Mapping Urban Land Cover by Using Landsat, Sentinel Images and Open Social Data

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Abstract Mapping urban land cover is one of the important issues in urban planning of the developing country. This paper investigates a methodology to classify land cover of Yangon by using the web-based remote sensing platform, Google Earth Engine (GEE). Features are extracted from 30m Landsat-8 images by using pixel-based approach and 10m Sentinel-2 images by using object-based approach for land cover classification. In addition, open social data extracted from Open Street Map (OSM) and ground truth data are applied as additional features to enhance the accuracy of the classifier.

1. INTRODUCTION

Remote sensing satellite images are considered as one of the important data sources for mapping urban land cover because of their large-scale geographical coverage and timely information. Land cover map can be obtained by using remote sensing image classification methods with different machine learning algorithms. However, remote sensing community still has challenges in the accuracy and processing time of land cover classification using satellite images.

In this study, we combine the spatial, spectral and temporal features extracted from the Landsat-8 and Sentinel-2 images with the vector features from OSM to obtain reasonable accuracy. The proposed machine learning image classification is implemented through the cloud-based GEE to reduce the processing time.

2. STUDY AREA AND MATERIALS

The research was conducted in Yangon region that is located in the southern part of Myanmar and 40 km north of the Gulf of Martaban of the Andaman Sea. Yangon is the capital city of Myanmar and also the industrial and commercial center of the country.

The data that are used in this method are Landsat-8 Operational Land Imager images, Sentinel-2 Multispectral Instrument images, ground truth GPS metadata and open social data. Open social data are obtained from OSM that is a volunteered geographic information project aiming at supporting open, user-generated maps.

3. DATA PROCESSING AND METHODOLOGY

3.1 Image Preprocessing

Geometric, atmospheric and topographic corrections are applied over Landsat-8 and Sentinel-2 image collection of 2017 in GEE. Most of the satellite images contain noise signals that can cause distortion and image enhancement using low pass median filter is performed as a preprocessing stage to reduce noises in satellite images.

3.2 Feature Extraction

Spectral and spatial features from Landsat-8 images are extracted by using true color composite and false color composite method based on the pixels of the images. For Sentinel-2 images, the appropriate scale level and merge level is computed in the segmentation algorithm based on the objects of the images and the spectral, spatial and texture features are generated. Moreover, vector layers from OSM map are rasterized to a 5-m grid, which was superimposable with the satellite images. Feature fusion is investigated by combining features from satellite images with vector features from OSM and GPS metadata.

The slope is calculated in degrees from SRTM DEM and used as input feature for land cover classification. In addition, normalized difference vegetation index (NDVI) and normalized difference buildup index (NDBI) are derived from Landsat-8 and Sentinel-2 images and these spectral indexes are also considered as the input features. NDVI is calculated as equation (1) and NDBI is calculated as equation (2):

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \tag{2}$$

Where NIR and RED in Equation (1) represent the near infrared and red reflectance values and SWIR and NIR in Equation (2) are the shortwave infrared reflectance values.

4. EXPERIMENT AND RESULTS

Two parameters: the number of trees (ntree) and the number of features in each split (mtry) are set to implement random forest (RF) classifier in GEE. Different objects have different spectral signatures and classification can be effectively performed by using these spectral values. The proposed method uses different spectral bands combination as the input bands in RF classifier and 7 combinations are tested. The overall accuracy (OA) and the kappa statistic of the classifier due to the relative combination are described in TABLE I.

TABLE I Spectral bands combination Used and Their Relative OA and Kappa Statistic

Spectral Bands Used in Classifier	OA	Kappa Statistic
L8 B2,B3,B4 and S2 B2,B3,B4	94.44%	0.92
L8 B2,B3,B4,B5,B6 and S2 B2,B3,B4,B8,B11	96.25%	0.95
L8 B2,B3,B4,B5,B6,B9 and S2 B2, B3,B4,B8,B11	96.19%	0.94
L8 B2,B3,B4,B5,B6 and S2 B2,B3, B4,B8	96.19%	0.94
L8 B2,B3,B4,B5 and S2 B2,B3,B4, B8	95.33%	0.93
L8 B1,B2,B3,B4,B5,B6,B9 and S2 B1,B2,B3,B4,B8,B10,B11	96.71%	0.95
L8 B1,B2,B3,B4,B5,B6 and S2 B1, B2,B3,B4,B8,B11	96.73%	0.95

Among the OA results obtained from TABLE I, the combination of Landsat-8 Ultra Blue, Blue, Green, Red, NIR and SWIR1 bands and Sentinel-2 Coastal Aerosol, Blue, Green, Red, NIR and SWIR1 bands get the best accuracy. TABLE II shows the precision and recall of each classified class for this combination. Land cover classification map with 7 classes (shrub land, bare land, Forest, Agriculture, Urban Area, Lake and River) is obtained from the proposed method as shown in Figure 1.

TABLE II Precision and Recall of Classified Classes

Classified Class	Precision (%)	Recall (%)
Shrub Land	59.054	60.166
Bare Land	78.989	81.706
Forest	97.191	97.233
Agriculture	96.723	97.211
Urban Area	96.512	95.518
Lake	98.862	99.160
River	99.246	99.381

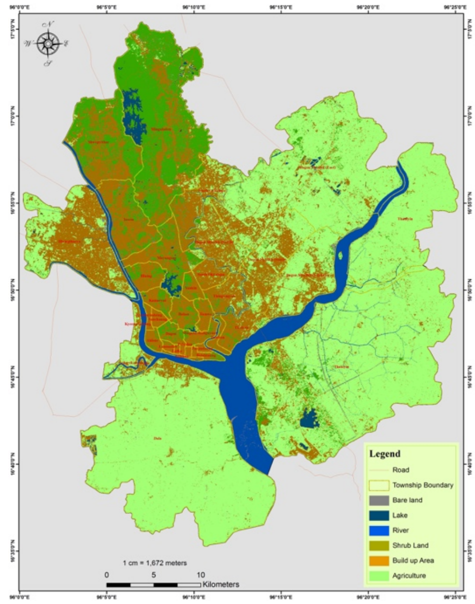

Fig. 1 Land Cover Classification Map of Yangon in 2017

5. CONCLUSION

In this paper, the land cover mapping is evaluated by fusing features extracted from the satellite images and the open social data in GEE using random forest classifier. Furthermore, the spectral indexes can be considered as the input features to achieve better accuracy.

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