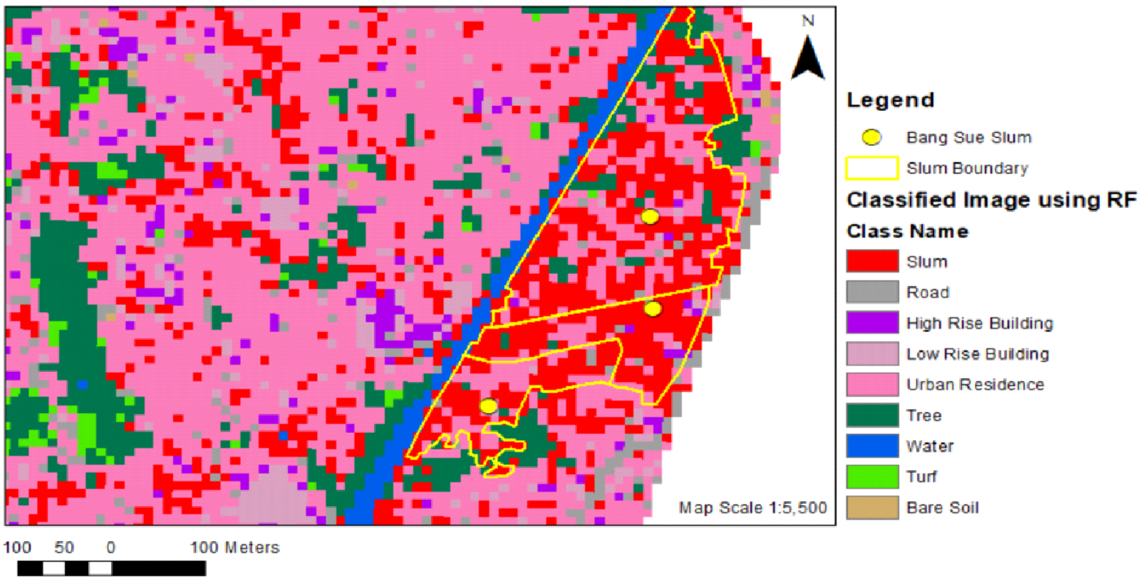


Figure 5: *The mapping result using RF classifier*

reference pixels×100

PA formula:

User accuracy = Total number of correctly classified pixels in each classTotal number of reference pixels in that class (Row total)×100

UA formula:

Producer accuracy = Total number of correctly classified pixels in each classTotal number of reference pixels in that class (Column total)×100

The confusion matrix is improved by an unbiased estimate of the proportional area of cells in the matrix. Area proportions of mapped classes are included in the results, because each class requires its own assessment weight. These proportions are essential to estimation OA and PA conducive to involve differences in sampling between classes. Equally, UA is computed from within a given class and it is repossessed directly from the confusion matrix (Olofsson et al., 2013).

4 RESULTS AND DISCUSSION

Classification results The confusion matrix in Table 3 and Table 4 show corrects and incorrect cross-tabulations of the evaluation samples by the SVM and RF algorithm respectively. The error matrices form the basis for the calculation of the performance matrices shown in Tables, including the producer's accuracy (PA) and user's accuracy (UA) of each class and lastly the overall accuracy (OA). Table 3 shows the accuracy assessment estimates for predicted classes using SVM. The overall accuracy of the urban classification is 70%. While the accuracy assessment of slum settlement shows the producer's accuracy of 50% and the user's accuracy of 53%, which is relatively low compared with the other classes. In addition to the SVM result, the accuracy assessment estimates for predicted classes using RF shows the overall accuracy of 72%. Table 4 shows the accuracy assessment estimates for predicted classes using RF of which the accuracy assessment for slum area is 44% in the user's accuracy aspect; while the producer's accuracy is 73% which shows a higher performance of that using SVM.

