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# Detection of Urban Forest Change in Jabodetabek Megacity Using Sentinel 2 and Landsat 8 Imagery Through Google Earth Engine Cloud Computing Platform

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**Abstract.** The urban forest is a green area in urban areas overgrown with woody vegetation and provides physiological, sociological, economic, and aesthetic benefits for urban communities. Unfortunately, urban forest change is still happening everywhere, especially in Jabodetabek Megacity until now, and is a problem because the arrangement of cities is more in favor of economic interests. This is considered to be the main cause of runoff, flooding, and erosion which in turn causes reduced air supply and increased air pollution which can change the microclimate of urban areas. Research is needed to detect how many changes in urban forests in Jabodetabek Megacity are so that the changes can be controlled. This research is based on the application of the Google Earth Engine cloud computing platform with data sources in the form of Sentinel-2 MSI and Landsat-8 OLI satellite imagery. Classification of land use through the Random Forest algorithm method with the help of several indexes is carried out to obtain the area of the yard of the vegetation that is part of the urban forest. The results of this study are expected as recommendations and considerations in making policies to manage urban forests and minimize the impact of urban communities.

## 1. Introduction

The urban forest is a stretch of green area with an area of at least 0.25 ha located in urban areas and multidisciplinary activities that include the design, planning, establishment, and management of trees, forests, and related flora and open spaces, which are usually physically linked to form a vegetation mosaic in or near built-up areas [1,2]. Subarudi et al. [1] explained that based on the results of the analysis of the contents of Government Regulation 63 of 2002 concerning Urban Forests and P71 of 2009, the purpose of implementing urban forests is for the preservation, harmony, and balance of urban ecosystems which include environmental, social and cultural elements with functions to improve and maintain the climate. micro and aesthetic values, absorb water, create balance and harmony in the physical environment of the city and support the preservation of Indonesia's biodiversity. The demands of urban social, economic, and ecological development determine the objectives of urban forest management. stakeholders and communities have an important role in the decision-making process of urban forest planning and management [3]. However, the development of infrastructure and settlements as well as population growth harms the sustainability of urban forests, if they do not pay attention to the needs of urban communities for green open spaces [4,5]. The process of change that occurs in urban forests under the pressure of air pollution and waste has a series of serious obstacles. These changes occur continuously, enter, grow, and develop with a succession of biological components [6]. Changes in urban forests occurred in several parts of Indonesia, such as in Java, Kalimantan, and Sumatra [1]. The island of Java, especially the Jabodetabek area, won the title for the area with the highest urban forest change because it has a very small percentage of urban forest area. This is especially true when compared to the rapid development of large cities in and around Jakarta, which has been able to exacerbate environmental damage in urban areas [7,8]. Changes in urban forests must be followed up immediately to restore urban ecosystems in some of these areas. Sustainable urban forest planning and management must be carried out immediately with an ecological inventory and mapping [1].

Efforts to manage, plan and restore urban forests can be done by mapping and are useful for clearly describing the condition of urban forest areas [9]. Various efforts in mapping urban forests have been carried out, such as using remote sensing satellites. Improved sensor technology and object-based image analysis processing (Object-Based Image Analysis or abbreviated OBIA), as well as remote sensing data with a higher spatial and spectral resolution, can be found in Landsat (Thematic Mapper (TM)/Enhanced Thematic Mapper (ETM)/ Operational Land Imager (OLI)) and SPOT [9]. These data are remote sensing data that are most often used in urban mapping [10]. According to Woodcock et al. [11], this happens because the use of the Landsat series of satellite images is the most widely used because of its rich archives and open access. In contrast to the Sentinel 2 MSI (Multispectral Instrument) imagery developed by ESA (European Space Agency) in the Copernicus program and producing 10 m high-resolution images [12,13].

Google has developed a cloud computing platform called Google Earth Engine (GEE), to help effectively address the challenges of big data analysis [14,15]. GEE was launched by Google in 2010 with features linked to Sentinel and Landsat image data sources. As stated by Amani et al. [16], Liss et al. [17], and Sazib et al. [18], that GEE is the most popular big geodata processing platform, facilitating the scientific discovery process by giving users free access to various remote sensing datasets. GEE also provides various pixel-based tools such as cloud computing and unattended classifiers, including machine learning type algorithms, for mapping implementations [19]. Cloud computing is an efficient way to store, access, and analyze data sets on very powerful servers, which virtualize supercomputers for users [20]. This system is a combination of the use of computer technology with the development of internet-based mapping [14,21,22]. Chi et al. [23] stated that this system also provides Google's computing infrastructure, platforms, storage services, and open-access software. Users can access GEE through an internet-based Application Programming Interface (API) and a web-based Interactive Development Environment [24]. The mapping to be analyzed using remote sensing data must have a high level of vegetation signal to be more accurate in estimating the approximate size of the distributed vegetation. This requires special analysis to detect the distribution of vegetation with the help of an index.

Generally, the vegetation index is one of the alternatives when doing mapping as revealed by Hunt Jr et al. [25] that Vegetation Indices (VI) is a method for reducing variation between images and increasing contrast between vegetation and soil. According to Rees [26], the basis of the vegetation index is the high reflectance of leaves in the near-infrared due to some scattering in the mesophyll, together with the absorption of visible wavelengths due to the presence of plant pigments, especially chlorophyll. Until now, many indexes have been developed, especially vegetation indexes that can be used specifically to help identify vegetation. As is the case with the ARVI index (Atmospherically Resistant Vegetation Index) developed by Kaufman and Tanre in 1992, by correcting for atmospheric effects on the wavelengths reflected by vegetation [27,28]. Other researchers such as Baloloy et al. [29] developed the MVI index (Mangrove Vegetation Index) which is used specifically to detect mangrove vegetation. While the GNDVI index (Green Normalized Difference Vegetation Index) was developed from the NDVI index (Normalized Difference Vegetation Index) by replacing the red band in the NDVI equation with a green band [30,31]. The use of these indices has been applied in various studies on spatial-based vegetation detection. Some use only one index, and some use a combination of several vegetation and non-vegetation indices. Like the research of Asy'Ari and Putra [32] which involved the NDVI vegetation index in assessing mangrove density, and the research of Sonobe et al. [33] which involved 82 indices to classify agricultural land using the Random Forest (RF) and Support Vector Machine (SVM) algorithms.

One algorithm that is often used for remote sensing classification that is quite efficient and detailed is random forest [34]. Random Forest is a machine learning algorithm proposed by Breiman in 2001 to perform regression and classification [35]. The Random Forest classifier can be described as a collection of tree-structured classifiers. According to Akar and Güngör [36], Random Forest divides each node using the best among the subsets of predictors chosen at random at that node. The parameters used in conducting the Random Forest analysis are N and m, which are the number of trees to be planted and the number of variables used to divide each node, respectively. Random Forest logarithms have been used in remote sensings such as mapping landslides [37], urban areas [38], and agricultural land [39]. The advantages offered by Random Forest according to Lin et al. [40] are to have a balance of error and automatic feature selection, as well as an easy-to-parallel algorithm. Random Forest is also very fast and powerful, and it is possible to shape trees according to the user's wishes.

