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Land Cover Mapping and Prediction Using Cellular Automata and Markov Chain (Case Study: Depok City, Indonesia)

Muhammad Arya Pradipta, Megivareza Putri Hanansyah*, Filsa Bioresita, Noorlaila Hayati, Lalu Muhamad Jaelani, Bangun Muljo Sukojo, Husnul Hidayat
Departemen Teknik Geomatika, Institut Teknologi Sepuluh Nopember, Surabaya, 60111, Indonesia
*Corresponding author: megivareza.hanansyah@its.ac.id

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Abstract: Depok City, a satellite city of Jakarta, is experiencing massive urbanization due to Jakarta's role as an economic hub, leading to significant land-use changes. This study analyses land cover in Depok City annually from 2017 to 2024 across five categories: Built-up Area, Vegetation, Agricultural Land, Bare Land, and Water Body. This process utilizes the Extreme Gradient Boosting algorithm applied to Sentinel-2 Level-1C satellite imagery for the specified period. Subsequently, we predict Depok City's land cover conditions for the year 2042 using a Cellular Automata-Markov Chain simulation. This simulation incorporates historical land cover maps, which were generated previously, along with driving factors such as distance from main roads and distance from health and educational facilities. The year 2042 was chosen to coincide with the expiration of Peraturan Daerah Nomor 9 Tahun 2022, law product concerning the Depok City Spatial Plan for 2022-2042. The final outputs of this research are land cover maps of Depok City for each year from 2017 to 2024, as well as a predicted land cover map for Depok City in 2042. The study found that from 2017 to 2024, the built-up area and vegetation land cover category showed an increasing trend in extent, while the remaining land cover categories decreased. Prediction model of year 2042 shows predicted expansion of Built-Up land and Vegetation land cover categories, while other land cover categories predicted to decrease.

Keywords : Depok City; Land Cover; Extreme Gradient Boosting; Cellular Automata-Markov

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Introduction

Land cover refers to the physical and biological materials occupying the Earth's surface, encompassing various types of vegetation, water bodies, built infrastructure, and bare land. The Food and Agriculture Organization (FAO) defines land cover as the observable biophysical cover on the Earth's surface (Kumar Gupta et al., 2023). Depok City is a satellite city located south of the larger city of Jakarta. Satellite cities refer to urban areas whose growth is driven by population increases in a nearby larger city, enabling them to manage such population explosions (Gu et al., 2023)]. According to the 2020 census, Depok City has a population of 2.06 million, with an annual growth rate of 3.64% since 2010. This growth is accelerated by migration and urbanization from Jakarta (Budi Hartono et al., 2022).

Land cover change is a crucial instrument for studying urban area growth (Seto et al., 2012). Land cover change is the transformation of the Earth's surface, affecting both physical and biological elements (Bajocco et al., 2012). Land use and land cover patterns within a region are the result from natural and socio-economic factors (Muhammed, 2020) and are often linked to economic growth and urban expansion (Raharti et al., 2022). Therefore, in the context of Depok City's growth, this expansion can also be observed through land cover change analysis. Synonymous to land conversion, change of land cover is proven to directly affects economical growth, mainly in land cover categories that are economically productive and contributes directly to a region's economical output (Harewan et al., 2023).

For land cover prediction, the Cellular Automata-Markov (CA-Markov) model is a method used widely in land cover prediction, notably due to its ability to simulate complex spatial dynamics in a structured manner. Generally, this model represents land cover as cells categorized by their land cover type, which change according to rules influenced by surrounding cells. Temporal dynamics are a primary influence in the CA-Markov prediction process, requiring several years of historical land cover maps as input for the simulation (Keshtkar & Voigt, 2016). To support this process, land cover classification in Depok City will also be performed using Sentinel-2 Level 1 satellite imagery from 2017 to 2024. This land cover classification will utilize a Machine Learning approach with the Extreme Gradient Boosting method. In research by McCarty et al., the accuracy of the Gradient Boosting method outperformed two other commonly used land cover classification methods: Support Vector Machine (SVM) and Random Forest (RF) (McCarty et al., 2020). The use of Extreme Gradient Boosting method in this research is a relatively new approach, as prior research assesing land cover change in the same area relied on methods like Region-based Convolutional Neural Networks (R-CNN), Artificial Neural Networks (ANN) and Deep Learning. Sentinel-2 Level 1C satellite imagery was chosen for its open access to general users and its 10-meter spatial resolution, which surpasses other open-data remote sensing satellites. The use of this sentinel advances previous studies that utilizes lower spatial resolution imageries, such as those using Landsat 8 and 9 Satellites with 30-meter resolutions.

