Land-cover Mapping from Sentinel Time-Series Imagery on the Google Earth Engine: A Case Study for Hanoi

Nam Ba Bui
Center of Multidiciplinary Intergrated Technology for Field Monitoring
University of Engineering and Technology, VNU
Hanoi, Vietnam
nambb@fimo.edu.vn

Anh Phan
Center of Multidiciplinary Intergrated Technology for Field Monitoring
University of Engineering and Technology, VNU
Hanoi, Vietnam
anhp@fimo.edu.vn

Thanh Thi Nhat Nguyen
Center of Multidiciplinary Intergrated Technology for Field Monitoring
University of Engineering and Technology, VNU
Hanoi, Vietnam
thanhntn@fimo.edu.vn

Over the past decade, satellite image processing is an overwhelming bulk of work. Recently, with rapid development in information technology, Google released Google Earth Engine (GEE), which is a powerful cloud computing platform, to help to improve the performance of geospatial big data archives and processing. In this study, we deployed a machine learning model to evaluate the capability of time series Sentinel imagery (Sentinel 2 A/B and Sentinel 1A) in landcover mapping for Hanoi in 2019. First, we evaluated several traditional machine learning models, as a result, XGBoost classifier stands out as the best model with 86% overall accuracy (OA). As Hanoi is a frequent cloud-covered area, the combination of optical data and radar data helps to improve the quality of the landcover map in 2019. The use of GEE has made it easier and faster through the provided JavaScript API when ensuring high accuracy

Keywords—Google Earth Engine, Landcover mapping, Sentinel 2 A/B, Sentinel 1A, Hanoi.

I. Introduction and Related Works

Free satellite images enable the monitoring promise in complex earth surface [1]. Land-cover, land use is recognized for the diversity in usage of the land and the footprint of human activities. Thus, mapping land-cover is essential for urban planning and nature resource management [2]. Using spatial satellite data has been an effective way to monitor the earth surface since the biophysical cover could be characterized by multi-type of sensors such as optical and microwave. Recently, landcover mapping is getting easier due to the growing amount of free satellite data [3]. In Vietnam, Chuc et al., proposed an ensemble machine learning model with LandSat-8 time-series composites to improve the land-cover classification over Hanoi, where is a frequently cloud-cover area [4]. Multi-temporal Landsat data was also used to detect change for built-up area in Hanoi by applied Support Vector Machine (SVM) classifier [5] while thresholding approach with multi-temporal Sentinel 1A data was studied by Hang et al. [6]. There are also several related works focusing on agricultural land change monitoring applied machine learning approach with Sentinel 1A [7][8], Landsat 8 [9], Envisat ASAR [10]. The implementation and experiments of the previous studies mostly carried out by Python, R and Matlab programing languages due to their powerful support packages and libraries [11][12].

As briefly introduced above, it can be seen that various data sources, approaches and software were carried out to solve the problem in land-cover and land-use change. Besides, there is a growing concern on hardware and software infrastructure to handle a massive spatial data. Until recently, most of previous works that have been done, were locally conducted with different capacity of hardware and software infrastructure. Over the past decade, the technology in geospatial data processing varied significantly. However, the whole process of landcover mapping mainly consists of several common processing steps including: data preprocessing, data sampling, training classifiers, tuning model's parameters, and making maps.

Google Earth Engine (GEE) is a web-based cloud computing platform, that brings a massive computational capability of Google to bear on a variety of social issues including deforestation, land-cover change, disaster [13]. It is an integrated platform designed for traditional remote sensing scientist and much wider user that lacks the technical and infrastructure capacity needed to carry out massive geospatial analysis [13]. GEE has been widely used in a large number of studies related to land-cover mapping due to its powerful resources [14][15][16]. However, its use in Vietnam is not so popular because it requires a certain knowledge in programming language such as Python and JavaScript to be a proficient user. The aim of this paper is to evaluate the capability of Google Earth Engine (GEE) to carry out temporal spatial data analysis and aggregation in our study area. We focused on a small study area with a simple, yet data-dense computational problem of pixel classification in land-cover of Hanoi. Besides, our work is the first attempt of using the both radar (Sentinel 1A) and optical (Sentinel 2 A/B) sensors from Sentinel constellation for land-cover mapping in Vietnam.

