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Research Article **Open Acces**

Analysis of Land Use and Land Cover Changes using Random Forest through Google Earth Engine in Depok City, Indonesia

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Abstract: The development of human activities in a location causes land use and land covers (LULC) changes. If the activities are concentrated for a long time, it can lead to a change from a rural characteristic to an urban one, known as urbanization. This phenomenon has occurred rapidly in Depok City after a change in administrative status, changing into a city with 11 districts. The urbanization process in Depok City from 2013-2022 experienced a very rapid LULC change, so monitoring is essential. The purpose of this study is to monitor LULC changes from 2013-2022. The method used is classification using Random Forest available on the Google Earth Engine (GEE) platform, with four input indices consisting of Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Bareness Index (NDBaI), and Normalized Difference Built-up Index (NDBI). The images used are median Landsat-8 Operational Landsat Imager and Thermal Infrared Sensor (OLI/TIRS) atmospherically corrected surface reflectance. LULC characteristics based on the indices are visualized in boxplot. NDVI is able to increase vegetation values, NDBaI has limitations in distinguishing open land from built-up areas, NDBI is able to increase built-up area values, and NDWI is able to increase water body values but still overlaps with built-up area values. The results show that the biggest change is the conversion of prepared barren land into built-up areas. In supporting population growth, Depok City has expanded its built-up area by 72.355 km^2, while barren land, which was mostly prepared, decreased by 70.300 km^2 from 2013-2022. The accuracy of the classification process has good performance with User's Accuracy (UA) and Producer's Accuracy (PA) of 80-100%. The average values of Overall Accuracy (OA) and Kappa have high accuracy which are above 90%.

Keyword: Index Algorithm, Landsat 8 OLI/TIRS, Urban Expansion

INTRODUCTION

Land use and land cover (LULC) changes are a world-wide phenomenon that has drawn the attention of researchers from various countries around the world (Noszczyk *et al.* 2019). Research on LULC changes has been increasingly expanding from highland to coastal regions. Several studies related to LULC dynamics have been conducted, such as LULC changes analysis in urban areas (Mitra *et al.* 2022), river basins (Twisa and Buchroithner 2019; Souza *et al.* 2022), and coastal areas (Zhang and Yang 2020). Research related to LULC is also progressing towards further studies, such as monitoring LULC for controlling urban physical development (Murtadho *et al.* 2022), its relationship with land surface temperature (Moisa *et al.* 2022), and its relationship with groundwater availability (Dasgupta and Sanyal 2022). Generally, lowland areas experience more intensive LULC changes than highland areas. The topography that facilitates human activities causes land use in lowland areas to be more developed.

Human activity has led to an increasing need for land over time (Li *et al.* 2022). This demand for land is driven by population growth and increased food needs. Almost every human activity involves land, and due to the continuously growing human population, land has become a scarce resource. Population growth results in increased food needs, leading to the conversion of forest areas to agricultural land. Moreover, the expansion of built-up areas also causes irreversible conversion of forest and agricultural land.

The increasing development of human activities in a certain location leads to LULC changes. If these activities persist over a long period of time, they can cause a shift from a rural to an urban characteristic, which is known as urbanization. The term sub-urban is biased due to the merging of space between urban areas and their surroundings. The expansion of urban activities can also result in the conversion of agricultural land into urban functions (Ustaoglu and Williams 2021).

The phenomenon of urbanization has occurred in Depok City. The administrative change from the Depok sub-district, Bogor Regency to Depok City cannot be separated from the increasingly complex development of the region and the need for larger administrative management. Since April 20, 1999, Depok sub-district, Bogor Regency has been designated as a second-level regional city based on Law Number 15 of 1999, covering an area of 200.29 km² consisting of six sub-districts, namely Sawangan, Pancoran Mas, Sukmajaya, Cimanggis, Beji, and Limo. Based on the Depok City Regional Regulation Number 8 of 2007 concerning the Formation of Regions in Depok City, Depok City now has 11 sub-districts. The change in sub-district status to a city has also had an impact on the intensity of LULC changes in Depok City.

In 2013, many policies were made by the local government for the development of Depok City, such as Depok Regional Regulation Number 14 of 2013 regarding the Provision of Infrastructure, Facilities and Housing and Settlement Utilities and Depok City Regional Regulation Number 15 of 2013 regarding the Implementation of Child-Friendly City. Various infrastructure development programs were also carried out. These policies were an effort by the government to prepare for the increase in population in Depok City and to provide infrastructure, comfort, and security for Depok residents. This has caused the intensification of LULC changes in Depok City (Utami and Hendarto 2020). Therefore, monitoring of LULC changes in Depok City needs to be carried out.

LULC changes monitoring can use satellite imagery and processed with geographic information system (GIS) software. Manual LULC mapping can use digitization methods, but the accuracy of this technique is subjective and depends on the digitizer's precision. An advanced technique can be done using machine learning. The application of machine learning for monitoring LULC changes in Indonesia has been widely done. However, not many have applied it using Google Earth Engine (GEE). GEE is a cloud-based GIS platform that makes it easy for users to access and process large geospatial data without requiring super devices (Gorelick et al. 2017). This is because all data processing is done by GEE's infrastructure, so users only need to enter the required inputs, write scripts, and have an internet connection.

