Identifying the Land Use Land Cover (LULC) Classifications and Change Using Google Earth Engine (GEE): A Case Study of Narayanganj District, Bangladesh

S. M. Nazmul Haque
nazmul.ce@aust.edu

Ahsanullah University of Science and Technology (AUST)

A S M Shanawaz Uddin
Erasmus Mundus Joint Masters Student in CoastHazar

Research Article

Keywords: Change detection, classification map, Google Earth Engine, Landsat 7, LULC

Posted Date: June 6th, 2024

DOI: https://doi.org/10.21203/rs.3.rs-4366221/v1

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Theoretical and Applied Climatology on January 10th, 2025. See the published version at https://doi.org/10.1007/s00704-024-05340-8.

Abstract

Natural landscape has been changing day by day in the cities of developing countries like Bangladesh due to rapid urbanization, industrial development and population growth. The current research focuses on LULC classification and changes of a fastest growing district Narayanganj, Bangladesh over the past twenty years. A soft computing supervised machine learning algorithm have been developed using cloud-based computing platform Google Earth Engine to perform the LULC classification and change detection analysis. Landsat-7 TOA imageries are used with Random Forest classifier to classify the LULC for the five different years (2000, 2005, 2010, 2015 and 2020). LULC change detection analysis between 2000 and 2020 has shown that 88.06% increase in urban area, 70.77% decrease in bare area and 36.72% decrease in water area.

1. Introduction

The surface of the earth is used by people mainly for living, cultivation, and transportation. Rivers, forests, and hilly areas are the natural users of the earth's surface. The use of the earth's surface has been altering day by day due to the necessity of people. This alteration to the land surface on earth is referred to as “Land Use and Land Cover (LULC) Change” (Gasirabo et al., 2023). Over the last few decades, the LULC has been changed due to population growth and economic development (Gasirabo et al., 2023). This population growth and economic improvement tend to expand the number as well as the area of cities. These are considered to be human and natural factors for land use changes. A number of detrimental effects result from LULC change, including deforestation, diminished agriculture and streams, conversion of grassland to urban areas, and Urban Heat Island (UHI). Hence, the factors of LULC change like population growth, rapid urbanization, and industrialization are becoming the major challenges against the sustainable development of an area. Based on the research of Garcia-Ruiz et al. (García-Ruiz et al., 1996) and Musa et al. (Ibrahim Musa et al., 2018), sustainable development has been affected due to the LULC change. To reduce the interconnected land use challenges in the upcoming future for sustainable development, observation on LULC variations data is very crucial. Hence the LULC monitoring is considered to be an important part of achieving sustainable development against these challenges (Hakim et al., 2020).

Developing countries in the South Asian regions have faced these challenges frequently (Kotharkar et al., 2018). Bangladesh like others developing countries has also faced these challenges now a days. The increased population growth in different cities of Bangladesh is accelerating the reduction of vegetation, water bodies and the increase in urban areas (Rashid et al., 2022). The capital city of Bangladesh, Dhaka was experienced a rapid change in LULC between 1975–2003 i.e., an increase in urban areas about 10553 hectares and a substantial reduction in water bodies, vegetation, crop lands and, wetlands (Dewan & Yamaguchi, 2009). Due to urbanization, the Chittagong City Corporation faced an increase of built-up area by 13.72% and a reduction in water bodies, fallow land and hilly vegetation areas (Hussain et al., 2016). In Rajshahi City Corporation region Kafy et al. (Kafy et al., 2020) showed that there was an increase of urban area almost about 16% since 1999 and a decrease of vegetation (19%) and water bodies (4%), which leads to an increase of average Land Surface Temperature (LST) by 9.83°C. On the same way, Narayanganj is considered to be a potential area in Bangladesh for its rapid industrialization (Rashid et al., 2022). Rashid et al. (Rashid et al., 2022) evaluated urban heat island effects based on numeric parameters i.e., LULC, land surface temperature (LST), normalized difference vegetation index (NDVI) for Narayanganj city area with increasing LST of 1.8°C during 2011 and 2019. Islam & Haque (Islam & Haque, 2022) identify the LULC change on Narayanganj Upazila over the year 2001 and 2021. However, there is no existence of district scale (bigger scale) quantitative analysis of LULC change and most of the previous studies had been conducted based on downscale of Narayanganj district to access the UHI effect so far. Focusing on this background, to achieve a sustainable development, this research aims to quantify the LULC change over last 20 years (2000 ~ 2020) on district scale.

