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LAND USE LAND COVER (LULC) CHANGE ANALYSIS IN BAGUIO CITY USING GIS-BASED TRANSITION POTENTIAL MODELING

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ABSTRACT:

Baguio City experienced rapid LULC changes in the past decades due to rising population resulting in increasing demand in residential and commercial areas. The LULC change from 2003 to 2011 was quantified through a transition potential model using Artificial Neural Network and Cellular Automata. Potential driving factors considered in this study were barangay population and population density, land category, elevation, slope, soil type, and distances from the Central Business District, roads, and sinkholes. Multilayer Perceptron with Backpropagation technique was employed in the modeling simulations where various value combinations for the five hyperparameters were tested. Among the combinations of hyperparameter values tested, the combination that achieved the highest simulation accuracy was 1, 0.001, 1000, 10, and 0.01 for Neighborhood, Learning Rate, Iterations, Hidden Layers, and Momentum respectively. The prediction results for the year 2035 show that built-up areas in Baguio City will increase by 760.79 hectares while vegetation and bare soil will decrease by 347.64 hectares and 413.26 hectares, respectively. Built-up areas are expected to form mostly in Alienable and Disposable lands, barangays with high population density, and areas near roads and pre-existing development. On the other hand, minimal built-up expansion is expected in vacant forests, forest reserves, and areas near sinkholes. These findings are in line with the city government's expectations. With an accuracy of 72.80% and a Kappa statistic of 0.61, it can be concluded that the model is capable of predicting future LULC change and may serve as a viable guide for future land use development plans.

1. INTRODUCTION

1.1 Land Use/Land Cover (LULC) Changes in Baguio City

Dubbed the "Summer Capital of the Philippines", Baguio City experienced rapid urbanization over the past decades due to its increasing population, booming tourism industry, and rise in demand for residential and commercial areas. Classified land cover maps derived from Landsat satellite images using a machine learning method employing the random Forest algorithm showed that from 1987 to 2015, the area covered by impervious surface in Baguio City increased by 4379 hectares while open/green spaces had a total loss of 3,115 hectares (Estoque & Murayama, 2017). While residential areas already take up 59.1% of Baguio's land area, the demand for housing continues to rise, leading to the formation of congested high-density residential areas and the encroachment of housing in open and forested areas as recorded by the city government.

1.2 Modeling LULC changes

Studies showing the trend of urban growth and LULC change in previous years provide valuable insight to urban planners and city planning officials for the formulation of their Comprehensive Land Use Plan (CLUP). However, these studies only show the trend in LULC change that has already occurred in the past years. The formulation of a CLUP may be further supplemented if future LULC changes are forecasted by analyzing LULC change trends from the past. Such is the study conducted in Turkey (Buğday & Erkan Buğday, 2019) where a model capable of simulating LULC change was created from remotely sensed data using Artificial Neural Networks (ANN) – systems that try to imitate how the human brain functions, how it receives, processes, weighs and finalizes information to develop algorithms that can help model complex patterns as an aid to estimate and predict possible scenarios (Jahnavi, 2017).

In the field of geoinformatics, Cellular Automata and ANN approaches were used for simulating and predicting LULC changes in past studies covering the Black Tisza River in Ukraine (Mkrtchian & Svidzinska, 2016) and in North Sumatra, Indonesia (Saputra & Lee, 2019).

2. METHODOLOGY

The methodological approach implemented in this study was adapted from previous works of Aneesha Satya et al. (2020), Rahman et al. (2017), Buğday & Erkan Buğday (2019), and Mkrtchian & Swidzinska (2016). These studies use the ANN Multilayer Perceptron with Backpropagation (MLP-BP) method, the most commonly used supervised learning approach for modeling the transition potential and simulating/predicting LULC changes. The main stages in these methodologies are (1) Data Pre-processing and Image Classification, (2) Transition Potential Modeling and Simulation, and (3) Simulation Validation. The detailed processes are shown in Figure 1.

