JPPIPA 10(4) (2024)

Jurnal Penelitian Pendidikan IPA

Journal of Research in Science Education

http://jppipa.unram.ac.id/index.php/jppipa/index

Study of Urban Growth Center Development Factors and Simulation The Mamminasata Urban Area

Emil Salim Rasyidi[1]*, Jumadil[2], Syafri[1], Rahmawati Rahman[1], Rusneni[1], Hamsinah[3], Muh. Khalil Jibran[4]

[1]Departement of Urban dan Regional Planning, Faculty of Engineering, Bosowa University, Makassar, Indonesia.
[2]Departement of Environment, Faculty of Engineering, Bosowa University, Makassar, Indonesia.
[3]Departement of Chemical Engineering, Faculty of Engineering, Universitas Bosowa, Makassar, Indonesia.
[4]Departement of Magister Environtment, Faculty of Engineering, Universitas Hasanuddin, Gowa, Indonesia.

Received: December 04, 2023
Revised: February 09, 2024
Accepted: April 25, 2024
Published: April 30, 2024

Corresponding Author:
Emil Salim Rasyidi
Emil.salim@universitasbosowa.ac.id

DOI: 10.29303/jppipa.v10i4.6380

Abstract: Urban growth starts from a center and affects the surrounding areas, this is due to the emergence of additional centers that will each function as growth poles, to study the dynamics related to urban growth center information, several data and extraction and analysis methods are needed. This study examines several methods of extracting information on urban growth centers from Landsat 8 OLI/TIRS in 2013 and 2023 by utilizing the spectral resolution of Landsat imagery in the Mamminasata area, and integrating spatial modeling to simulate the growth centers of the Mamminasata area in the next 10 years (2043). The results of this research classification method show an accuracy rate of 71.48%. The results of the determinant factor test show that the most influential factors are the distance from the center of shops, slope, then the distance from the university, and the distance from the main road in 2013-2023 Mamminasata Urban Area. The results of this variable drive test are then used in spatial simulations using the markov chain simulation method in the LCM module and show an increase in the area of the growth center in the Mamminasata region, for the entire scope of the Mamminasata region, the Makassar City area shows the highest intensity of regional growth centers and becomes the center of growth in the Mamminasata urban area. The planning concept applied to the results of this study is based on resources, geographic location, and factors affecting the growth center.

Keywords: Mamminasata; OBIA; Regional Growth Center; Spatial Simulation;

Introduction

Urban growth starts from a center and affects the surrounding area, this is due to the emergence of additional centers, each of which will function as a growth pole and give birth to a city structure that has growth cells. Rapid urban growth is considered responsible for issues such as climate change, degradation of ecosystem services and loss of agricultural land, and challenges sustainable urban land use (Bai et al., 2018; Estoque & Murayama, 2013), The expansion of built-up land would be at the expense of main farmland, and to a lesser extent, of ecological land. Coordinating the contradiction between urban growth and the protection of farmland and ecological land would be the key to sustainable urban development (Q. He et al., 2018), Rapid urban growth has created challenges in both developing and developed countries (Aldalbahi & Walker, 2015). They include water shortage (McDonald et al., 2011), increasing surface runoff (Dinka & Klik, 2019; Guzha et al., 2018), minimizing global biodiversity, and vegetation carbon losses (Seto et al., 2012). Since the last century, developed countries have put forward many urban growth management tools, including green belts, urban growth boundaries (UGB), urban service boundaries, priority

How to Cite:
Rasyidi, E. S., Jumadil, Syafri, Rahman, R., Rusneni, Hamsinah, & Jibran, M. K. (2024). Study of Urban Growth Center Development Factors and Simulation The Mamminasata Urban Area. *Jurnal Penelitian Pendidikan IPA*, *10*(4), 1976–1988. https://doi.org/10.29303/jppipa.v10i4.6380

funding areas, agricultural protection zoning, etc., to contain urban and suburban sprawl (Ewing et al., 2022).

Seeing the impact of an urban growth center, the Mamminasata Area (Makassar, Maros, Sungguminasa, and Takalar) which is an urban area will have an impact on the development of the area within it and the surrounding areas, in accordance with the presidential regulation of the Republic of Indonesia number 55 of 2011 in article 6 point a stated that the Mamminasata urban area (Makassar, Maros, Sungguminasa, and Takalar) as one of the regional growth centers and / or international service orientation centers and the main driving force in Eastern Indonesia, the establishment of the Mamminasata area as an urban area will have an impact on changes in urban structure, especially changes in land use and closure that will trigger the emergence of new regional growth centers and the need for methods for analyzing problems related to urban dynamics.

Extracting information related to urban dynamics in the Mamminasata urban area (Makassar, Maros, Sungguminasa and Takalar) which has an area of ± 2,431 km², provides several problems related to the availability of effective data sources both in terms of time, cost, and good quality used in the analysis. Data that is often used in literature studies in the study of urban dynamics is Landsat imagery, but Landsat imagery still has several problems related to physical identification of cities and modeling dynamics related to regional development.

The development of regional growth centers has several determinant factors or factors that influence the development and distribution of regional growth centers (Oum & Park, 2004; Pribadi et al., 2015). Spatial theory explains the development of an area seen from the physical complexity of an area, so the factors that cause the development of regional growth centers in the Mamminasata area need to be studied with several physical aspects that can be modeled. besides that, monitoring and simulation of the region are needed, in order to see the direction of development of an area so that it can be taken into consideration in a plan.

Method

The method for analyzing regional growth centers in this study examines several spectral transformations for urban areas, and analyzes the location of the distribution of regional growth centers in the Mamminasata area. The data used is sourced from Landsat satellite remote sensing data, this data will be used as a fact of the increasing intensity of growth center points in the research area and developed into some spatial data with the help of geophraphic information systems. Using of dynamic models which include spatial–temporal information are useful for simulating complex geographic systems (He et al., 2015).

The CA approach has become one of the most popular models for simulating urban growth due to its simplicity and effectiveness (X. Liu et al., 2010; Santé et al., 2010), such as logit-CA model (Cheng & Masser, 2004), artificial neural networks (ANN) CA (Yang et al., 2016), FLUS (X. Liu et al., 2017), and SLEUTH (Osman et al., 2016; Silva & Clarke, 2002). In general, the constrained cellular automaton model involves an array of cells with different temporary states and calculates cell state transition rules while incorporating previous state and neighborhood effects. When used to simulate land-use change, CA models predict land-use state based on the analysis of historical urban land-use dynamics and relevant driving factors (Li & Yeh, 2002), including topography, such as slope and river (He et al., 2018; Liu et al., 2016; Müller et al., 2010); socio-economic factors, such as population and GDP (Liu et al., 2017; Wu & Zhang, 2012); transportation facilities, including roads, railways, stations, and airports (He et al., 2018; Y. Liu et al., 2016; Sunde et al., 2014); urban functions, such as distance to city center and climate (Liu et al., 2017).