LULC change pattern analysis by direct field visits are very time-consuming, laborious and error-prone (Kafy et al., 2020). Therefore, various geographic models and publicly available remote sensing data are thought to be highly useful tools for managing and keeping track of the state and evolution of LULC (Gasirabo et al., 2023). Now-a-days researchers are using various Geographic Information System (GIS) technologies and machine learning algorithms for the thematic mapping of LULC classification and LULC change (Dr. C. Pande, 2022). To classify a LULC image, multiple functions like supervised and unsupervised classification, machine learning programming, fuzzy grading, and Google Earth Engine (GEE) platform are used as the GIS and Remote Sensing (RS) technology (Dr. C. Pande, 2022). GEE is promising platform for big geospatial data processing with comprehensive analysis (Dr. C. Pande, 2022). Moreover, machine learning approach in the GEE platform is quicker to access, process, and analyze large imagery data within a very few seconds comparing with RS and GIS software.(Dr. C. Pande, 2022).

GEE is a cloud-based computing platform of Google and was officially released in 2010 with substantial computational facilities (Zhao et al., 2021). In this platform, various supervised and unsupervised algorithms are available for LULC classification task. K-means clustering, ISODATA (Iterative Self-Organizing Data Analysis) clustering, artificial neural network, Fuzzy C-means clustering

are available unsupervised classification approaches. On the other hand, K-nearest neighbor (KNN), support vector machine (SVM), random forest (RF) classifier, maximum likelihood classifier (MLC), minimum distance classifier are available supervised classification approaches (Jangid et al., 2023). Among these, Random Forest (RF) classifier is an ensemble classifier (Pal, 2005) which provide better accuracy than any other single classifier (Giacinto & Roli, 1997). Pal (Pal, 2005) suggested that in terms of classification accuracy and training time, the RF classifier is just as effective as SVMs but the RF classifier required a smaller number of user-defined parameters. Hence, the RF supervised classification approach is more widely used by researchers (Amani et al., 2020). Also in this study, the RF classifier is used to classify the LULC due to its popularity.

2. Materials and Methodology

2.1. Description of the study area

Narayanganj is one of the oldest and most prominent river ports of Bangladesh. The study area as shown in **Fig. 1**, is located between 23°33' and 23°57' north latitudes and between 90°26' and 90°45' east longitudes (B. Statistics & Statistics, n.d.). It was considered to be a “Ganj” because of its prominent place of trade and commerce in the long past (B. B. O. Statistics, 2013). It was also referred to as “The Dundee of East” due to its extensive jute markets and jute processing businesses (Rashid et al., 2022). It is flanked by Shitalakshya river and became an economic heart of Bangladesh because of its strategic location and friendly business environment (Noman et al., 2016). The district has five upazila namely Araihazar, Bandar, Narayanganj Sadar, Rupganj and Sonargaon. Total amount of area covered by the district is about 68437 hectares within which the riverine area is 11146 hectares (B. B. O. Statistics, 2013). It has a population of about 3 million (B. B. O. Statistics, 2011) with an average density of five thousand people per square kilometer (B. B. O. Statistics, 2013).

2.2. Description of data

Enhanced Thematic Mapper Plus (ETM+) sensor-based satellite Landsat 7 top of atmosphere (TOA) reflectance image collections for 2000, 2005, 2010, 2015, 2020 were used in this study

Table 1
Source and Description of Used Data

Year	Sensor Type	Acquisition Time	Resolution	Source
2000	Landsat 7 ETM+	2000-01-01 to 2000-12-31	30	USGS
2005		2005-01-01 to 2005-12-31		
2010		2010-01-01 to 2010-12-31		
2015		2015-01-01 to 2015-12-31		
2020		2020-01-01 to 2020-12-31		

to classify the LULC of the study area. Source of the satellite datasets used in this research is listed in Table 1. Global Administrative Unit Layer (GAUL) 2015 was used to identify the region of interest (ROI). For more accurate classification, three indices namely normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI) and enhanced vegetation index (EVI) were added to the reduced image (Feng et al., 2022). The formula of these indices are as follows:

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

$$MNDWI = \frac{Green-SWIR1}{Green+SWIR1} \tag{2}$$

$$EVI = 2.5 \times \frac{NIR-Red}{NIR+6\times Red-7.5\times Blue+1} \tag{3}$$

In this study, total five types of LULC namely urban, bare, water, vegetation, and cropland were considered to classify the reduced image. Classification map considering Ground Control Points (GCPs), validation, and area calculation were performed in GEE platform. Information of GCPs is listed in Table 2. The classified image and calculated area were imported in QGIS and Python respectively for further processing.