The paper is organized as followings: First, we gave a brief of the introduction and related works, thus we address our research problem. Next, the study area and data used in the study was presented. Our proposed methodology was described in Section 3. Section 4 is experiment results and discussions. Finally, the conclusion and future work was shown in Section 5 followed by the acknowledgement.

II. Study Area And Data

A. Study area

Hanoi is the capital of Vietnam, which is a cloud-prone area [4]. Hanoi is the second largest city in Vietnam, located in centre of the Red River Delta covering 3300 km^2, with the estimated population of approximately 20 million within metropolitan area. The administrative boundary map of Hanoi is presented in Fig. 1. We investigated seven land-cover classes for Hanoi including bare-land, built-up, rice, crop, water, forest, grass.

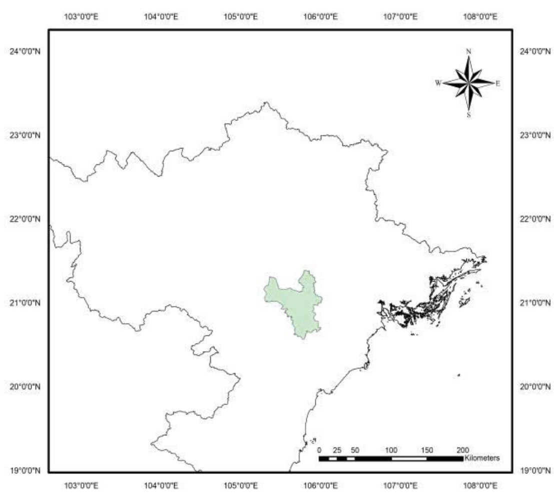

Fig. 1. The administrative boundary of Hanoi (area with pink color)

B. Data

1) Reference Data

Our reference dataset was a stratified random based on the official land-use from Hanoi Environment and Nature Resource [17] to seven classes including bare-land, built-up, rice, crop, water, forest and grass. The RGB high resolution of the seven classes are shown as in Fig. 2.

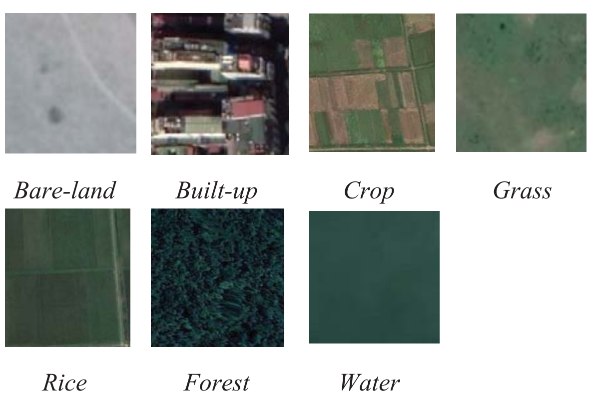

Fig. 2. The administrative boundary of Hanoi (area with pink color)

The sample distribution for each land-cover class is shown as in Table. I. Total numbers of training and test set are 3437 and 1726, respectively. The detail of training and test sample distribution is: bare-land (37, 22), built-up (644, 300), rice (968, 519), crop (364, 205), water (393, 170), forest (788, 402) and grass (243, 108).

TABLE I. THE DISTRIBUTION OF SAMPLES FOR TRAINING AND TEST DATASET

Training dataset						
Bare-land	***Built-up***	***Crop***	***Grass***	***Rice***	***Forest***	***Water***
37	644	364	243	968	788	393
Test dataset						
22	300	205	108	519	402	170

2) Sentinel 2 A/B

Sentinel-2 is a high-resolution and multi-spectral imaging mission supporting Copernicus Land Monitoring studies, including the monitoring of vegetation, soil and water cover. Together with Sentinel 1, Sentinel 2 is a satellite constellation from European Space Agency (ESA). Sentinel 2 includes two satellites Sentinel 2 A/B with a 6-day revisit with the availability in Hanoi. Sentinel 2 A/B products is freely provided by GEE with the resolution of 10m x 10m. In this study, the full-year 2019 time-series Sentinel 2 was collected and preprocessed to use as predictor variables for the land-cover classification in the study area.