Seeing the dynamics of population growth that occurs in the Jabodetabek Megacity, certainly requires management that is specifically focused on the sustainability of the urban forest. Moreover, there is still a lack of research on detailed-scale mapping and monitoring involving Google Earth Engine and the involvement of various vegetation indices. So, this research was conducted to detect urban forests in Jabodetabek Megacity through the Google Earth Engine using the Random Forest (RF) classification method and involving 18 indices (including vegetation, water, and built-up index).

## 2. Methods

### *2.1. Study area*

Administratively, the study area is located in three provinces, namely West Java, Banten, Jakarta Province, and according to its role, it is included in the Jabodetabek Megacity metropolitan area. The study of Rustiadi et al. [41], and Pribadi and Pauleit [42] emphasized that this area is one of the largest urban complexes that are interconnected between regions and have their respective roles. For example, the Jakarta City area is the center of the economy and government, and the Bogor-Depok-Bekasi-Tangerang area is a buffer city that functions as an industrial and housing complex. According to Firman [43], and Firman [44], this area which was formerly known as JMA (Jakarta Metropolitan Area) which covers the entire Jakarta-Bogor-Tangerang-Bekasi area is the largest concentration of urban population in Indonesia. Judging from its geographical location, the Jabodetabek Megacity area (especially the city of Jakarta) is located in Jakarta Bay to the north and is bordered by the Java Sea [45] (Figure 1).

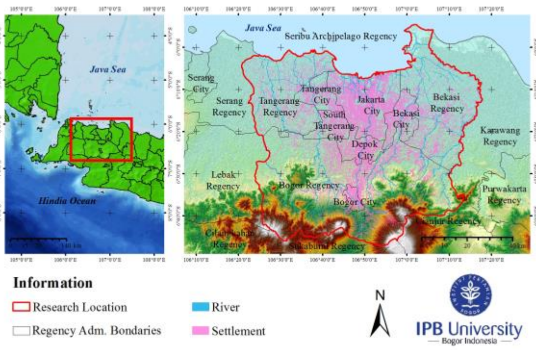


**Figure 1.** Location research map

### *2.2. Data and data process*

This research involves two main data sources in the form of satellite images based on time series, namely Landsat-8-OLI/TIRS images with time series 2014 - 2021 and Sentinel-2-MSI images from 2017 - 2021. The satellite images are processed using the Google Earth Engine platform. based on cloud computing to obtain land use classification and then through the urban forest separation stage. The land classification process is carried out with the help of training sample data which is divided into five types of land use, namely water body (145), forest area (285), built-up (590), agricultural area (147), and barren land (199) (Table 1). In addition, this study involves other data sources such as SRTM (Shuttle Radar Topography Mission) data with a spatial resolution of 30 meters, as well as a combination of RBI (Indonesian Rupa Bumi) map data.

**Table 1.** Training sample data

| No | Variable | Total training sample |
|---|---|---|
| | ***Land-use type*** | |
| 1 | Waterbody | 145 |
| 2 | Forest area | 285 |
| 3 | Built-up area | 590 |
| 4 | Agricultural area | 147 |
| 5 | Barren land | 199 |

#### *2.2.1. Citra Sentinel-2 MSI*

The Sentinel-2 satellite is a recording mission that produces high-resolution multispectral imagery that was launched in 2015 and as part of the European Space Agency (ESA) program. Sentinel-2 is a twin satellite launched in stages: Sentinel-2A on 23 June 2015, then Sentinel-2B launched on 7 March 2017. The Sentinel-2 mission carries a single payload, the MultiSpectral Instrument (MSI) which can produce recordings of up to 13 spectral bands: four bands with 10 m resolution, six bands with a spatial resolution of 20 m, and three bands with a spatial resolution of 60 m, with an orbital swath width of 290 km and a high frequency of repeat visits (Table 2). The Sentinel-2 spectrum band allows providing data for land cover/change classification, atmospheric correction, and cloud/snow separation. The launch of Sentinel-2 aims to provide high-resolution satellite data for Land monitoring, Emergency management, Security, and Climate change [13]. The study that has been done by Phiri et al. [13] demonstrated that Sentinel-2 has potential for worldwide land cover/use monitoring. Sentinel-2 has a high spatial resolution so that the accuracy of Sentinel-2 data is higher than other medium spatial resolution satellite images such as Landsat. However, since the Sentinel-2 images are relatively new at about 5 years old, many areas have not been tested compared to the Landsat satellite imagery.

In line with the research conducted by Duan et al. [46] which successfully mapped the distribution of urban forests in China using eight bands (B2–B8, B11) and three Sentinel-2 indices (NDVI, NDWI, and NDBI) using the Random Forest machine learning algorithm at a pixel scale with the support of Google Earth Engine (GEE). The results of this study can be used as a basis for identifying urban forests and urban forest planning in China and can be used to compare the spatial distribution of urban forests in China with data from other countries.

**Table 2.** Sentinel-2 spectral bands registered by the Multispectral Instrument (MSI)

| Band Number | Band Description | Wavelength Range (nm) | Bandwidth (nm) | Resolution (m) |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| B1 | Coastal aerosol | 433–453 | 20 | 60 |
| B2 | Blue | 458–523 | 65 | 10 |
| B3 | Green | 543–578 | 35 | 10 |
| B4 | Red | 650–680 | 30 | 10 |
| B5 | Red-edge 1 (RE1) | 698–713 | 15 | 20 |
| B6 | Red-edge 2 (RE2) | 733–748 | 15 | 20 |
| B7 | Red-edge | 773–793 | 20 | 20 |
| B8 | Near-infrared (NIR) | 785–900 | 115 | 10 |
| B8a | Near-infrared narrow (NIRn) | 855–875 | 20 | 20 |
| B9 | Water vapor | 935–955 | 20 | 60 |
| B10 | Shortwave infrared/Cirrus | 1360–1390 | 30 | 60 |
| B11 | Shortwave infrared 1 (SWIR1) | 1565–1655 | 90 | 20 |
| B12 | Shortwave infrared 2 (SWIR2) | 2100–2280 | 180 | 20 |

*2.2.2. Citra Landsat-8 OLI/TIRS*

The Landsat Data Continuity Mission (LDCM) or now known as Landsat-8 is a successor mission to Landsat-7 which aims to expand the capability to detect and quantitatively characterize changes in global land surface at a scale where changes caused by nature and humans can be detected and distinguished. Landsat-8 belonging to the United States Geological Survey (USGS) was successfully launched on February 11, 2013. Landsat-8 offers a clearer view with better spatial resolution and greater sensitivity to brightness and color than the previous Landsat series. Landsat-8 comes with two instrumentals, namely The Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Instrumental OLI aims to collect and archive medium resolution reflective multispectral imagery data that provides seasonal coverage of the global landmass for not less than 5 years. While the TIRS instrumental aims to collect and archive medium resolution data in the form of thermal multispectral imagery that provides seasonal coverage of the global landmass for not less than 3 years. [47,48].