Spectral Transformation

According to Danoedoro (2012), special transformations are used for various studies, ranging from observing the stages of vegetation growth (phenology), and according to their development. Special transformations can also be used for various urban studies, with the character of building land cover objects, spectrally, building roofs in cities in Indonesia are dominated by tile, clay, and concrete roofs, so that mid-infrared spectral reflections are sensitive to these objects and have differences in natural objects such as vegetation and water bodies. The spectral transformation used in this study is the Normalize difference built-up index (NDBI) spectral transformation which is an image transformation to provide information on built-up areas. Zha et al. (2003) performed NDBI transformation to map the built-up area in Nanjiing city in China, the formula for this transformation as seen in Formula 1.

$$NDBI = \left(\frac{Mid-infrared\ 1 - near\ infrared}{Mid-infrared\ 1 + near\ infrared}\right) \quad (1)$$

Geographic Object Based Image Analysis

The nearest neighbor algorithm on the image and the image transformation results will be classified using the GEOBIA approach. The mapping process with the GEOBIA approach begins with the segmentation process, creating a class hierarchy, taking sample locations or training areas and nearest neighborhood supervised classification and developing land use and land cover structures with field data and local knowledge. The results of the Normalize difference built-up index (NDBI) image transformation will be classified according to the average value of the two image transformation results by following the NOAA (2006) USGS Land Cover/Use classification system (Table 1), where each intensity classification represents a class for the growth center map.

Testing the spectral transfromation of urban index in eCognation software with the OBIA classification method, it is necessary to make a rule set by entering the value of the digital number range of the transformation results, the digital number used is the original pixel value of the transformation results, so that the object features used are pixel-based features. The probability of the conversion of a cell as a function of the driving forces of urban growth and position of all neighboring cells calculated according to Transition rules (Al-Kheder, 2006; Feng et al., 2011). The rule set used will include conditions for changing the land cover class into 4 classes, namely; High intensity, medium intensity, low intensity, and undeveloped land. Class changes that are given the condition of the urban index value, namely, the built-up land cover class or it can also be called the main class (parent) and the high intensity, medium intensity, low intensity class which is a derivative of the main class (child).

Table 1. Land Cover/Use Classification System According to USGS NOAA Version

Classification	Description
Developed, High intensity	Contains significant land covered by buildings, concrete, and other built-up land. Vegetation cover is approximately less than 20 percent. Built-up material is about 80-100 percent of total land cover. This class includes city centers and large building surfaces in both sub-urban and rural areas with a variety of land uses.
Developed, Medium Intensity	Contains land with a mix of buildings and vegetation or other land cover, with buildings accounting for 50-79 percent of the total area. This class typically includes family housing areas mainly in sub-urban environments, but includes all types of land use.
Developed, Low Intensity	Containing areas with a mix of vegetated buildings and open land, buildings in these areas cover 21-49 percent of the area, these areas are usually in rural environments.
Non Built- Up	Land cover classes other than buildings include open land, vegetation and water bodies.

Sources: USGS Land Cover/Use classification

The spatialization model of factors affecting the location of growth centers or the development of regional growth centers in the Mamminasata urban area is carried out with various models, including euclidean distance to determine the distance of the variables, slope to determine the slope, and reclassify to create classes based on the dominant value of the data. The atomized variables will be statistically tested and used as variables for the probability value of changes in the Mamminasata area, then the results of the probability value will be simulated and produce a prediction map of the Mamminasata urban area in 2027 using cellular automata, Cellular automata (CA) are a computational method, capable of simulating growth process by describing a complex system through a set of simple rules (Mantelas et al., 2008).

Statistical analysis of determinant factors of regional growth center development aims to find out what variables or factors affect the development of regional growth centers in the Mamminasata region. The statistical analysis model used in this research is Multilayer Perception (MLP) network analysis. MLP network analysis is a nonlinear equation. The results of multilayer perceptron (MLP) network analysis in the LCM module of the terrset software are data related to the level of influence and dependence of independent variables on dependent variables. In addition to data related to the influence and results of running the multilayer perceptron (MLP) network analysis model, the LCM module also produces a map of potential transitions from the sub-models used (dependent variables) to independent variables, each transition is worth 0-1 intervals.

The transition modeled and simulated in this study is the growth center class, then the class that makes a major contribution in the development of the growth center area, will be specifically selected as the output value in the potential transition map and simulated. Spatial simulation of growth center development in the Mamminasata area, will use the markov model in the LCM module, and Validation of the model is carried out using the Cohen's Kappa (K) statistical coefficient.

Result and Discussion

Classification of Growth Centers in Mamminasata Region

The central growth area often has the physical characteristics of high building intensity, this is due to the emergence of additional centers, each of which will function as a growth pole and give birth to an urban structure where there are growth cells around the regional growth center.

Spatial information on building intensity can be obtained using several spectral transformations of urban indices, in this study the urban index used is the Normalize Difference Built-Up Index (NDBI) transformation. The image used for testing the spectral transformation of urban indices and used to extract building intensity information in the Mamminasata area is the Landsat 8 OLI image which has been atmospherically corrected and calibrated.

The classification of regional growth centers in this study will be processed based on the generalization of the land cover/use classification system according to the USGS with the NOAA (2006) version (Table 1), in the selected urban index spectral transformation results, namely the Normalize difference built-up index (NDBI) building intensity class in 2023 and 2021 will be changed based on the description in table 1 thus the low building intensity class is an area with a mixture of vegetation buildings and open land, buildings in this area cover 21-49% of the area and are usually located in rural environments, in this description then in the theory of urban structure, this area is known as the Town-Rural area.

Medium intensity buildings in the description of table 1 is a class that includes family housing areas, mainly in sub-urban neighborhoods, but includes all types of land use. In urban structure theory, sub-urban neighborhoods are also commonly referred to as transitional areas, while for high intensity buildings according to the USGS with NOAA version (2006), is a class that includes city centers and building surfaces that dominate the land cover, high intensity classes are often in sub-urban and rural areas with various land uses in it, so urban structure theory considers this area as a growth center area.

To prove the level of relationship between high building intensity and regional growth centers, the accuracy test of selected high building intensity areas, namely Normalize difference built-up index (NDBI) with the location of shopping centers in the Mamminasata area, the sample was selected based on the level of service of shopping centers, such as malls, markets, and plazas.

The results of the Normalize difference built-up index (NDBI) high building intensity area accuracy test with the location of the shopping center in the Mamminasata area using 42 sample locations. from the results of the field accuracy test, 33 of them are in the high intensity building area. While 9 sample locations are in areas outside the high intensity building. This result can be said that 78.57% of shopping centers in the Mamminasata area are in the high building intensity area which is classified based on the selected urban index, namely the Normalize difference built-up index (NDBI) urban index.