3) Sentinel 1A

Sentinel 1 is a satellite constellation from the European Space Agency (ESA). Sentinel 1 includes two satellites—Sentinel 1A and Sentinel 1B which carry C-band SAR imagery with a 6-day revisit only in Europe and in some other limited areas while in the rest of the world, the data are available within every 12 days. Sentinel 1 provides dual-polarized Interferometric Wide (IW) swath data with Vertical Transmit-Vertical Receive (VV) and Vertical Transmit-Horizontal Receive (VH) polarizations data. Sentinel 1A images used in the study including Level-1 Ground Range Detected (GRD) images in 2019 with Relative Orbit Number (RoN) of 91 and 128 [7].

4) Digital Elevation Model

In this study, we used the DEM Shuttle Radar Topography Mission (SRTM) map from the U.S. Geological Survey (USGS) [18] with a spatial resolution of 30m. The main purpose of using DEM data is to reduce the noise caused from radar sensor in the high mountainous areas [7].

III. Methodology

The overall workflow of the proposed methodology is shown in Fig. 3, which contains of five main steps: (1) Data preprocessing, (2) Feature Extraction, (3) Training classifiers, (4) Evaluation, (5) Mapping. The further detail of each step is described in the following sub-sections.

A. Data preprocessing

Sentinel 2 A/B images needs to be pre-processed to remove clouds contained. We filtered out the images with the cloud coverage is higher than 70%.

SAR data were pre-processed for thermal noise removing, radiometric calibration and geometric terrain correction. Thermal noise is additional background energy caused by microscopic motions of electrons due to temperature. SAR backscatter values were adjusted by radiometric calibration, meanwhile, effects of side-looking geometry were removed by geometric terrain correction. In this study, SAR imagery pre-processing was rapidly implemented using the Google Earth Engine [7].

Both preprocessed Sentinel 1 and Sentinel 2 data were then sampled at the spatial resolution of 10m for further processing. This step results an amount of 68 images in total for a year 2019, of which, 9 images are belong to Sentinel 2 data collection and 59 images are belong to Sentinel 1A collection of data.

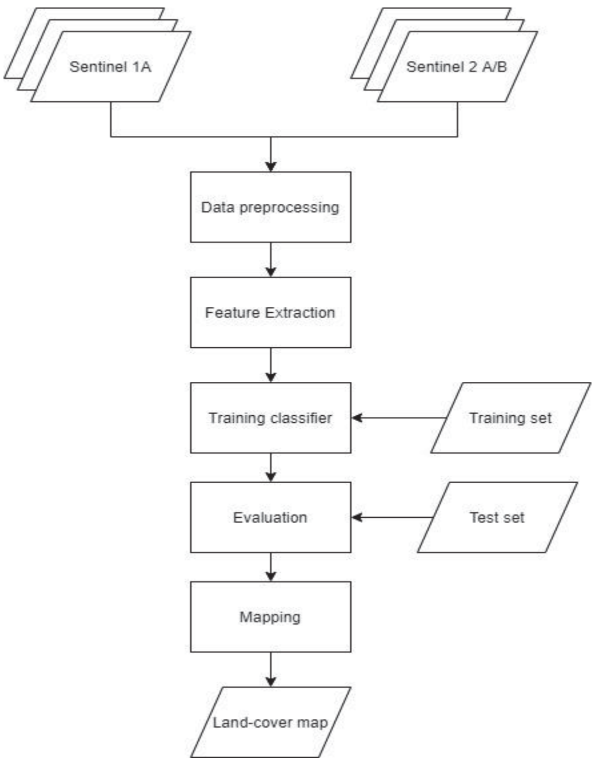

Fig. 3. The overall workflow, which was implemented in GEE

B. *Feature Extraction*

In this study, we extracted a set with feature dimensions including Vertical Transmit-Vertical Receive (VV), and Vertical Transmit-Horizontal Receive (VH) channels from Sentinel 1A and 12 spectral bands of Sentinel 2 A/B. DEM data was considered as a feature also, which helps to reduce SAR noise when training the classifiers. In doing so, other spectral indices features such as Green Normalized Difference Vegetation Index – GNDVI (1), Sentinel-2 Red-Edge Position index – S2REP (2), Normalized Difference Vegetation Index – NDVI (3), Modified Soil-adjusted Vegetation Index – MSAVI (4) were also investigated to evaluate its efficiency to distinguish various land-cover classes from the others.

$$GNDVI = \frac{Green - Red}{Green + Red} \tag{1}$$

$$S2REP = 705 + 35 \times \frac{\frac{Red + VNIR3}{2} - \times VNIR}{VNIR2 - VNIR} \tag{2}$$

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{3}$$

$$MSAVI = \frac{(NIR - Red)(1 + l)}{(NIR + Red + L)}, L = 0.5 \tag{4}$$

Where Green, Red and NIR denotes for the green channel, red channel and near-infrared channel in Sentinel 2 A/B imagery, respectively. VNIR2 and VNIR3 respectively, are the order of visible near-infrared in Sentinel 2 A/B image products.

