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Spatial dynamic prediction of landuse / landcover change (case study: tamalanrea sub-district, makassar city)

A M Y Hakim[1] *, S Baja[2], D A Rampisela[2] and S Arif[3 4]

[1] Post Graduate Student, Agricultural Science Study Program, Hasanuddin University, Makassar 90245, Indonesia
[2] Departement of Soil Science, Faculty of Agriculture, Hasanuddin University, Makassar 90245, Indonesia; sbja02@yahoo.com.au; agnes.unhas@gmail.com
[3] Department of Physics, Faculty of Mathematics and Natural Science, Hasanuddin University, Makassar 90245, Indonesia; samsu_arif@unhas.ac.id
[4] Center for Regional Development and Spatial Information (WITARIS), Hasanuddin University, Makassar 90245, Indonesia

* Correspondence: andiyasserpwk@gmail.com

Abstract. The phenomenon of landuse change from an undeveloped area into a built-up area is often the case, especially in big cities. Population growth, both in birth and migration rates, is one of the factors that causes the need for land for various human activities. Tendency for landuse change is expected to continue in the following years along with a region development. The city of Makassar has a tendency for landuse change. This is due to the position of Makassar as the capital of the South Sulawesi province which has A-level public service and it has become a separate magnet for people from outside the city to conduct activities and live in the city. The purpose of this research is to predict landuse/landcover (LULC) change until 2033 by classifying using Landsat satellite imagery include 2008, 2013, and 2018 into 5 landuse/landcover classes in Tamalanrea Sub-District with the Modules for Land Use Change Simulations (MOLUSCE): Multi-Layer Perceptron Neural Network and Geographic Information System method. This research shows the percentage of changes in 5 classes of landuse from 2018 to 2033, are: agriculture area with -0,30%; built-up area with 3.15%; barren area with -5.11%; vegetation with 0.98%; and water body with 1.27%.

1. Introduction

There are fundamental differences between land use (LU) and land cover (LC). According to Baja [1], land use is related to human activities that are directly related to land, where there is use and utilization of land and resources that exist and cause impacts on the land. Meanwhile, land cover is related to vegetation (natural or planted) or construction by human (buildings, etc.) that cover the land surface.

Changes in LULC in the implementation of development are inevitable. These changes occur because of the need to meet the growing needs of the population. There are several factors that influence LULC change, such as environmental, geographical, socio-economic [2] [3] [4], institutional and policy factors [5].

In detail, some researchers used driving factors for LULC change in the form of population density, distance from roads, distance from rivers, distance from nearby cities, distance from urban centers, distance from existing built-up areas, distance from existing agricultural areas, distance from tourist locations, and elevation, slope, rock, soil type [2] [3].

The development of science related to Geographic Information Systems has become increasingly rapid as well as its methods. One of the method is Multi-Layer Perceptron (MLP) Neural Network. This method is used in various purposes, such as detecting surface cracks [6], mapping land suitability [7], predicting land use / cover changes [8] [9] [10], species distribution modelling [11], predicting the performance of waste stabilization ponds [12], traffic crash modelling [13], and so on.

The main objective of this research is to predict changes in land use / land cover (LULC) in the Tamalanrea Sub-district of Makassar City using the Multi-Layer Perceptron (MLP) Neural Network method.

2. Methodology

The following flow chart explains the analytical procedure for carrying out this research work and will be explained on the next part.