Table 2
Information of Ground Control Points (GCPs)

Land Use Type		**Year**				
		2000	**2005**	**2010**	**2015**	**2020**
GCPs	Urban	38	20	14	12	15
	Bare	40	25	20	31	33
	Water	48	27	31	31	31
	Vegetation	38	20	30	29	30
	Crop land	45	22	26	26	28
Total GCPs		209	114	121	129	137

2.3. Classification methods

2.3.1. Data Processing

In this article, the GEE Data Catalog has been used for accessing the imagery datasets. It is free of cost and includes more than forty years of historical imagery and scientific datasets, updated and expanded daily. To process the datasets, GEE Code Editor has been used. It is an interactive environment providing JavaScript code editor for developing the Earth Engine application. The Landsat 7 data was loaded in the environment using an Earth Engine Snippet. It is a collection of images covering the entire earth since May 28, 1990. The collection was filtered by a date range and geometry i.e., region of interest (ROI) and resulted in a relatively small collection of images. The collection was then reduced to a single image by calculating the median of all values at each pixel. Nine bands were selected and three indices were added to the image. Finally, the reduced image was clipped by a geometry (ROI) for LULC classification. The classification procedure and several others steps are shown in Fig. 2.

2.3.2. LULC Classification, Accuracy Assessment, and Area Calculation

To classify the image, RF classifier is utilized which is an ensemble classifier and with the help of a randomly selected subset of samples and variables, it produces multiple decision trees (Belgiu & Drăguţ, 2016). The final classification is determined by the voting process of all trees during the classification process (Feng et al., 2022). For the classification of LULC, all land use type GCPs for a particular year were merged together and were labelled a property with value for identification. Among these, 60% were used as training GCPs to collect designated features from reduced image for training the RF classifier and the remaining 40% were used as validation GCPs.

The classifier generally takes six input parameters such as number of decision trees, number of variables (or features) per split, minimum leaf population, fraction of input to bag per tree, maximum number of leaf nodes in each tree and randomization seed

(Amini et al., 2022). In this study, the number of decision trees were five hundred (Belgiu & Drăguţ, 2016) and other input parameters were as default value of GEE RF classifier. The classifier grew the forest up to the defined number of decision tress i.e., 500. Each tree was generated using randomly selected GCPs (here, 50% of input GCPs) with replacement and it contains node. Each node was split using randomly selected features (here, number of features is square root of input features) until the pure leaf nodes were obtained (Pal, 2005). These leaf nodes are the final class (or property) of the decision tree. A new unlabeled data was passed through the all-decision trees to let them vote for a class. The class which gained maximum votes, is the final class of this data.

To strengthen the confidence of classified image, a quantitative measure of accuracy is required (Foody, 2002). In this study, 40% randomly selected GCPs were used for a particular year to assess the accuracy of the classifier. Many scientists like Pande et. al. [25, 26], Seyam et. al. (Seyam et al., 2023), used three famous accuracy measures such as overall accuracy (OA), user accuracy (UA), and producer accuracy (PA) for the classification correctness. Accuracy level for LULC classification have been recommended above 90 % in the previous study for the excelleny and reliability (Gasirabo et al., 2023). The accuracy has been calculated using GEE with the help of confusion matrix.

Table 3
Accuracy of LULC types and maps in different years

LULC Map year	User's Accuracy (%)					Producer's Accuracy (%)					Overall Accuracy (%)
	Urban	Bare	Water	Vegetation	Crop land	Urban	Bare	Water	Vegetation	Crop land	
2000	100	100	92.3	100	100	100	100	100	100	91.3	97.8
2005	100	100	100	100	100	100	100	100	100	100	100
2010	100	100	100	92.3	91.6	75	100	100	100	91.6	95.8
2015	100	100	100	100	85.7	100	100	100	92.8	100	97.8
2020	100	94.4	100	91.6	100	80	100	100	100	87.5	96.4

2.3.3. Mapping and change pattern analysis

Mapping of the classified images using proper coordinate system and scaling is very important to visualize the result nicely. In this study the classified images were exported as GeoTIFF file from the GEE platform and imported in the QGIS for further analysis.

Change detection analysis is important to identify, describe and quantify differences between images of different times or conditions. Many tools such as ArcGIS, QGIS, GEE can be used independently for the change detection analysis. In this study, GEE was used to detect change patterns because of its simplicity and free-of-cost.