The ultimate goal of this research is to create land cover classification maps for Depok City for each year from 2017 to 2024, as well as a predicted land cover map for Depok City in 2042. This year was chosen because it coincides with the expiration of the Depok City Spatial Plan (RTRW) as stipulated in Peraturan Daerah Nomor 9 Tahun 2022. This will allow observation of the capacity in this legal product in supporting Depok City's population growth, which at the moment are overlooked by existing literatures.

Methodology

Data and Research Location

This researches primarily utilizes imagery from Sentinel-2 Level 1-C that is taken annually from 2017 to 2024 in Depok City. The Depok City Research Area can be seen in Figure 1. In total, there are 8 imageries that are classified into 5 land cover classification, with exposure dates as listed in Table (1). This classification map is then combined with Road Network data from BIG, Educational Facilities coordinates compiled from Kementrian Pendidikan Dasar dan Menengah, and Hospital and Puskesmas Network compiled from Dinas Kesehatan Provinsi Jawa Barat, to produce the final 2042 Depok City Land Cover Prediction Map. The flowchart of the entire research process can be seen in Figure 2.

Table 1. Sentinel-2 Imagery Observation Times

No	Imagery Year	Exposure Date
1	2017	July 4th, 2017
2	2018	September 17th, 2018
3	2019	August 18th, 2019
4	2020	May 24th, 2020
5	2021	July 18th, 2021
6	2022	July 18th, 2022
7	2023	December 20th, 2023
8	2024	August 21st, 2024

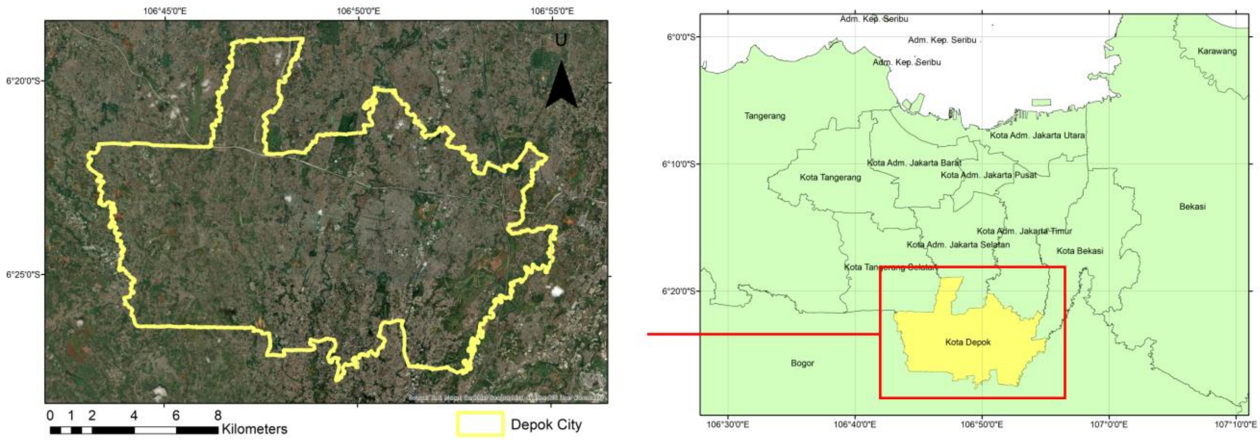

Figure 1. Depok City Research Area

Land Cover Analysis using Extreme Gradient Boosting

Sentinel-2 Level-1C satellite imagery, was downloaded and clipped to cover the entire administrative area of Depok City. One image was acquired for each year during the dry season, resulting in a total of eight images used in this study. For each image from 2017 to 2024, training points were prepared by visually interpreting and selecting 100 points for each land cover category, yielding a total of 500 points with land cover labels and coordinate values in a points shapefile format. Training points are chosen randomly at different places around the original raster of the Sentinel-2 Imagery, under the conditions that the whole map has to be evenly populated with training points, as such that the model can benefit from learning different geographical features of the research area across different landscapes. The land cover categories used were: (1) Built-up Area, (2) Vegetation, (3) Agricultural Land, (4) Bare Land, and (5) Water Body.