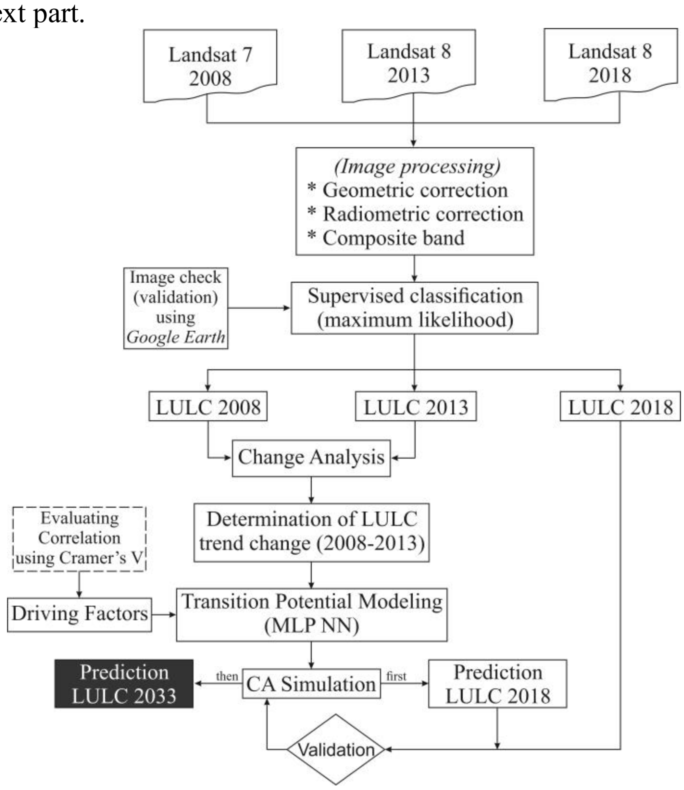

Figure 1. Flow chart of research method.

2.1. Research Area

Tamalanrea Sub-district is one of fifteen sub-districts located in Makassar City (**Figure 2**), which borders the Makassar Strait in the north, Biringkanaya Sub-district in the east, Panakkukang Sub-district in the south and in the west. The area of Tamalanrea Sub-district is recorded at 31,84 km^2 or 18,2% of the total area of Makassar City which includes six villages namely Tamalanrea Indah, Tamalanrea Jaya, Tamalanrea, Kapasa, Parangloe, and Bira.

The topography of the Tamalanrea Sub-district area starts from the lowlands to the highlands with elevations 1-22 m above sea level. Landuse/landcover in this sub-district varies greatly from settlements, offices, shops to educational facilities. One of them is Hasanuddin University which is the largest university in the Eastern Indonesia Region. To the south of this sub-district, there is Tallo River and the people who live around the edge of river, use it to make a pond.

Tamalanrea Sub-district is divided into coastal and non-coastal areas. Four villages that non-coastal areas are Tamalanrea Indah, Tamalanrea Jaya, Tamalanrea and Kapasa. While the two areas (Parangloe and Bira) are coastal areas. According to local statistical data, total population living in this area in 2017 is 112.170.

Figure 2. Makassar City and the location of study area.

2.2. Data Processing and Classification

Landsat images acquired in 2008, 2013, and 2018 (**Table 1**) were obtained from United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/) and processed (geometric correction, radiometric correction, the preparation of the composite image) using raster based image processing program (ErMapper 7.1 software). After that, three of such imagery were classified in ArcGis 10.5 software using supervised classification (maximum likelihood) method and delineated into five LULC classes [2] [14] [15], such as agriculture area, built-up area, barren area, vegetation, and water body (**Table 2**). Furthermore, the interpretation and checking of the image of landsat satellites with high resolution satellite images (Google Earth) is carried out based on each recording year.

Table 1. Satellite data specifications.

Data	Year of acquisition	Bands/color	Resolution (m)	Composite band for getting natural color	Source
Landsat 7 ETM+	2008	Multi-spectral	30	Band 3 (red) Band 2 (green) Band 1 (blue)	USGS
Landsat 8 OLI/TIRS	2013, 2018	Multi-spectral	30	Band 4 (red) Band 3 (green) Band 2 (blue)	USGS

2.3. Multi-Layer Perceptron (MLP) Neural Network Method

The analysis used Multi-Layer Perceptron (MLP) Neural Network method works inside Geographic Information System. This method is carried out on the Quantum GIS 2.18.24 software in which there is a Modules for Land Use Change Simulations (MOLUSCE) plugin. There are six stages of LULC prediction in the MOLUSCE plugin.

Table 2. Classes delineated on the basis of supervised classification.

Class name	Description
Agriculture area	Crop fields and fallow lands
Built-up area	Residential, commercial, industrial, transportation, roads, mixed urban
Barren area	Land areas of exposed soil and barren area influenced by human impact
Vegetation	Mixed forest land

Water body	River, open water, lakes, ponds and reservoirs

2.3.1. Data Entry. The image of the satellite landsat that has been processed and treated is inserted into the MOLUSCE plugin along with the variables/driving factors of LULC changes that have also previously been processed in accordance with the extent of the three LULC maps. This study used seven driving factors including distance from road, distance from sea coast, distance from river, distance from capital, population density, elevation, and slope (**Table 3** and **Figure 3**).

Table 3. Driving factors.