Based on a survey on the use of Landsat-8 satellite imagery conducted by Miller [49], the use of Landsat-8 is widely applied to environmental sciences and management, followed by land use/land cover, education, agriculture, and planning and development. As research has been done by Deng et al. [50] which uses the Landsat-8 time series to map land use/land cover in dense urban areas with high spatial-temporal resolution. In addition, according to research conducted by Shimizu et al. [51] uses a combination of Landsat-8 and Sentinel-1 to detect disturbances that cause changes in tropical monsoon forests with an accuracy rate of 83.6%.

**Table 3.** Landsat-8 spectral bands registered by the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

| Band Number | Band Description | Wavelength Range (nm) | Bandwidth (nm) | Resolution (m) |
|---|---|---|---|---|
| B1 | Coastal aerosol | 0.43–0.45 | 16.0 | 30 |
| B2 | Blue | 0.45–0.51 | 60.0 | 30 |
| B3 | Green | 0.53–0.59 | 57.3 | 30 |
| B4 | Red | 0.64–0.67 | 37.5 | 30 |
| B5 | Near-infrared (NIR) | 0.85–0.88 | 28.3 | 30 |
| B6 | Short-wave Infrared (SWIR) 1 | 1.57–1.65 | 84.7 | 30 |
| B7 | Short-wave Infrared (SWIR) 2 | 2.11–2.29 | 186.7 | 30 |
| B8 | Panchromatic | 0.50–0.68 | 172.4 | 15 |
| B9 | Cirrus | 1.36–1.38 | 20.4 | 30 |
| B10 | Thermal Infrared 1 | 10.60-11.19 | 59 | 100 |
| B11 | Thermal Infrared 2 | 11.50-12.51 | 101 | 100 |

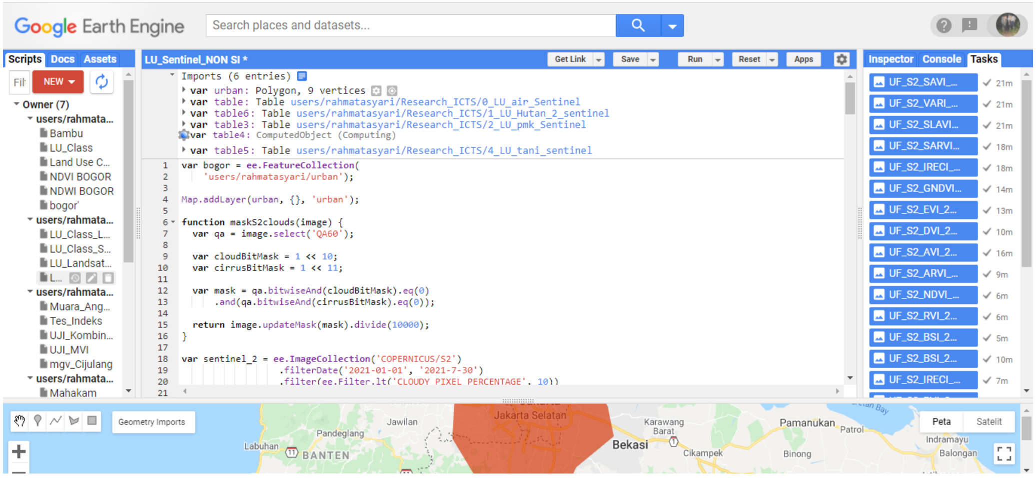


**Figure 2**. Google Earth Engine platform

### *2.3. Google Earth Engine and Random Forest algorithm for land use classification*

The capabilities of Google Earth Engine (GEE) are quite good in identifying and classifying land use types (Figure 2). This ability can be seen from the classification method tools provided by GEE, especially Random Forest (RF) [52]. Random Forest (RF) is a potential classification method because it is fast and accurate in mapping Land Use/Land Cover (LULC) from satellite imagery. There have been many studies using the Random Forest method for land use classification, such as the research conducted by Gislason et al [53]. which shows that Random Forest works well in remote sensing classification because it is more efficient, fast, the algorithm is not redundant and can detect outliers, does not require guidance, and has a high level of accuracy.

University of California statistician Leo Breiman in 2001, developed a Machine Learning algorithm in improving the classification of diverse data by taking random samples, selecting attributes, and involving the Random Forest algorithm [35]. Random Forest Machine Learning is learning that consists of many individual participants (trees) themselves [54]. This theory is very useful in land use classification and urban forest detection because it can assess land subsidence, provide a basis for forest and environmental protection, and provide an overview of community economic development [55]

### *2.4. Vegetation-Water-Built up Index.*

Some of the indices used in this study are NDVI, NDWI, EVI, SAVI, ARVI, SLAVI, IBI, GNDVI, DVI, RVI, IRECI, MNDWI, LSWI, AVI, BSI, SARVI, VARI, NDBI (Table 4). The ability of Google Earth Engine (GEE) to reach satellite data sources makes it easy for us to involve multiple indexes [15,19]. The formulas of these indices are written in script form on the GEE platform and run according to the classification we want. The involvement of these many indices was chosen by considering the focus of the use and the ability of the index in the land use classification process such as the effects of soil, atmosphere, water, and buildings.

Moulin and Guerif [56] revealed that the main purpose of the vegetation index is to enhance the information contained in the spectral reflectance data by extracting variability due to vegetation characteristics and minimizing soil and atmospheric effects. Similar to the use of SAVI (Soil Adjusted Vegetation Index) as a correction factor for the NDVI index for the effect of soil brightness [57]. Others such as the Atmospherically Resistant Vegetation Index (ARVI), which is used to consider the effect of the atmosphere on the land use classification process [27]. The list of indices used in this study is presented in the following table.