The training process was conducted using the XGBoost library in Python, where the training points were applied to the satellite imagery of the corresponding year. 70/30 split is applied, where 70% of the training point will be actual training points, and the remainder will act as test data to validate model. This training/validation split combination is proven to be robust and popular among wide range of classification problems (Vrigazova, 2021), and in this research is expected to realise acceptable performance. This allowed the model to learn the correlation between the satellite image's reflectance values and the land cover labels, resulting in a land cover model saved in .pkl format. GridSearch CV Plugin is utilized to maximize the performance of each model by applying Hyperparameter Tuning (Table 1), that is different combinations of n_estimators, maximum depth, and learning rate. This tuning will help maximize the final integrity of the model, as this step consistently improves overall accuracy for training models (Yaloveha et al., 2022). Three options for every parameter are initially introduced before training;

Table 2. Hyperparameter Tuning Options

Parameters	Options
n_estimators	100, 200, 300
max_depth	4, 6, 8
learning_rate	0.05, 0.1, 0.2

Land cover maps were then generated by reapplying this trained model to the satellite imagery, classifying each pixel into one of the five land cover labels based on the developed algorithm. The output of this processing was a raster (.tif) containing pixels classified into the five land cover classes.

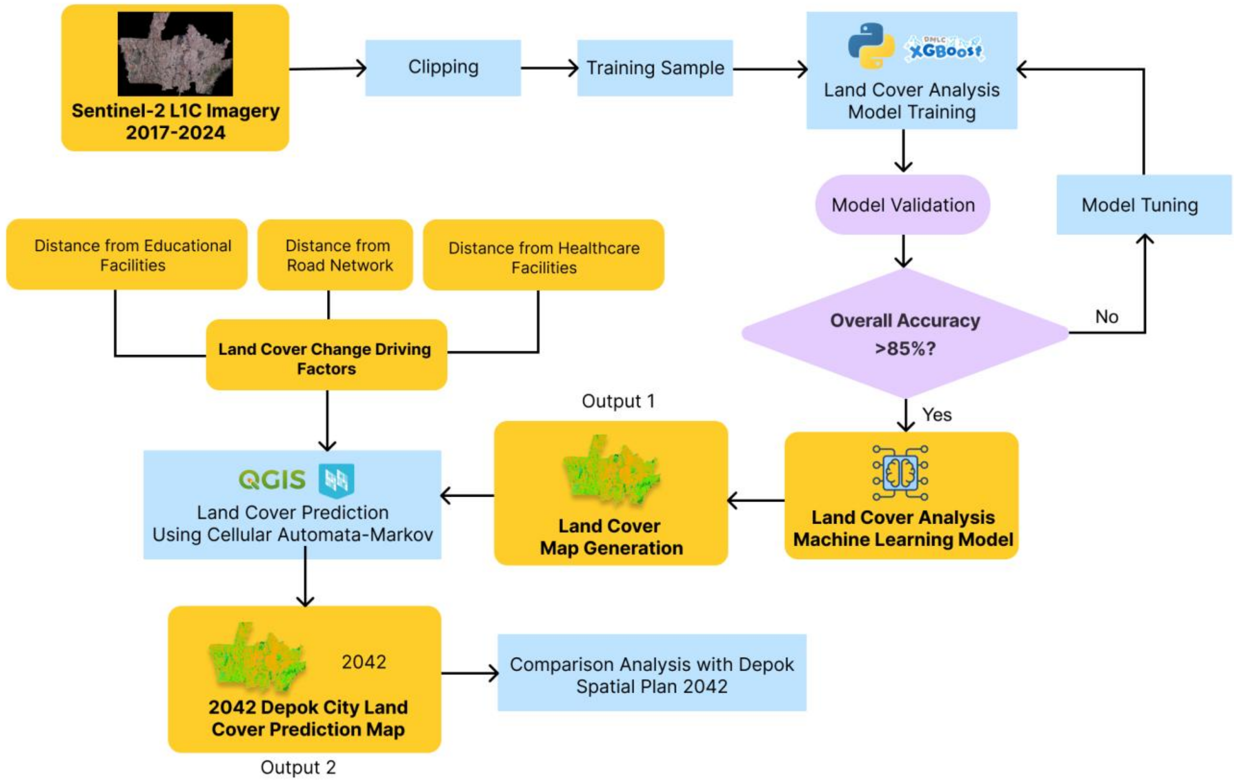

Figure 2. Research Process Flowchart

Land Cover Analysis Validation

The land cover model was validated using the 2024 analysis map. Validation data consisted of 50 points, which is collected by means of field survey, where coordinates of the five land cover categories are recorded using handheld GNSS receiver. From this step, 50 coordinates are collected, which then overlayed against the most recent 2024 land cover analysis. By comparing the validation coordinates against the modeled land cover map, confusion matrix is generated. A Confusion Matrix is a table that represents the accuracy of a land cover classification algorithm by comparing the predicted classification results with the actual ground truth data. This matrix can then be used to calculate several accuracy metrics, which help users understand the effectiveness of the classification algorithm. (Li et al., 2023; Lukas et al., 2023).