With the increasing demand for accurate LULC data from satellite imagery over large areas, it is increasingly important to study machine learning methods and their performance on the GEE cloud-computing platform. Most available studies focus on comparisons between LULC classifiers, which are then used for various purposes or further research. In this case, changes in land use and land cover in Depok are monitored to determine the urban expansion from 2013-2022, during which massive infrastructure, facilities and infrastructure development occurred. The main goal of this research is to monitor LULC changes in Depok City from 2013-2022 using multispectral satellite imagery from Landsat-8 and the Random Forest machine learning algorithm on the GEE platform.

METODOLOGI

Study area

The scope of the area study was conducted in Depok City, West Java Province, which is geographically located at 6° 19' 00" - 6° 28' 00" South Latitude and 106° 43 '00" - 106° 55' 00" East Longitude (Figure 1). Its geographic boundaries are directly adjacent to Jakarta City. Depok City has an area of 200.29 km². Depok city elevation is between 50 to 140 meters above sea level, with a slope of less than 15%. Its geographic conditions are traversed by two major rivers, namely Ciliwung and Cisadane, and 13 sub-watersheds. Depok has developed from a district in Bogor Regency to become a metropolitan city and a satellite city of Jakarta. Its location adjacent to Jakarta has caused an increase in population growth and an expansion of built-up areas.

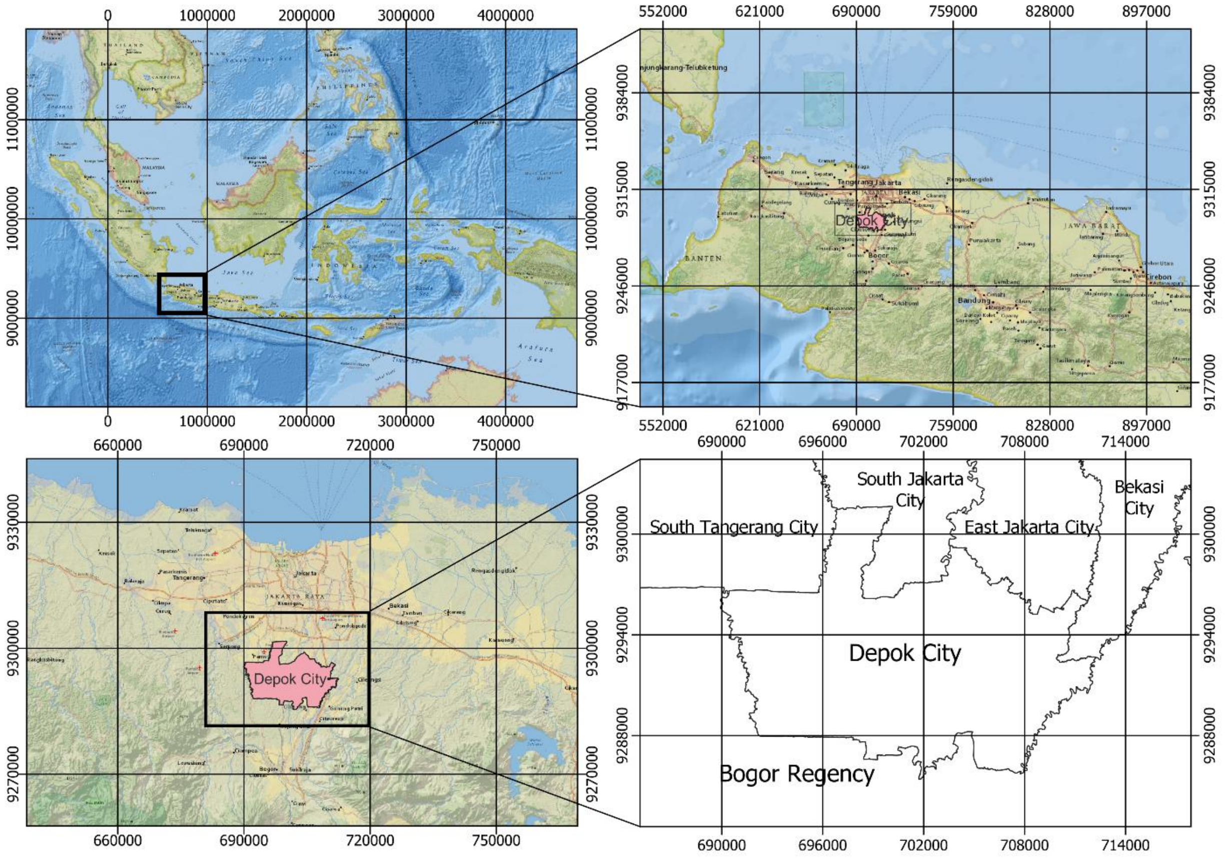

Figure 1. Research location

Data Source and Data Process

The satellite imagery used in this study is Landsat 8 Operational Landsat Imager and Thermal Infrared Sensor (OLI/TIRS) that has been atmospherically corrected and accessed through the GEE catalog. This is one of the advantages of GEE as a cloud computing-based geospatial platform (Kumar and Mutanga, 2018). Landsat 8 OLI/TIRS is considered a reliable satellite with open-source status, featuring a spatial resolution of 30-100 meters and comprising 10 bands (Table 1). In the data processing, various steps were conducted to extract information on land use and land cover changes from the Landsat 8 OLI/TIRS imagery. In this study, we used satellite imagery from 2013 and 2022, with cloud masking filters applied to eliminate pixels that were contaminated by clouds. The time filter was set from June - December to obtain a median composite image with minimal cloud cover. The time filter was set from June - December to get a median composite image with minimal cloud cover. Landsat 8 images taken between June and December are combined into one image using the median filter. The selection from June was used due to 2013 because Landsat 8 data became available in June.