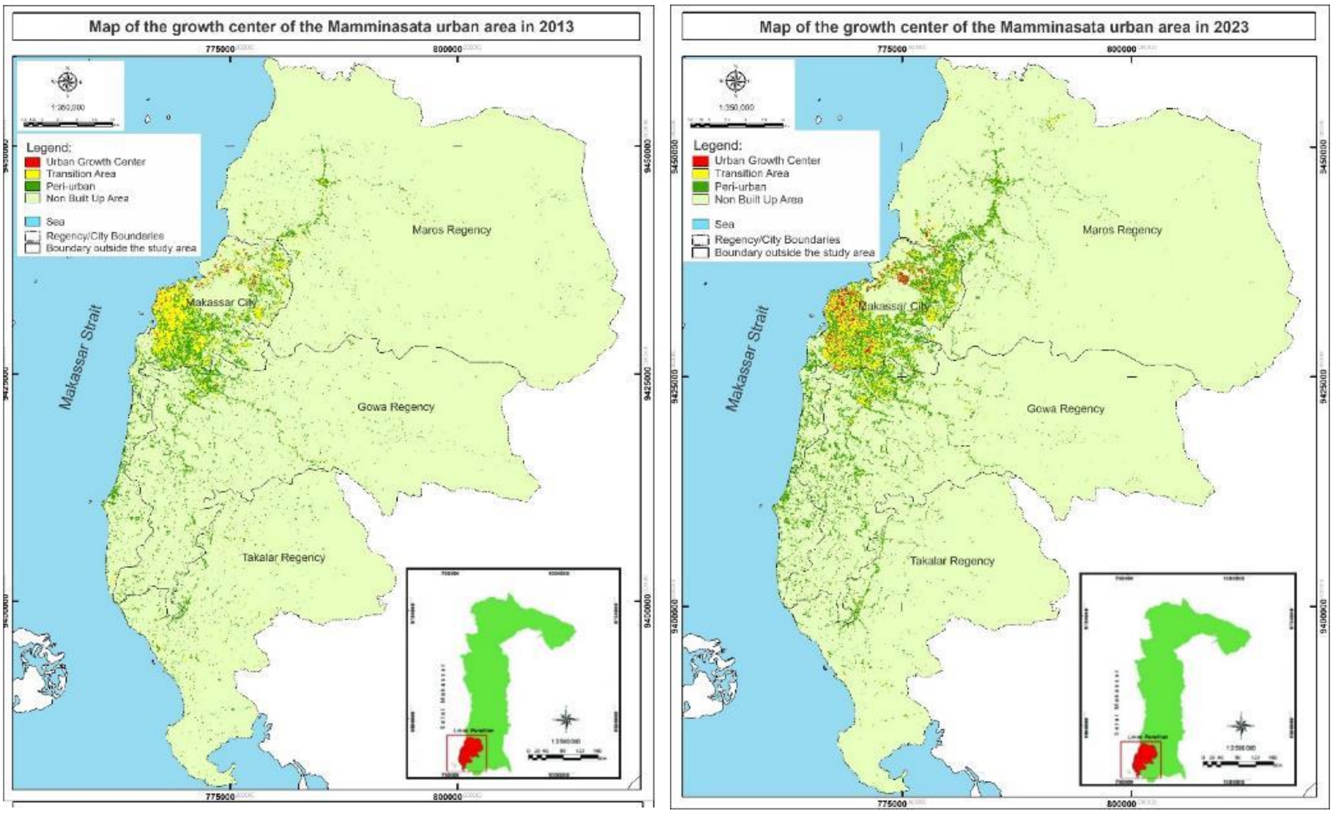
Once the classification used has been determined, the overall rule set process for creating growth center maps from Landsat 8 OLI/TIRS imagery in 2023 and 2013 can be run (Bouhennache et al., 2019; Shahfahad et al., 2023; Yasin et al., 2022). The results of this mapping can be seen in Figure 1, while the comparison of land area changes between the building intensity map and the growth center map can be seen in Table 2 and Table 3.

Table 2. Land Area (Ha) on the Classification Map of Building Intensity and Regional Growth Center

Classification	Area (Ha)	
	2013	2023
Non Built- Up	230,198.54	25,158.69
Developed, Low Intensity	8,690.97	12,067.88
Developed, Medium Intensity	3,889.32	4,814.90
Developed, High intensity	317.55	1,054.91
Total	43,096.38	243,096.38

Table 3. Land Area (Ha) on the Classification Map of Regional Growth Center

Classification	Area (Ha)	
	2013	2023
Non Built- Up Ares	230,268.19	225,332.16
Peri-urban	8,690.97	12,067.88
Transitioon Area	3.889,32	4,814.90
Growth Center	247.90	881.43
Total	243,096.38	243,096.38

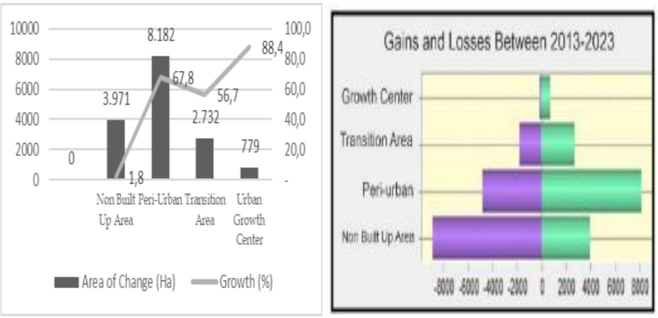


(a) (b)

Figure 1. Map of the growth center of Mamminasata urban area 2013-2023, (a) Map of the growth center of Mamminasata urban area 2013; (b) Map of the growth center of Mamminasata urban area 2023

Development and Spatial Distribution of Regional Growth Centers in the Mamminasta Region

The development of growth centers in the Mamminasta area in 2013-2023 was analyzed using the Change Analysis method, the regional growth center map for 2013-2023 using earlier landcover image data with the 2013 growth center map as input data and the 2023 growth center map as later land cover image data, while the time interval for changes in both data is 10 years. The results of the area and location in both data can be seen in Figure 2.



(a) (b)

Figure 2. Area of Change Map of the growth center of Mamminasata urban area 2013-2023, (a) Area and Growth Change Mamminasata urban area 2013-2023,; (b) Gains and Loss Classification Area of Change Map of the growth center of Mamminasata urban area 2013-2023

Figure 2. shows the diagram of gains and losses of land area increase in the growth center classification. The classification that has the largest land reduction is undeveloped land with 8905 Ha, followed by urban-rural 4806 Ha, transition area 1808 Ha, and the smallest is the growth center 146 Ha, this shows that the land change component in 2013-, as well as in the growth ratio where the growth center is the classification that has the highest percentage value of 88.41%, the contribution area of each class can be seen in Figure 4.

Current Location of Regional Growth Centers in the Mamminasata Region

The location of regional growth centers in the Mamminasata area is currently displayed spatially on the map of regional growth centers and the 2013-2023 land cover change map (Figure 1), but administratively, information on the area and administrative boundaries of each location of regional growth centers at the district and district levels cannot be displayed spatially, so information on the area of growth centers per district and district can be seen in the table in Figure 3, where this information is obtained by union / overlaying the map of regional growth centers with the Mamminasata area administration map (Figure 1).