We prepared four feature sets which are denoted by S1A, S2, S1A_SI_DEM, S1A_S2_DEM, respectively. Regarding each feature profile and dimensions, in S1A set, we stacked two VV and VH channels from 59 Sentinel 1A images. In S2 set, 12 data channels for each image among total 9 Sentinel 2 A/B scenes were stacked together. Next, for the S1A_SI_DEM set, we combine, S1A set with four spectral indices (SI) derived from S2 time-series and DEM together. The last one, S1A_S2_DEM was the alternative of using S2 set with S1A and DEM instead of using SI. The details are described in the following table (TABLE II).

TABLE II. THE FEATURE PROFILES AND ITS DIMENSIONS.

Feature Set	**Description**	**Feature dimension**
S1A	VV and VH	118
S2	12 spectral bands	108
S1A_SI_DEM	VV, VH, GNDVI, S2REP, NDVI, MSAVI, DEM	155
S1A_S2_DEM	VV, VH, 12 spectral bands, DEM	227

C. *Training classifier*

From the extracted feature as described above in the previous sub-section, we deployed two well-known supervised classifiers which are SVM and XGBoost for land-cover classification in Hanoi. SVM classifier has been widely used for image classification task and is known as an effective binary classifier [19][20]. In remote sensing field, SVM classifier has also been proved to be good for the aspect of land-cover mapping in many previous works [21][22]. The model parameters (penalty C and gamma) were optimized with kernel function Radial Basis Function (RBF) using cross-validation to reach the best performance of classification [7][4].

Besides, XGBoost has acquired its reputation since this model dominate many Kaggle competitions. XGBoost is a decision-tree based ensemble machine learning algorithm which a highly scalable end-to-end tree boosting system [23]. XGBoost takes many hyper-parameters for the training process, thus we only focused on tuning the three most important ones which are the number of boosted trees, maximum tree depth and minimum sum of weights of all observations required in a child to prevent the overfitting from happening.

The best classifier was obtained by training set and then was evaluated with separated test set. The implementation was carried out in Google Earth Engine platform.

D. *Evaluation*

We use several metrics to evaluate the performance of the classifiers including Overall Accuracy – OA, F1-Score, Kappa coefficient and Confusion matrix. These metrics are popular applied to assess the quality of the land-cover classifier [4]. Besides, the final landcover map was also visually inspected for further accuracy assessment.

E. *Mapping*

The last step is making map from the best classifier. Normally, the work has been done before by the support of powerful programming language Python and the well-known library for satellite image processing which is Geospatial Data Abstraction software Library – GDAL [24]. The implementation is usually carried out by local infrastructure and self-development source code and takes times to finish up to the size of the image and the local infrastructure capacity. With the help of GEE, the implementation of producing map is getting easier and faster than ever by the powerful JavaScript API. We then careless about manually image registration and georeferencing.

IV. Experiment Results

We evaluated the performance of SVM and XGBoost classifiers for each feature set including S1A, S2, S1A_SI_DEM, S1A_S2_DEM. The detail is shown in TABLE III. S1A resulted the least accuracy for both classifiers among the feature sets. SVM and XGBoost performed similar results. The OA, F1-score and Kappa coefficient for SVM and XGBoost are 0.75, 0.73, 0.68, 0.74, 0.72 and 0.67, respectively. Compared to S1A, S2 set was outperformed with the highest accuracy (OA 0.84, F1 0.83, Kappa 0.8) resulted by XGBoost classifier. It is observed that, optical sensor is more effective in distinguished bare-land, built-up, crop, forest, grass, rice and water from the others than S1A. The combination of S1A, SI and DEM improve the SVM classifier performance from 0.75 to 0.77 in OA, 0.73 to 0.75 in F1-score, 0.68-0.71 Kappa but preserve the XGBoost classifier. The best model was achieved by using the last feature set S1A_S2_DEM with XGBoost, this combination performed best with 0.86 OA, 0.85 F1-score and 0.82 Kappa. The experiment results indicated that feature set that used both the optical and radar combined achieved a significant improvement of up to 12% compared to that using original optical/radar data alone. A same agreement is also concluded in the study by Zhang et al. [25].