4.1 Discussion

The SVM algorithm shows a bit lower overall accuracy of urban classification compared to the RF classifier for the Sentinel-2A dataset used in this study. The numbers show a minor difference (70% and 72% using SVM and RF respectively). For the user aspect, the result for slum identification shows that the SVM is out performed over the RF method with the number of 50% and 44% respectively, while the producers accuracy shows a better result using RF than that using SVM with the number of 73% and 53% respectively. In each ML performance, SVM shows a similar accuracy result of slum identified in both producer's and user's accuracy (53% and 50% respectively). While the RF has a different result between producer's and user's accuracy with the number of 73% and 44% respectively. This means that, using RF method, even though 73% of the reference slum areas has been correctly identified as slum, only 44% of the areas identified as slum in the classification area is actually slum. Interestingly, both ML algorithms with the medium resolution satellite data, which is Sentinel-2A (10 m-resolution), show relatively low accuracy of slum areas compared to the other classes. This

Table 3: *Confusion matrix of SVM algorithm*

		Observed Classes										
	Classes	Slum	Road	High build.	Low build.	Urban res.	Tree	Water	Turf	Bare soil	Total	UA
Predicted Classes	Slum	8	2	0	0	3	2	1	0	0	16	0.50
	Road	0	7	0	0	0	0	0	1	1	9	0.78
	High build.	0	0	4	3	1	0	0	0	0	8	0.50
	Low build.	1	0	0	11	1	0	0	0	0	13	0.85
	Urban res.	6	3	2	3	30	3	1	1	0	49	0.61
	Tree	0	0	0	0	0	21	0	1	0	22	0.95
	Water	0	0	0	1	0	1	8	0	0	10	0.80
	Turf	0	0	0	0	1	2	0	7	0	10	0.70
	Bare soil	0	0	0	0	0	0	0	0	1	1	1.00
	Total	15	12	6	18	36	29	10	10	2	138	0.50
	PA	0.53	0.58	0.67	0.61	0.83	0.72	0.80	0.70	0.50	0	OA=0.70

Table 4: *Confusion matrix of RF algorithm*

		Observed Classes										
	Classes	Slum	Road	High build.	Low build.	Urban res.	Tree	Water	Turf	Bare soil	Total	UA
Predicted Classes	Slum	8	0	0	0	7	2	0	1	0	18	0.44
	Road	0	7	0	0	1	1	0	0	0	9	0.78
	High build.	2	0	3	3	1	0	0	0	0	9	0.33
	Low build.	0	0	1	11	1	0	0	0	0	13	0.85
	Urban res.	1	2	1	3	31	2	1	1	1	43	0.72
	Tree	0	1	0	0	2	17	0	0	0	20	0.85
	Water	0	0	0	0	0	1	9	0	0	10	0.90
	Turf	0	0	0	0	0	0	0	9	1	10	0.90
	Bare soil	0	1	0	0	1	0	0	1	7	10	0.70
	Total	11	11	5	17	44	23	10	12	9	142	0.44
	PA	0.73	0.64	0.60	0.65	0.70	0.74	0.90	0.75	0.78	0	OA=0.72

can be noted that Bangkok slums and the low-income communities, look like informal settlement but not slum, have similar characteristics, i.e. the shelters' roof are mostly constructed by zinc plate and also informal settlements and slums are shaped as irregular. Therefore, the higher resolution of satellite dataset cloud be beneficial to differentiate between slum and low-income community in Thailand.

5 CONCLUSION

This study proposed machine learning methods for classifying and mapping urban area in a Bangkok district, Bang Sue. The classification map was extracted from the multi bands image of Sentinel-2A satellite data using ArcGIS 10.7.1 software. The training samples were selected on the help of remote sensing indices (NDVI, NDWI, and NDBI), computed from the multispectral bands. SVM and RF algorithms were used to extract 9 feature classes that are distinctly contained in the study area, including slum area, road, high rise building, low rise building, urban residence, tree, water, turf, and bare soil. The SVM algorithm produced the overall accuracy of 70%. The user's and producer's accuracy of slum settlement class using SVM show the similar result of 50% and 53% respectively. While the RF model generates the overall accuracy of 72%, with the user's and producer's accuracy of slum class show 44% and 73% respectively.

As a result, the overall accuracy assessment of applying SVM and RF show a lower performance of urban classification. While the predicted slum class using RF shows better accuracy than that using SVM. However, the accuracy assessment of slum class using both algorithms show a relatively low compared to the literature regarding slum classification using VHR satellite data. Therefore, a study of classifying and mapping slum settlements using state-of-the-art classifiers and high-resolution remote sensing data is needed for more powerful slum mapping methods that could improve the credibility of the results and provide a reference for further implementation of slum upgrading programs and urban management.

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