Table 1. Landsat-8 band information from GEE Catalog, which were used for LULC classification

Band	Central Wavelength (µm)	Resolution (m)	Description
SR B3	0.561	30	Band 3 (green) surface reflectance
SR B4	0.655	30	Band 4 (red) surface reflectance
SR B5	0.865	30	Band 5 (near infrared) surface reflectance
SR B6	1.609	30	Band 6 (shortwave infrared 1) surface reflectance
SR B10	10.895	100	Band 10 surface temperature.

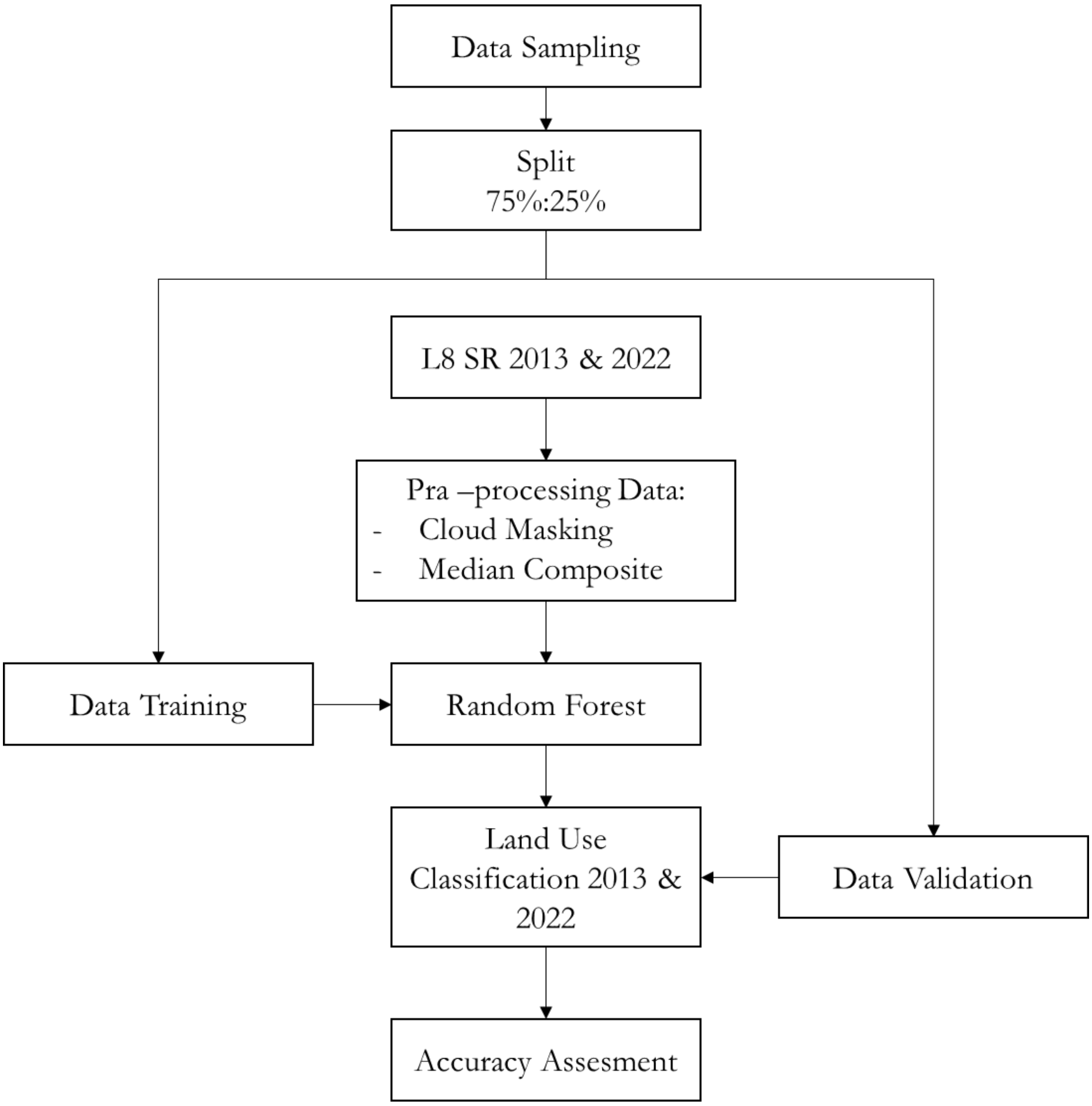

Figure 2. Flow chart of research step

For the purpose of classification, it is necessary to have training data to provide classification references for the classification algorithm. Additionally, there is validation data that is obtained through data sampling and is divided according to LULC class. The sample data is 800 points divided into 75% training data (600 points) and 25% validation data (200 points). Each LULC consists of 150 training data points and 50 validation data points (Table 2). The data sampling was conducted using the Google Earth Pro software, which provides high-resolution time series images, allowing for data sampling to be adjusted to the target time period of 2013 and 2022.

The administrative boundary map for Depok City as the scope of research was obtained from the Website of the Geospatial Information Agency of the Republic of Indonesia (https://tanahair.indonesia.go.id).

Data Analysis

The data analysis process in this study involved several stages, including image preprocessing (cloud masking; area clipping), band calculation (using vegetation, water, bare land, and built-up indices), LULC classification (using a random forest algorithm), and accuracy assessment. The data analysis process is presented in Figure 2.