**Table 4.** Several analytical formulas were used in this study

| No | Method | Formula | References |
|---|---|---|---|
| 1. | Normalized Difference Vegetation Index (NDVI) | NDVI = (NIR - Red) / (NIR + Red) | [58] |
| 2. | Normalized difference water index (NDWI) | NDWI = (Green - NIR) / (Green + NIR) | [59,60] |
| 3. | Enhanced Vegetation Index (EVI) | EVI = G ((NIR - Red) / (NIR + C1 x Red - C2 x Blue + L)) | [61] |
| 4. | Soil Adjusted Vegetation Index (SAVI) | SAVI = 1.5 (NIR - Red)/ (NIR + Red + 0.5) | [57] |
| 5. | Atmospherically Resistant Vegetation Index (ARVI) | ARVI = (NIR - (Red - (Blue - Red))) / NIR + ( Red - (Blue - Red))) | [27] |
| 6. | Specific Leaf Area Vegetation Index (SLAVI) | SLAVI = NIR / (Red + SWIR) | [62] |
| 7. | Modified Normalized Difference Water Index (MNDWI) | MNDWI = (Green - SWIR1) / (Green - SWIR1) | [63] |
| 8. | Green Normalized Difference Vegetation Index (GNDVI) | GNDVI = (NIR - Green) / (NIR + Green) | [30] |
| 9. | Difference Vegetation Index (DVI) | DVI S2 = NIRn / Red<br>DVI L8 = NIR -Red | [64] |
| 10. | Ratio Vegetation Index (RVI) | RVI = NIR / Red | [65] |
| 11. | Inverted Red-Edge Chlorophyll Index (IRECI) | IRECI = (NIR – R) / (RE1/RE2) | [66] |
| 12. | Index-Based Built-up Index (IBI) | IBI = ((NIR)/NIR + Red)) + ((Green)/Green + SWIR1)) | [67] |
| 13. | Land Surface Water Index (LSWI) | LSWI = (NIR - SWIR) / (NIR + SWIR) | [68] |
| 14. | Advanced Vegetation Index (AVI) | AVI = (1 - Red) x (NIR - Red) | [69] |
| 15. | Bare Soil Index (BSI) | BSI = ((SWIR1 + Red) - (NIR + Blue)) / ((SWIR1 + Red) + (NIR + Blue)) | [69] |
| 16. | Soil and Atmospherically Resistant Vegetation Index (SARVI) | SARVI = ((NIR - (Red - 1 x (Blue - Red))) / (NIR + (Red - 1 x (Blue - Red)))) x (1 + 0.5) | [27] |
| 17. | Visible Atmospherically Resistant Index (VARI) | VARI = (Green - Red) / (Green + Red - Blue) | [70] |
| 18. | Normalized Difference Built-up Index (NDBI) | NDBI = (SWIR - NIR) / (SWIR + NIR) | [71] |

Where,

| | |
|---|---|
| Blue | : blue band |
| Green | : green band |
| Red | : red band |
| RE | : red-edge |
| NIR | : near-infrared band |
| SWIR | : shortwave-infrared band |

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| | |
|---|---|
| L | : calibration factor of canopy and soil effects (value 1) |
| C1 C2 | : the aerosol coefficients were 6.0 and 7.5, respectively |
| G | : gain factor (value 2.5) |
| L8 | : Landsat 8 OLI/TIRS |
| S2 | : Sentinel 2 MSI |

## 3. Results and discussion

### *3.1. Location research*

Jabodetabek Megacity consists of several administrative areas, namely Jakarta Province (66,401 ha), Bogor Regency (271,062 ha), Bogor City (11,850 ha), Depok City (20,029 ha), South Tangerang City (14,719 ha), Tangerang City (15,393 ha) , Tangerang Regency (101,186 ha), Bekasi City (20,661 ha), and Bekasi Regency (122,488 ha). This area is the center of the concentration of urban society and is surrounded by densely populated settlements [72,73,74]. DKI Province (Capital Special Region) Jakarta itself is the center of the Indonesian government, so it affects the use of space in the area. Prasasti et al. [75] added that the process of rapid city development and growth in the Jakarta area is influenced by its position as the capital city of the Republic of Indonesia, the center of government, the center of the economy, and the center of business. In addition, population growth and population migration from rural to urban areas have increased the demand for land. Tursilowati et al. [76], stated that urbanization will have an impact on city development which is marked by the construction of buildings, parking lots, roads, highways, and driveways.

Yamashita [77] explained that the Jakarta Metropolitan area is developing outside DKI Jakarta (Special Capital Region of Jakarta) and includes Bogor and Bekasi in West Java Province and Tangerang in Banten Province. This can be seen from the results of the analysis of changes in land use/cover patterns which have succeeded in detecting built-up areas in Jakarta that have expanded in all directions since 1989. Sari et al. [78] reported that along with the increase in population and the increasing need for housing in the DKI Jakarta area, people tend to use the remaining space such as riverbanks and river bodies that should be prohibited to live in.

Uncontrolled urban development makes many ecological impacts appear and befall urban communities without us predicting it. Excessive land conversion and expansion of development disrupt the ability of the soil to store water. In the urban area of DKI Jakarta alone, every year it is affected by environmental impacts in the form of flooding during the rainy season. Moreover, this area is located on the slopes of eight watersheds [72]. The study of Jati et al. [79] explains that increasing land-use changes, especially from vegetated areas to built-up areas in the provinces of Banten, DKI Jakarta, and West Java will increase the chance or possibility of flooding. As reported by Firman et al. [8], the worst flood in Jakarta occurred in 2002 which inundated nearly 90 locations in a city covering an area of more than 16 thousand hectares, or almost one-fifth of the total area of Jakarta. In addition, another problem is land subsidence that occurs in various areas in Jakarta from 1982 to 2010 and the speed is around 1–15 cm/year [74]. Shatkin [80] explained that the worst flooding hit the city of Jakarta in 2007, which was caused by the location of the urban area that used to be a river delta and was exacerbated by uncontrolled urbanization and building expansion. It is known, 13 rivers across the city of Jakarta, and historically are marshy areas [81]. Many efforts have been continuously made by the local government in tackling this environmental problem, one of which is by moving settlements on the banks of the river and replacing them with green open spaces [82].