For binary classification, a Confusion Matrix consists of four components (Table 2):

- True Positives (TP): The number of instances correctly predicted as positive (e.g., classified as vegetation, and the ground truth data confirms it is vegetation).
- True Negatives (TN): The number of instances correctly predicted as negative (e.g., classified as not vegetation, and the ground truth data confirms it is not vegetation).
- False Positives (FP): The number of instances incorrectly predicted as positive (e.g., classified as vegetation, but the ground truth data shows it is not vegetation).
- False Negatives (FN): The number of instances incorrectly predicted as negative (e.g., classified as not vegetation, but the ground truth data shows it is vegetation).

Table 2. Confusion Matrix Diagram

	Actual Positive	***Actual Negative***
Predicted Positive	TP	FP
Predicted Negative	FN	TN

$$Overall\ Accuracy = \frac{\sum TP + TN}{\sum TP + TN + FP + FN} \quad (1)$$

Overall Accuracy is used the primary accuracy metric for this study, which is based on Peraturan BIG Nomor 15 Tahun 2014.

Cellular Automata-Markov Simulation

Cellular Automata relies on discrete values in time and space, where future changes depend on the state of a cell and its neighbors at the previous time step. The main elements of this simulation are the cellular field, the cells, the state of each cell, the cell's neighborhood, and the rules of change.

A Markov Chain, on the other hand, is a mathematical system where the next state depends only on the current state, not on the sequence of events that preceded it—a mathematical concept known as "memorylessness." (Hanafi et al., 2021; Keshtkar & Voigt, 2016; Koko et al., 2020; Meng & Chen, 2013). The probability of a cell transitioning from state (i) to state (j) at time (n) is explained by the following equation:

$$p_{(i,j)}(n) = \Pr(X_n = j | X_0 = i \quad (2)$$

Where:
$p_{(i,j)}(n)$ = probability of system turning into *j* on step *n*
X_n = system condition in step-n
X_0 = initial system condition
i = initial
j = target

The prediction of future land cover utilizes not only historical land cover data but also driving factors. In this study, distance from the road network and distance from activity centers were utilized as such factors. The distance from the road network was determined by calculating the Euclidean distance for each pixel in the satellite image raster relative to the vectorized road network shapefile, a process performed using Euclidean distance toolbox. An identical methodology was applied to ascertain the driving factor for distance from education facilities and healthcare facilities.

Following the generation of land cover maps for the years 2017-2024 and the preparation of the supporting factors for land cover change, the land cover prediction for 2042 was executed using QGIS. Specifically, the MOLUSCE (Modules of Land Use Change Evaluation) plugin within QGIS, designed for this type of simulation, was employed. This plugin accepts raster inputs and processes their pixel values. The input rasters included Depok City's land cover data for 2017 and 2024, alongside the previously processed driving factors of distance from the road network and activity centers. MOLUSCE calculated the annual percentage change rate for each land cover type and subsequently generated the 2042 land cover map based on a Cellular Automata-Markov Chain model, driven by a transition matrix.

Results and Discussion

From the land cover analysis, 8 map of Depok City Land Cover map that are based on 5 categories are generated can be seen in Figure 3.