Band Calculation

The band calculation indices used as input for the classification process using Random Forest are NDWI, NDVI, NDBaI, and NDBI. The formula for each index is presented in Table 3.

Table 3. The index formula used

No	Index	Formula	Sources
1	Normalized Difference Vegetation Index (NDVI)	NDVI = (NIR - Red) / (NIR + Red)	Rouse jr *et al.* 1974
2	Normalized Difference Bareness Index (NDBaI)	NDBaI = (SWIR1 - TIRS1) / (SWIR1 + TIRS1)	Zhao and Chen 2004
3	Normalized Difference Built-uo Index (NDBI)	NDBI = (SWIR - NIR) / (SWIR + NIR)	Zha *et al.* 2003
4	Normalized Difference Water Index (NDWI)	NDWI = (Green - NIR) / (Green + NIR)	McFeeters 1996

Random Forest

This study uses a popular machine learning classification algorithm, videlicet Random Forest (RF). This algorithm utilizes multiple decision trees in decision-making (Breiman 2001). By combining predictions from multiple randomly generated decision trees, RF can provide more stable and accurate predictions. The decision to use RF in this study was based on previous research that demonstrated better performance of RF compared to other decision tree-based learning methods such as CART, C4.5, and ID3 (Kulkarni 2016; Chen *et al.* 2017; Jin *et al.* 2018; Purwanto *et al.* 2023). RF is able to handle overfitting better than singe decision tree due to bagging (Colkesen and Ozturk 2022; Wu *et al.* 2021). In the classification process, the RF classification algorithm requires balanced data to reduce the classification error rate (Mellor *et al.* 2015).

Accuracy Assessment

The classification process often results in misclassification, especially for LULC classification which is important data that can be used for land use evaluation. There are several accuracy assessments commonly used to assess the accuracy of LULC classification, namely OA (Overall Accuracy), KC (Kappa Coefficient), UA (User's Accuracy), and PA (Producer's Accuracy) which are calculated from the prediction and validation results in the Confusion Matrix.

GEE has an expression to assess the accuracy of all of these. The confusion matrix displays the predicted class with the actual class. The matrix columns represent the predicted class, while the rows represent the actual class. If illustrated, the confusion matrix is i as the row and j as the column, then the way to read it is that the predicted class is j and the actual class is i. The confusion matrix can provide information not only about classification errors but also about the errors produced.

UA is a measure of commission errors that measures how accurately the classification reflects the actual conditions. PA measures omission errors, which measure how accurately LULC types can be classified (Rwanga and Ndambuki 2017). OA compares the truth of each pixel classified using training data with validation data. In addition, KC is also commonly used to evaluate classification accuracy. The kappa coefficient is used as a measure of classification accuracy. In practical classification problems, KC is often used as an indicator of "bias" of the model instead of OA when there is poor balance between samples.

RESULTS AND DISCUSSION

LULC Changes

Spatially, in 2013, the distribution of LULC in Depok City showed a good balance between built-up and vegetated areas (Figure 3). The built-up area was distributed in the central-eastern part of Depok City's administrative region, while vegetated areas were still abundant in the western part of Depok City. This was also reflected in the statistical pattern in Figure 4, where each sub-district had a balanced percentage of land cover. However, over the course of almost a decade, the 2022 LULC condition showed significant changes. The built-up area almost covered the entire Depok City, indicating the dominance of land use by the built-up class and drastic changes from vegetated to built-up areas.