Data	Range	Classifying Method
Distance from road (m)	0 – 1.177	Euclidean Distance
Distance from sea coast (m)	0 – 9.000	Ranked
Distance from river (m)	0 – 4.557	Euclidean Distance
Distance from capital (m)	0 – 14.000	Ranked
Population density (population/sq.km)	0 – 8.531	Ranked
Elevation (m)	0 - 22	Ranked
Slope (%)	0 - 8	Ranked

2.3.2. Evaluating Correlation. At this stage, a correlation test was carried out between the driving factors using the Cramer's Coefficient or Cramer's V methods. Cramer’s V is a statistic that transforms chi-square (for a contingency table larger than two rows by two columns) to a range of 0 - 1, where the unit value indicates complete agreement between the two nominal variables (9). A high Cramer’s V value (more than 0,15) indicates that the potential explanatory value of the variable are good or useful, value that less than 0,15 can be rejected [9] [14] [16].

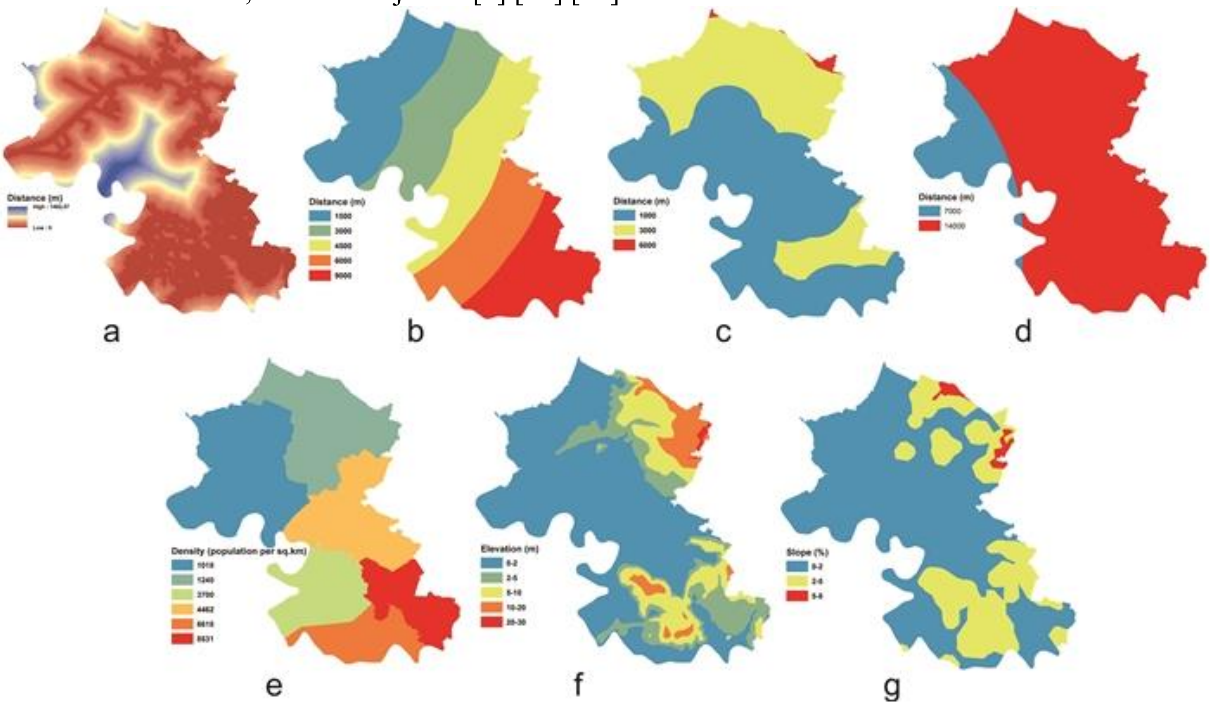

Figure 3. Driving factors (a. distance from road; b. distance from sea coast; c. distance from river; d. distance from capital; e. population density; f. elevation; g. slope).

2.3.3. Area Changes (Change Analysis). This stage results the value of change between the first recording year of LULC and the second recording year of LULC. In this research, the first recording year is 2008 and the second recording year is 2013. The value of this LULC change is mapped which will then be used for the fourth stage.

2.3.4. Transition Potential Modeling. MOLUSCE provides four methods for predicting LULC change, including Artificial Neural Network (Multi-Layer Perceptron), Weights of Evidence, Multi Criteria Evaluation, and Logistic Regression. This research used Artificial Neural Network (Multi-Layer Perceptron) method to train a model of LULC prediction. After the train, the result will show the value of kappa validation.