We further assessed the accuracy of the model by its confusion matrix that is shown in TABLE IV. It can be seen that bare-land and grass are in the top two most misclassified classes. The classifier confuses bare-land with built-up and water. The model has the same confusion in grass with crop, rice and forest. The other classes including built-up, crop, forest, rice, water is better identified in time-series classification.

Other related studies for land-cover mapping in Hanoi were investigated for further analysis. The first study was conducted by Chuc et al. in 2018 [4]. In this study, the authors proposed a compositing method to pre-process LandSat 8 cloud images with the spatial resolution of 30m. The composited images were then feed to ensemble classification model which achieved 84% OA. Another work in Hanoi using Sentinel 1A time-series with thresholding technique is carried out by Hang et al in 2017 [6]. The study reported an OA of 84.7%. Our study outperforms among these works with 86% OA due to a higher frequency and higher spatial resolution of Sentinel data in comparison to the Landsat 8 data in Chuc's study [4]. Besides, the use of fusion radar-optical data and XGBoost classifier improved the classification performance from 84.7% OA to 86% OA, compared to Sentinel 1A data only with thresholding model in [6].

We examined a visual inspection for the land-cover map obtained by the best model with 86% OA derived from XGBoost (Fig. 4) and the model with 76% OA derived from SVM (Fig. 5) with S1A_S2_DEM. It is noticed that the higher accuracy model produces a smoother land-cover map and is less noisy than the second classifier.

TABLE III. OA, F1 score and Kappa coefficient average for each feature set and land-cover classifier model.

Feature set	SVM			XGBoost		
	OA	*F1*	*Kappa*	*OA*	*F1*	*Kappa*
S1A	0.75	0.73	0.68	0.74	0.72	0.67
S2	0.83	0.82	0.78	0.84	0.83	0.8
S1A_SI_DEM	0.77	0.75	0.71	0.74	0.72	0.67
S1A_S2_DEM	0.76	0.75	0.7	**0.86**	**0.85**	**0.82**

TABLE IV. The confusion matrix of the best classifier with 86% OA

	Bare-land	*Built-up*	*Crop*	*Forest*	*Grass*	*Rice*	*Water*
Bare-land	**6**	5	2	0	4	0	5
Built-up	1	**268**	16	4	4	3	4
Crop	0	13	**161**	10	6	15	0
Forest	0	5	12	**369**	10	3	3
Grass	0	8	19	18	**42**	18	3
Rice	1	1	21	1	7	**480**	8
Water	1	2	4	2	1	11	**149**

TABLE V. Compared to related studies.

Sources	Classifiers	Data	OA (%)
Chuc et al., 2018 [4]	Ensemble learning	Landsat 8	84
Hang et al., 2017 [6]	Thresholding	Sentinel 1A	84.7
Our study	**XGBoost**	**Sentinel 1A, 2 A/B**	**86**

V. Conclusion

We proposed a methodology for land-cover mapping using time-series Sentinel 1A and Sentinel 2 A/B on the Google Earth Engine. We conducted an experiment for Hanoi in 2019, the land-cover map was produced by the model with the highest accuracy after evaluating four feature sets with two well-known classifiers XGBoost and SVM. As a result, XGBoost and S1A_S2_DEM achieved the highest performance with 86% OA. The whole process was implemented GEE to reduce processed time while ensuring high accuracy.

In the future, deep learning approach will be the target of the research team to improve the performance of land-cover mapping with time-series high resolution satellite imagery.