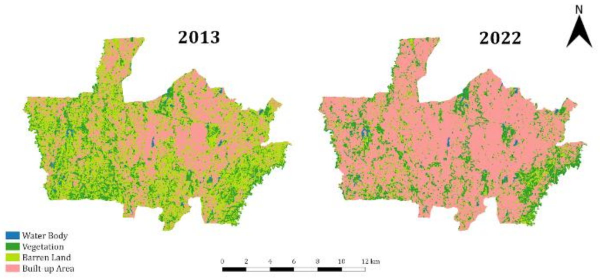

Figure 3. LULC Classification in 2013 and 2022

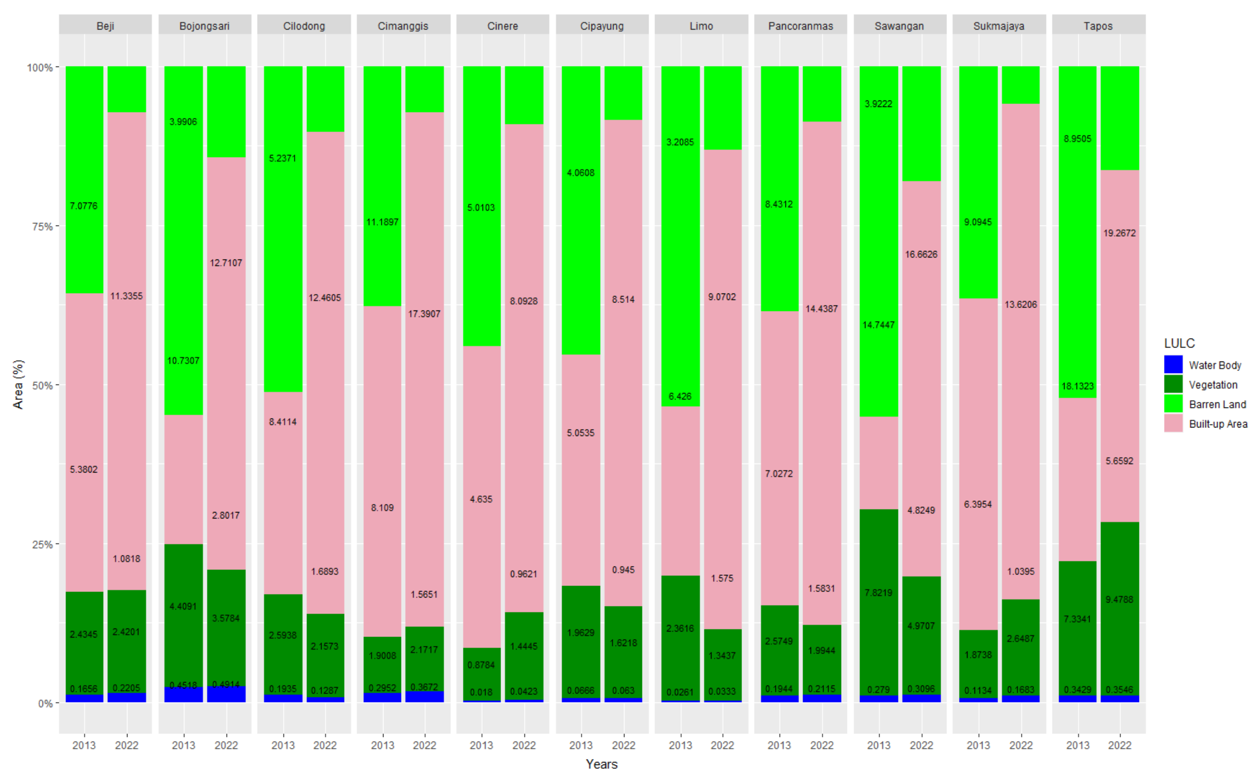

Figure 4. Statistically of LULC change, per district

In 2013, the area of each LULC was as follows: water bodies 2,115 km², built-up area 69,217 km², vegetation 35,515 km², and barren land 93,671 km². By 2022, each LULC had undergone area changes. Water bodies covered an area of 2,355 km², vegetation covered 33,220 km², built-up areas expanded to 141,572 km², and barren land decreased to 23,371 km2. Detection results showed a decrease in the area of vegetation by 2,295 km² (Figure 4). Nor *et al.* (2017) stated that urban development has a significant impact on the structure of green spaces. This is a serious issue, as urban residents are in great need of vegetation areas as a natural facility to improve physical and mental health (Zhong *et al.* 2019).

This study successfully reveals land conversion activities that occur in each LULC classes tested. The most dominant land conversion is the change to built-up areas that spreads from the eastern to southern parts of Depok. Figure 4 shows an increase in built-up areas in each district of Depok City. In 2022, there were areas that had already been converted to built-up areas, as well as areas under construction. Vegetated areas also