2.3.5. Cellular Automata Simulation. After the kappa value from the previous stage is in accordance with the assessment standard, then the third year LULC change prediction process is carried out using the cellular automata simulation method. The third year LULC in this study is 2018. The number of iteration simulation should be filled with the value is 1 (for the validation process first).

2.3.6. Validation. At this stage, validation is carried out between the reference map (actual third year LULC) and simulated map (third year LULC prediction) by calculating the overall kappa value. After the overall kappa value is in accordance with the assessment standard, then return to the celluar automata simulation stage to predict future LULC. The year of prediction depends on the number of iterations multiplied by the second year minus the first year. In this research, the iteration values were filled in as much as 4 for projections in 2033.

3. Result and Discussion

The result and discussion in this research are divided into four parts, (i) multi-temporal LULC changes; (ii) assessment of correlation between driving factors; (iii) MLP method; and (iv) prediction model of LULC in 2033.

3.1. Multi-Temporal LULC Change

Multi-temporal LULC maps classified into five LULC classes are shown in **Figure 4**. In 2008, LULC for agricultural areas dominated land use in Tamalanrea Sub-district. It was only in 2013 to 2018 that the increase in population that was directly proportional to the needs of land for population activities increased rapidly so that LULC for built areas also increased. Statistics of changes in area of the five multi-temporal LULC classes are shown in **Table 4**.

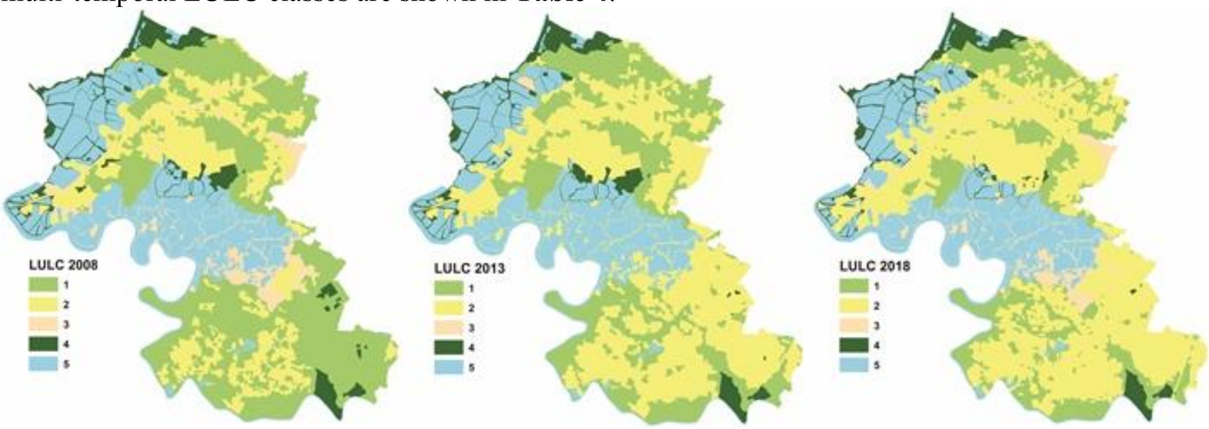

Figure 4. Multi-temporal LULC
(1. agriculture area; 2. built-up area; 3. barren area; 4. vegetation; and 5. water body).

Table 4. Class statistics (2008, 2013, and 2018).

Class statistics of LULC between 2008 - 2013						
Class name	2008 (ha)	2013 (ha)	Δ (ha)	2008 (%)	2013 (%)	Δ (%)
Agriculture area	1.544,73	1.021,15	-523,58	40,04964	26,47521	-13,57443
Built-up area	822,29	1.619,83	797,54	21,31927	41,99677	20,6775
Barren area	241,16	8,01	-233,15	6,25246	0,20760	-6,04486
Vegetation	236,18	223,61	-12,57	6,12322	5,79741	-0,32581
Water body	1.012,68	984,43	-28,25	26,25538	25,52301	-0,73237
Class statistics of LULC between 2013 - 2018						
Class name	2013 (ha)	2018 (ha)	Δ (ha)	2013 (%)	2018 (%)	Δ (%)
Agriculture area	1.021,15	741,19	-279,96	26,47521	19,21663	-7,25857
Built-up area	1.619,83	1.810,11	190,28	41,99677	46,93017	4,93340
Barren area	8,01	197,24	189,23	0,20760	5,11378	4,90618
Vegetation	223,61	183,84	-38,77	5,79741	4,76643	-1,03097
Water body	984,43	924,64	-59,78	25,52301	23,97299	-1,55002

3.2. Evaluating Correlation

The assessment of the correlation between the driving factors causing the LULC change was evaluated using the Creamer's Coefficient or Cramer's V method. Cramer's V value for the seven drivers of LULC change are above 0,15 (**Table 5**). It shows that the seven driving factors can be used in LULC modeling.

