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Land Change Modeler For Evaluating Urbanization Driven By Universities In The Periurban Area Of Yogyakarta City, Indonesia

Yogyakarta City and its peri urban areas have experienced a rapid land cover change in the last two decades from non-urban to urban areas. Understanding the driving factors and their level of influence will facilitate well-informed decisions in planning sustainable urbanization. This study formulated a hypothesis that the area hosting a university is most likely to have higher urban area and urbanization rate and verified it by using a land change model (LCM). The LCM which implemented a multi-layer perceptron algorithm using LANDSAT 5 TM in 1999 and 2005 successfully produced a robust land change model with accuracy rate of 81.24% and model's skill measure 0.6248, and predicted the urban area in 2030, 2040, and 2050. The urban area between LCM and Statistics Indonesia showed strong positive correlation with R^2 values of 0.73 and 0.83 in 2005 and 2010 to validate the model. The model showed that urbanization in Yogyakarta city was prominently triggered by the density of universities. Furthermore, a quantitative analysis on urban area percentage, urbanization rate and number of universities in each district corroborated the presence of universities has boosted the urbanization rate in the host and neighboring districts. The findings have guided local government not only to implement policies into actions pertain to educational area development strategies but also to address the potential sustainability issues affected by those implementations.

Keywords

Land Change Modeler, urbanization, LANDSAT-5 TM, Yogyakarta, university

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INTRODUCTION

Urbanization that involves a complex interaction of socio-economic development and population increase is the significant and urgent issue of sustainable development in the world. The United Nations (UN) projected that urban areas will be occupied by 68% of the world's population by 2050, mostly by urban dwellers in Africa and Asia (United Nations, Department of Economic and Social Affairs, Population Division 2019). Urbanization greatly contributes to economic development as more than 80% of global gross domestic product (GDP) is generated in cities (Baeumler et al. 2021). However, the GDP value does not measure any environmental issues due to consumption and production patterns (Munier 2005). Economic growth comes at the expense of high energy and natural resource consumption (Baeumler et al. 2021) and an upsurge in greenhouse gas emissions (Shahbaz et al. 2014). With limited earth carrying capacity, sustainable development is jeopardized, especially in countries that cannot afford the conservational cost of their natural surroundings (Capps et al. 2016). Therefore, it is urgent to balance socio-economic growth with environmental protection (Turok and McGranahan 2013). Initiated in Rio de Janeiro in 2012, the UN has been working to set goals and targets to reach this equilibrium called Sustainable Development Goals (SDGs) globally to provide better frameworks to assess sustainability (United Nations n.d.). As two-thirds of the world's population lives in urban areas, cities and towns wield the potential to determine global sustainability (Zinkernagel et al. 2018; Wiedmann and Allen 2021). Goal 11 target number 3 in particular has mentioned that sustainable urbanization of all nations shall be achieved by 2030 (United Nations n.d.).

There is no universal impetus for urbanization. Despite similar findings on urbanization drivers from previous studies, their level of influence was distinctive due to infrastructure and institutional settings (Thapa 2009; Turok and McGranahan 2013). Understanding the driving factors and their level of influence will facilitate well-informed decisions in planning (and/or managing) sustainable urbanization. Kim et al. (2020), classified the driving factors into the natural environment, built environment, socio-economic, and others. However, Li et al. (2020) simplified the classification into geographic environmental factors for the first category and anthropogenic factors for the latter three categories. Geographic environmental factors are biophysical elements, such as topography, slope, distance to natural resources, and land surface temperature, whereas anthropogenic factors are human-induced elements, such as plans and policies, population density, GDP, job opportunity, distance to transportation elements, and distance to land use types (Kim et al. 2020; Li et al. 2020). Anthropogenic factors are broadly recognized as key drivers of urbanization, such as GDP value (Lin et al. 2018), foreign investment (Gurskiene et al. 2019), employment opportunities (Mlambo 2018; Waseem and Talpur 2021), availability of facilities for economic development and road infrastructure (Hasan et al. 2020; Peng et al. 2021), accessibility to public facilities (Wang et al. 2021; Waseem and Talpur 2021), political powers (Tripathi and Rani 2018), existence of a royal palace (Liu et al. 2014), electricity (Tripathi and Rani 2018), and number of educational facilities per population (Tripathi and Rani 2018; Kim et al. 2020). Although these dynamic anthropogenic factors work as the direct drivers of urbanization, geographic environmental factors also contribute as regulators that proliferate the influence of the direct drivers.

The presence of colleges and universities is the impetus for economic growth and shapes the dynamics of the society in its vicinity. Academic-related activities generate prominent economic growth for the host city (Dyason and Kleynhans 2017) as students do not only need quality education but also a livable neighborhood (Insch and Sun 2013) and leisure spots (Zasina 2020). Den Heijer and Magdaniel (2018) found that the location of university in relation to its host city is very important to determine the functional relationship of city-university. The closer location of a university to its host city, the more likely it is able to share functional features with the host city such as education and research (e.g., museums and libraries), housing for the migrant students, retail and leisure (e.g., photocopy and printing center, café and restaurants, shopping malls, theatres, sports center, bookstores, and laundries), and campus infrastructure (e.g., accessibility by public transportation, parking area, and public parks). Thus, they are potential factors for establishing a vigorous urban area (Baltzopoulos and Broström 2013; den Heijer and Magdaniel 2018; Kim et al. 2020). Many European cities economically benefited from the existence of several famous universities in the area despite various challenges to deal with (Russo et al. 2003; Baltzopoulos and Broström 2013; Magdaniel 2013; Miessner 2021). Universities in the US have been part of urban revitalization since the 1960s but the success depended on the institutions adapting to the local urban setting (Melhuish 2016; Soo 2010). United States Environmental Protection Agency (US EPA) (2021) mentions that universities play significant roles in development, such as shaping the land use, passing on empirical knowledge of development patterns to the inhabitants, and offering professional assistance to society and planners. Nowadays, the relationship between universities and urban development has grown more complicated. Spatially, a university can be located in one city but its influences and services affect larger areas beyond administrative borders (Liu 2019), as in the case of National Kentucky University and Portland State University (Soo 2010). Recently, Asian cities have become conscious of the important roles of universities in urbanization and have investigated the potential of mutual relationships between universities and the city's growth, such as in Vietnam (Ngo and Trinh 2016) and Japan (Mohammed and Ukai 2021). University areas with open gates are more likely to have potential contributions to urban growth (Mohammed and Ukai 2021). Also, accessibility to public facilities and institutions are determinants for future development (Kim et al. 2020), and high quality schools (Kim et al. 2020) such as universities can be the attractors of development. With the flexibility in the structure of university institutions (e.g., virtual universities, franchise universities, international cooperation universities, and branch campuses) (Liu 2019), greater opportunities are wide open to investigate distinctive mutual engagement of university and urban development to manifest sustainable urbanization.

The availability of remotely-sensed data in medium spatial resolution and Geographic Information System (GIS) software has fostered studies on land use/land cover (LULC) change using post-classification comparison method (Alqurashi and Kumar 2013) in developed and developing countries worldwide, such as in Egypt (Abd El-Kawy et al. 2011; Shalaby and Tateishi 2007), Bangladesh (Dewan and Yamaguchi 2009), United Arab Emirates (Issa and Saleous 2019), Indonesia (Saifullah et al. 2017; Letsoin et al. 2020), Nepal (Wang et al. 2020), and Pakistan (Al-Rashid et al. 2021). Furthermore, the development of machine learning algorithms (MLA) in data science has simplified studies on land use and earth observation since they can be executed with minimum human supervision (Tan et al. 2021). The multifaceted interaction among spatiotemporal dimensions of environmental and human activities can be well-simulated using MLA-navigated computer modeling (Agarwal et al. 2002). The model's complexity and computing time depend on the study objective, geographical features, and existing data of the study area. However, there are limited built LULC models in the public domain (van Soesbergen 2016; Kim et al. 2020). Notably, an effective model should be lucid, robust, and data-feasible with a proper spatial resolution (Agarwal et al. 2002). Although it will

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not provide an instant solution to the problem, the LULC change model serves as a tool to understand the influencing factors of the LULC change, so that well-informed decisions can be made for sustainable urban development (Agarwal et al. 2002).