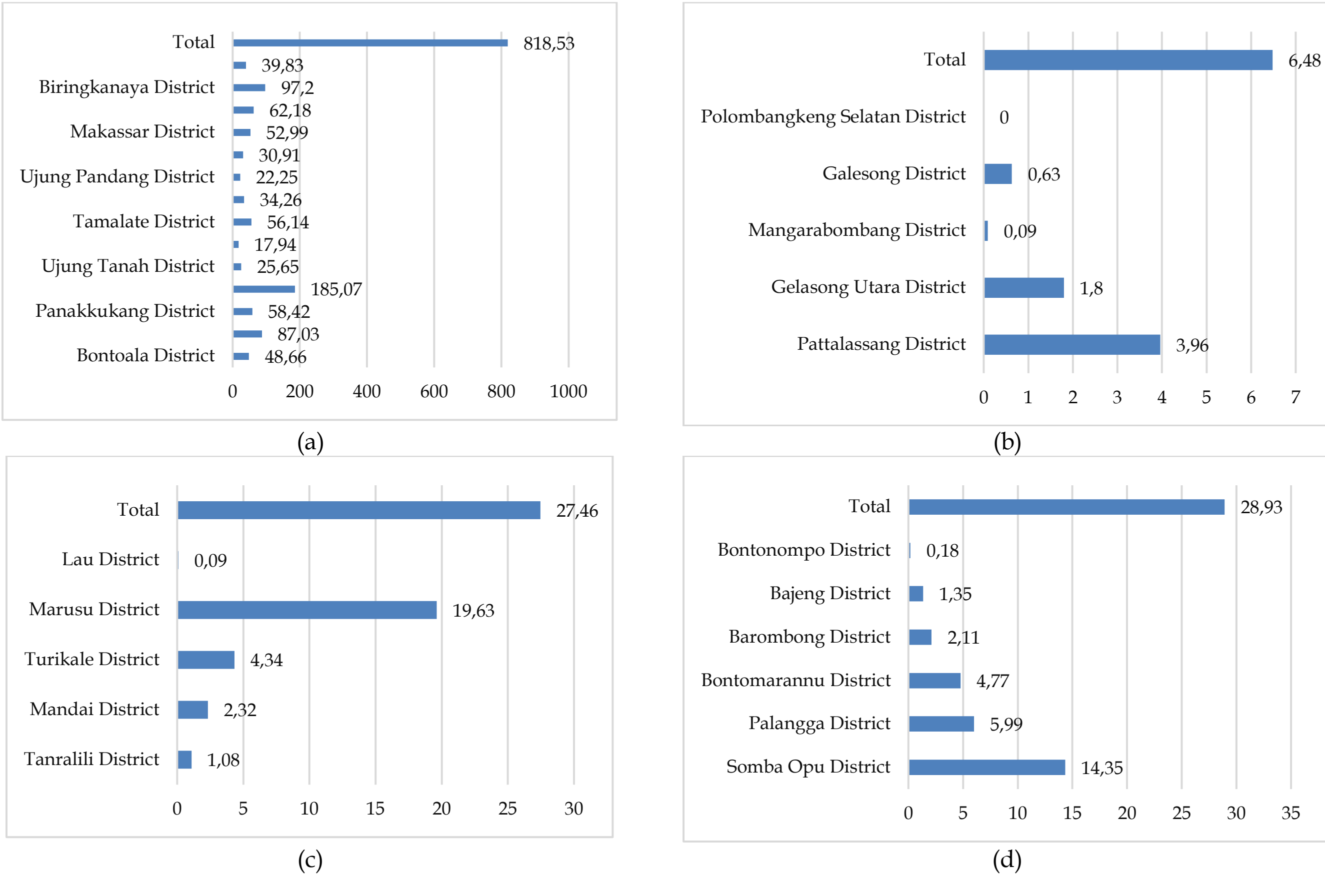


Figure 3. Land Area (Ha) on the Classification Map of Regional Growth Center 2023: (a) Urban Growth Center of Makassar City Area (ha); (b) Urban Growth Center of Takalar Regency Area (ha); (c) Urban Growth Center of Maros Regency Area (ha); (d) Urban Growth Center of Gowa Regency Area (ha)

Figure 3 shows that the largest distribution of urban growth centers in the Makassar city region in 2023 is in the Tamalanrea district with an area of 185.075 Ha, while the regional growth center area with the smallest area distribution is in the Manggala district with an area of 17.94 Ha. The largest distribution of growth centers in Takalar Regency in 2023 is in Pattalassang District with an area of 185,075 Ha where this district is the capital of Takalar Regency, while the growth center area with the smallest area distribution is in South Polombangkeng District with no growth center. In the Maros Regency area, the distribution and area of growth centers in table 4.28. shows that the largest distribution of growth centers in Maros Regency in 2023 is in Marusu District with an area of 19.63 Ha where this district is a district that is administratively directly adjacent to the City of Makassar, while Turikale District which is the capital of the Regency has the second largest distribution and area of growth centers, for the growth center area with the smallest area distribution is in Lau district with 0.09 Ha and is the most distant district administratively from the City of Makassar. The distribution and area of the regional growth center in Sungguminasa City, Gowa Regency in figure 3 shows that the largest distribution of growth centers in 2023 is in Somba Oppu District with an area of 14.35 Ha, Somba Oppu District is a district that is mostly located in Sungguminasa City, for the regional growth center area with the smallest area distribution is in Bontonompo District with 0.18 Ha and is a district that borders between Gowa Regency and Takalar Regency.

Information related to the distribution of growth centers in the Mamminasata region in 2017 as a whole region, can be viewed from the area of growth centers in each district and city (Figure 3), the Makassar City Region is an area that has the highest intensity of regional growth centers with an area of 818.55 Ha and is the center of growth in the Mamminasata urban area, with Sungguminasa Gowa with an area of 28.93 Ha, then Maros Regency with an area of 27.46, and the district with the lowest area of regional growth centers is Takalar Regency with an area of 6.48 Ha.

Determinants of the Development of Regional Growth Centers in the Mamminasata Region

The development of regional growth centers has several determinant factors or factors that influence the development and distribution of growth centers, spatial theory explains that the development of an area is seen from the physical complexity of an area, so the factors that cause the development of regional growth centers in the Mamminasata area need to be studied with several physical aspects that can be modeled and tested statistically.

The euclidean distance of the road to the classification of growth centers in 2023 is the average distance of the classification of growth centers (Bakshi & Esraz-Ul-Zannat, 2023; Ghosh et al., 2023; Liladhar Rane et al., 2023; Uhl et al., 2023) in the Mamminasata area to the road showing that the location of the regional growth center has the closest average value to the road of 224.18 m, for the closest maximum distance to the road which is 1,718.40 m, and the undeveloped land class has the farthest average value from the road location, which is 1,877.15 m with a maximum distance of 13,269.17 m. This shows that there is a relationship between the location of the road and the growth center (Figure. 4).

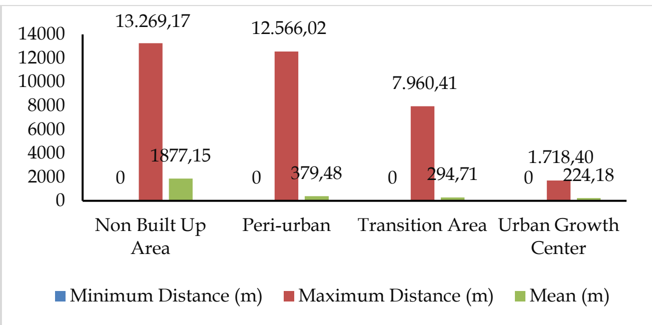


Figure 4. Distance of Urban Growth Center Map Classification to Roads in 2023

The distance of the shopping center to the classification of growth centers in 2023 shows that the location of the regional growth center class has the closest average value to the shopping center, which is 1,626.99 m and the closest maximum distance to the road is 15,573.93 m, while the undeveloped land class has the farthest average value from the location of the road, which is 13,448.20 m with a maximum distance of 35,541.40 m. This shows that there is a relationship between the shopping center and the growth center (Figure 5).

The determinant factor that will also be tested as a driver of the development or emergence of regional growth centers is the university, in Figure 6. shows the location of the regional growth center class has the closest average value to the location of the university, which is 2,829.91 m and the closest maximum distance to the university is 28,298.97 m, for the undeveloped land class has the farthest average value from the location of the university, which is 19,016.76 m with a maximum distance of 41,830.73 m away (Figure 6).