3. Results and Discussion

3.1. LULC Dynamics

Figure 3 shows Narayanganj district's spatial land cover dynamics for the years 2000, 2005, 2010, 2015, and 2020 with high accuracy (Table 3) and individual color ramp representing distinct land cover. The figure shows significant increase in urban land cover from 2000 to 2015 at around 23°38'N and 90°30'E. According to Fig. 3, there is a clearly observable urbanization process around 23°38'N and 90°30'E. From 2000 to 2015, urban land cover percentage increases from 3.7 to 13.9 of the overall land as reported in Table 4. Moreover, multiplication of vegetation cover is dominated among other land uses throughout the study period and conspicuous change is observed in the central part of Narayanganj district in Fig. 3. Table 4 shows that vegetation cover comprises 24.3% of the overall land in 2000 whereas it reaches 42.4% in 2020. From Fig. 3 it is clear that, the large amount of crop area is converted into vegetation area but the amount of overall cropland area is almost unchanged in 2000 and 2020 (Table 4). In 2000, the amount of crop area was about 30000 hectares (Table 4) and among which about 11000 hectares (Table 5) are converted into vegetation areas in 2020. This remarkable change indicates the land-filling process of crop area. However, reported attenuation in water body and bare land during 2000–2020 as shown in Fig. 3 and most of which converted into cropland and vegetation area. Hence, Narayanganj district's crop land change over the study period is not momentous.

Table 4
Areas and percentages of different LULC types for different years

LULC type	Area (ha)					% of total land (75852.66 ha)				
	2000	2005	2010	2015	2020	2000	2005	2010	2015	2020
Urban	2770.76	4939.624	5309.78	10568.64	5212.14	3.7	6.5	7	13.9	6.9
Bare	15322.1	4295.684	6723.61	6587.64	4478.47	20.2	5.7	8.9	8.7	5.9
Water	10064	4723.272	4803.39	6053.83	6368.69	13.3	6.2	6.3	8	8.4
Vegetation	18431.3	29812.79	45521.14	26052.14	32194.94	24.3	39.3	60	34.3	42.4
Crop land	29264.5	32081.29	13494.74	26590.41	27598.42	38.6	42.3	17.8	35.1	36.4

3.2. LULC Change Detection from 2000 to 2020

In this study, classification map in 2000 was considered as reference map. From the analysis the unchanged area was observed as 32229 hectares. The urban and vegetation area were increased by the amount of 2441 and 13763 hectares respectively whereas the bare land, water-body and crop land area were decreased by the amount of 10843, 3696 and 1665 hectares respectively. Bare, water, vegetation and crop land areas in 2000 were converted into urban area in 2020 by the amount of 1250, 363, 774 and 1842 hectares respectively. On the other hand, bare area in 2000 was converted into urban, water, vegetation and crop land area by the amount of 1250, 87, 8393 and 4640 hectares respectively. Other transition values are listed in the Table 5.

Table 5
LULC transition matrix from year 2000 to 2020

		2000					Total
		Urban	Bare	Water	Vegetation	Crop	
2020	Urban	984[a)]	1250	363	774	1842	5213
	Bare	498	952[a)]	617	734	1678	4479
	Water	125	87	5436[a)]	67	653	6368
	Vegetation	621	8393	838	11054[a)]	11288	32194
	Crop	544	4640	2810	5802	13803[a)]	27599
Total		2772	15322	10064	18431	29264	

[a)] (Unchanged area)

4. Conclusion

Over twenty years, the LULC classification map was observed for the year 2000, 2005, 2010, 2015 and 2020. There was an increasing trend of urban area and vegetation of about 88.06% and 74.64% respectively, whereas decreasing trend of bare land, crop land and waterbody of 70.77%, 36.72% and 5.69% respectively in between 2000 to 2020. This comprehensive study shows that abrupt change in LULC which will further create pressure on environment, climate and ecosystem services. The findings would be beneficial for the policy makers, project planners as well as city developers to manage the LULC in an effective and sustainable way.

Declarations

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by S. M. Nazmul Haque and A S M Shanawaz Uddin. The first draft of the manuscript was written by S. M. Nazmul Haque and other author commented on previous versions of the manuscript. Both authors read and approved the final manuscript.

Data Availability

The datasets used for analysis in the current study are available in the GEE Data Catalog repository, [https://developers.google.com/earth-engine/datasets/].