According to the UN World Urbanization Prospects 2018, the proportion of urban population in Southeast Asian countries is comparatively low, but the rate of urban expansion in is very high in the last two decades due to the shifting employment sectors from agriculture to service- and industry-oriented economy (Das and Paul 2021; Jones 2002). Moreover, distinctively urban population in Southeast Asia is not only living in mega cities such as Jakarta and Manila, but also in small to medium-sized cities that prominently support the region’s gross domestic product (GDP) during both the Asian economic crisis in 1997-1998 and the global financial crisis in 2008-2009 (Dahiya 2014). Despite similar trend of shifting employment sectors, each city has different functions and economic drivers. Yogyakarta is a rising secondary city in Indonesia whose socio-economic growth is enhanced by the investment to and return from cultural and academic activities, especially at the higher education level, in contrast with Jakarta, the center of politics and industry. One notable university in Yogyakarta is University of Gadjah Mada (UGM) that was established in 1949 and rapidly recognized regionally and internationally in 1960s that triggered the development of higher education institutions (HEIs) not only in Yogyakarta as the host city but also in Indonesia and South East Asia (Jokow 2020; Universitas Gadjah Mada 2019). In 2010, the expenditure of UGM alone had a contribution of 26.88% from the total GDP in its host region.

In order to understand the significant factors of urbanization in Yogyakarta City, Indonesia and its peri-urban area especially the influence of universities as the city’s specific feature, this study formulates a hypothesis that the area hosting a university will be likely more urbanized and having higher urbanization rate than that which is not hosting a university. To verify the hypothesis, we built and validated a land change model by geographic environmental factors using multitemporal satellite images and a MLA based classifier, and then analyzed the influence of universities on urbanization based on the valid predictions of districts in the area.

MATERIALS AND METHODS

Area of Interest

Located in 7° 47' S in latitude and 110° 22" E in longitude, Yogyakarta City covers 32.5 sq. km area in the epicenter of Yogyakarta Special Region (DIY) (www.LatLong.net n.d.). The city is located at an altitude between 100 and 120 m in the basin of mount Merapi’s south foot slope. It is surrounded by four other municipalities in the province, namely, Sleman (574.82 sq. km), Bantul (508.13 sq. km), Gunung Kidul (1431.42 sq. km), and Kulon Progo (586.28 sq. km) in cardinal points order. The area has a tropical climate with an annual temperature range from 20°C–30°C (Statistics Indonesia 2019; climate-data.org n.d). Rain falls monthly, but the highest is between November and April with an average annual precipitation of 2681 mm (climate-data.org n.d.). The total population of the province is 3,668,719 with only 10,18% living in Yogyakarta City. The highest percentage of the population stays in Sleman (30.69%) followed by Bantul (26.87%).

Yogyakarta City originated as the sultan palace of the Mataram Kingdom in 1755, one erudite monarchy of Java Island (Yunus 1991). It was legitimately united with the Republic of Indonesia as Yogyakarta Special Region (DIY Province) in 1945 (Statistics Indonesia 2019). Land development in DI Yogyakarta was influenced by the ancient Javanese philosophy on the imaginary linear axis from north to south with the sultan palace in the middle facing mount Merapi in the north and having its back to the Hindian Ocean to the south (Huriati 2008; Yunus 1991). From this axis, the south suburb was determined for the cultural development concerning historical inheritances of Mataram Kingdom and preserving the productive agricultural land, whereas the north suburb was determined for modernity with the University of Gadjah Mada (est.1949) as the center (Yunus 1991). The sprawled urbanization considerably occurred between 1997 and 2002 in the suburb areas (Divigalpitiya and Handayani 2015; Giyarsih 2001). Subsequently, from 2002–2013, the trend of urbanization shifted to densification, occupying any available vegetational land within the city and the suburbanized area (Divigalpitiya and Handayani 2015). Agricultural lands as much as 9.22 sq. km in Sleman and 18.89 sq. km in Bantul were lost in that they were predominantly converted to housing (Sudirman et al. 2010; Eko and Rahayu 2012; Susilo 2017).

Today, Yogyakarta is experiencing massive uncontrolled changes from vegetational land to urban use that put pressure on its society and environment over the last two decades, such as threatening food sovereignty (Bezlepkina et al. 2011; König et al. 2010; Sudirman et al. 2010), decrease in water reserves and infiltration areas (Sutanto et al. 2015), increased annual runoff (Prasena and Shrestha 2013), and water pollution due to uncontrolled waste management (Bezlepkina et al. 2011). As the adverse effects to the environmental are broadened to the wider suburbs area of Yogyakarta City, the study of current condition of driving factors to urbanization is urgently needed to facilitate the well-informed decisions for sustainable urbanization. To support this, this study aims to project the future LULC change of Yogyakarta City and its wider surroundings as well as to understand the underlying change drivers by examining the influence of factors that drive urbanization using a land use/land cover change modeling tools and analyzing to what extent the driving factors affect urbanization in the study area.

In particular, the area of interest in this study is a part of KARTAMANTUL (e.g., Yogyakarta, Sleman, and Bantul) region. KARTAMANTUL is the urban agglomeration area of Yogyakarta City which is hydro-geologically connected (see Figure 1) and managed by intra-governmental institution namely the Joint Secretariate of Kartamantul for the development of environmental-related facilities and urban infrastructures (Aryantie and Hidayat 2019; Prameswari et al. 2014; Sadono et al. 2018).