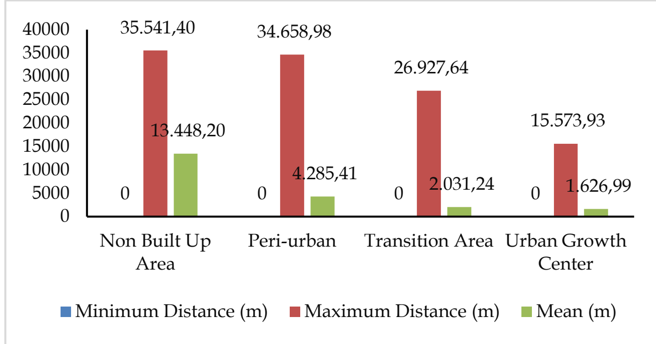


Figure 5. Distance of Urban Growth Center Map Classification to Shopping Centers in 2023

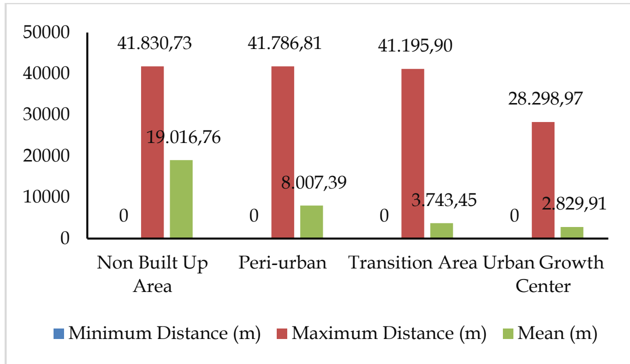


Figure 6. Distance of Urban Growth Center Map Classification to University in 2023

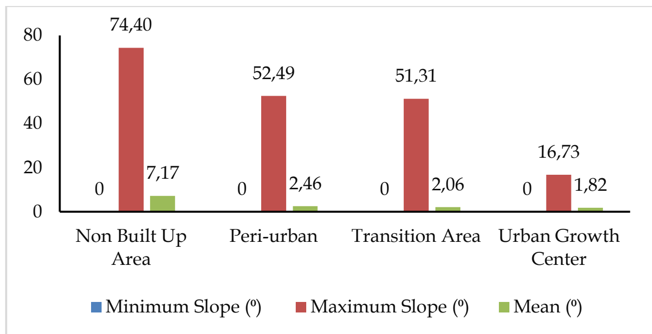


Figure 7. Slope of Urban Growth Center Classification in 2023

This class is 2.06⁰ and is almost the same as the average slope of the urban-rural class location, which is 2.46 and the maximum location of the slope of these two classes also has almost the same slope, namely, 51.31⁰ for the transition area class and 52.49⁰ for the urban-rural class. The average value of the highest slope is found in the location of the emergence of undeveloped land class with a slope of 7.12⁰, where the maximum slope of the undeveloped land class is 74.40⁰, The conclusion that can be drawn from the difference in slope between the map of the center of regional growth against the slope (⁰) in 2023 is that in 2023 there is an increase in the average value and maximum slope of the location of each class, then this indicates that the more years the location of development is expanding to areas with higher slopes (Figure 7).

Statistical Test Results of Determinants of Regional Growth Center Development in the Mamminasata Region

Statistical testing of the determinants of growth center development is a process of modeling the relationship between 2 or more independent variables (x) and dependent variables (y) (Carlino & Mills, 1987; Cheng & Masser, 2003). The independent variables are the determinants of the development of regional growth centers in the Mamminasata region (Figure 5 - Figure 8), the determinant factors tested are the results of spatial modeling of determinant factors, while the dependent variables tested are the results of change detection per time interval (Figure 1 and Figure 2), the classification in the change detection results is the classification of changes in regional structure on the growth center map, By considering the contribution of the area of change classification to the growth center class, change detection in 2013-2023 shows that the built-up land class and transition area have the largest contribution in the change of growth center class, while the urban-rural class has the lowest contribution in the development of the growth center class area, then the dependent variable is decided to be the built-up land class to the growth center and the transition area to the growth center (Cengiz et al., 2022; Grădinaru et al., 2015).

Statistical tests of determinants and transition probability maps of growth center development in the Mamminasata area will use the 2013-2023 change detection map to see the determinant factors that have the most influence on changes in regional growth centers in 2013-2023. The statistical analysis method used for statistical tests of determining factors and transition probability maps of growth center development in the Mamminasata region is MLP (Multilayer Perceptron) Neural Network. The statistical test model used is the driver variable test. The value used is based on Cramer's V value (Figure 8).

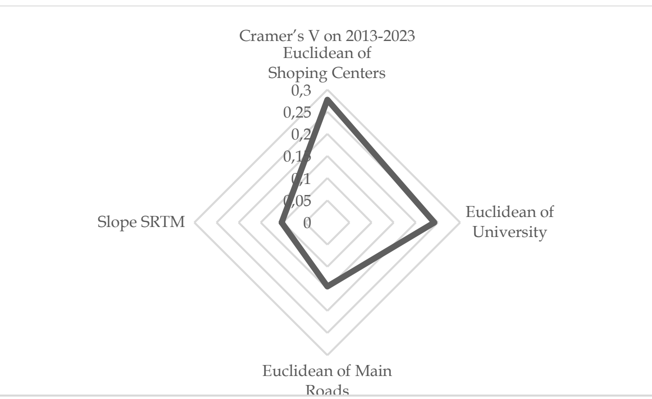


Figure 8. Driver variable test result

The results of the driver variable test analysis can be said to be well used in the model if the cramer's V value is low or close to 0, according to the manual terrset, if a condition of the cramer's v value has a value <0.4 then it is very useful in the transition model, this is shown in Figure 8. after knowing the cramer's V value of each variable, the next step is to model the determinant factor of the independent variable with the MLP Neural Network transition model. The MLP neural network transition model of regional growth centers in the Mamminasata urban area in 2013-2023 will use a random sample of 50% or as many as 2600 pixels, 4 hiden layers and a repetition process of 10000 (Figure 10).

The results of running statistics of MLP neural network of regional growth centers in Mamminasata urban areas in 2013-2023 show the value of training RMS sample gives a value of 0.3292, testing RMS 0.3423 and accuracy of 62.29%. Statistical information on the results of running MLP neural network statistics of regional growth centers in the Mamminasata urban area 2013-2023 can provide related constant values and the relationship of independent variables to the dependent variable (submodel layer (undeveloped land layer to the growth center and transition area layer to the growth center), as for the statistical results of independent variables on the dependent variable can be seen in Table 4.

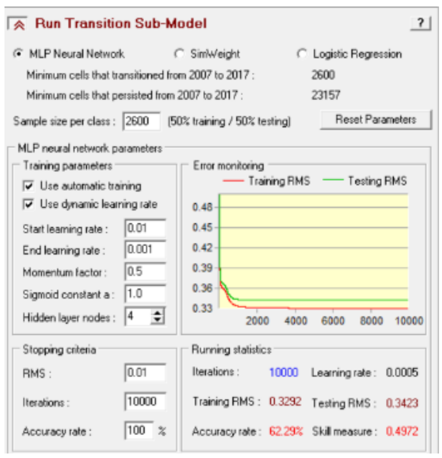


Figure 9. Run transition model in MLP neural network

Table 4. Forcing a Single Independent Variable to be Constant

Model	Skill measure	Influence order
With all variables	0.4972	N/A
Euclidean of Shoping Centers	0.2416	1
Euclidean of University	0.2593	2
Euclidean Main Roads	0.5044	4
Slope SRTM	0.4868	3

Table 4. Shows that the determinant factors that most influence the change in the class of undeveloped land and the class of transition areas to growth centers in the Mamminasta area in 2013-2023 in the change are distance from the center of shops, followed by distance from the university, slope and finally distance from the main road. All determinant factors that are considered to influence the development of growth centers have positive values, so they can be used for the growth center transition model and also used in the simulation of growth centers in Mamminasta urban area in 2043. The potential transition results of each submodel layer to the independent variables can be seen in Figure 10 and Figure 11.