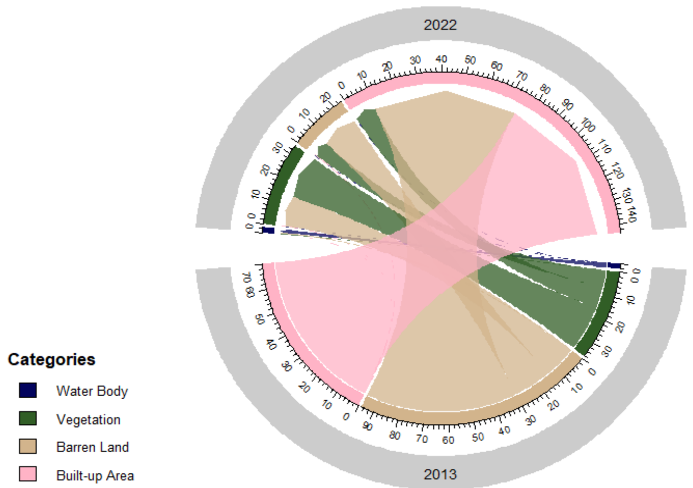

Figure 5. Direction of LULC changes

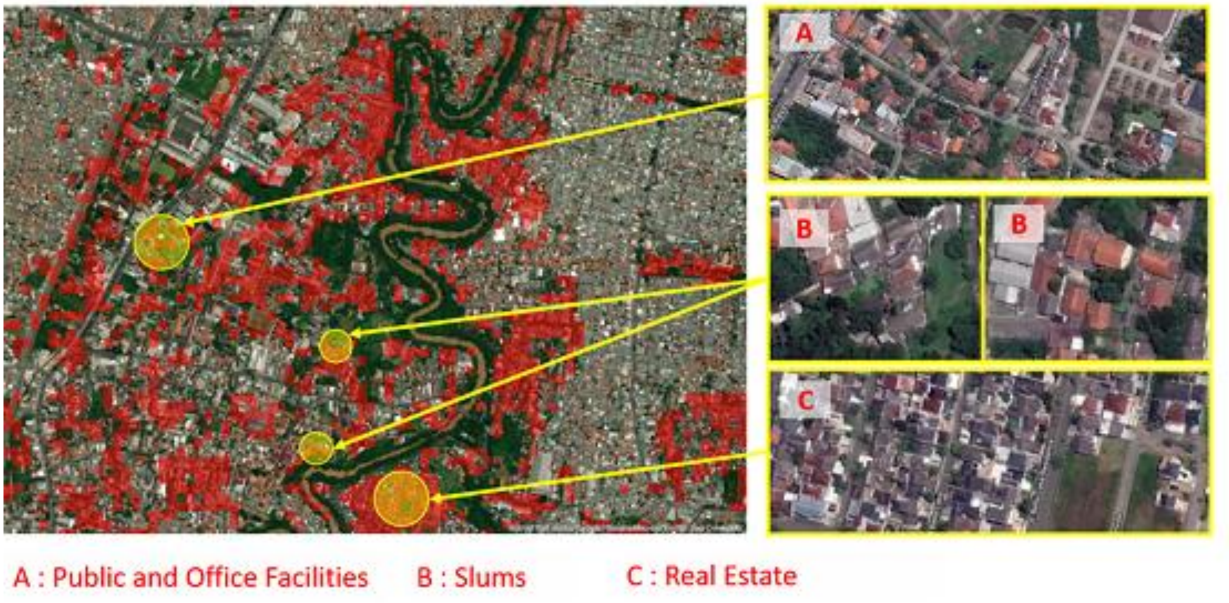

Figure 6. Visualization of affected areas using Google Earth pro (GE)

turned into barren land as preparation for residential, industrial, and toll road development. This is shown by a decrease in barren land of 70.30 km² (Figure 5). The conversion to built-up areas had a significantly higher percentage than other LULC classes, with an increase of 51.10%, or an expansion of 72.35 km² from 2013 to 2022.

The development of public infrastructure such as highways has a significant impact on the development of the region in the Jakarta or Jabodetabek metropolitan area (Pratama *et al.* 2022). Expansion of built-up areas usually starts from the closest distance to the urban area, and the closer the distance, the faster the conversion of land into built-up areas (Pravitasari *et al.* 2018; Rustiadi *et al.* 2021). To provide housing for urban communities, developers build residential areas around the urban areas. The distribution of urban development areas such as residential areas and public facilities can be seen in Figure 6. This development is evident in the addition of residential development around riverbanks, which affects the availability of vegetated areas as water catchment areas. This is an effect of urbanization, where land availability is critical for urban communities. This is in line with the study by Browder *et al.* (1995), which found that most of the residential areas developed around Jakarta are owned by urban workers. Spatial allocation policies that support the development of residential facilities are also utilized by developers to provide housing for urban workers (Archer 1994).

Index Characteristics for LULC

The band calculation result index is an important input for performing classification using machine learning. The index used should be able to distinguish one or more LULCs. To determine this, the distribution pattern of data can be seen using a boxplot. Figures 7 and 8 show the boxplot of index characteristics for each LULC. This visualization can also provide information on the distribution of index values for both training and validation data.

Vegetation reflects more Near Infrared (NIR) and green waves compared to other waves and absorbs more red waves. Therefore, relying on NDVI for vegetation identification can be done through the calculation of two bands, namely red and NIR. NDVI can increase the value of vegetation and distinguish it from other LULC classes. Vegetation training data in 2013 had an NDVI value range of 0.232 to 0.420 with validation of 0.312 to 0.421. In 2022, the NDVI value of vegetation training data changed to 0.467 - 0.847 with validation of 0.762 to 0.828. Other LULC classes generally did not undergo significant changes, but there were changes in bodies of water due to increased plant growth.

NDBaI was proposed by Zhao and Chen (2005) for identifying barren land and distinguishing it from other land uses and covers. NDBaI is the result of calculating the red band with the tir band. The highest reflectance value of land use and covers is actually in the built-up area, which results in a very high outlier value

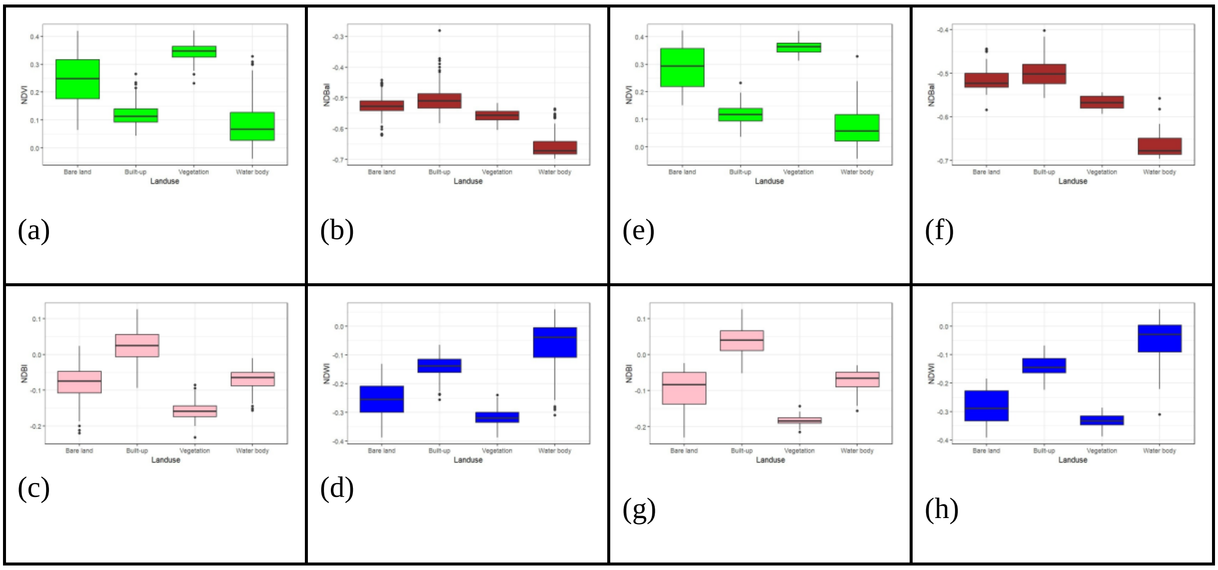

Figure 7. Index characteristics from training data for each LULC classes in 2013 (a) NDVI, (b) NDBaI. (c) NDBI, (d) NDWI, and validation (e) NDVI, (f) NDBaI, (g) NDBI, (h) NDWI