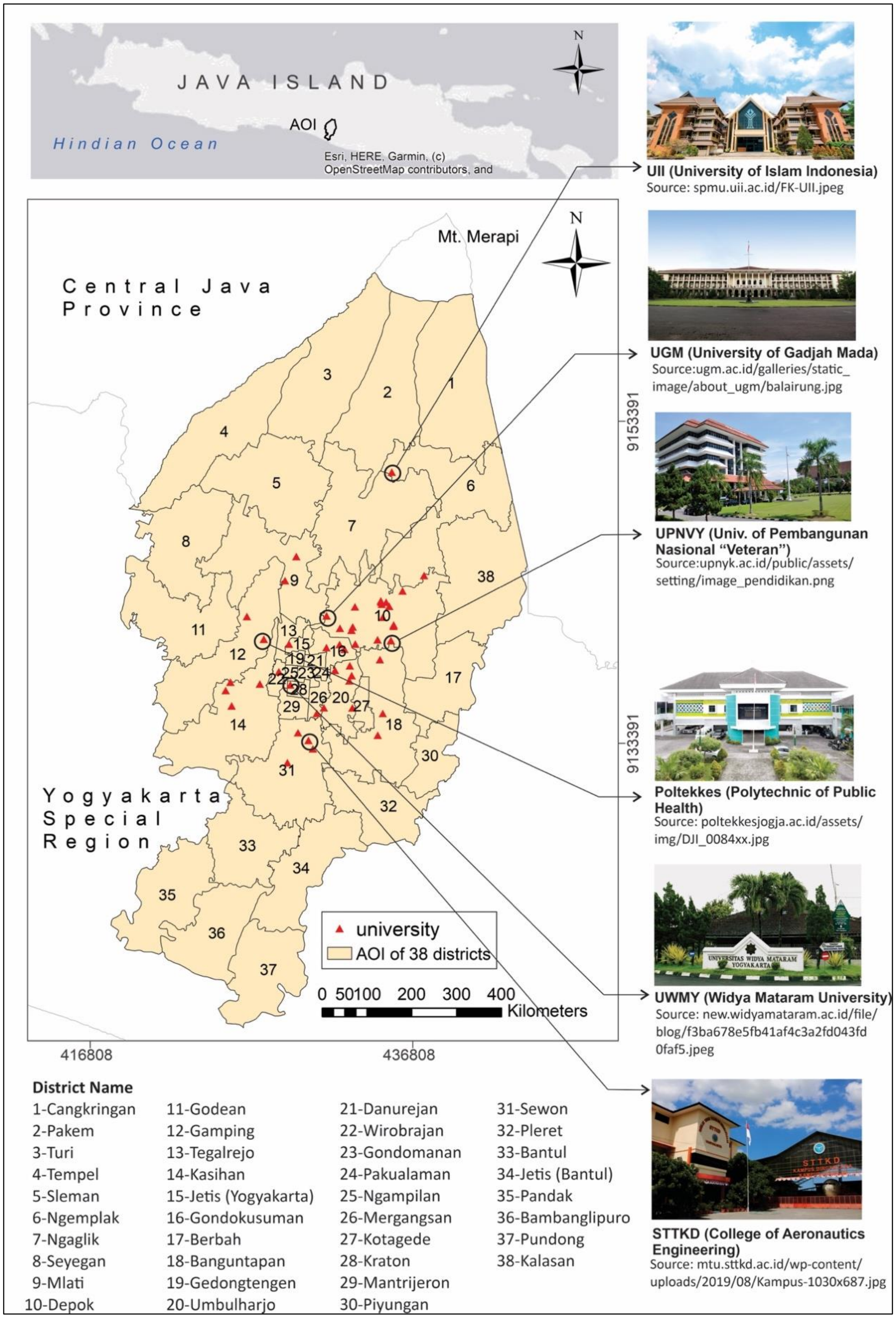

Figure 1. Location of the area of interest (AOI) in Java Island, Indonesia in the upper panel, and AOI of 38 districts with the location of universities in the lower panel

Land Cover Maps

Figure 2 shows the flow diagram of analysis in this study. It mainly consisted of two parts; land cover maps and land change modeling.

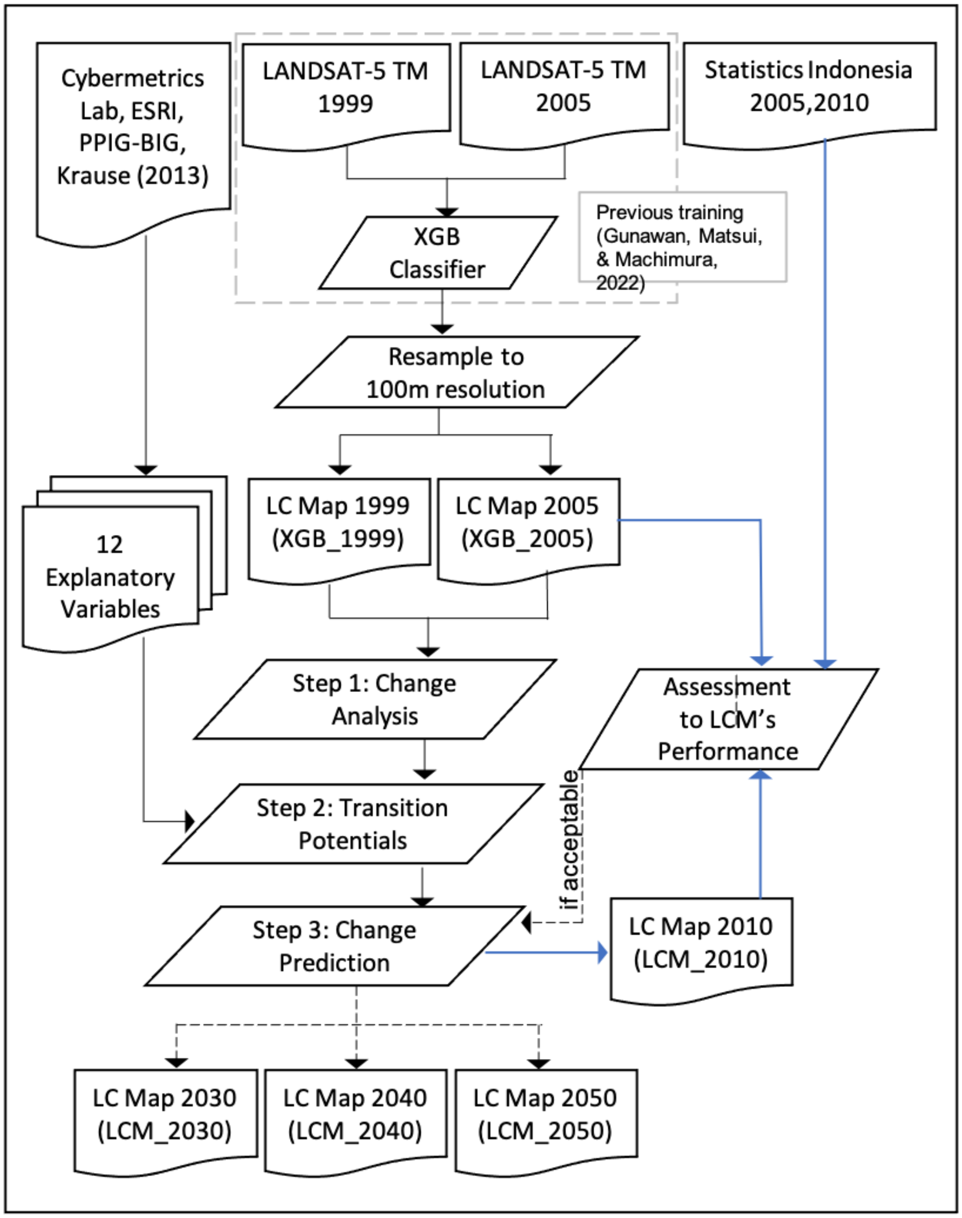

Figure 2. The flow diagram of methodology

Two years of land cover (LC) maps in 1999 and 2005 were prepared for use in the land change analysis. They were from our previous study (Gunawan et al. 2022) which classified the study area into two LC classes, namely, non-urban (NU) and urban (U) using LANDSAT-5/TM images. The classifier utilized XGBoost algorithm, input the 4 spectral bands (visible bands of 2 and 3, NIR band 4, and SWIR band 5) of an image in 30 m resolution at path/row: 120/65 acquired on 26 July 2005, and was trained by a reference LC map from Regional Planning and

Development Agency of Yogyakarta Province (Gunawan et al. 2022). The overall accuracy and AUC-ROC were 0.76 and 0.83, respectively. Because no other reference LC map was available, the classifier trained in 2005 was used to obtain the LC map in 1999 by inputting a LANDSAT-5/TM image acquired on 6 September 1999.The LC maps in 1999 and 2005 (XGB_1999 and XGB_2005, see Figure 3) were resampled into 100 m resolution (hereafter, LC_99 and LC_05).

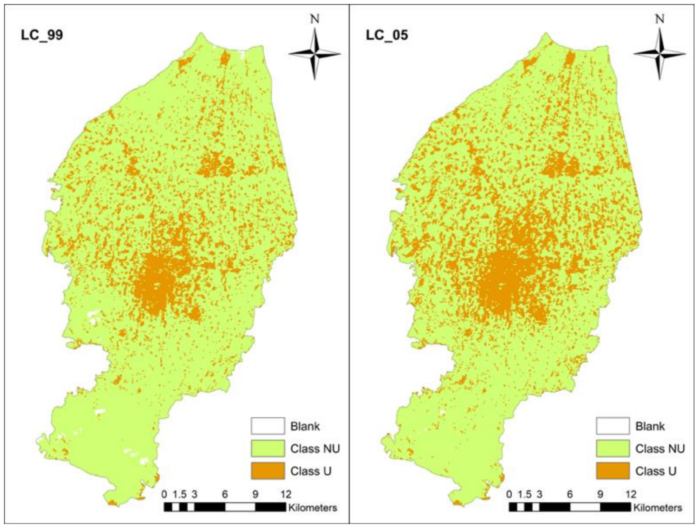

Figure 3. Land cover maps in 1999 and 2005 with non-urban (NU) and urban (U) classes predicted by XGB-Classifier from previous study (Gunawan et al. 2022) and resampled into 100m resolution for this study.