References

1. Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., Alizadeh Moghaddam, S., Mahdavi, S., Ghahremanloo, M., Parsian, S., Wu, Q., & Brisco, B. (2020). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 5326–5350. https://doi.org/10.1109/JSTARS.2020.3021052
2. Amini, S., Saber, M., Rabiei-Dastjerdi, H., & Homayouni, S. (2022). Urban land use and land cover change analysis using random forest classification of landsat time series. *Remote Sensing*, *14*(11), 2654.
3. Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, *114*, 24–31.
4. Dewan, A. M., & Yamaguchi, Y. (2009). Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization. *Applied Geography*, *29*(3), 390–401. https://doi.org/https://doi.org/10.1016/j.apgeog.2008.12.005
5. Feng, S., Li, W., Xu, J., Liang, T., Ma, X., Wang, W., & Yu, H. (2022). Land use/land cover mapping based on GEE for the monitoring of changes in ecosystem types in the upper Yellow River basin over the Tibetan Plateau. *Remote Sensing*, *14*(21), 5361.
6. Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, *80*(1), 185–201. https://doi.org/https://doi.org/10.1016/S0034-4257(01)00295-4
7. García-Ruiz, J. M., Lasanta, T., Ruiz-Flaño, P., Ortigosa, L., White, S., Gonzalez, C., & Marti, C. (1996). Land-use changes and sustainable development in mountain areas: A case study in the Spanish Pyrenees. *Landscape Ecology*, *11*, 267–277. https://doi.org/10.1007/BF02059854
8. Gasirabo, A., Xi, C., Hamad, B., & Dufatanye Umwali, E. (2023). A CA-Markov-Based Simulation and Prediction of LULC Changes over the Nyabarongo River Basin, Rwanda. *Land*, *Volume 12*, 20. https://doi.org/10.3390/land12091788
9. Giacinto, G., & Roli, F. (1997). Ensembles of neural networks for soft classification of remote sensing images. *European Symposium on Intelligent Techniques*, 20–21.

10. Hakim, A. M. Y., Matsuoka, M., Baja, S., Rampisela, A., & Arif, S. (2020). Predicting Land Cover Change in the Mamminasata Area, Indonesia, to Evaluate the Spatial Plan. *ISPRS International Journal of Geo-Information*, *9*, 481. https://doi.org/10.3390/ijgi9080481
11. Hussain, M. R., Paul, A., & Islam, A. (2016). Spatio-Temporal Analysis of Land Use and Land Cover Changes in Chittagong City Corporation, Bangladesh. 4, 56–72.
12. Ibrahim Musa, S., Hashim, M., & Md Reba, M. N. (2018). Geospatial modelling of urban growth for sustainable development in the Niger Delta Region, Nigeria. *International Journal of Remote Sensing*, *40*. https://doi.org/10.1080/01431161.2018.1539271
13. Islam, M., & Haque, M. (2022). Identifying Urban Heat Effect through Satellite Image Analysis: Focusing on Narayanganj Upazila, Bangladesh. *Journal of Applied Science & Process Engineering*, *9*, 1223–1241. https://doi.org/10.33736/jaspe.4747.2022
14. Jangid, A., Gupta, M., & Shrivastava, V. (2023). Techniques and Challenges of the Machine Learning Method for Land Use/Land Cover (LU/LC) Classification in Remote Sensing Using the Google Earth Engine. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*, 85–92. https://doi.org/10.17762/ijritcc.v11i7.7833
15. Kafy, A.- Al, Rahman, Md. S., Faisal, A.-A.-, Hasan, M. M., & Islam, M. (2020). Modelling future land use land cover changes and their impacts on land surface temperatures in Rajshahi, Bangladesh. *Remote Sensing Applications: Society and Environment*, *18*, 100314. https://doi.org/https://doi.org/10.1016/j.rsase.2020.100314
16. Kotharkar, R., Ramesh, A., & Bagade, A. (2018). Urban Heat Island studies in South Asia: A critical review. *Urban Climate*, *24*, 1011–1026. https://doi.org/https://doi.org/10.1016/j.uclim.2017.12.006
17. Noman, A., Mia, M. A., Banna, H., Rana, Md. S., Alam, A. S. A. F., Chan, S.-G., Isa, C., & Er, A. C. (2016). City profile: Narayanganj, Bangladesh. *Cities*, *59*, 8–19. https://doi.org/10.1016/j.cities.2016.05.020
18. Pal, M. (2005). Random forest classifier for remote sensing classification. *International Journal of Remote Sensing*, *26*(1), 217–222.
19. Pande, C. B., Moharir, K. N., & Khadri, S. F. R. (2021). Assessment of land-use and land-cover changes in Pangari watershed area (MS), India, based on the remote sensing and GIS techniques. *Applied Water Science*, *11*(6), 96.
20. Pande, C. B., Moharir, K. N., Khadri, S. F. R., & Patil, S. (2018). Study of land use classification in an arid region using multispectral satellite images. *Applied Water Science*, *8*, 1–11.
21. Pande, Dr. C. (2022). Land Use/Land Cover and Change Detection mapping in Rahuri watershed area (MS), India using the Google Earth Engine and Machine Learning Approach. *Geocarto International*, *37*. https://doi.org/10.1080/10106049.2022.2086622
22. Rashid, N., Alam, J. A. M., Chowdhury, Md. A., & Islam, S. L. U. (2022). Impact of Landuse Change and Urbanization on Urban Heat Island Effect in Narayanganj City, Bangladesh: A Remote Sensing-based Estimation. *Environmental Challenges*, *8*, 100571. https://doi.org/10.1016/j.envc.2022.100571
23. Seyam, M. M. H., Haque, M. R., & Rahman, M. M. (2023). Identifying the land use land cover (LULC) changes using remote sensing and GIS approach: A case study at Bhaluka in Mymensingh, Bangladesh. *Case Studies in Chemical and Environmental Engineering*, *7*, 100293.
24. Statistics, B. B. O. (2011). Statistical yearbook of Bangladesh. Statistics Division, Ministry of Planning, Dhaka, Government of the People’s Republic of Bangladesh.
25. Statistics, B. B. O. (2013). District statistics 2011. Ministry of Planning, Government of The People’s Republic of Bangladesh.
26. Statistics, B., & Statistics, B. (n.d.). Bangladesh educational statistics. Http://Lst-Iiep.Iiep-Unesco.Org/Cgi-Bin/Wwwi32.Exe/[In=epidoc1.in]/?T2000=002083/(100).
27. Zhao, Q., Yu, L., Xuecao, L., Peng, D., Zhang, Y., & Gong, P. (2021). Progress and Trends in the Application of Google Earth and Google Earth Engine. *Remote Sensing*, *13*, 3778. https://doi.org/10.3390/rs13183778