Table 5. Driving factors with Creamer's V.

	Elevation	Distance from road	Slope	Population density	Distance from river	Distance from capital	Distance from sea cost
Elevation	--	0,25543	0,52408	0,30058	0,35728	0,29507	0,27257
Distance from road		--	0,26188	0,24716	0,17186	0,17222	0,27158
Slope			--	0,32594	0,19662	0,24074	0,28753
Population density				--	0,37855	0,58918	0,65143
Distance from river					--	0,16870	0,22039
Distance from capital						--	0,55046
Distance from sea cost							--

3.3. MLP Method

The MLP method is carried out to predict LULC in 2018. The results of the 2018 LULC prediction map are juxtaposed with the actual LULC map 2018 with a Kappa overall value of 76%. It shows that LULC predictions can be continued because the Kappa value is good.

3.4. Prediction Model of LULC in 2033

The model of LULC change prediction in 2033 in the MOLUSCE plugin using cellular automata simulations is shown in **Figure 5**. These results show that the class of built-up area is increasing, especially in the area around the campus of Universitas Hasanuddin

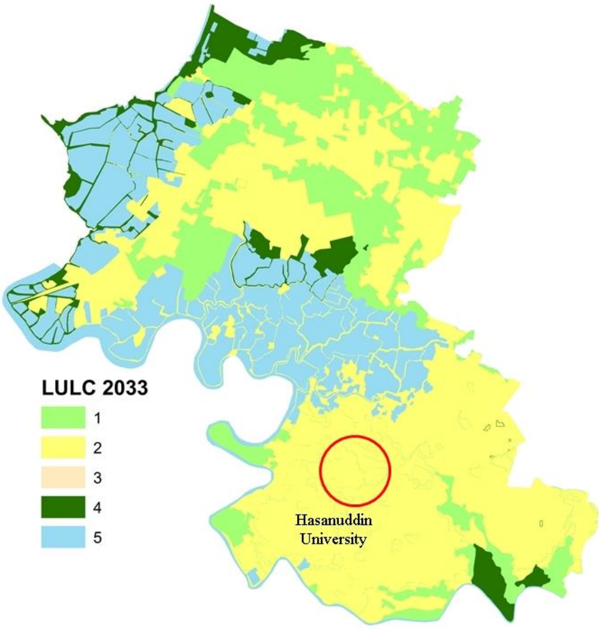

Figure 5. Prediction model of LULC 2033
(1. agriculture area; 2. built-up area; 3. barren area; 4. vegetation; and 5. water body).

Statistics of changes in the area of the five LULC classes from 2018 - 2033 (15 periods) are shown in **Table 6**.

Table 6. Class statistics (2018 - 2033).

Class name	2018 (ha)	2033 (ha)	Δ (ha)	2018 (%)	2033 (%)	Δ (%)
Agriculture area	741,19	729,39	-11,79	19,21663	18,91079	-0,30584
Built-up area	1.810,11	1.931,88	121,78	46,93017	50,08776	3,15759
Barren area	197,24	0,06	-197,18	5,11378	0,00149	-5,11229
Vegetation	183,84	221,75	37,91	4,76643	5,74923	0,98280
Water body	924,64	973,92	49,29	23,97299	25,25073	1,27774

4. Conclusion

The results of this research indicate that the multi-temporal LULC changes (2008, 2013 and 2018) provide Kappa overall accuracy values of more than 70%. The LULC class that experienced the biggest change in decrease from 2008 - 2013 was agriculture area and barren area, while the biggest change in increase was built-up area. In the range of 2013 - 2018, many agriculture areas were transformed into built-up and barren areas. In other side, the use of MLP as a transition potential model and LULC prediction for 2033 using cellular automata simulation showed that the results of built-up area were increasing along with vegetation and water body, the agriculture and barren areas had decreased. It means that, in this research, the driving factors have a very significant influence on the modeling of LULC prediction . This research can provide most of the input for decision makers in future LULC planning. The five common LULC classes only focuses in this research. Therefore, a deeper analysis and a more detailed theme is needed to produce more detailed predictions of LULC.

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