Land Cover Change Modeling

The land cover change modeling in this study was facilitated with Land Change Modeler (LCM) software, a convenient tool for predicting the land cover change using the simulation of two sequential periods of landcover maps. The scopes of urban study with LCM are urban growth (Mishra et al. 2014; Hasan et al. 2020; Jande et al. 2020), future prediction simulation (Megahed et al. 2015; Kumar et al. 2015; Iizuka et al. 2017; Jain et al. 2017), and growth impacts on the environment (Hamad et al. 2018; Shade and Kremer 2019; Leta et al. 2021).

LCM is embedded in the TerrSet software by Clark Labs with subsequent applications to analyze LULC change, simulate the complex relationships to explanatory variables, and assess plausible future change scenarios (van Soesbergen 2016; Mishra et al. 2014). It is a powerful tool since it adopts artificial neural networks (ANN) and Markov-chain for modeling computation (Eastman 2020a; Iizuka et al. 2017). ANN is one pungent MLA for detecting LULC changes since it can suggest change trends and produce a matrix of changes (Alqurashi and Kumar 2013). Markov-chain is a very well-known method for studying change probabilities of LULC dynamics at distinctive states so that change trends are recognized and future change can be estimated (Kityuttachai et al. 2013; Kumar et al. 2014; Zheng et al. 2015).

Step 1: Land Cover Change Analysis

The land cover change is estimated from two consecutive periods on the landcover maps. In this study, the change was calculated from 1999 to 2005 using the prepared data of LC_99 and LC_05 in 100m spatial resolution, as the input for earlier and later LC map in change analysis, respectively, to get information on gains and losses of change during that period of class U and class NU. The gains and losses of change can be presented on a map.

Step 2: Transition Potentials of Land Cover

The second step was transition potential calculation, where the sub-model structure and modeling operation were set up. The model structure was built with an emphasis on change from class NU to class U to meet the trend of urbanization in the study area. Multilayer Perceptron (MLP) neural network was selected to simulate the sub-modeling as the algorithm is powerful to deal with the non-linear correlations. The automatic training and the dynamic learning rate mode were activated in the hyperparameters training. Optimization of hyperparameters was executed by re-training the model with random combination of testing the sample size per class ranged from 50% to 100% of the minimum cell that transitioned from 1999 to 2005 calculated by the model, testing the momentum factor ranged from 0.5 to 0.7, testing the hidden layer nodes ranged from 1 to 12 as the number of explanatory variables used in the model, testing the iteration ranged from the default 10000 to 1000000 times, and let the other parameters set by the model's default. At the end of the iteration, the MLP training automatically produced model performance statistics in terms of accuracy rate and skill measure.

Twelve explanatory variables of potential urbanization drivers were selected for test simulation in this study. These variables for evaluating the sub-model were determined using previous studies of potential drivers of urbanization in Yogyakarta City that were corroborated with other studies from around the globe. Moreover, Cramer's V analysis was employed to assess the correlation of each variable to the model without explaining its degree of influence. Most variables revealed the Cramer's V value that indicated strong and very strong associations with the model (Akoglu 2018). This showed that the selection of potential explanatory variables was trustworthy. The variables were (1) evidence likelihood of LC_99; (2) elevation; (3) slope; (4) distance from CBDs; (5) distance from the university; (6) distance from the historical site; (7) distance from the urban area of LC_99; (8) distance from the municipality; (9) road density; (10) university density; (11) CBD density; (12) distance from the road. All variables were considered static which was assumed that they do not change over time. The complete datasets of explanatory variables are presented in Table 1, followed by the Cramer's V value for each variable in Table 2.

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Table 1. List of explanatory variables used in the transition potential model trained with multi-layer perceptron (MLP) with the unit, data source and reference.

No	Explanatory Variables	Unit	Data Source	Reference
1	Dummy variable for transformation of land cover category to numerical value (e.g., evidence likelihood)		LC_99 (raster)	(Eastman 2020b; Gunawan et al. 2022)
2	Elevation	m-asl	DEM Nasional (raster)	PPIG-BIG n.d.
3	Slope	degree	DEM Nasional (raster)	PPIG-BIG n.d.
4	Distance to commercial area	m	RBI map (shapefile)	PPIG-BIG n.d.
5	Distance to university	m	webometrics	Cybermetrics Lab n.d.
6	Distance to historical site	m	RBI map (shapefile)	PPIG-BIG n.d.
7	Distance to urban area in LC_99	m	LC_99 (raster)	(Gunawan et al. 2022)
8	Distance to governmental office area	m	RBI map (shapefile)	PPIG-BIG n.d.
9	Kernel density of road*)	m of road/sqkm of area	RBI map (shapefile)	PPIG-BIG n.d.; Krause 2013; ESRI n.d.
10	Kernel density of university*)	expected count/sqkm of land	webometrics	Cybermetrics Lab n.d.; Krause 2013; ESRI n.d.
11	Kernel density of commercial area*)	expected count/sqkm of land	RBI map (shapefile)	PPIG-BIG n.d.; Krause 2013; ESRI n.d.
12	Distance to road	m	RBI map (shapefile)	PPIG-BIG n.d.

Notes *): Search radius (bandwidth) is computed specifically to the input dataset using a spatial variant of Silverman's Rule of Thumb that is robust to spatial outliers (that is, points that are far away from the rest of the points).

Table 2. The Cramer's V value for each explanatory variable and its interpretation of association from Akoglu (2018).

Explanatory Variables	Cramer's V Value *)	Interpretation of Association
Evidence likelihood	0.6885	Very Strong
Distance to disturbance 99	0.3854	Very Strong
Road density	0.2750	Very Strong
Distance to historic site	0.2649	Very Strong
Historic site density	0.2504	Very Strong
Distance to university	0.2412	Strong
Elevation	0.2345	Strong
University density	0.2328	Strong
CBD density	0.2306	Strong
Distance to urban center	0.1837	Strong
Distance to road	0.1668	Strong
Distance to CBD	0.1040	Moderate
Slope	0.0873	Weak

Notes *): Cramer's V value interpretation = > 0.25 is Very strong; > 0.15 is Strong; > 0.10 is Moderate; > 0.05 is Weak; > 0 is No or very weak (Akoglu 2018)

Step 3: Change Prediction

The extent of change in transition potentials was used to generate future land cover change projection using the transition probability matrix by Markov-chain analysis involving the selected explanatory variables (Eastman 2020a). The change prediction module of the LCM can facilitate the integration of several dynamic variables, however, due to limited land development data and information (Firman 2004), this study did not incorporate any dynamic variables to the future change prediction. To observe the current trend of urbanization in the study area, future prediction dates are determined with Business-as-Usual scenario using the default transition probability matrix without any modification in the years 2030, 2040, and 2050. As there are no reference LC maps available to validate the predicted LC change, we calculated the predicted urban areas of 38 districts and compared with those values from land use data of Statistics Indonesia in 2005 and 2010.

RESULTS

Land Cover Change Analysis from 1999 to 2005

The change analysis calculation from LCM revealed that the total gain and loss of urban land between 1999 and 2005 were 5077 ha (28.65 %) and 2010 ha (11.34 %), respectively, with a net urban gain of 3067 ha (17.30 %) due to the loss of a similar size of the NU land. Generally, the land cover (LC) change between 1999 and 2005 showed that the urban classes were mostly spread out in the suburbs with their high persistence within the city area, as shown in Figure 4.

The statistical figure of gain and loss, including the persistence quantity of class U, according to the region from 1999–2005 was presented in Table 3. Table 3 confirmed that Yogyakarta city has the highest persistence quantity of class U with a record of 86.29%, followed by the north suburb (Sleman) and south suburb (Bantul) at 60.20% and 33.57%, respectively. Class U gain was highest in the north suburb at 50.47% with a 9.42% loss, whereas the gain of class U in the city was 12.78% with a loss of 2.68%. This indicates that the trend of urbanization in Yogyakarta City from 1999–2005 was shifting to the north suburb.