2.1 Data Processing and Image Classification

The data necessary for this study were acquired from various databases and agencies. This includes but is not limited to administrative maps, population data per barangay, Digital Elevation Models (DEM), Landsat imagery, soil maps, road network maps, location of sinkholes, Forest Reservations maps, and Alienable and Disposable Lands maps.

The driving factors of LULC change that were considered in this study are summarized in Table 1. They were identified based on

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characteristics unique to Baguio City as well as factors considered in other related studies.
In order to include these driving factors in the model, it was first necessary to convert them into a readable raster format. Geoprocessing tools were used to convert these raw data into raster files of matching geometries such that each file aligns perfectly with each other and has the exact same number of rows and columns. Additionally, atmospheric correction and supervised classification of the 2003 and 2011 Landsat images were performed using the Semi-Automatic Classification Plugin (SCP) in QGIS in order to generate land cover maps for their respective years.

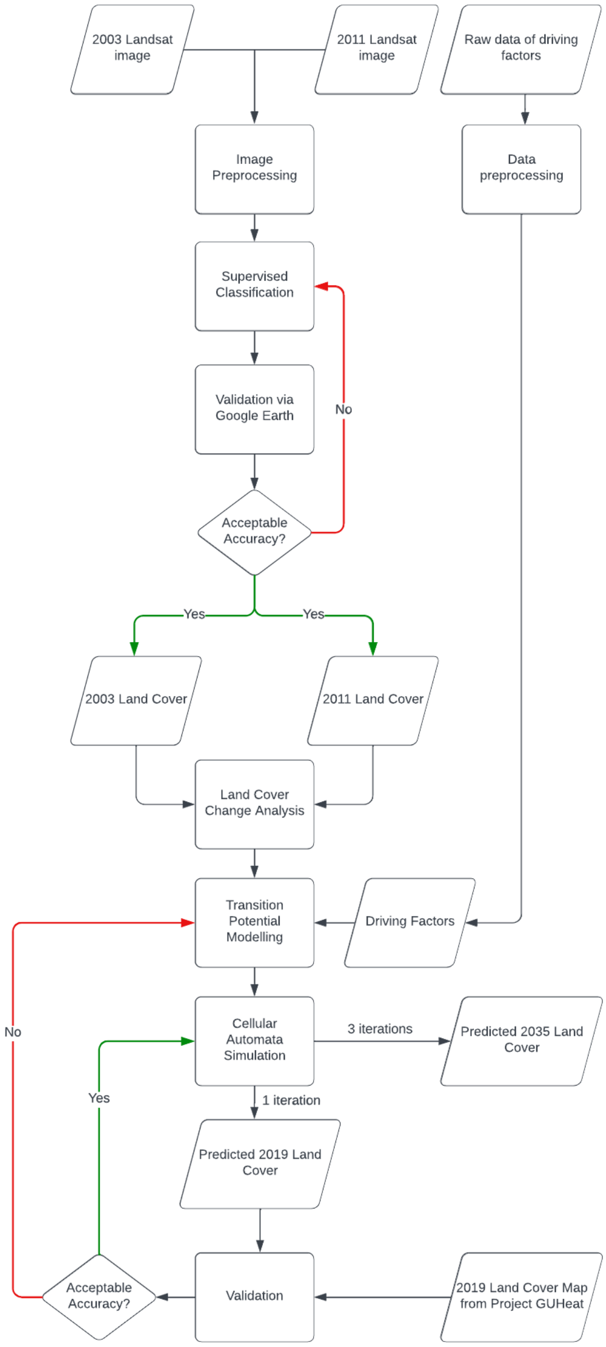

Figure 1. The research methodology

Driving Factor	**Effect on LULC Change**
Barangay Population	The rising population in Baguio City led to an increase in demand for residential and commercial areas (Gonzales, 2016)
Barangay Population Density	
Land Category	In Baguio City, development is allowed only in Alienable and Disposable lands and restricted in Forest Reservations (E. Cayat, personal interview, February 26, 2020).
Distance from the CBD	The local government of Baguio City aims to create growth nodes along strategic areas of the city in order to decongest the Central Business District (The City Government of Baguio, 2011)
Distance from roads	Better accessibility to the road network attracts settlement and urban growth (Singh, 2003).
Distance from sinkholes	Areas in close proximity to sinkholes are not expected to develop into built-up areas (E. Cayat, personal interview, February 26, 2020).
Elevation	Certain geophysical attributes are known to either encourage or resist urban growth (Singh, 2003).
Slope	
Soil Type	Development will be avoided in areas with a soil type that is prone to erosion. (The City Government of Baguio, 2018)