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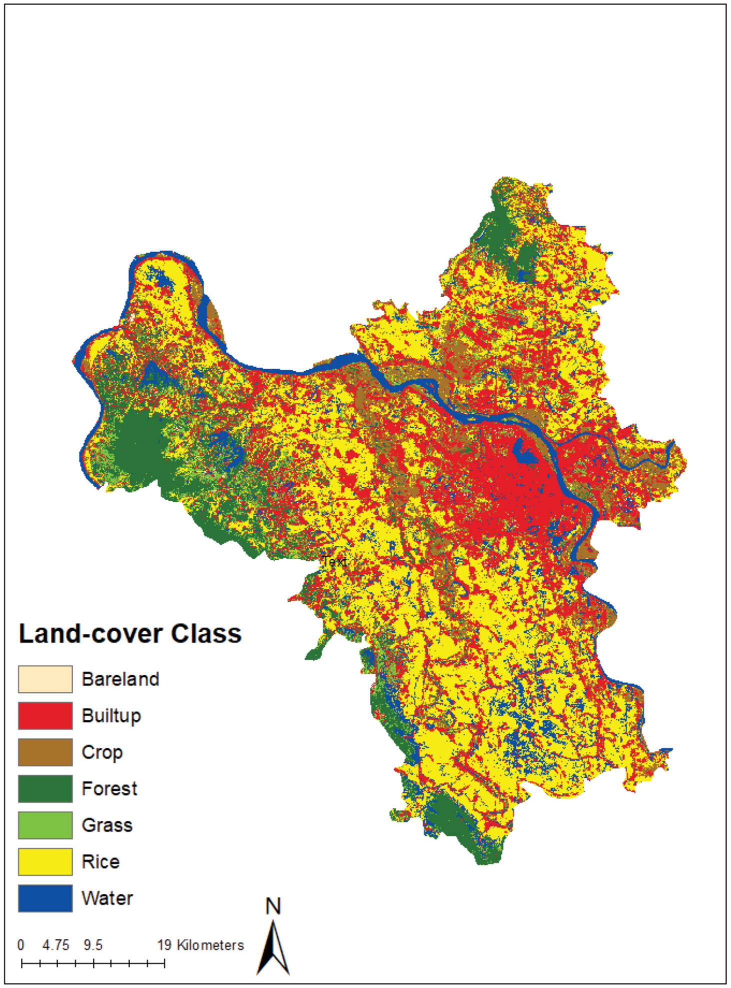

Fig. 4. Land-cover map of Hanoi in 2019 obtained with OA of 86%

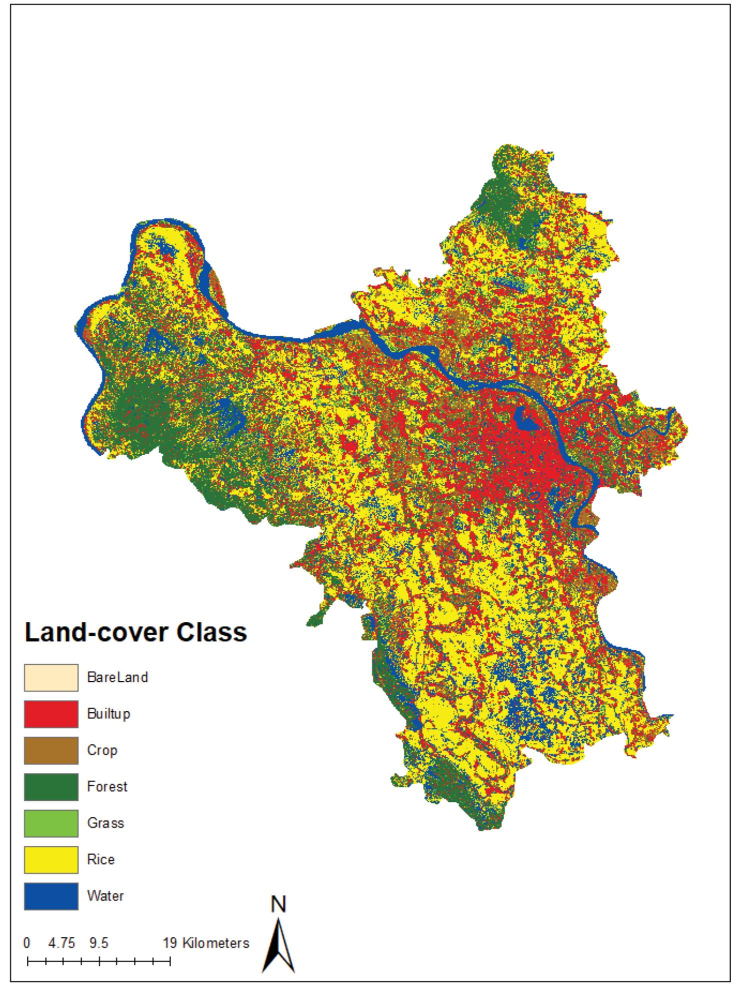

Fig. 5. Land-cover map of Hanoi in 2019 obtained with OA of 78%

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