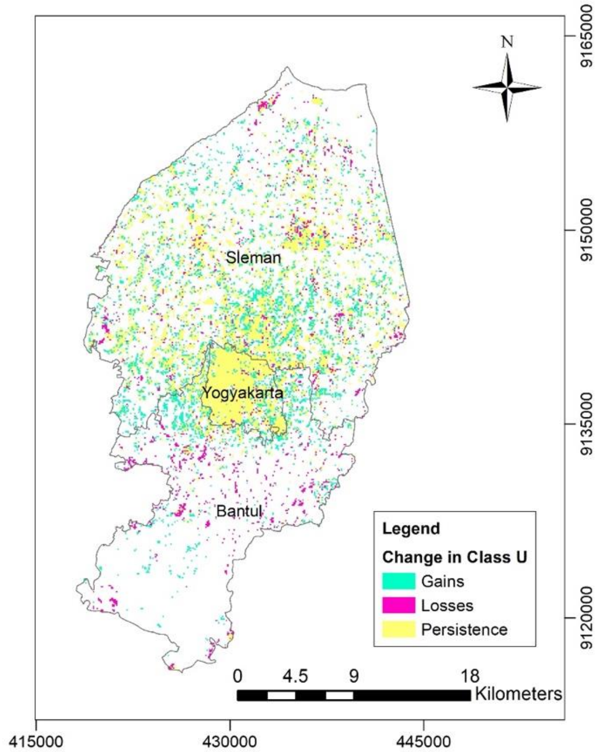

Figure 4. Change map of class U from 1999 to 2005 in the area of interest.

Table 3. Gains (G), losses (L), and persistence (P) in class U from 1999 to 2005 of the regions in the area of interest in pixel, hectare (ha) and percent (%) unit.

Region	Gain (G), Loss(L), and Persistence (P) in Class U from 1999 to 2005								
	G	L	P	G	L	P	G	L	P
	(in pixel)			(in ha)			(in %)		
Sleman	3,688	1,143	7,308	3688	1143	7308	50.47	9.42	60.20
Yogyakarta	304	74	2,379	304	74	2379	12.78	2.68	86.29
Bantul	1,085	793	949	1085	793	949	38.38	28.05	33.57

Analysis of Transition Model 'NU to Urban' Scenario

Model's Performance

LCM model was trained using an MLP neural network with a sample size per class of 5125 cells. Most parameters in the MLP were set to optimize the training operation. The model could automatically modify the dynamic learning rate (Eastman 2020a). The MLP training produced an accuracy rate of 81.24% with the model's skill measure of 0.6248 in selected hyperparameters. The information on hyperparameters in the MLP training is presented in Table 4.

Table 4. Hyperparameters and their value and unit in multi-layers perceptron training.

Hyperparameters	Parameter Value	Unit
Input layer	12	neurons
Hidden layer	7	neurons
Output layer	2	neurons/nodes
Requested samples per class	5124	pixel/cell
Final learning rate	0.0003	step size
Momentum factor	0.5	-
Sigmoid constant	1	-
Acceptable RMS	0.01	-
Iterations	10000	times

Determining Explanatory Variables

The most important result of MLP training, which is also the final process, is the backward stepwise constant forcing statistic. It revealed the potential influencing driving forces out of the 12 selected urbanization variables. The statistics showed each variable's degree of influence on the model. Notably, the model with all 12 variables has the optimum accuracy of 81.24% with a skill measure of 0.6248 that will be selected for LC projection in the study area. The model's accuracy dropped from 81.05% to 80.85% when the university density variable (variable no.10) was omitted. This showed that university density was the critical variable in the NU to urban transition model. The comprehensive result of backward stepwise constant forcing statistics was presented in Table 5.

Table 5. The result of the backward stepwise constant forcing statistics from the MLP indicates the relationship of each explanatory variable to the model's accuracy in percent (%) and the model's skill measure level.

Variables Included	Accuracy (%)	Skill Measure
All variables	81.24	0.6248
[1,2,4,5,6,7,8,9,10,11,12]	81.34	0.6268
[1,2,4,5,6,7,8,9,10,12]	81.42	0.6283
[2,4,5,6,7,8,9,10,12]	81.42	0.6283
[2,4,5,6,7,8,9,10]	81.40	0.6280
[2,4,5,6,7,8,10]	81.05	0.6209
[2,4,5,6,7,8]	80.85	0.6170
[2,5,6,7,8]	80.71	0.6143
[2,5,6,7]	80.27	0.6053
[2,6,7]	79.48	0.5897
[2,7]	79.35	0.5870
[7]	79.39	0.5877

Validity of the Predicted Land Cover Change

In order to assess the validity of predicted LC change, the predicted urban areas of 38 district were compared with that by Statistics Indonesia in 2005 and 2010 (Figure 5). Urban area in 2005 by the LCM showed good agreement with that by Statistics Indonesia in 27 districts, however was significantly smaller than Statistics Indonesia in 11 districts. This bias was not attributed to the accuracy of the XGBoost LC classifier because the reference LC map in 2005 used for the classifier training showed the similar bias from Statistics Indonesia in 2005 (Gunawan et al. 2022). The possible cause of this inconsistency between the reference LC map and Statistics Indonesia was the difference of data source of them; the reference LC map of 2005 was created from the first nation-wide built topography map of 2002 from Geospatial Information Agency (e.g., it was Badan Koordinasi Survey dan Pemetaan Nasional (BAKOSURTANAL) at that moment and changed into Badan Informasi Geospasial (BIG) in 2011) (Rais et al. 2009) whereas the urban area in Statistics Indonesia was collected from administrative data source from the village level. In the other hand, the urban area change between 2005 and 2010 (arrows in Figure 5) by the LCM was significantly smaller than that by Statistics Indonesia in some districts. This indicates that the transition potential of LCM in this study could not represent the actual urbanization progress in these districts, and therefore, is not valid in future projection.

To eliminate the districts of which urbanization progress prediction is invalid, the districts were screened by the gap between LCM and Statistics Indonesia in urban area change rate from 2005 to 2010 at the threshold of ±20%. As a result, 27 districts were valid including all 14 districts in Yogyakarta City, 9 in Sleman Regency, and 4 in Bantul Regency. The urban area of selected districts showed strong positive correlation between LCM and Statistics Indonesia with R^2 values of 0.73 and 0.83 in 2005 and 2010, respectively. Whereas, the 11 invalid districts were located in Sleman Regency (e.g., districts no. 1, 2, 3, 5, and 8) and Bantul Regency (e.g., districts no. 30, 31, 33, 34, 35, and 37), and were having weak positive correlation between LCM and Statistics Indonesia with R^2 values of 0.09 and 0.39 in 2005 and 2010, respectively. The complete statistics for LCM validation was presented in Table A1 of Appendix A, followed by a scatterplot of 2005 data validation in Figure A1.

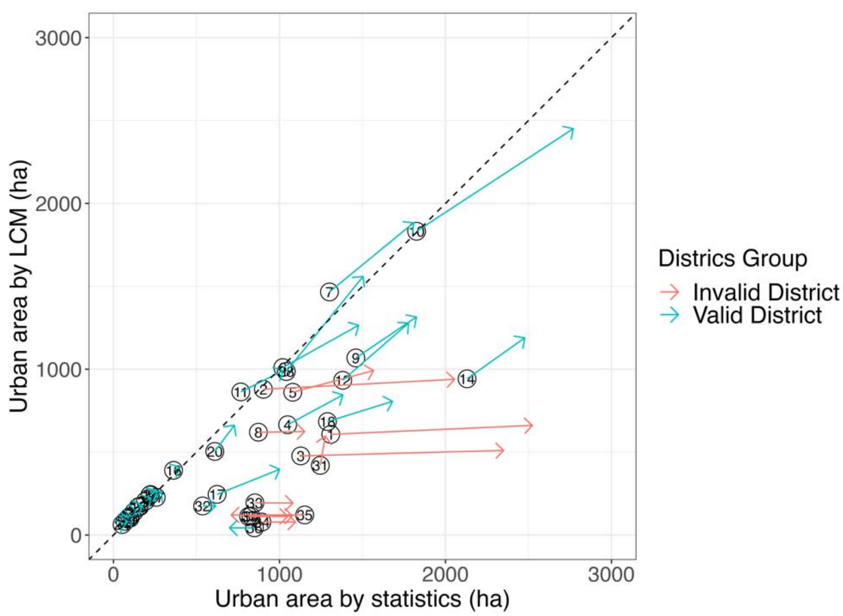

Figure 5. Urban area of districts by Statistics Indonesia and by the LCM in 2005 and 2010. Circled numbers denote urban area in 2005 whereas arrows denote urban area change from 2005 to 2010.