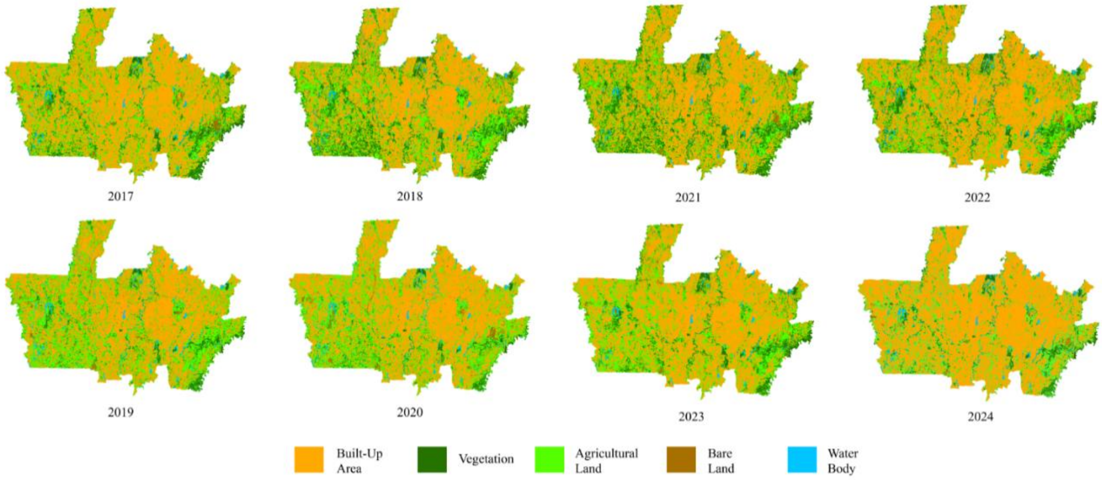

Figure 3. Land Cover Analysis Results

Land Cover Analysis Results

Figure 2 shows the visualization of the Land Cover Analysis that has been conducted on individual imagery of every year in Depok City from 2017 to 2024. Further details about the area of every land cover category in each individual years are tabulated in Table 3.

Table 3. Land Cover Areas in hectares

	Land Cover Areas (ha)				
Year	**Built-Up Area**	**Vegetation**	**Agricultural Land**	**Bare Soil**	**Water Body**
2017	10,213.41	2,670.81	5,935.38	580.05	595.01
2018	10,397.91	1,206.15	6,875.47	969.33	545.8
2019	11,224.7	813.29	6,467.34	946.83	542.5
2020	10,568.21	3,323.47	5,323.75	446.64	332.59
2021	11,462.85	2,248.76	4,868.72	826.1	588.23
2022	11,410.28	1,600.7	6,055.55	588.91	339.22
2023	11,787.91	2,034.89	5,308.33	415.34	448.19
2024	13,516.19	1,104.79	4,623.83	304.14	445.71

Extreme Gradient Boosting Model Performance

To ensure the highest integrity of every machine learning model in the analysis process, model quality is assesed using Overall Accuracy performance, where every model is individually tested on the previous 30% split of the selected training data. This can be shown in Table 4, where there are the final combinations of parameters found by GridSearchCV to achieve the highest Overall Accuracy.

Table 4. XGBoost Model Performance and final parameters

Year	*n_estimators*	*max_depth*	*learning_rate*	*Overall accuracy*
2017	300	6	0.2	92%
2018	200	6	0.05	92.28%
2019	300	4	0.2	92%
2020	300	6	0.2	94.57%
2021	200	6	0.1	93.43%
2022	200	4	0.05	92.28%
2023	300	6	0.1	91.43%
2024	200	8	0.1	89.14%

Land Cover Change Trends 2017-2024

The built-up land category saw a 32.33% increase in its area in 2024 compared to 2017. However, there were annual fluctuations with both increases and decreases. In 2020, a reduction of 656.49 hectares was observed, a 5.84% decrease from the previous year. A downward trend in built-up land cover was also evident in 2022, with a decrease of 52.57 hectares, representing a 0.45% reduction from the prior year. Apart from these two years, the area of built-up land consistently increased compared to the previous year in 2018, 2021, 2023, and 2024. At its peak in 2024, this category covered 67.59% of Depok City's total area. The built up land cover change trends can be seen in Figure 4(a).

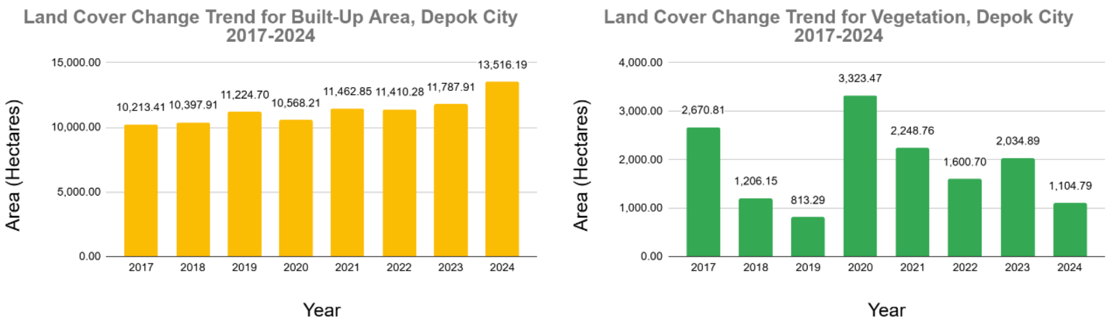

Figure 4. (a) Built Up Land Cover Change Trends (b) Vegetation Land Cover Change Trends

The area of Vegetation showed a decreasing trend when comparing 2024 to 2017, with a reduction of 1566.02 hectares, or a 58.63% decrease from its 2017 size. Over this period, there were two instances of increase: in 2020 and 2023. In 2020, there was a significant expansion of 308.64% compared to the previous year. Similarly, in 2023, the area expanded by 27.12% from the year before. In 2019, this category reached its smallest extent at 813.29 hectares, accounting for only 4.06% of Depok City's total area. Vegetation land cover change trends can be seen in Figure 4(b).