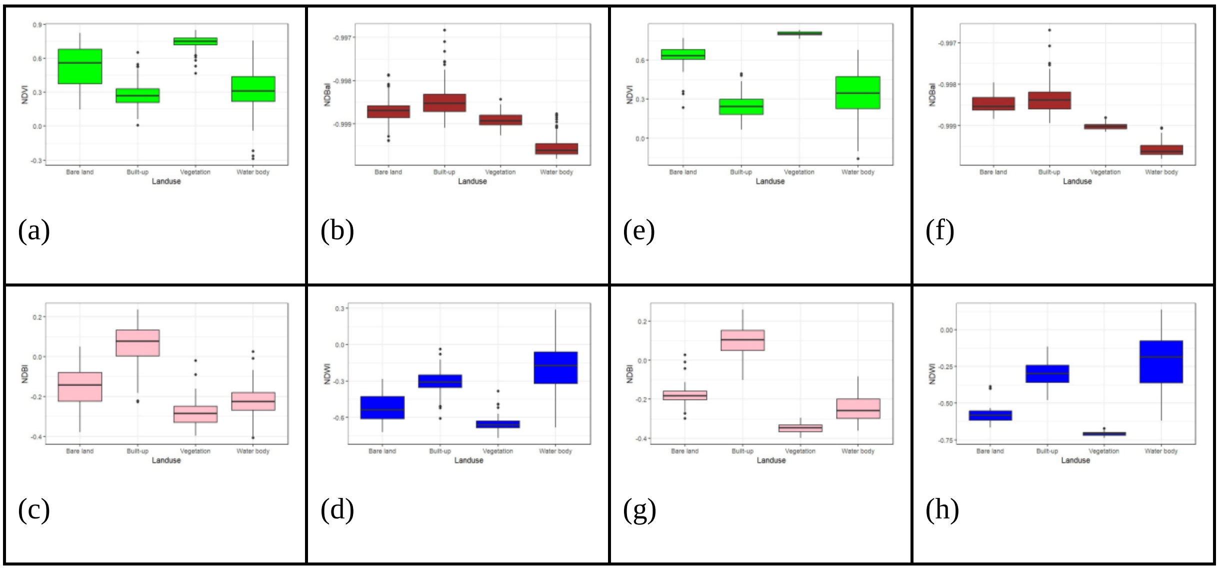

Figure 8. Index characteristics from training data for each LULC classes in 2022 (a) NDVI, (b) NDBaI. (c) NDBI, (d) NDWI, and validation (e) NDVI, (f) NDBaI, (g) NDBI, (h) NDWI

of NDBaI, and the results also show that the NDBaI value of barren land overlaps with that of built-up area. The 2013 training and validation data for barren land showed a value range of -0.622 to -0.442 and -0.584 to -0.444. In 2022, it decreased to a value range of -0.999 to -0.998 for both training and validation data. This indicates that as built-up areas become denser, the NDBaI value will approach -1. NDBaI shows limitations in distinguishing barren land from built-up areas. It also shows very negative values in areas that are increasingly hot. This index can actually distinguish bodies of water by suppressing their reflectance values.

NDBI was proposed by Zha *et al.* (2003) and is derived from the calculation of two bands, SWIR and NIR. SWIR can reflect more reflectance values than NIR. NDBI can help overcome the limitations of NDBaI by differentiating between built-up area and barren land. NDBI increases the reflectance value of built-up area and suppresses the reflectance value of other LULC classes. The training and validation data from 2013 and 2022 for built-up areas have values ranging from -0.220 to -0.023, -0.231 to -0.023, -0.379 to -0.050, and -0.298 to -0.028, respectively. NDWI used is proposed by McFeeters (1996) and is calculated from two bands, Green and NIR. The NDWI values for the training and validation data from 2013 are the same, ranging from -0.310 to 0.058, but change in 2022 to -0.379 to -0.050 for the training data and -0.619 to 0.135 for the validation data. NDWI can increase the reflectance value of water bodies and differentiate them from other LULC classes. However, the wide range of the whiskers on the NDWI bar plot overlaps with the reflectance value of other land uses and covers.

Accuracy Assesment

Several studies have shown that classification can generate errors in the data processing results, thus evaluation analysis should involve accuracy assessment. This is an effort to evaluate the methods, approaches, and data involved. The evaluation of classification results through accuracy analysis can be seen from the values of UA and PA for each land use. The values of these two parameters depend on the accumulation of accuracy in the error matrix obtained from the investigation and matching of all validation points.

Based on the confusion matrix of 2013, the predictions for vegetation and built-up area showed the best results, which led to an almost perfect PA of 98.00%. Only one prediction from vegetation and built-up area showed an incorrect result. As for the UA, the water body classification showed the best results with a 100% accuracy rate. In the confusion matrix of 2022, the best prediction was for vegetation, where each prediction was the same as the actual result, resulting in a perfect PA of 100%. However, in terms of UA, vegetation showed the smallest results. This is due to many LULC, aside from vegetation, being predicted as vegetation, namely 3 water bodies and 6 barren lands that were detected as vegetation. The small and large values of UA and PA are a consequence of the value of the index algorithm used. The more capable the index algorithm is in distinguishing values from LULC, the higher the UA and PA values.