Future Land Cover Change Simulation

After model validation, simulation of future LULC prediction was done for the years 2030, 2040, and 2050 to conform with the decadal urban planning in the study area. The prediction trend showed steady urbanization growth in the city and its suburbs and the consequent loss of green area until 2050, as shown in Figure 6 and Table 6.

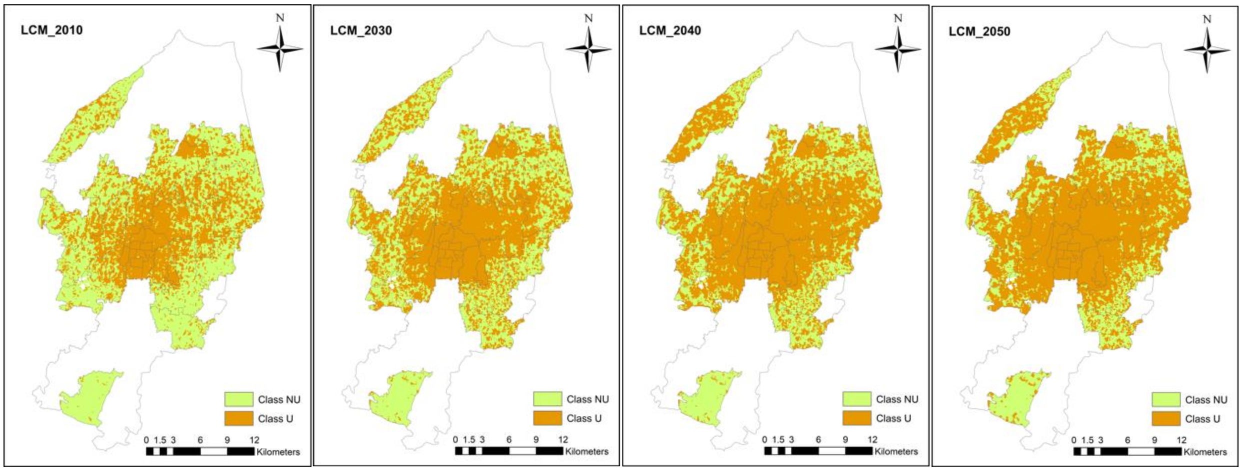

Figure 6. Maps of predicted land cover change in selected 27 districts by LCM model with MLP algorithm in 2030, 2040, and 2050

Table 6. Area of class U and NU of the regions in the area of interest in predicted years 2010, 2030, 2040, and 2050 in pixel and hectare (ha) unit.

Regency	**2010**		**2030**		**2040**		**2050**	
	U	**NU**	**U**	**NU**	**U**	**NU**	**U**	**NU**
(in pixel)								
Sleman	11,984	15,950	16,281	11,653	19,464	8,470	20,802	7,132
Yogyakarta	3,053	250	3,256	47	3,298	5	3,299	4
Bantul	2,213	7,925	4,928	5,840	5,089	5,049	5,713	4,425
(in ha)								
Sleman	11984	15950	16281	11653	19464	847	20802	7132
Yogyakarta	3053	250	3256	47	3298	0.05	3299	004
Bantul	2213	7925	4928	5840	5089	5049	5713	4425

Table 7 showed the predicted urban ratio and annual change rate. It demonstrated that by 2040, the city area was predicted to be fully saturated. Furthermore, urbanized areas in the north suburbs (Sleman Regency) were predicted to have reached 70%, whereas those in the south suburbs (Bantul Regency) were predicted to be approximately 50%. Moreover, despite the steady increase of urban ratio in each region from 2010 to 2050, the trend of the annual change rate was predicted to decrease, except for the north suburbs. The trend of change rate in the north suburb increased from the first period (2010–2030) to the second period (2030–2040), then it decreased between the second and third periods (2040–2050).

Table 7. Urban ratio and annual change rate in percent (%) of the regions in the area of interest predicted for the years 2010, 2030, 2040, and 2050.

Region	**Urban Ratio (in %)**				**Annual Change Rate (in %)**		
	2010	**2030**	**2040**	**2050**	**2010-2030**	**2030-2040**	**2040-2050**
Sleman	42.90	58.28	69.68	74.47	0.769	1.139	0.479
Yogyakarta	92.43	98.58	99.85	99.88	0.307	0.127	0.003
Bantul	21.83	42.39	50.20	56.35	1.028	0.780	0.616

DISCUSSION

This study investigated for a deeper understanding of the projection and driving force of future land cover change in Yogyakarta City and its agglomeration area, facilitated with LCM using LU maps 1999 and 2005 as early and later images, respectively. The change analysis in LCM showed a significant gain in urban land in the transition from NU to urban class between 1999 and 2005, and this change was strongly driven by the density of universities as shown from the contribution of variables (Table 5).

To assess the impact of universities on urbanization in relation with the progress level, urbanized areas percentage (UAP) in predicted 2010 LC map and urbanization rate (UR) calculated from the urban change rate during 2005 to 2010 of the selected 27 districts in regards to the number of university (NOU) existed in its area was shown in Table 8. The premise is that in addition to the positive correlation between urbanized area and urbanization rate, the district with a university will have a higher urbanized area and urbanization rate than the one without a university.

Table 8. The selected districts with their predicted urbanized area percentage (UAP) in 2010, urbanization rates (UR) during 2005-2010 period, and number of universities (NOU). The district numbers correspond to those shown in Figure 1.

District No.	District Name	UAP(%)	UR(%)	NOU
4	Tempel	25.64	5.46	4
6	Ngemplak	34.73	7.00	1
7	Ngaglik	49.18	10.89	0
9	Mlati	46.16	8.67	2
10	Depok	71.62	18.09	18
11	Godean	37.06	4.79	0
12	Gamping	43.72	11.80	3
13	Tegalrejo	91.10	8.56	0
14	Kasihan	36.93	7.67	3
15	JetisY	99.43	2.29	1
16	Gondokusuman	98.79	4.36	3
17	Berbah	23.16	8.83	0
18	Banguntapan	28.05	4.25	3
19	Gedongtengen	100.00	2.04	0
20	Umbulharjo	80.34	19.17	6
21	Danurejan	100.00	0.90	0
22	Wirobrajan	100.00	4.44	1
23	Gondomanan	97.39	8.70	0
24	Pakualaman	100.00	7.35	0
25	Ngampilan	100.00	2.38	0
26	Mergangsan	97.39	8.26	1
27	Kotagede	86.56	12.13	0
28	Kraton	100.00	0.00	1
29	Mantrijeron	97.77	7.06	0
32	Pleret	9.28	0.00	0
36	Bambanglipuro	1.93	0.00	0
38	Kalasan	43.29	15.93	0

Next, a scatter plot was created to observe the relationship between UAP and UR of the selected districts (Figure 7). Figure 7 showed a bell-shaped distribution of UR against UAP peaked at around 70% of UAP indicating that urbanization progressed at maximum rate in the three-quarter part of UAP and then saturated when UAP exceeds 90%. Figure 7 also showed that the UR of districts with universities tended to exceed those without universities at similar UAP levels > 30%. Districts 6 (Ngemplak), district 9 (Mlati), district 10 (Depok), district 12 (Gamping), district 14 (Kasihan), and district 20 (Umbulharjo) showed relatively higher UR than almost all districts with no university. Nonetheless, the districts with UAP near 100% had already saturated in urbanization and thus, their UR dropped to near zero.