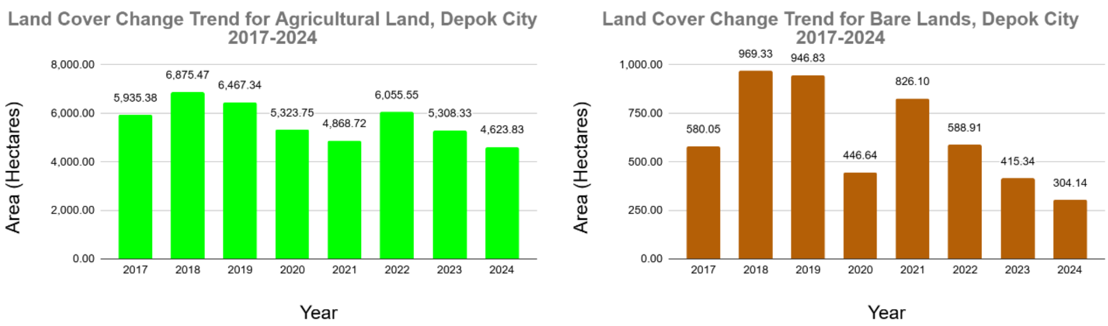

Figure 5. (a) Agricultural Land Cover Change Trends (b) Bare Land Cover Change Trends

The area of agricultural land showed a decreasing trend from 2017 to 2024, with a total reduction of 1311.55 hectares, which is a 22.09% decrease from its 2017 size. However, there were two periods of growth during this time. In 2018, agricultural land expanded by 15.83% compared to the previous year. Another expansion occurred in 2022, with an increase of 24.37% over the year before. By the final year of the study, agricultural land covered 23.12% of Depok City's total land area. Agricultural land cover change trends can be seen in Figure 5(a).

For the bare land category, its area showed a decreasing trend when comparing 2024 to 2017, experiencing a 47.56% reduction compared to its 2017 size. Throughout this period, the area of this land cover category underwent significant fluctuations. In 2018, there was an expansion of 67.11% compared to the previous year. Following a sharp decline of 52.82% in 2020, there was another substantial increase of 84.95% in the subsequent year, 2021. In the final year of the study, 2024, bare land in Depok City accounted for 1.52% of the total land cover. Bare land cover change trends can be seen in Figure 5(b).

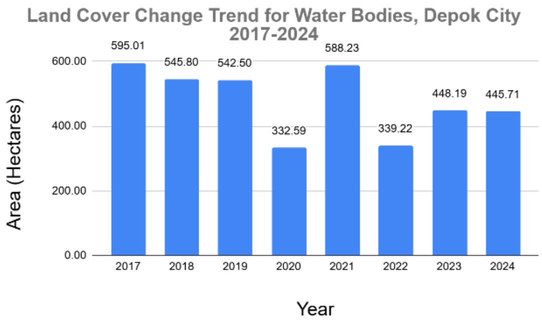

Figure 6. Water Body Land Cover Change Trends

For the water body category, this land cover type shows a decreasing trend when comparing 2024 to 2017, with a 25.09% reduction from its 2017 extent. Over this period, there were two instances of increase: in 2021, where an expansion of 76.86% occurred, and in 2023, with an increase of 32.12% compared to the previous year. In 2024, the area of water bodies in Depok City constituted 2.22% of the total land cover.

Land Cover Analysis Model Validation

A confusion matrix is generated based on the comparison of ground truth data with 2024 land cover analysis map.