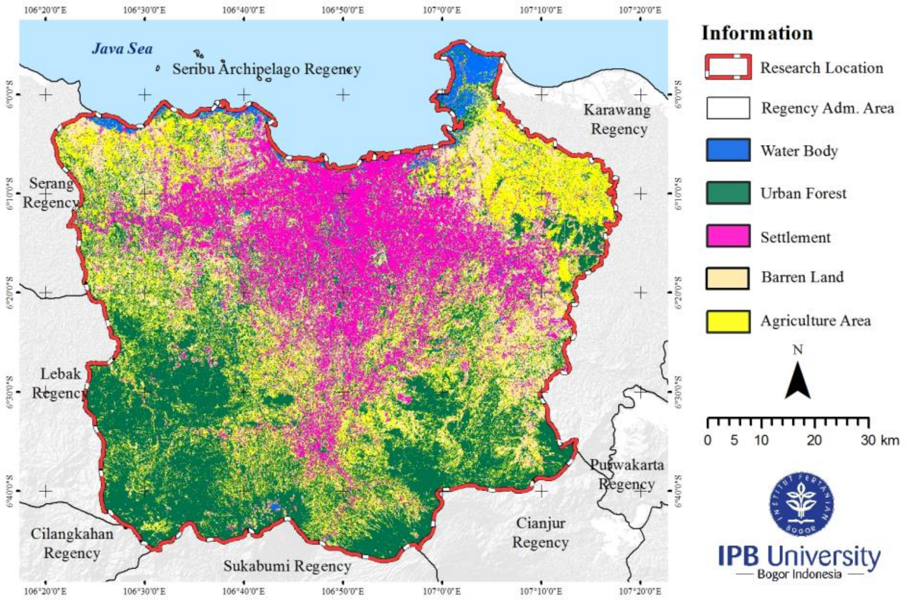


**Figure 3**. Land use map in Jabodetabek Megacity and surrounding

### *3.2. Land use classification*

Wahyudi et al. [83] reported that Jabodetabek Megacity since 1994 - 2017 has doubled with an average expansion of nearly 40 km2 per year, and urban areas have developed into sparsely vegetated areas on the outskirts of Jakarta and along the east-west and south corridors of the JMA (Jakarta Metropolitan Area). The results of the land use classification analysis show that there are five types of land use in Jabodetabek Megacity, namely built-up area, barren land area, urban forest area, agriculture area, and water body area. Figure 4 shows the changes in the five types of use over the last five years. The built-up area is the largest land use type but has decreased from 95,652.67 ha in 2018 to 90,390.73 ha in 2021. However, it is different from Suwandana [84] which says that there is additional land or commonly called accretion and some conversion of ponds become elite housing. In addition, this decrease was made possible by the eviction of illegal housing along rivers in DKI Jakarta and its surroundings to be used as green open areas, resulting in a decrease in the type of land use in the form of built-up land. As reported by Batubara et al. [82], there has been the construction of green open spaces along rivers in DKI Jakarta, former illegal settlements.

Pribadi and Pauleit [42], Cahya [85], and Chandra and Diehl [86] explain that agriculture in urban areas is under strong pressure due to urbanization. According to the results of spatial analysis, the agricultural area has decreased from 2018 covering an area of 22,488.93 ha to 15,157.56 ha in 2021. Meanwhile, in its role, peri-urban agriculture is important to maintain in ensuring urban food availability [42]. In addition, peri-urban helps urban residents who are classified as poor [87]. As reported by Cahya [85] that urban agriculture, especially in West Jakarta, is a source of food and an alternative for household food security, a source of income and employment opportunities, as well as controlling the quality of the urban environment. Chandra and Diehl [86] stated that urban agriculture occupies about 21% of the total green space area in Jakarta, and its potential contribution to urban food security has not been realized by the local government. However, this is very difficult to consider, due to the lack of understanding of the role of peri-urban so that urban agricultural areas move to non-urbanized areas [42]. This is different from the type of land use in the urban forest area which has increased from 12,947.14 ha in 2018 to 16,483.33 ha in 2021 even though the total urban forest area is very small compared to the total built-up area.

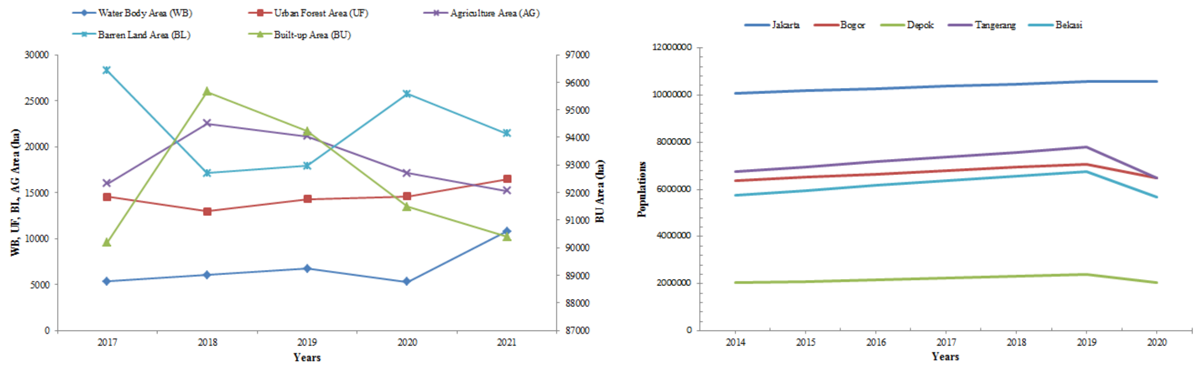


**Figure 4**. Land use area and population in Jabodetabek Megacity

**Table 5.** Land use classification in Jabodetabek Megacity

| **Land use type** | **Area (ha)** | | | | |
|---|---|---|---|---|---|
| | **2017** | **2018** | **2019** | **2020** | **2021** |
| Water body | 5,315.07 | 6,027.96 | 6,712.06 | 5292.75 | 10,779.80 |
| Urban Forest area | 14,527.60 | 12,947.14 | 14,281.75 | 14,593.82 | 16,483.33 |
| Built-up area | 90,202.15 | 95,652.67 | 94,221.66 | 91,488.08 | 90,390.73 |
| Agricultural area | 15,969.91 | 22,488.93 | 21,137.41 | 17,130.01 | 15,157.56 |
| Barren land | 28,230.58 | 17,128.61 | 17,892.43 | 25,740.65 | 21,433.89 |

The water body area has also increased from 6,027.96 ha in 2018 to 10,779.80 ha in 2021. However, historically, prior to 2014 silting and excessive macrophyte cover had caused more than 25% of the existing lakes to shrink in area and volume, and based on an assessment of lake morphology, almost 50% of the lake has been damaged [88]. Maybe during the period 2017 to 2021, there will be the rehabilitation of lakes and along the banks of rivers in Jakarta. While the built-up area has increased and decreased significantly from 2017 to 2021. In 2021 the built-up area is 9,0390.73 ha. Based on data from the Statistics Indonesia (BPS) that was collected from 2014 to 2020, the population of Jabodetabek Megacity has increased every year but has decreased since 2019. It is known that metropolitan cities are the cities with the largest population when compared to other cities in Indonesia [89].

### *3.3. Urban forest distribution*

Rahmawati et al. [90] explained that urban development that increases the conversion or conversion of land into built-up land requires the existence and function of urban forests. Meanwhile, Lukito [91] states that urban forests are needed by visitors to natural attractions in urban areas and green landscapes can provide a comforting effect. Several classification methods for urban studies have been proposed in the remote sensing literature, one of which is the classification algorithm [92]. The results of the classification analysis using the Random Forest (RF) algorithm show that there are positive dynamics of change in the urban forest in the Jabodetabek Megacity during the 2018 - 2021 period, although there is a decline in the 2017 - 2018 range (Figure 4; Table 5; Figure 6). This is a good effort to maintain in developing urban areas. If seen from the distribution, Tangerang City has the largest urban forest in Jabodetabek Megacity during the period 2017 to 2019, and the following year, Jakarta City has the largest urban forest area until 2021 (Figure 5; Table 6).