Figures

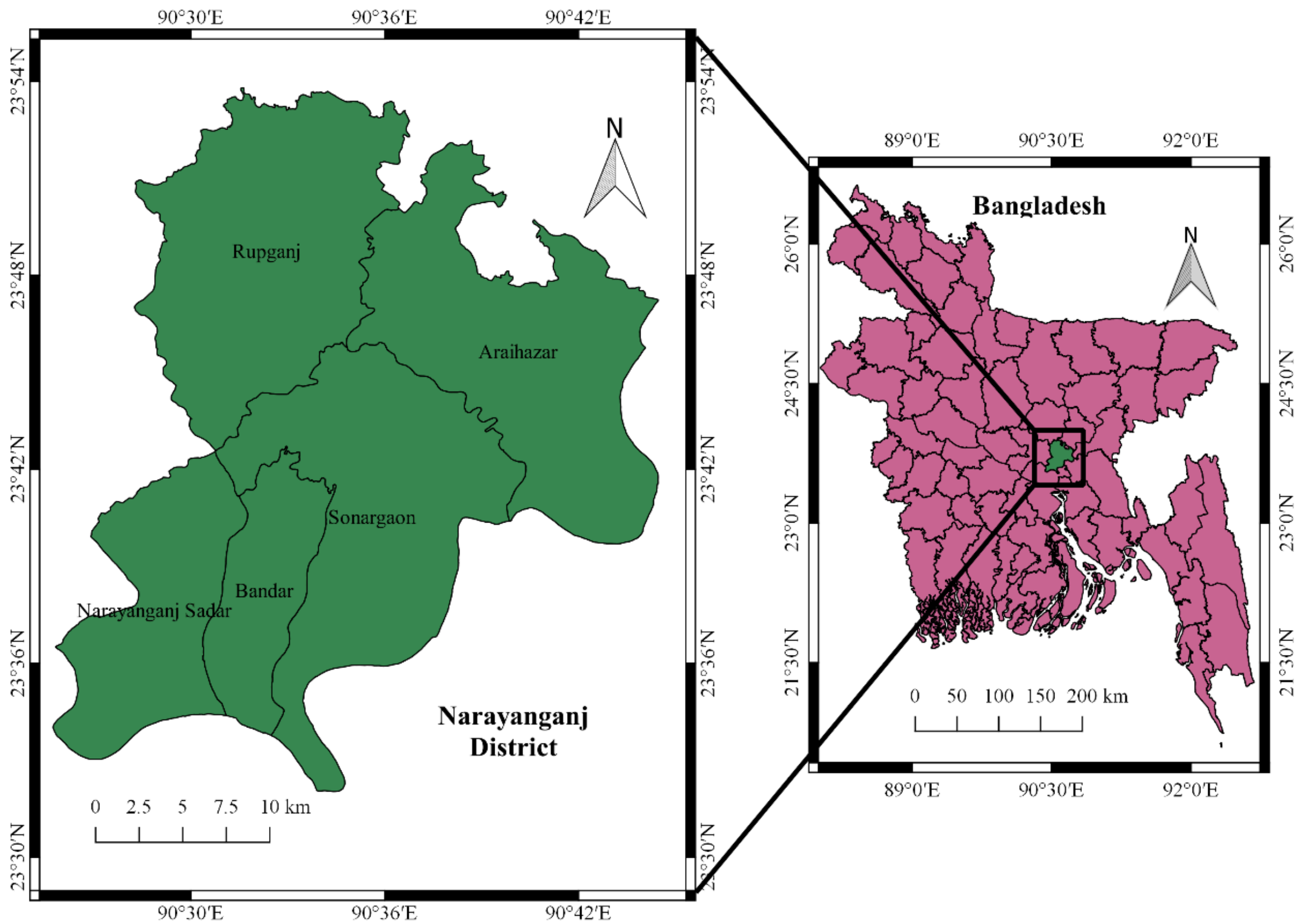

Figure 1

Location of Narayanganj District, Bangladesh (Study Area)