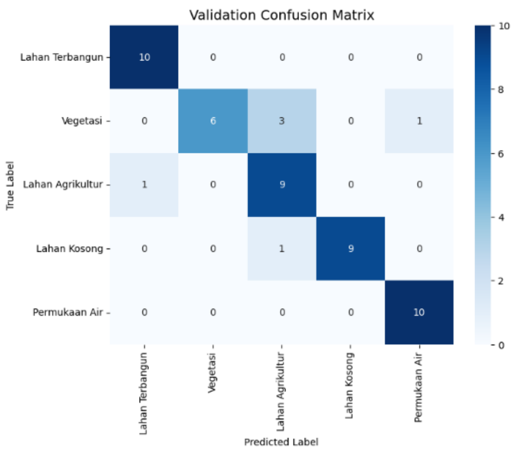

Figure 7. Confusion Matrix

According to *Peraturan BIG Nomor 15 Tahun 2014*, the accuracy of Land Cover map (Figure 7) is assesed using overall accuracy metric obtained from confusion matrix, that is, the percentage of the diagonal of the matrix compared to the whole data sample. It is calculated as follows;

$$Overall\ Accuracy = \frac{10 + 6 + 9 + 9 + 10}{50} = 0.88$$

The value of Overall accuracy is 0.88 and meets the minimum value described in the law product, which states the minimum value of overall accuracy to be 85% or 0.85. This number, is generally lower than previous studies which consistently scores aboves 90% by using Landsat-8 Imageries, and can be attributed to more complexity of processing due to a higher resolution by three-fold, as in Sentinel-2's own 10-meter resolution.

Land Cover Prediction for year 2042

The land cover prediction for the year 2042 was performed using a Cellular Automata-Markov Chain simulation. This study incorporated three driving factors: distance from major roads, distance from healthcare facilities, and distance from educational facilities. To prepare these factors, the coordinates of the facilities were collected and each was converted into a raster. In these rasters, the pixel values represent the distance in meters from that pixel to the nearest Point of Interest (POI), with the visualization provided in figure 8. After all driving factors are processed, the Artificial Neural Network model generates the prediction map for the land cover conditions in 2042 (Figure 9).

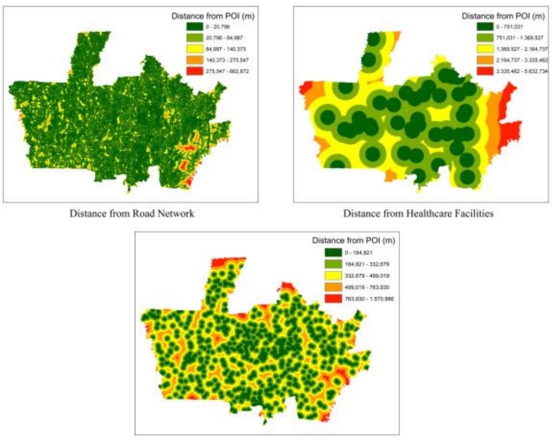

Figure 8. Driving Factors Distance Visualization

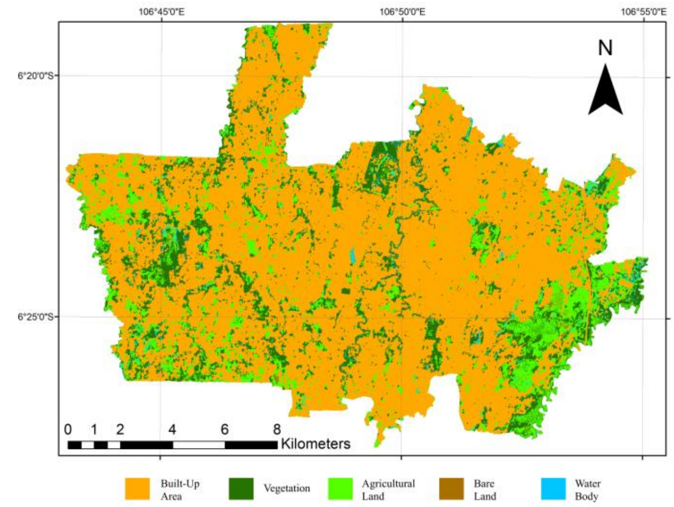

Figure 9. Land Cover Prediction Map

Table 5. Land Cover Prediction Areas in hectares

Category	Area (Ha)
Built-Up Land	14509.82
Vegetation	2523.86
Agricultural Land	2527.75
Bare Land	193.90
Water Bodies	204.26

In this land cover map, it can be observed that agricultural land distribution is scattered throughout the city, with some clustering visible, prominently in the southeastern part of the city. evenly . Vegetation can be seen along the western and eastern borders of Depok City, while a very small amount of bare land is also visible in the eastern part of the city. Built-up land is the most extensive land cover category, which is consistent with its proportion on the land cover maps from 2017 to 2024. When compared to the land cover conditions in 2024, there is a 7,35% expansion in the built-up land category, and 128,44% expansion in Vegetation. Conversely, the agricultural land, bare land, and water body categories experienced reductions of 45,33%, 54,36%, and 33,94%, respectively. Land Cover Prediction Areas in hectares explained in Table 5.