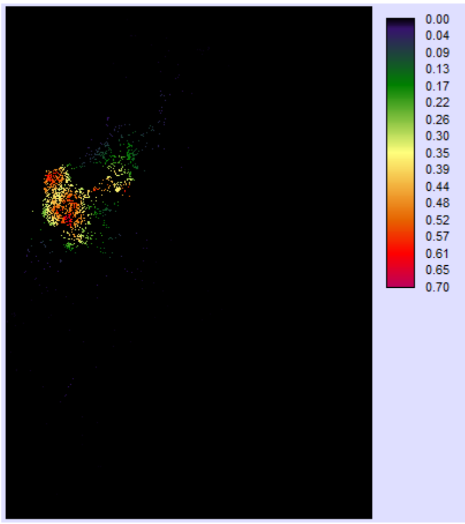


Figure 10. Potential transition of each submodel layer to independent variables in Mamminasta urban area, Potential transition of undeveloped land to growth centers in 2013-2023.

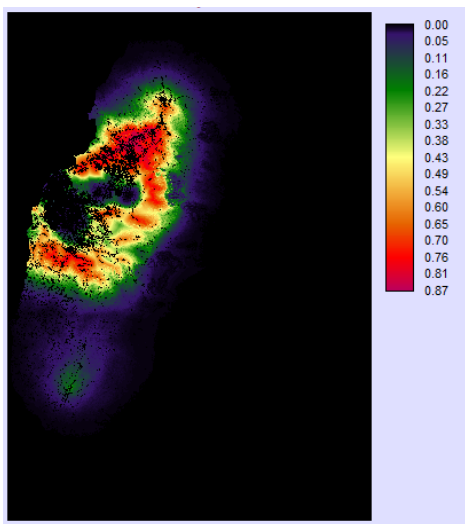


Figure 11. Potential transition of each submodel layer to independent variables in Mamminasta urban area, Potential transition of transition area to growth center in 2023-2043.

Spatial simulation of Regional Growth Centers in the Mammiasata Region in 2043

The process of simulating the growth center in the Mamminasata region in 2043 uses data from the spatial model of change detection and potential in 2013-2023. The time interval between the two data is 10 years, while the number of time periods in the simulation for 2043 is 20 years, for the results of the basic transition probability matrix is the growth center map in 2023-2043 can be seen in table 5. while for the results of the simulation of the regional growth center map in the Mamminasata region in 2043 can be seen in Figure 12 and Figure 13.

Table 5. Basic Transition Probability Matrix of Change of Each Class on the Growth Center Map 2023-2043

Parameters	Non Built Up Area	Peri-urban	Transition Area	Urban Growth Center
Non Built Up Area	0.961	0.032	0.006	0.001
Peri-urban	0.390	0.447	0.153	0.010
Transition Area	0.143	0.204	0.536	0.118
Urban Growth Center	0.098	0.084	0.407	0.412

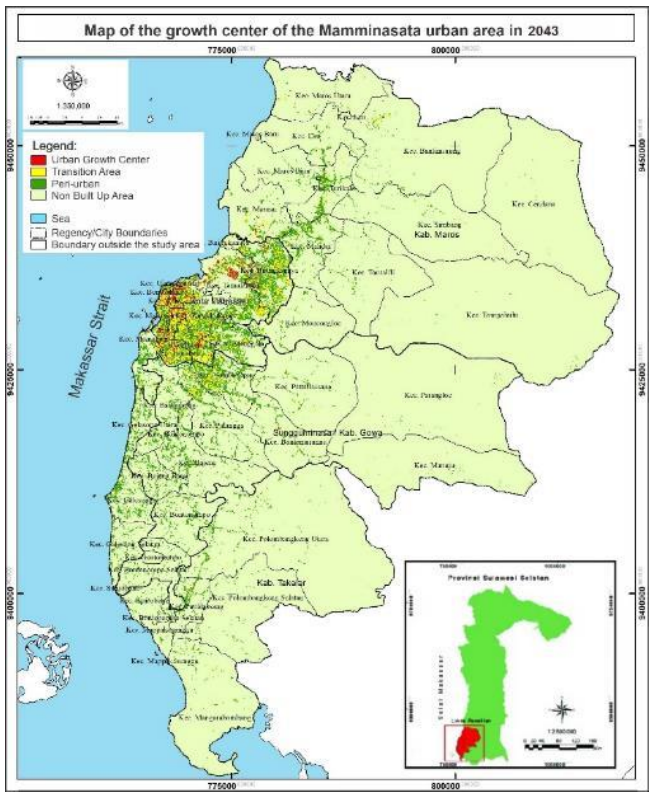


Figure 12. Map of regional growth centers with District scale administrative information in Mamminasata area in 2043.

Simulation of the location of the regional growth center in the Mamminasata area in 2043 (Figure 12) provides information on the size of the growth center will have an area of 1,645.98 Ha.