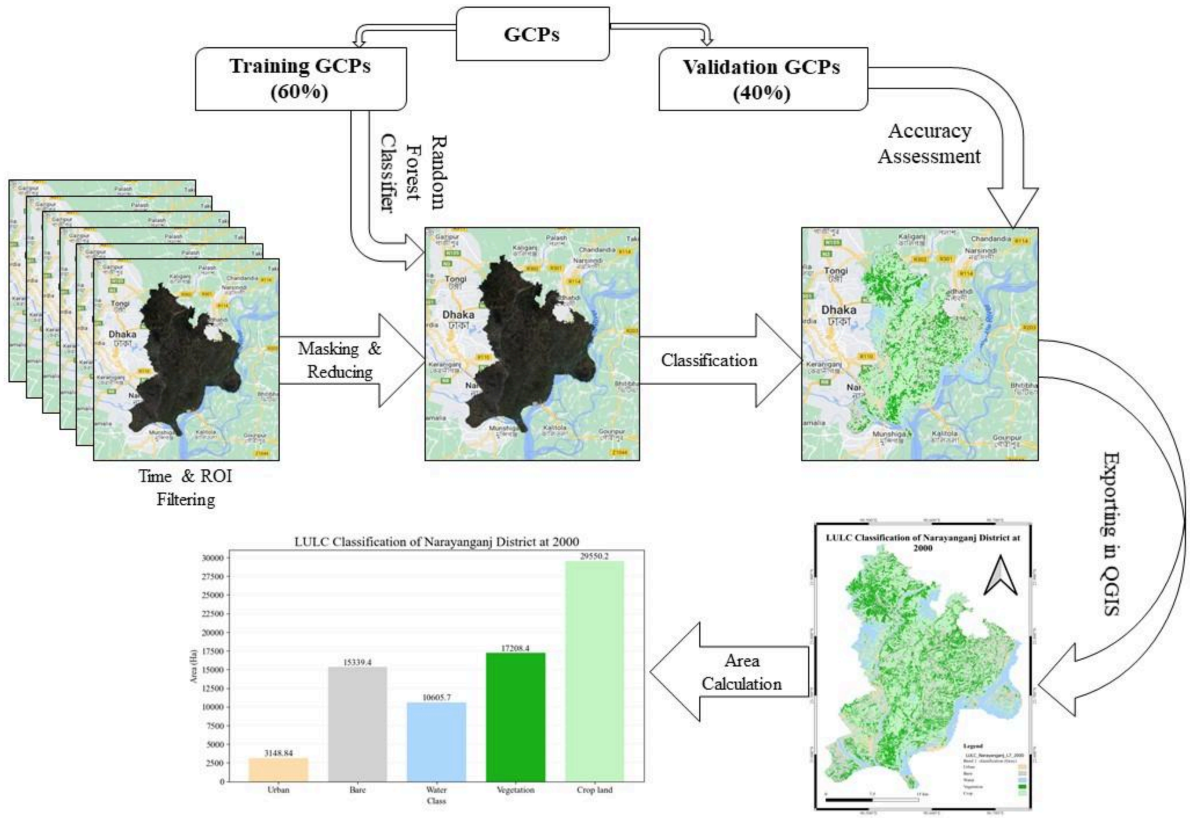

Figure 2

Flow chart of LULC mapping, validation and area calculation