Comparisons with Depok Spatial Plan for 2042

The regulations concerning the Depok City Spatial Plan (RTRW 2022-2042) are outlined in Peraturan Daerah Nomor 9 Tahun 2022, which covers the period from 2022 to 2042. This regulation details the planned division of areas and their corresponding sizes in hectares. Several of these planned areas were then matched to the land cover categories used in this study, as shown in the following table 6;

Table 6. Land Cover Categorization based on regulation

No	Area Categorization (*Peraturan Daerah No 9 Tahun 2022*)	Area (Ha)	Land Cover
1	Water Bodies	248	Water Bodies
2	Local Protected Area	553	Vegetation
3	Green Open Area	842	Vegetation
4	Conservation Area	7	Vegetation
5	Road Shoulder	170	Built Up Area
6	Agricultural Areas	69	Agricultural Area
7	Sustainable Food Agriculture Area	5.84	Agricultural Area
8	Fishing Area	15	Water Bodies
9	Industrial Area	341	Built Up Area
10	Settlement Area	16015	Built Up Area
11	Trade and Services Area	1495	Built Up Area
12	Office Area	19	Built Up Area
13	Defense and Security Area	209	Built Up Area
14	Transportation Area	6	Built Up Area
	Total	19994.84	

Based on the division of these planned areas, the total area for each land cover category is as shown in Table 7 below:

Table 7. RTRW Final Categorization Result

Category	Area (Ha)
Built-Up Land	18255
Vegetation	1402
Agricultural Land	74.84
Bare Land	0
Water Bodies	263

The difference between two aspect is visualized in figure 10, where the closer the meeting between two data in the middle, the closer the difference.

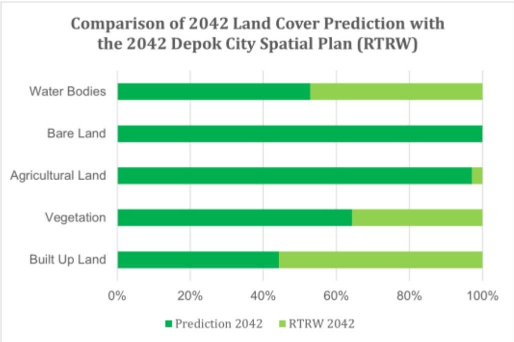

Figure 10. Prediction Comparison with Spatial Plans

The predicted area for built-up land is smaller than what is outlined in the RTRW 2022-2042 plan. Conversely, the predicted areas for vegetation and agricultural land are larger than the RTRW's figures, with agricultural land showing a particularly significant difference. This is because the RTRW's categorization of agricultural land refers specifically to horticultural areas scattered across western Depok, which contrasts with the prediction map where agricultural areas are more widely distributed, especially in the eastern part of the city. Meanwhile, the water body category shows the closest match between the prediction and the RTRW. Since the RTRW does not have a specific definition for bare land, no comparison could be made for this category.

Conclusions

Land Cover Analysis for Depok City from 2017-2024 using Extreme Gradient Boosting reveals the trends of land cover change over the course of 8 years, where 7,35% expansion in the built-up land category, and 128,44% expansion in Vegetation observed. Conversely, the agricultural land, bare land, and water body categories experienced reductions of 45,33%, 54,36%, and 33,94%, respectively in 2024, compared to 2017 conditions. This land cover analysis model is validated by means of overall accuracy score, which yielded a score of 0.88, which is well within the thresholds of Peraturan BIG No 15 Tahun 2014.

Simulation of Depok City future Land Cover condition in 2042 is completed with distance from road network, healthcare facilities and educational facilities introduced as driving factors. Comparing this results with land cover conditions in 2024 that are based from the previous data processing, reveals a predicted expansion of Built-Up land and Vegetation land cover categories, while other land cover categories such as agricultural land, bare land, and water bodies are predicted to decrease in 2042. This results are then compared with Depok Spatial Plan 2042 (RTRW 2042) that are based on Peraturan Daerah Nomor 9 Tahun 2022. The result shown that predicted area for built-up land is smaller than what is outlined in the RTRW 2042 plan. Predicted areas for vegetation and agricultural land are larger than the RTRW's figures, with agricultural land showing a significant difference. Water body category shows the closest match between the prediction and the RTRW. This comparison should not be taken as a measure of the accuracy of the prediction results or the validity of the Depok City Spatial Plan 2022-2042.

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