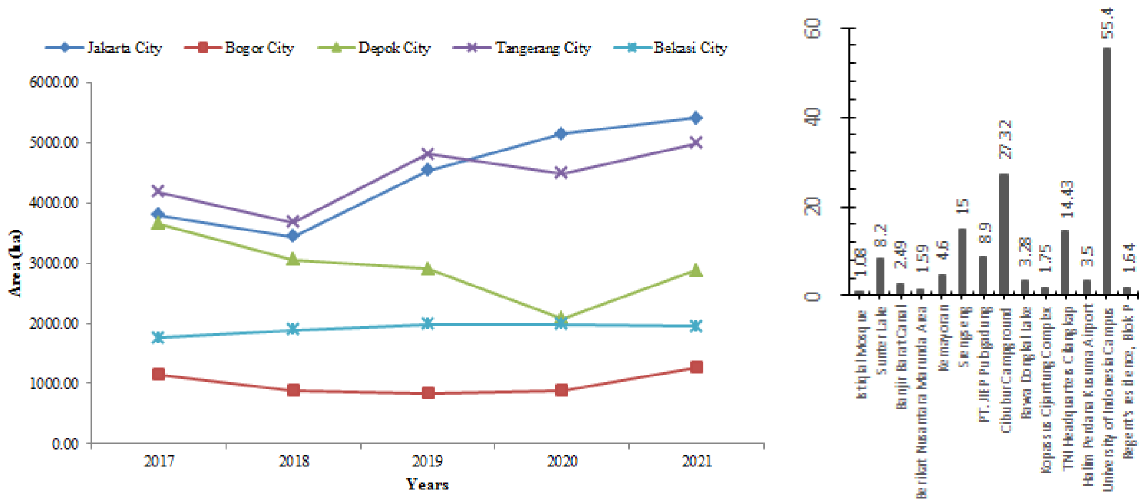


**Figure 5.** Graph of urban forest distribution in various cities at the study site and urban forest in Jakarta City

**Table 6.** Urban forest in Jakarta City

| Cities | Urban forest area (ha) | | | | |
|---|---|---|---|---|---|
| | **2017** | **2018** | **2019** | **2020** | **2021** |
| Jakarta City | 3,798.78 | 3,437.26 | 4,533.99 | 5,149.44 | 5,408.91 |
| Bogor City | 1,146.10 | 885.64 | 840.20 | 882.58 | 1,262.15 |
| Depok City | 3,648.07 | 3,054.78 | 2,904.60 | 2,084.48 | 2,877.09 |
| Tangerang City | 4,176.11 | 3,680.41 | 4,811.60 | 4,488.00 | 4,988.51 |
| Bekasi City | 1,753.28 | 1,884.58 | 1,985.23 | 1,985.23. | 1,942.06 |

In 2021, the City of Jakarta will have the largest urban forest compared to other cities. There is approximately 5,408.91 ha of the urban forest in Jakarta, which is spread over almost all regencies/cities in DKI Jakarta Province, except for the Thousand Islands Regency. According to data from urban forest managers belonging to the DKI Jakarta Provincial Government, it shows that there are 14 urban forest areas managed by several agencies and companies with a total area of 149.18 ha (Table 7). When compared with other studies, Subarudi et al.[1] reported that the total area of the urban forest is different, which is 6,152 ha or equal to 9.3% of the total area. Data from Subarudi et al. [1] when compared with the results of satellite imagery analysis in 2017, it is certainly different. This indicates a significant decline from 2014 to 2017.

In addition, according to the report of Sitorus et al. [93], that there was a decrease in green open space (including forests, mixed gardens, rice fields, shrubs, and grasses) in the period 2002 to 2007 by 362.21, and was followed by conversion of land to built-up land in 1972 - 2005, an increase of 27%. This decline has been going on for a long time and is proven by research on the estimated area of the urban forest. This was influenced by the striking expansion of urban areas from 2001 to 2015 which resulted in changes in vegetated land and barren land so that vegetated land decreased from 54% to 30% of the total metropolitan area. in Bogor and Depok decreased by about 4% in 2015 in line with the development of population settlements in Bogor [94]. The different results obtained depend on the method used in the study. The urban forest in DKI Jakarta certainly needs to be improved in procurement and utilization, especially riverbanks and beaches as protection for abrasion, such as the mangrove area along the coast of the Angke Kapuk estuary which is flanked by residential complexes that are used as urban forests for greenbelts [95], as stated by Soesanti et al. [96] explain n that the protected forest that extends from the East to the West Coast along the coastline is 50.6 ha.