Table 1. The driving factors of LULC change that were considered in this study

2.2 Transition Potential Modeling using MOLUSCE plugin

LULC change assessment and modeling was done using the Modules for Land Use Change Evaluation (MOLUSCE) plugin in QGIS following these five major steps: (1) Evaluation Correlation, (2) Area Changes Evaluation, (3) Transition Potential Modeling, (4) Cellular Automata Simulation, and (5) Validation.

In step 1, the raster files representing the potential driving factors were accessed in order to generate the Correlation Matrix based on Pearson's Correlation. In step 2, the 2003 and 2011 land cover maps were compared and analyzed, generating the Change Map and the transition matrix showing how each land cover class changed from 2003 to 2011. The outputs from the two previous steps, along with the driving factors raster files, were used for Transition Potential Modeling using ANN MLP-BP in steps 3 and 4.

The hyperparameters are the variables that determine the structure of a neural network and how it is trained. As such, determining the appropriate values for each hyperparameter is an integral part of the modeling stage. The hyperparameters in this simulation are as follows: Neighbourhood, Learning rate, Iterations, Hidden Layers, and Momentum. Among these hyperparameters, Learning Rate and Momentum are the ones that play a significant role in training the network and are usually tuned/adjusted in a sensitivity analysis to come up with good accuracy of the model (Brownlee, 2019; Kavzoglu & Mather, 2003; Lek & Park, 2008).

21 combination sets, summarized in Table 2, were tested in this study. Being the ones that play a significant role in training a neural network, the values of Neighborhood and Learning rate were adjusted for testing one at a time while keeping the others at their default values in order to obtain the combination that yields the most accurate results. The values used for these parameters were set based on recommendations from similar studies (Brownlee, 2019; Mack, 2018) and evaluated based on the highest accuracy in the validation step.

Set	Neighborhood	Learning Rate	Iterations	Hidden Layers	Momentum
1	1	0.1	100	10	0.05
2	2	0.1	100	10	0.05
3	3	0.1	100	10	0.05
4	1	1	100	10	0.05
5	1	0.01	100	10	0.05
6	1	0.001	100	10	0.05
7	1	0.001	1000	10	0.05
8	1	0.001	10000	10	0.05
9	1	0.001	1000	5	0.05
10	1	0.001	1000	20	0.05
11	1	0.001	1000	50	0.05
12	1	0.001	1000	10	0.99
13	1	0.001	1000	10	0.9
14	1	0.001	1000	10	0.5
15	1	0.001	1000	10	0.01
16	1	0.001	1000	10	0.001
17	1	0.001	10000	10	0.01
18	1	0.001	100	10	0.01
19	1	0.001	1000	100	0.01
20	2	0.001	1000	10	0.01
21	3	0.001	1000	10	0.01

Table 2. The 21 combination sets applied in the study considering the five adjustable hyperparameters in the simulation

2.3 LULC simulation and validation

The generated transition potential model together with the 2011 land cover map and raster maps of the potential factors were used in the Cellular Automata step to produce the simulated land cover map of 2019. Each iteration of the Cellular Automata Simulation has an interval of 8 years, as set by the number of years between the initial and final land cover maps (2003 and 2011). The 2019 prediction was then validated with the 2019 Land Cover map produced by the Project Geospatial Assessment and Modelling of Urban Heat Islands in Philippine Cities (GUHeat), a research project funded by the Department of Science and Technology in 2019.

3. RESULTS AND DISCUSSION

3.1 Accuracy assessment of land cover maps

The 2003 and 2011 Land Cover maps were validated through 100 random points using historical imagery from Google Earth. The 2003 and 2011 land cover maps achieved an overall accuracy of 85% and 86% respectively. Furthermore, each map achieved Kappa values of 74.50 and 76.03 respectively. Accuracy results are summarized in Table 3.