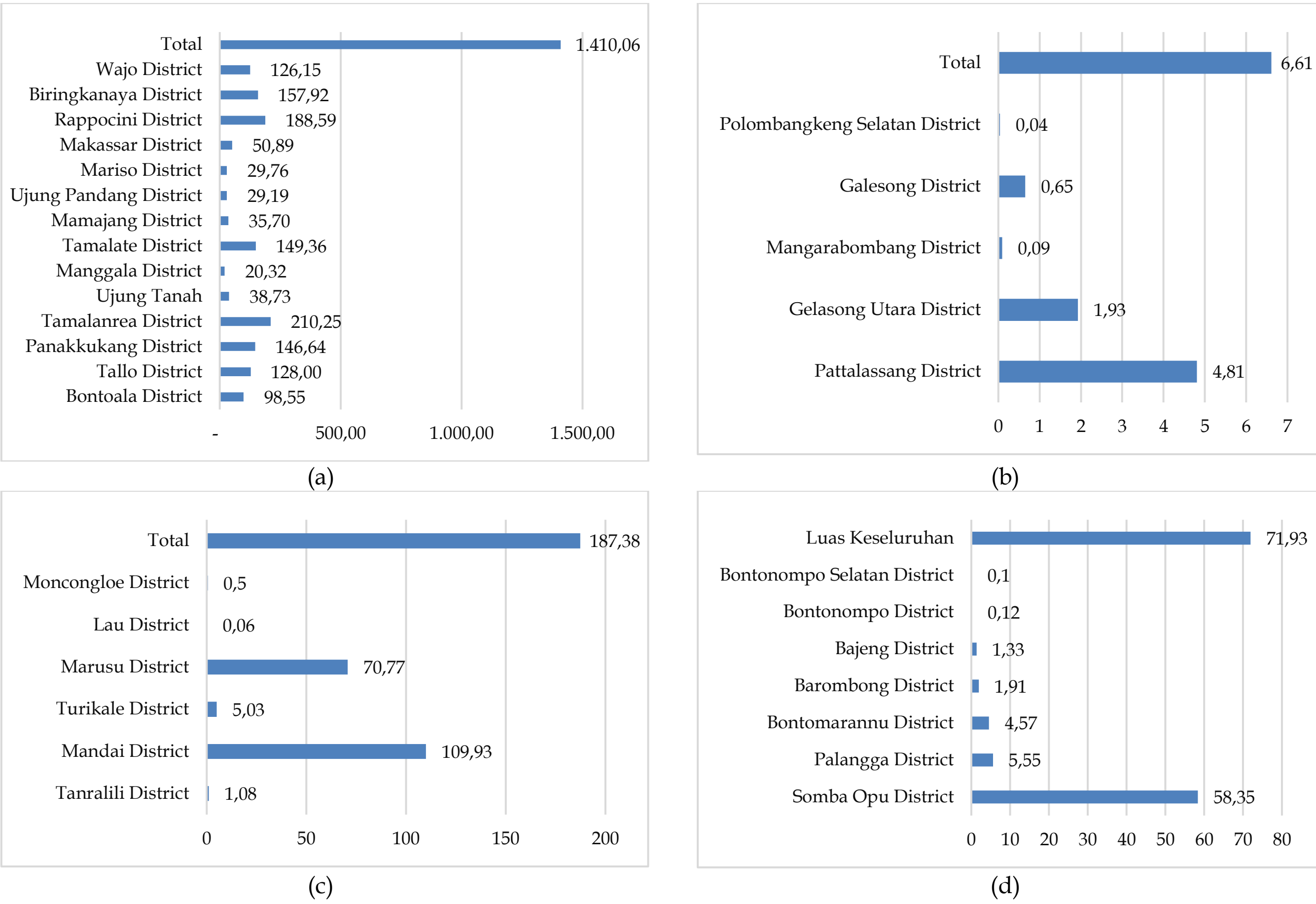


Figure 13. Land Area (Ha) on the Classification Map of Regional Growth Center 2043 , (a) Urban Growth Center of Makassar City Area (ha),; (b) Urban Growth Center of Takalar Regency Area (ha),; (c) Urban Growth Center of Maros Regency Area (ha),; (d) Urban Growth Center of Gowa Regency Area (ha)

Simulation of the location of regional growth centers in the Mamminasata area in 2043 (Figure 13) provides information on the size of the growth center will have an area of 1,645.98 Ha, Figure 14. shows that the largest distribution of urban growth centers in the Makassar city area in 2043 is still found in Tamalanrea district with an area of 210.25, while the regional growth center area with the smallest area distribution is in Manggala district with an area of 20.32 Ha, although there is an increase in area of 2.38 Ha from the growth center area in 2023. The distribution and area of growth centers in Takalar Regency shows that the largest distribution of growth centers in Takalar Regency in 2043 is still in the capital city of Takalar Regency, namely Pattalassang District with an area of 4.81 Ha, while the growth center area with the lowest distribution is in South Polombangkeng District 0.04 Ha. In the Maros Regency area in 2043, the distribution and area of growth centers show that the largest distribution of growth centers is in Mandai District with an area of 109.93 Ha and then Marusu District with an area of 70.77 Ha, these two sub-districts are sub-districts that are administratively directly adjacent to Makassar City. In the Sungguminasa City area of Gowa Regency, the distribution and area of growth centers show that the largest distribution of growth centers in 2043 is still in Somba Oppu District with an area of 58.35 Ha and indicates an increase of 43.99 Ha.

Conclusion

The determinant factors that most influence the change in the class of undeveloped land and the class of transition areas to growth centers in the Mamminasta area in 2013-2023 in the change are distance from the center of shops, followed by distance from the university, slope and finally distance from the main road. Information related to the distribution of growth centers in the Mamminasata region in 2043 as a whole region, can be viewed from the area of growth centers in each district and city, the Makassar City Region is still an area that has the highest intensity of regional growth centers with an area of 1,410.06 Ha and is the center of growth in the Mamminasata urban area, but it should be noted that the sub-district that has the most rapid increase in the Makassar city area is Biringkanaya District. From Figure 14, the most rapidly growing areas of Maros Regency are Mandai and Marusu Sub-districts, where the two most rapidly growing sub-districts are administratively directly adjacent to Biringkanaya Sub-district, Makassar City, in addition, Mandai and Marusu Sub-districts are sub-districts that make the area and distribution of growth centers in Maros Regency in 2043 will increase rapidly compared to Sungguminasa City and Takalar Regency.

Acknowledgments
Thanks to Universitas Bosowa for allowing me to compose this research article.

Author Contributions
Conceptualization, Emil Salim Rasyidi. Jumadil and Syafri; methodology, Emil Salim Rasyidi; software, Emil Salim Rasyidi. Rusneni; validation, Syafri. and Rahmawati rahman; formal analysis, Emil Salim Rasyidi; investigation, Rusneni; resources, Hamsina; data curation, Emil Salim Rasyidi.; writing—original draft preparation, Emil Salim Rasyidi; writing—review and editing, Emil Salim Rasyidi; visualization, Rusneni; supervision, Emil Salim Rasyidi. And Syafri.; project administration, Hamsina; funding acquisition, Emil Salim Rasyidi.

Funding
This research was funded by Universitas Bosowa.

Conflicts of Interest
No Conflicts of interest.

References

Al-Kheder, S. A. (2006). *Urban growth modeling with artificial intelligence techniques*. Purdue University. Retrieved from https://docs.lib.purdue.edu/dissertations/AAI3259984/

Aldalbahi, M., & Walker, G. (2015). Attitudes and policy implications of urban growth boundary and traffic congestion reduction in Riyadh, Saudi Arabia. *International Conference Data Mining*, 1–2. Retrieved from http://iieng.org/images/proceedings_pdf/2526E0215016.pdf

Bai, Y., Deng, X., Jiang, S., Zhang, Q., & Wang, Z. (2018). Exploring the relationship between urbanization and urban eco-efficiency: Evidence from prefecture-level cities in China. *Journal of Cleaner Production*, *195*, 1487–1496. https://doi.org/10.1016/j.jclepro.2017.11.115

Bakshi, A., & Esraz-Ul-Zannat, M. (2023). Application of urban growth boundary delineation based on a neural network approach and landscape metrics for Khulna City, Bangladesh. *Heliyon*, *9*(6). Retrieved from https://www.cell.com/heliyon/pdf/S2405-8440(23)03479-5.pdf

Bouhennache, R., Bouden, T., Taleb-Ahmed, A., & Cheddad, A. (2019). A new spectral index for the extraction of built-up land features from Landsat 8 satellite imagery. *Geocarto International*, *34*(14), 1531–1551. https://doi.org/10.1080/10106049.2018.1497094

Carlino, G. A., & Mills, E. S. (1987). The determinants of county growth. *Journal of Regional Science*, *27*(1), 39–54. https://doi.org/10.1111/j.1467-9787.1987.t

Cengiz, S., Görmücs, S., & Ouguz, D. (2022). Analysis of the urban growth pattern through spatial metrics; Ankara City. *Land Use Policy*, *112*, 105812. https://doi.org/10.1016/j.landusepol.2021.105812

Cheng, J., & Masser, I. (2003). Urban growth pattern modeling: a case study of Wuhan city, PR China. *Landscape and Urban Planning*, *62*(4), 199–217. https://doi.org/10.1016/S0169-2046(02)00150-0

Cheng, J., & Masser, I. (2004). Understanding spatial and temporal processes of urban growth: cellular automata modelling. *Environment and Planning B: Planning and Design*, *31*(2), 167–194. https://doi.org/10.1068/b2975

Danoedoro, P. (2012). *Pengantar penginderaan jauh digital*. In Yogyakarta: Penerbit Andi.