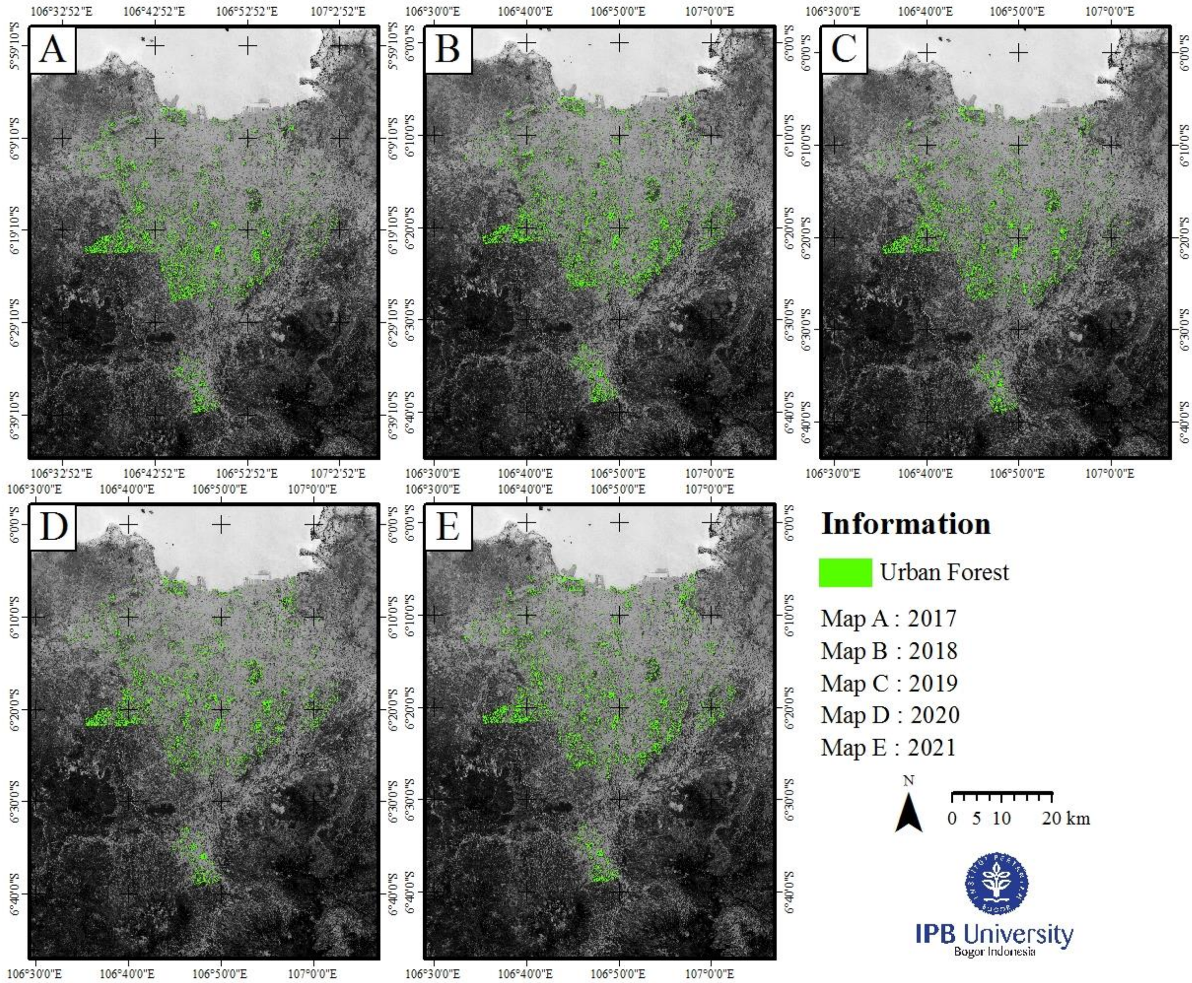


**Figure 6.** Spatial distribution of urban forest

From a policy perspective, the urban forest in Jabodetabek Megacity has not yet met the government's target. Subarudi et al. [1] reported that the area of the urban forest in Jabodetabek Megacity still does not meet the target set in Article 29 of Law no. 26 of 2007 concerning Spatial Planning, it is known that the minimum proportion of Green Open Space is 30% (minimum area of 20% for public green open space and 10% for private green open space) of the total city area. Yet globally, cities such as Australia are embracing the idea that the trees on their roads, parks, and private gardens are part of the urban forest and managed to address complex policy issues and create more livable and sustainable cities [97]. Urban forest plays a role in reducing flood intensity in the capital city [98,99]. Considering that this area often experiences severe flooding caused by deforestation around the river during the development of large cities around it [100,101,102,103,104,80,81,82]. Even the severity of the flooding in the area caused many casualties and property loss [105,106]. As reported by Xiao et al. [107], that the role of urban forest can reduce flooding in urban areas. Green open spaces in urban areas increase the resilience of hydrological systems in urban areas and reduce peak flows from storms that can cause flooding [99,103]. Inkiläinen et al. [108] and Armson et al. [109] reported that urban forests can reduce the amount of rainwater runoff, and others by regulating flow through canopy rainfall interception.

Dwyer et al. [110] explained that with effective planning and management, urban forest areas will provide various benefits such as a more pleasant, healthy, and comfortable environment to live, work, and play, reduce costs of providing various urban services, and increase the welfare of individuals and communities. In addition, urban forests can help improve water quality in urban zones, and of course, this is one solution to overcome the poor water quality in Jakarta Province and surrounding areas

[110,102]. Urban forest planning must begin with the consideration of these benefits against community needs [110,107,111,112].

**Table 7.** List of urban forests in Jakarta City

| | Urban forest | Area (ha) | Founded (Years) | Regency/city |
|---|---|---|---|---|
| 1. | Istiqlal Mosque | 1.08 | 2005 | Central Jakarta |
| 2. | Sunter Lake | 8.2 | 1999 | North Jakarta |
| 3. | Banjir Barat Canal | 2.49 | 2005 | - |
| 4. | Berikat Nusantara Marunda | 1.59 | 2005 | North Jakarta |
| 5. | Kemayoran | 4.6 | 2002 | - |
| 6. | Srengseng | 15 | 1995 | West Jakarta |
| 7. | PT. JIEP Pulogadung | 8.9 | 2003 | East Jakarta |
| 8. | Cibubur Campground | 27.32 | 2003 | East Jakarta |
| 9. | Rawa Dongkal Lake | 3.28 | 2005 | East Jakarta |
| 10 | Kopassus Cijantung Complex | 1.75 | 2003 | East Jakarta |
| 11. | TNI Headquarters Cilangkap | 14.43 | 2003 | East Jakarta |
| 12 | Halim Perdana Kusuma Airport | 3.5 | 2002 | East Jakarta |
| 13. | University of Indonesia Campus | 55.4 | 1999 | South Jakarta |
| 14. | Regent's residence, Blok P | 1.64 | 1999 | South Jakarta |
| | ***Total: 14 area*** | ***149.18*** | | |

*Source: DKI Jakarta Provincial Government Integrated Data Portal*

*3.4 Vegetation Index assessment*

Gitelson et al. [30] and Li et al. [113] stated that the techniques that are often used in mapping urban forests are remote sensing with satellite imagery and by using a vegetation index. The results produced in urban forest mapping depend on the composition of the use of the vegetation index, water, and built-up. Tests conducted on the vegetation index in detecting urban forests need to be carried out to determine the effect of the indexes involved.

Houborg and McCabe [114] stated that mapping of the earth's surface, especially vegetation monitoring can be used through a vegetation index approach. Meanwhile, Beret and Guyot [115], and Rees [26] explained that the vegetation index is a mathematical combination of different spectral bands of the electromagnetic spectrum, and is more sensitive than individuals to vegetation parameters. Each index has a range of different threshold values and according to the type of land use and its effects. For example, the SAVI index can correct for NDVI which is affected by the effect of ground brightness [57]. The results obtained, there are various changes in each index per year. The pattern of change there is an increase and there is also a decrease. This shows that there is a change in the condition of the urban forest in the study location, either by reducing the area or increasing the area of vegetated land cover. For example, the RVI, NDVI, ARVI, GNDVI, IRECI, SARVI, SAVI, SLAVI, and VARI indices, which form a pattern of change with negative changes (decreases) that occur in 2018 and after that occur until 2021. This is in contrast to the EVI, BSI, AVI indexes, which experienced an increase in 2018 and after a decline. While the DVI index, in 2018 there was an increase until 2019, after experiencing a decline in 2020 and increasing again in 2021 (Figure 7).