	2003		2011	
	Producer's Accuracy	**User's Accuracy**	**Producer's Accuracy**	**User's Accuracy**
Vegetation	85.965	94.231	87.037	88.679
Built-up	84.375	87.097	88.095	84.091
Bare	80.000	50.000	33.334	50.000
Water	100.000	100.000	100.000	100.000

Table 3. Producer's and User's Accuracy of the 2003 and 2011 LC maps

From 2003 to 2011, the land cover with the largest expansion was built-up, increasing from 27.16% of Baguio's land area in 2003 to 44.71% in 2011, as shown in Table 4 and 5. This is a 17.55% increase in the span of 8 years, or about 2.19% annually. This expansion of built-up came mostly at the expense of vegetation with 941.68 hectares of previously vegetated areas developed into built-up. Meanwhile, 337.168 hectares of bare land were converted to built-up.

		TO			
		Vegetation	**Built-up**	**Bare**	**Water**
FROM	Vegetation	2704.150	941.683	41.075	0.075
	Built-up	187.735	1438.600	24.808	0.198
	Bare	321.465	337.168	86.440	0.000
	Water	0.183	0.180	0.000	0.718

Table 4. A transition matrix showing the land areas (hectares) that transitioned from each land cover class to another from 2003 to 2011

		TO			
		Vegetation	**Built-up**	**Bare**	**Water**
FROM	Vegetation	2607.870	413.920	182.878	0.125
	Built-up	698.505	1780.493	236.475	0.248
	Bare	57.808	85.883	8.310	0.000
	Water	0.138	0.375	0.070	0.408

Table 5. A transition matrix showing the land areas (in hectares) for each land cover class from 2011 to 2019

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Analyzing the land cover change between 2011 and 2019, it is observed that the expansion of built-up mostly occurred at the peripheries of the city, far from the Central Business District. This contrasts the pattern from 2003 to 2011 where existing neighborhoods near the CBD expanded outwards, encroaching on nearby vegetated lands (in Figure 2). City development usually leads to built-up areas encroaching into previously vegetated areas. Interestingly, the largest transition that occurred from 2011 to 2019 was built-up areas transforming into vegetation. This transition amounted to 698.505 hectares, resulting in the decline of the overall area occupied by built-up. This is a sharp deviation from the trend from 2003 to 2011 where built-up areas increased while vegetation decreased. The transition from vegetation to built-up, on the other hand, amounted to only 413.92 hectares.

3.2 LULC change analysis

Land cover changed more dynamically in the 2019 map of Project GUHeat compared to the prediction results as there were 1676.423 hectares of land which transitioned to a different land cover class, as observed in Figure 3. Overall, the simulation results show areas with relatively high potential to change, highlighting areas where built-up expansions occurred. Furthermore, the simulation was able to properly represent protected areas maintaining their vegetation and resisting significant built-up expansion.