Table 6. Overall accuracy and Kappa coefficient

Year	Landsat-8	
	Overall Accuracy	Kappa Coefficient
2013	95.50%	0.940
2022	93.50%	0.913

RF with 100 ntree was used and it also produced good results. From Table 6, it is found that the overall accuracy of RF classification for Landsat-8 was 95.50% in 2013 and 93.50% in 2022ss. In addition, the kappa coefficient of RF classification was 0.940 in 2013 and 0.913 in 2022. Overall accuracy is the percentage of the number of correctly predicted classifications divided by the total number of classifications described correctly, divided by the total number of classifications used.

Table 4. Confusion Matrix, producer and user's accuracy LULC classification 2013

	Water Body	Vegetation	Barren Land	Built-up Area	Row Total	Producer's Accuracy
Water Body	46	1	3	0	50	92.00%
Vegetation	0	49	1	0	50	98.00%
Barren Land	0	1	42	2	50	94.00%
Built-up Area	0	0	1	49	50	98.00%
Column total	46	52	47	51	200	
User's Accuracy	100%	96.07%	90.38%	96.07%		

Table 5. Confusion Matrix, producer and user's accuracy LULC classification 2022

	Water Body	Vegetation	Barren Land	Built-up Area	Row Total	Producer's Accuracy
Water Body	46	3	1	0	50	92.00%
Vegetation	0	50	0	0	50	100.00%
Barren Land	0	6	43	1	50	86.00%
Built-up Area	0	0	2	48	50	96.00%
Column total	46	59	46	49	200	
User's Accuracy	100.00%	84.74%	93.47%	97.95		

Machine learning approaches have potentials and limitations in data analysis. In this study, a machine learning approach was used, which resulted in a classification accuracy of 95.50% (OA) and 0.940 (KS) for 2013, and 93.50% (OA) and 0.913 (KS) for 2022. The accuracy assessment was carried out through the GEE geospatial platform.

An OA assessment reaching 90% is considered highly accurate. Recent studies such as Bayrakdar *et al.* (2022), Nasiri *et al.* (2022), and Pech-May *et al.* (2022) have also achieved OA values exceeding 90% using random forest classification methods. This method is considered more accurate compared to other machine learning methods, but a careful comparison with the same treatment must be done to determine the most suitable method in identifying land use and land cover changes. The use of Landsat-8 imagery with a resolution of 30 x 30 m was chosen to avoid classifying small LULC such as a single tree in the middle of built-up areas or a small hut located in the middle of barren land. However, if the classification of small LULC is also necessary, satellite imagery with higher resolution can be used.

LULC Condition: 2013-2022

The process of expanding built-up land in Depok City is a complex phenomenon, caused by both internal and external factors of the region. Most of the expansion of built-up areas is carried out in a planned manner by developers. The development of residential areas begins in strategic locations with high selling prices. Land that was previously used for vegetation (mixed gardens and cropland) is then converted into barren land for use as plots. The high price of plots of land forces less affluent communities to buy land at cheaper prices, which are usually located on the outskirts of the city. This phenomenon continues and causes urban sprawl. In addition, the construction of various infrastructures also contributes to this phenomenon.

Various road networks have been built to support the mobility of Depok's residents. In the process, there has been a displacement of vegetation to built-up areas. Several toll roads have been constructed, including Depok-Antasari (Desari), Cinere-Jagorawi (Cijago), and Depok Outer Ring Road. Depok-Antasari toll road has a length of 21 km connecting three cities: Jakarta, Depok, and Bogor. Cinere-Jagorawi toll road stretches from Bogor Raya to Kukusan, Beji, and is also connected to the Jakarta Outer Ring Road (JORR) network that connects to Tanjung Priok. Cinere-Serpong toll road is connected to the Jakarta-Serpong toll road. This route facilitates mobility from the Soekarno-Hatta Airport toll road and the Jagorawi toll road. The rapid development of roads in Depok shows a tendency to favor private vehicle users. However, the increase in road networks is still insufficient to overcome traffic congestion and inefficiency in mobility.

Limitation and Recommendation

Classification of land use and land cover using Landsat 8 images with a 30-meter resolution and Random Forest method can produce good accuracy with four land use and land cover classes. The available data can be used for monitoring from 2013 to 2022, during which there was rapid development in the city of Depok. However, in 2013, Depok was characterized as a desakota area, which is evident from the fragmentation of paddy fields in urban areas, rivers, and mixed gardens. This characteristic of Depok as a desakota area is not fully reflected in the 30-meter pixel resolution image. This is because many desakota-LULC have an area of less than (30 x 30) m². A more detailed resolution image is needed to reflect this. Therefore, if we want to observe changes in the desakota characteristics of Depok, a higher resolution image is required.

CONCLUSIONS

Depok City's preparation to accommodate population growth has led to an expansion of urban areas by 72,355 km², while barren land that has been prepared has decreased by 70,300 km² between 2013 and 2022. Index algorithms can explain the characteristics of surface reflectance values for each LULC. NDVI can increase vegetation values, NDBaI has limitations in differentiating barren land from built-up areas, NDBI can increase built-up area values, and NDWI can increase water body values but still overlaps with built-up area values. In detecting changes, Random Forest with balanced data sampling for each LULC and the selected index algorithm has high accuracy, with OA and KC scores above 90%.

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