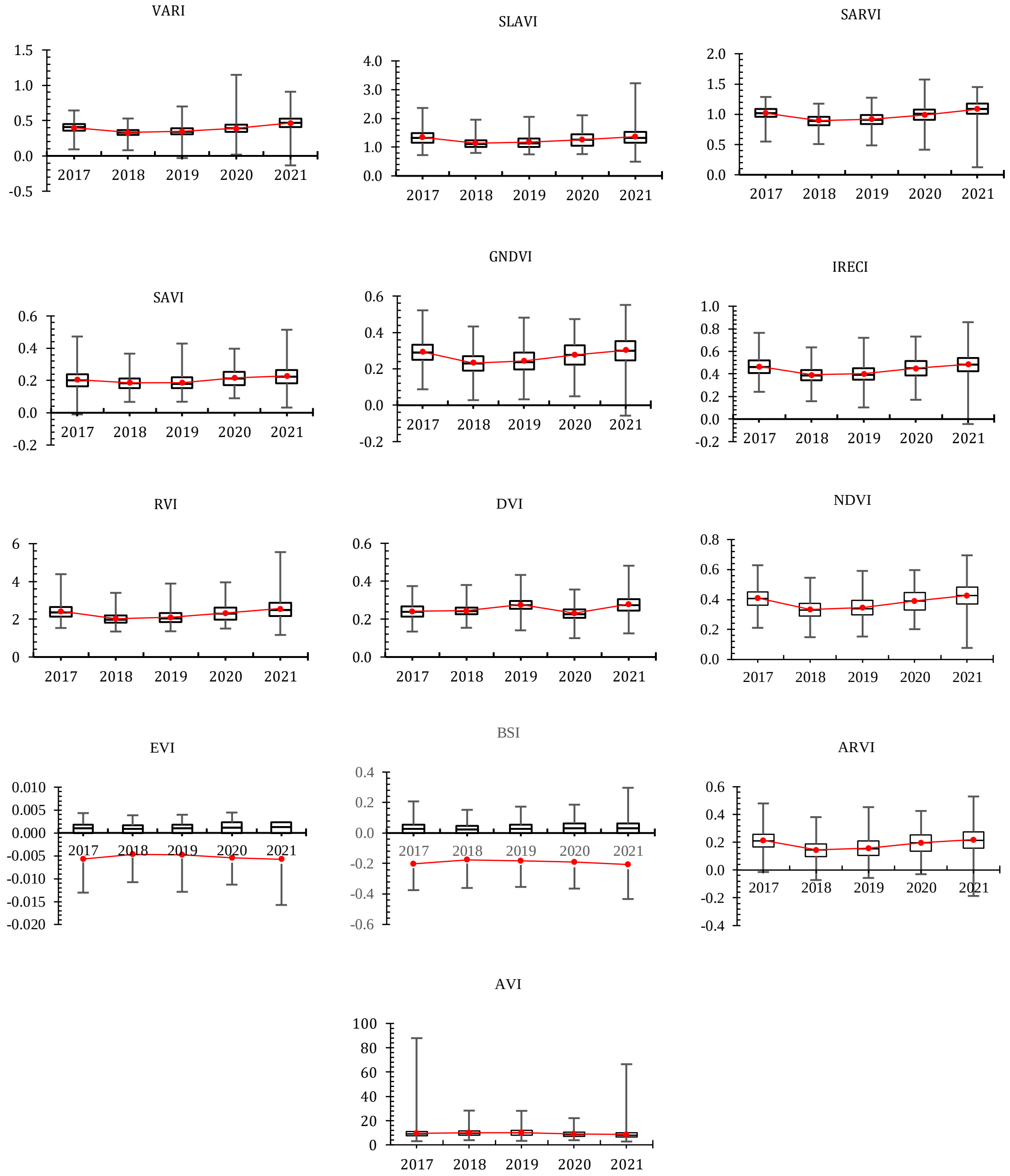


**Figure 7.** The threshold value of each index

*3.5 Ratings and Recommendations*

The lack of urban forests in Indonesia should be an evaluation material for us and more specifically for decision-makers at the government level. Seeing that urban growth is the cause of land use and land cover changes in many areas around the world, especially developing countries including Indonesia [116,89,94,102,109,103]. The results of our research show that almost all areas have increased land area for urban forest except for Bekasi City, and it should be maintained and improved. Because according to previous research there has been a decrease in green open space such as in Depok City [117,94]. Bogor City [94,16], and South Jakarta [93]. And consider the important role of urban forests such as flood control [99,108], water quality improvement [110,102], and green ecological space providers [119], it is necessary to plan by creating a lot of space for urban forest development.

Muzadi [111], Dwyer et al. [110], and Xiao et al. [107] explained that urban planning is carried out by looking at community needs, environmental quality, and disaster risk. Socio-economic, natural, and anthropogenic factors will shape land use and land cover patterns in an area [111]. The institutional framework covering policy, enforcement, differences in coordination between levels of government, and property rights will influence the development of urban forests. As stated by Rustiadi et al. [41] that the continued rate of population growth will make it difficult to procure urban forest areas. In developing countries with weak institutional capacity, it will be a barrier to the provision of urban forests because of its relationship with the ineffectiveness of market mechanisms in allocating resources, inadequate policy and regulatory enforcement, unclear property rights, lack of cross-sectoral cooperation, and lack of scientific input [120,121].

Considering the space in the Jabodetabek Megacity urban zone which is often used as a place to live by the urban poor, urban forest planning does not escape the socio-economic effects. Akmalah et al. [101] explained that many poor people live in slum areas in some parts of Jakarta, which are very vulnerable to flooding, such as illegal riverbanks. Whereas space on the banks of rivers and beaches has the potential to be used as an urban forest area. Jabodetabek Megacity has two functions, namely an economic function that is supported by advanced economic and social infrastructure and is centralized in Jakarta, Bogor, Tangerang, and Bekasi, and an environmental function, namely an area with natural green stretches that functions like water and soil conservation, especially Bogor Regency [122]. The utilization of green open space has the potential to be applied in public services infrastructure zones such as toll roads, hospitals, schools and universities, and many more.

## 4. Conclusions

Detection of the urban forest is carried out using the Random Forest method and through the Google Earth Engine platform. This platform can detect urban forest in the study area (Jabodetabek Megacity) with an area of 14,527.60 ha in 2017 an area of 12,947.14 ha, 2019 an area of 14,281.75 ha, 2020 an area of 14,593.82 ha, 2021 an area of 16,483.33 ha. Meanwhile, if viewed by region, the City of Jakarta has an area with the largest urban forest which is 5,408.91 ha, followed by Tangerang City (4,988.51 ha), Depok City (2,877.09), Bekasi City (1,942.06 ha), and Bogor City (1,262.15 ha). From the distribution recorded during the period 2017 to 2021, there are several dynamics of changes in the distribution of urban forests.

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