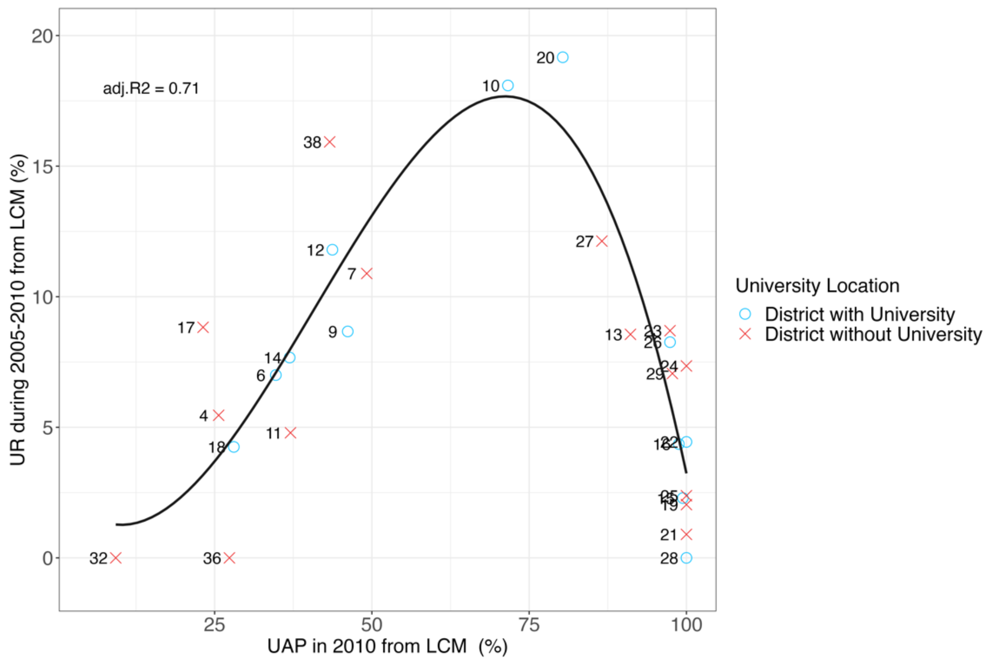

Figure 7. Scatter plot of UAP from LCM in 2010 against UR from LCM 2005–2010 of selected districts with and without universities. Numbers within the scatterplot indicate a few districts with deviation.

There were few districts without universities showing high UR. District 38 (Kalasan) was adjacent to district 6 (with one university) and district 10 (with eighteen universities). This indicated that the positive impact of the presence of universities on the urbanization rate was not only experienced by the host district but also by the neighboring district. This is consistent with previous findings (Rachmawati et al. 2004; Huriati 2008) that showed universities triggered suburbanization due to land vacancies (e.g.: vegetational land) in the suburbs (Susilo 2017). Similarly, district 17 was adjacent to district 10 (with 18 universities) and district 18 (with three universities). Meanwhile, district 4 (Tempel) had no adjacent district with university. By an expert judgement, the high urban growth rate in district 4 was driven by the position of the district as the west gate of Yogyakarta Special Region connecting the Central Java Region with an arterial road.

In addition, the effect of NOU on UR of the selected district was assessed. Pearson's correlation coefficient between NOU and UR was 0.53 with a p-value = 0.004, which indicated a positive correlation between the number of universities and the urbanization rate in the study area.

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Land Use Policy in Yogyakarta City Associated with Universities

The most influential land use policy was inscribed in the urban plan of 1947 upon dividing the city into two sections, south and north zones (Yunus 1991). The south zone was designed for cultural-traditional development with the sultan's palace as its center, whereas, the north zone was meant for modern life development with the establishment of the University of Gadjah Mada campus as its first course (Yunus 1991).

From the comprehensive plan of Yogyakarta Special Region 2005–2025 (e.g., Rencana Pembangunan Jangka Panjang Daerah (RPJP) Daerah Istimewa Yogyakarta (DIY) 2005–2025), some issues have been observed due to the presence of the university in Yogyakarta City for 20 years. They include:

1. A decreasing trend of interest for prospective students to study in Yogyakarta City because of the decentralization law issued in 2004 (e.g., Law No.32 2004) triggered regional competitiveness, including establishing a world-class university in each region
2. A threat of globalization and liberalization to the socio-cultural order of the local society, which affects the academic ambiance in the city and its surrounding, such as moral and behavior changes, drug abuse, misdemeanor and violation, and promiscuity.

To address these issues, the local government of Yogyakarta set some targets in the comprehensive plan, such as:

T1. Development of excellent yet affordable higher education for society;
T2. Enforcement of an integrated system of formal/informal education with employment to attract prospective students;
T3. Development of information and communication technology (ICT)-based education using local wisdom and global perspective;
T4. Encouraging the conducive ambiance and accommodating erudite facility and infrastructure for education, research, and scientific awareness development.

Recently, these aforementioned development targets were implemented in the spatial plan of Yogyakarta Special Region in 2019–2039 (e.g., Rencana Tata Ruang Wilayah (RTRW) DIY 2019–2039) that affirms the vision of the province to make Yogyakarta Special Region a center of world-class education, culture, and tourism. To put the vision into action, the local government set some strategies, such as:

S1. Optimization and reinforcement of educational area development in Yogyakarta City and Sleman Regency;
S2. Expansion of educational area development outside Yogyakarta City to the suburbs.

Although the goals and plans corresponding to these strategies are presently not formulated, the results of this study can guide the local government to implement them into actions. The optimization and reinforcement of educational area development in S1 demand vacant land, which are however difficult in the highly urbanized districts. Coupling high UAP districts having universities with neighboring low UAP districts into unified planning areas is a possible solution. Based on Figures 1 and 7, district groups of 6 (UAP=34.73%)-10 (UAP=71.62%), 9 (UAP=46.15%)-15 (UAP=99.43%)-16 (UAP=98.79%), and 14 (UAP=36.93%)-22 (UAP=100%)-28 (UAP=100%) are recognized as the potential targets for S1. Furthermore, expansion of educational area development outside in S2 is adaptable to districts without university and whose UAP is moderate to ensure that urban infrastructure has already established to support the development. Districts 7 (UAP=49.18%), district 11 (UAP=37.06%) and district 17

(UAP=23.16%) of Sleman Regency are selected by these conditions, where, this selection is in accordance with the initial notion of land use policy of Yogyakarta City in 1947 that determined northern suburb as educational area.

Sustainable Development Issues Affected by Universities in the City

The relationship between universities and cities entails the physical entity of buildings and facilities and the people who occupy them, such as students, lecturers, staff, their activities, and the surroundings engaged in any particular research and training from the university (Liu 2019). For sustainable development, the presence of universities in the city prominently facilitated the enhancement of social structures. The university significantly played a role in developing the human and social capital (Liu 2019) and served as the tank engine for implementing the SDGs (Purcell et al. 2019). However, their existence may also contest the implementation of SDGs in the city. Several studies (Leon et al. 2020; Venetoulis 2001) estimated that the main sector of the ecological footprints of a university is associated with transportation that generates greenhouse gases and air pollutants. This issue should be much considered in the expansion of the new educational area development strategy (S2). For example, for the suggested districts with no university mentioned above, the service level of the roadway based on V/C (vehicles volume to road carrying capacity) ratio (Directorate of Urban Road Development, 1997) in districts 7, 11, and 17 reached 0.99, 0.99, and 0.97, respectively in 2019 (Dinas Perhubungan DIY 2021). Moreover, due to university commotion, five activities have significantly affected biodiversity. They include (in descending order): the supply chain for research activities (such as for chemicals, organic matters, medical products, and plastics); the supply chain for the daily operation of buildings (for stationeries and information technology), food consumption, electricity consumption, and the supply chain for construction (Bull et al. 2022). However, further study is needed to assess the sustainability issue in biodiversity due to university-related activities.