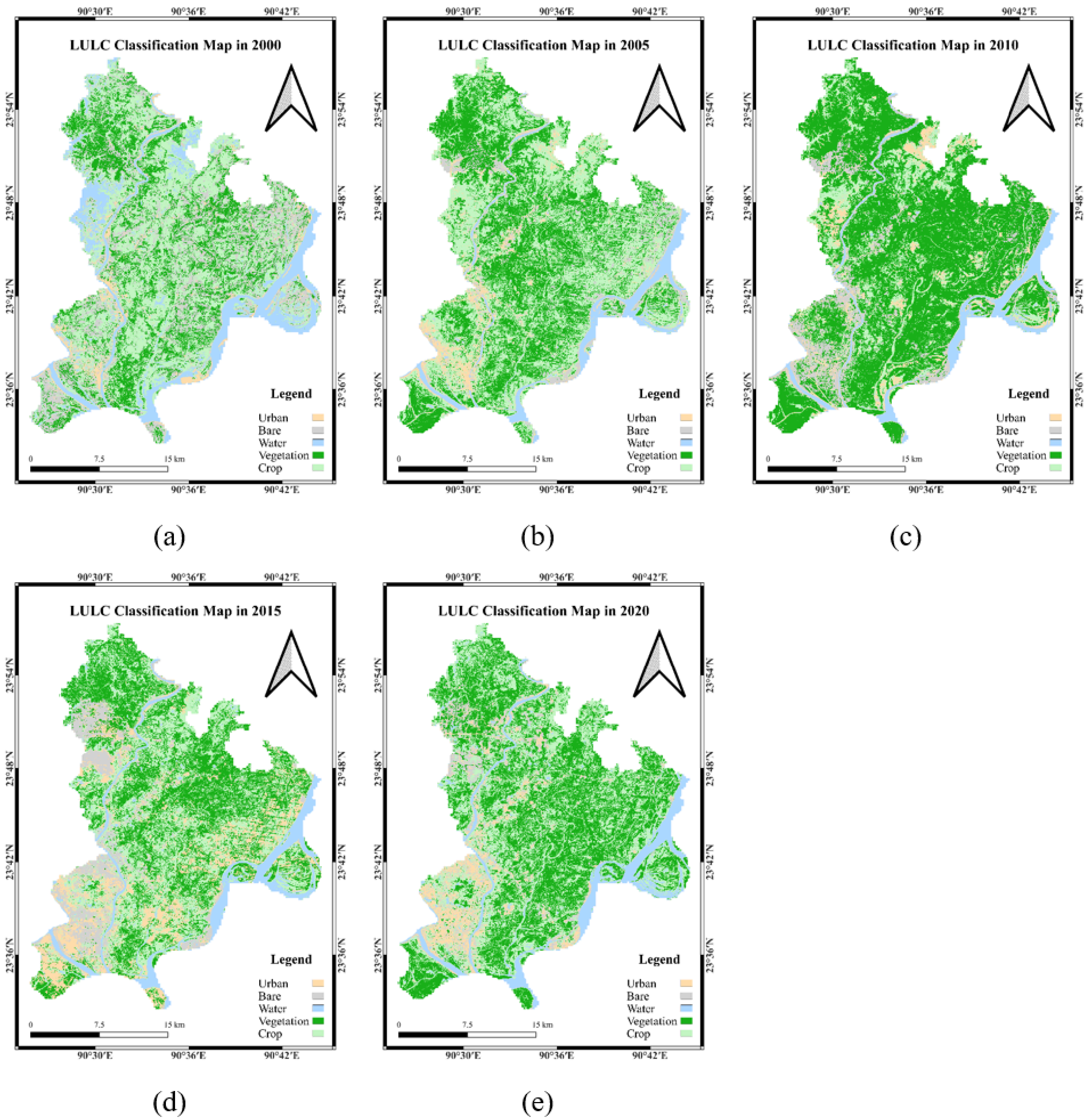

Figure 3

LULC classification map in different years