Dinka, M. O., & Klik, A. (2019). Effect of land use--land cover change on the regimes of surface runoff—the case of Lake Basaka catchment (Ethiopia). *Environmental Monitoring and Assessment*, *191*(5), 278. https://doi.org/10.1007/s10661-019-7439-7

Estoque, R. C., & Murayama, Y. (2013). Landscape pattern and ecosystem service value changes: Implications for environmental sustainability planning for the rapidly urbanizing summer capital of the Philippines. *Landscape and Urban Planning*, *116*, 60–72. https://doi.org/10.1016/j.landurbplan.2013.04.008

Ewing, R., Lyons, T., Siddiq, F., Sabouri, S., Kiani, F., Hamidi, S., Choi, D., & Ameli, H. (2022). Growth management effectiveness: A literature review. *Journal of Planning Literature*, *37*(3), 433–451. https://doi.org/10.1177/08854122221077457

Feng, Y., Liu, Y., Tong, X., Liu, M., & Deng, S. (2011). Modeling dynamic urban growth using cellular automata and particle swarm optimization rules. *Landscape and Urban Planning*, *102*(3), 188–196. https://doi.org/10.1016/j.landurbplan.2011.04.004

Ghosh, A., Ng, K. T. W., & Karimi, N. (2023). An evaluation of the temporal and spatial evolution of waste facilities using a simplified spatial distance analytical framework. *Environmental Development*, *45*, 100820. https://doi.org/10.1016/j.envdev.2023.100820

Grădinaru, S. R., Iojua, C. I., Onose, D. A., Gavrilidis, A. A., Puatru-Stupariu, I., Kienast, F., & Hersperger, A. M. (2015). Land abandonment as a precursor of built-up development at the sprawling periphery of former socialist cities. *Ecological Indicators*, *57*, 305–313. https://doi.org/10.1016/j.ecolind.2015.05.009

Guzha, A. C., Rufino, M. C., Okoth, S., Jacobs, S., & Nóbrega, R. L. B. (2018). Impacts of land use and land cover change on surface runoff, discharge and low flows: Evidence from East Africa. *Journal of Hydrology: Regional Studies*, *15*, 49–67. https://doi.org/10.1016/j.ejrh.2017.11.005

He, Q., Tan, R., Gao, Y., Zhang, M., Xie, P., & Liu, Y. (2018). Modeling urban growth boundary based on the evaluation of the extension potential: A case study of Wuhan city in China. *Habitat International*, *72*, 57–65. https://doi.org/10.1016/j.habitatint.2016.11.006

He, Y., Ai, B., Yao, Y., & Zhong, F. (2015). Deriving urban dynamic evolution rules from self-adaptive cellular automata with multi-temporal remote sensing images. *International Journal of Applied Earth Observation and Geoinformation*, *38*, 164–174. https://doi.org/10.1016/j.jag.2014.12.014

Li, X., & Yeh, A. G.-O. (2002). Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science*, *16*(4), 323–343. https://doi.org/10.1080/13658810210137004

Liladhar Rane, N., Achari, A., Hashemizadeh, A., Phalak, S., Pande, C. B., Giduturi, M., Khan, M. Y. A., Tolche, A. D., Tamam, N., Abbas, M., & others. (2023). Identification of sustainable urban settlement sites using interrelationship based multi-influencing factor technique and GIS. *Geocarto International*, *38*(1), 2272670. https://doi.org/10.1080/10106049.2023.2272670

Liu, X., Li, X., Shi, X., Zhang, X., & Chen, Y. (2010). Simulating land-use dynamics under planning policies by integrating artificial immune systems with cellular automata. *International Journal of Geographical Information Science*, *24*(5), 783–802. https://doi.org/10.1080/13658810903270551

Liu, X., Liang, X., Li, X., Xu, X., Ou, J., Chen, Y., Li, S., Wang, S., & Pei, F. (2017). A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning*, *168*, 94–116. https://doi.org/10.1016/j.landurbplan.2017.09.019

Liu, Y., He, Q., Tan, R., Liu, Y., & Yin, C. (2016). Modeling different urban growth patterns based on the evolution of urban form: A case study from Huangpi, Central China. *Applied Geography*, *66*, 109–118. https://doi.org/10.1016/j.apgeog.2015.11.012

Mantelas, L., Hatzichristos, T., & Prastacos, P. (2008). Modeling urban growth using fuzzy cellular automata. *11th AGILE International Conference on Geographic Information Science, Girona, Spain,* 1-12. Retrieved from https://agile-gi.eu/images/conferences/2008/documents/60_doc.pdf

McDonald, R. I., Green, P., Balk, D., Fekete, B. M., Revenga, C., Todd, M., & Montgomery, M. (2011). Urban growth, climate change, and freshwater availability. *Proceedings of the National Academy of Sciences*, *108*(15), 6312–6317. https://doi.org/10.1073/pnas.1011615108

Müller, K., Steinmeier, C., & Küchler, M. (2010). Urban growth along motorways in Switzerland. *Landscape and Urban Planning*, *98*(1), 3–12. https://doi.org/10.1016/j.landurbplan.2010.07.004

Osman, T., Divigalpitiya, P., & Arima, T. (2016). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on land use in the Giza Governorate, Greater Cairo Metropolitan region. *International Journal of Urban Sciences*, *20*(3), 407–426. https://doi.org/10.1080/12265934.2016.1216327

Oum, T. H., & Park, J.-H. (2004). Multinational firms' location preference for regional distribution centers: focus on the Northeast Asian region. *Transportation Research Part E: Logistics and Transportation Review*, *40*(2), 101–121. https://doi.org/10.1016/S1366-5545(03)00036-X

Pribadi, D. O., Putra, A. S., & Rustiadi, E. (2015). Determining optimal location of new growth centers based on LGP--IRIO model to reduce regional disparity in Indonesia. *The Annals of Regional Science*, *54*, 89–115. https://doi.org/10.1007/s00168-014-0647-8

Santé, I., García, A. M., Miranda, D., & Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning*, *96*(2), 108–122. https://doi.org/10.1016/j.landurbplan.2010.03.001

Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, *109*(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109

Shahfahad, Talukdar, S., Naikoo, M. W., Rahman, A., Gagnon, A. S., Islam, A. R. M. T., & Mosavi, A. (2023). Comparative evaluation of operational land imager sensor on board landsat 8 and landsat 9 for land use land cover mapping over a heterogeneous landscape. *Geocarto International*, *38*(1), 2152496. https://doi.org/10.1080/10106049.2022.2152496

Silva, E. A., & Clarke, K. C. (2002). Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems*, *26*(6), 525–552. https://doi.org/10.1016/S0198-9715(01)00014-X

Sunde, M. G., He, H. S., Zhou, B., Hubbart, J. A., & Spicci, A. (2014). Imperviousness Change Analysis Tool (I-CAT) for simulating pixel-level urban growth. *Landscape and Urban Planning*, *124*, 104–108. https://doi.org/10.1016/j.landurbplan.2014.01.007

Uhl, J. H., Hunter, L. M., Leyk, S., Connor, D. S., Nieves, J. J., Hester, C., Talbot, C., & Gutmann, M. (2023). Place-level urban--rural indices for the United States from 1930 to 2018. *Landscape and Urban Planning*, *236*, 104762. https://doi.org/10.1016/j.landurbplan.2023.104762

Wu, K., & Zhang, H. (2012). Land use dynamics, built-up land expansion patterns, and driving forces analysis of the fast-growing Hangzhou metropolitan area, eastern China (1978--2008). *Applied Geography*, *34*, 137–145. https://doi.org/10.1016/j.apgeog.2011.11.006

Yang, X., Chen, R., & Zheng, X. Q. (2016). Simulating land use change by integrating ANN-CA model and landscape pattern indices. *Geomatics, Natural Hazards and Risk*, *7*(3), 918–932. https://doi.org/10.1080/19475705.2014.1001797

Yasin, M. Y., Abdullah, J., Noor, N. M., Yusoff, M. M., & Noor, N. M. (2022). Landsat observation of urban growth and land use change using NDVI and NDBI analysis. *IOP Conference Series: Earth and Environmental Science*, *1067*(1), 12037. https://doi.org/10.1088/1755-1315/1067/1/012037

Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, *24*(3), 583–594. https://doi.org/10.1080/01431160304987