Another sustainability issue is associated with institutional growth of universities that consumes more vacant land for expansion either within the city or in the suburbs (den Heijer and Magdaniel 2018) that has been further discussed in the previous sub-chapter. Moreover, architectural-wise, the space surrounding the campus is prone to urban spatial distortion due to the overprovision of low-quality “student” services, such as food stalls and photocopy kiosks (Grabkowska and Frankowski 2016). This threat is likely happened in the sprawled area such as indicated in the suggested expansion districts in the suburb that showed urban land uptake per capita beyond the average land uptake per capita in city (Tikoudis et al. 2022). Based on the result of estimated urban area in 2010 and population data of Statistics Indonesia in the comparable year, the urban land uptake per capita in district no.7, no.11, and no.17 are 184.8, 150.4, and 78.0, respectively, where average land uptake per capita in the city was 75.1. Nevertheless, further assessment is needed in order to measure the sprawl meticulously.

CONCLUSION

Yogyakarta City and its peri urban areas have experienced a rapid LC change in the last two decades from NU to urban areas posing some burdens to the environment. Understanding the driving factors and their level of influence will facilitate well-informed decisions in planning sustainable urbanization. There are several land change models using remote sensing data developed to better understand the land use functioning in a given area. The method is greatly

facilitated by a machine learning algorithm that makes the model execute with minimum human supervision. This study estimated the projection of LULC change in Yogyakarta City in 2030, 2040, and 2050, and to understand the influencing factors behind the change to help local governments and planners to manage the change and keep up with the targets of SDGs. The result of the study showed that the MLP algorithm can generate a robust land change model with accuracy rate of 81.24% and model's skill measure 0.6248. Furthermore, it showed that the density of universities is the main driving force behind urbanization in Yogyakarta City and its surrounding. A quantitative analysis to measure the urbanization rate in the districts with universities against those without universities was performed to corroborate the result and it affirmed that the presence of universities boosted the urbanization rate not only in the host district but also in the neighboring district. The findings can guide the local government to implement the policies into actions although no plan has been formed corresponding to the educational area development strategies as well as to address the potential sustainability issues affected by those implementations.

Appendix A

Table A1. The statistics data for LCM model's validation for all 38 districts that include the urban area in hectare (ha) unit in 2005 and 2010 from Statistics Indonesia, from referenced land use map of 2005, from LCM constructed land cover map in 2005, from LCM predicted land cover map in 2010 that were used to estimate the percentage of the difference between urban area in 2005 from Statistics Indonesia and the referenced land cover map, the urban change rate from 2005 to 2010 by LCM prediction and Statistics Indonesia, the agreement of urban change rate between LCM prediction and Statistics Indonesia. In addition, the number of university for each district is included in the last column.

No.	District	Urban Area in hectare (ha)					Difference between StatsIndo_2005 and Ref.LC 2005 (%)	Change rate of 2005-2010 in LCM (%)	Change rate of 2005-2010 in StatsIndo (%)	Agreement of change rate between LCM and StatsIndo from 2005 to 2010 (%)	Number of University
		StatsIndo 2005	StatsIndo 2010	Ref.LC 2005	LC_05	LCM_2010					
1	Cangkringan	1309	2523	625	607	661	52.25	8.90	92.74	-83.85	0
2	Pakem	903	2055	826	879	939	8.53	6.83	127.57	-120.75	0
3	Turi	1128	2350	846	477	510	25.00	6.92	108.33	-101.42	0
4	Tempel	1049	1382	977	665	845	6.86	27.07	31.74	-4.68	0
5	Sleman	1080	1567	963	861	992	10.83	15.21	45.09	-29.88	0
6	Ngemplak	1020	1477	983	1010	1265	3.63	25.25	44.80	-19.56	1
7	Ngaglik	1301	1808	1310	1466	1883	0.69	28.44	38.97	-10.53	0
8	Seyegan	873	1152	866	620	624	0.80	0.65	31.96	-31.31	0
9	Mlati	1460	1825	1170	1068	1315	19.86	23.13	25.00	-1.87	2
10	Depok	1826	2770	1682	1832	2451	7.89	33.79	51.70	-17.91	18
11	Godean	767	1022	915	863	991	19.30	14.83	33.25	-18.41	0
12	Gamping	1381	1777	1020	933	1278	26.14	36.98	21.71	15.27	3
13	Tegalrejo	220	264	226	241	266	2.79	10.37	20.16	-9.79	0
14	Kasihan	2130	2477	1237	942	1189	41.92	26.22	19.37	6.85	3
15	JetisY	150	169	168	170	174	12.08	2.35	13.05	-10.70	1
16	Gondokusuman	362	399	381	390	408	5.27	4.62	10.12	-5.50	3
17	Berbah	624	1001	411	245	396	34.13	61.63	60.42	1.22	0
18	Banguntapan	1289	1681	888	684	806	31.11	17.84	31.82	-13.98	3
19	Gedongtengen	85	96	93	96	98	9.45	2.08	12.98	-10.90	0
20	Umbulharjo	610	728	560	504	662	8.23	31.35	19.26	12.09	6
21	Danurejan	97	110	105	110	111	7.87	0.91	13.01	-12.10	0
22	Wirobrajan	159	175	170	172	180	6.92	4.65	10.34	-5.68	1
23	Gondomanan	100	112	110	102	112	9.79	9.80	11.79	-1.99	0
24	Pakualaman	52	63	68	63	68	31.51	7.93	21.22	-13.29	0
25	Ngampilan	70	82	84	82	84	20.41	2.44	16.85	-14.41	0

(**Table A1.** The statistics data for LCM model's validation for all 38 dist., *continued*)

No.	District	Urban Area in hectare (ha)					Difference between StatsIndo_ 2005 and Ref.LC 2005 (%)	Change rate of 2005-2010 in LCM (%)	Change rate of 2005-2010 in StatsIndo (%)	Agreement of change rate between LCM and StatsIndo from 2005 to 2010 (%)	Number of University
		StatsIndo 2005	StatsIndo 2010	Ref.LC 2005	LC_05	LCM_2010					
26	Mergangsan	193	226	209	205	224	8.03	9.27	16.94	-7.67	1
27	Kotagede	258	289	243	227	264	5.68	16.30	12.18	4.12	0
28	Kraton	124	140	137	139	139	10.48	0.00	12.90	-12.90	1
29	Mantrijeron	223	258	246	244	263	10.25	7.79	15.82	-8.03	0
30	Piyungan	828	1078	175	114	114	78.86	0.00	29.88	-29.88	0
31	Sewon	1246	1276	938	420	597	24.72	42.14	2.50	39.64	4
32	Pleret	537	616	474	175	175	11.73	0.00	-18.29	18.29	0
33	Bantul	852	1081	860	194	193	0.94	-0.52	26.73	-27.25	0
34	JetisB	894	1097	715	78	78	20.02	0.00	21.44	-21.44	0
35	Pandak	1152	709	592	121	121	48.61	0.00	-38.58	38.58	0
36	Bambanglipuro	849	699	595	43	43	29.92	0.00	-18.56	18.56	0
37	Pundong	814	1049	413	112	112	49.26	0.00	28.55	-28.55	0
38	Kalasan	1041	1504	1002	986	1560	3.75	58.22	44.48	13.74	0

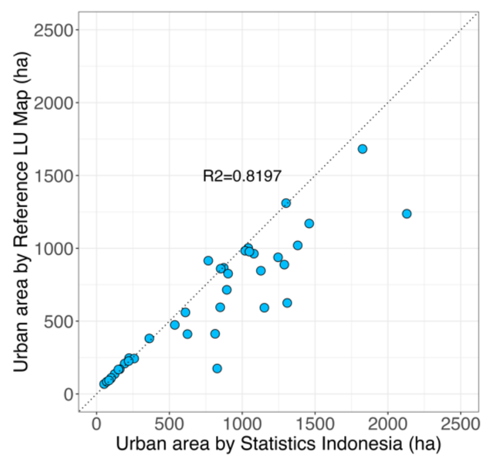

Figure A1. A scatterplot of agreement of the urban area by Statistics Indonesia 2005 and by reference LU map in 2005 from previous classification training

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