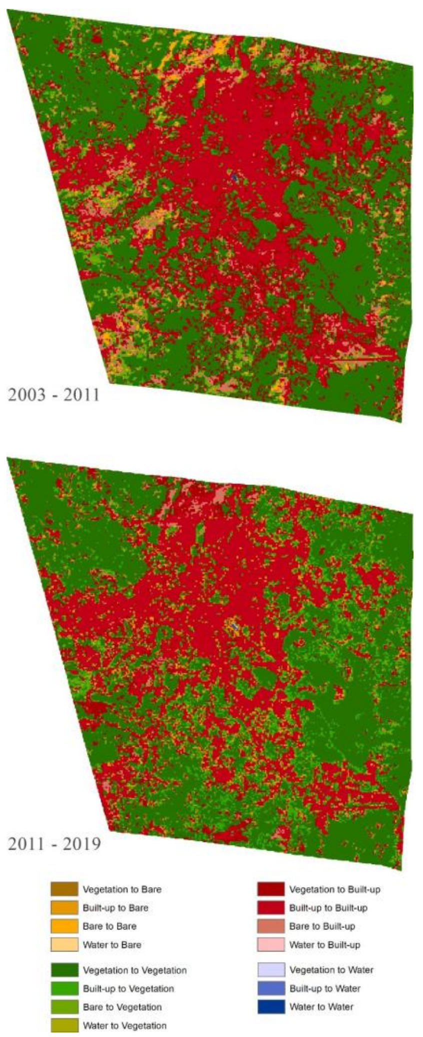

Figure 2. LULC changes in Baguio City from 2003 to 2011 and from 2011 to 2019

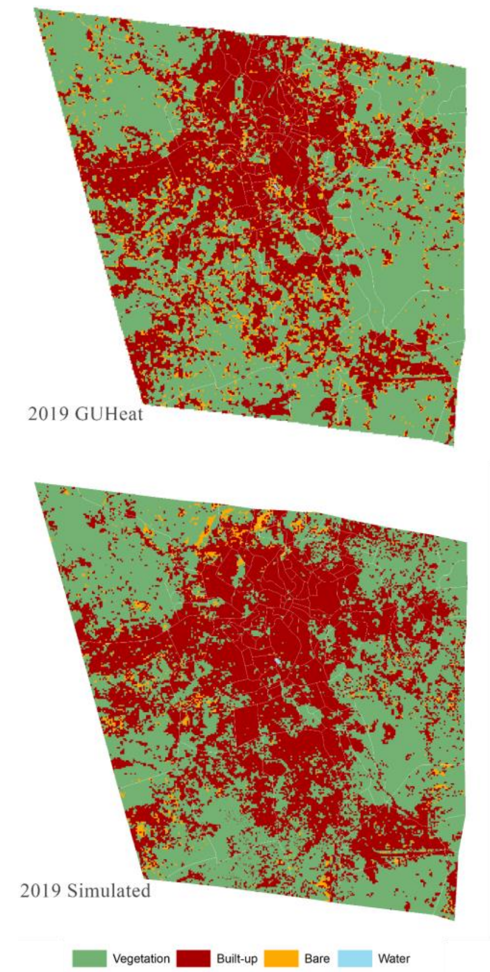

Figure 3. 2019 LULC map from Project GUHeat (top) vs. the simulated 2019 LC map (bottom)

3.3 Land cover prediction maps

The simulation predicted that by 2035, the land distribution in Baguio City will be 3016.68 hectares (49.67%) vegetation, 3041.46 hectares (50.08%) built-up areas, 14.47 hectares (0.24%) bare Soil, and 0.90 hectares (0.01%) water. These areas are illustrated in Figure 4.

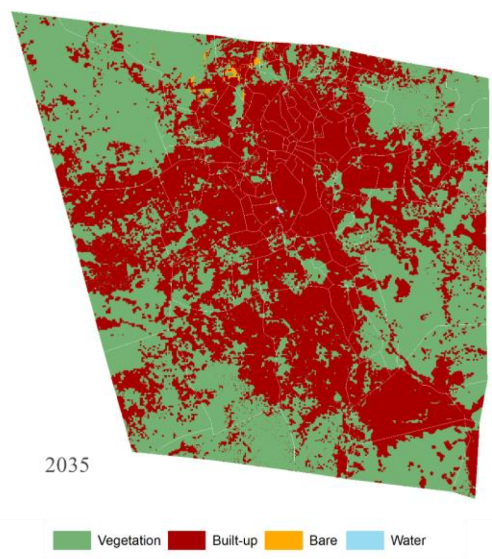

Figure 4. LULC prediction map of 2035

From 2019 to 2035 (shown in Figure 5), the simulation predicted that vegetated lands will decrease by 347.64 hectares (5.72%), built-up areas will increase by 760.79 hectares (12.53%), bare soil will decrease by 14.47 hectares (6.80%) and water will slightly increase by 0.12 hectares (0.002%). The very little change in water classification is due to the fact that pixels classified as water only cover Burnham Lake located in Burnham Park, the only water body present in Baguio City. Given the fact that its boundaries are fixed and manmade, it is likely there will be no changes in its coverage unless a major renovation is to be done in Burnham Park.

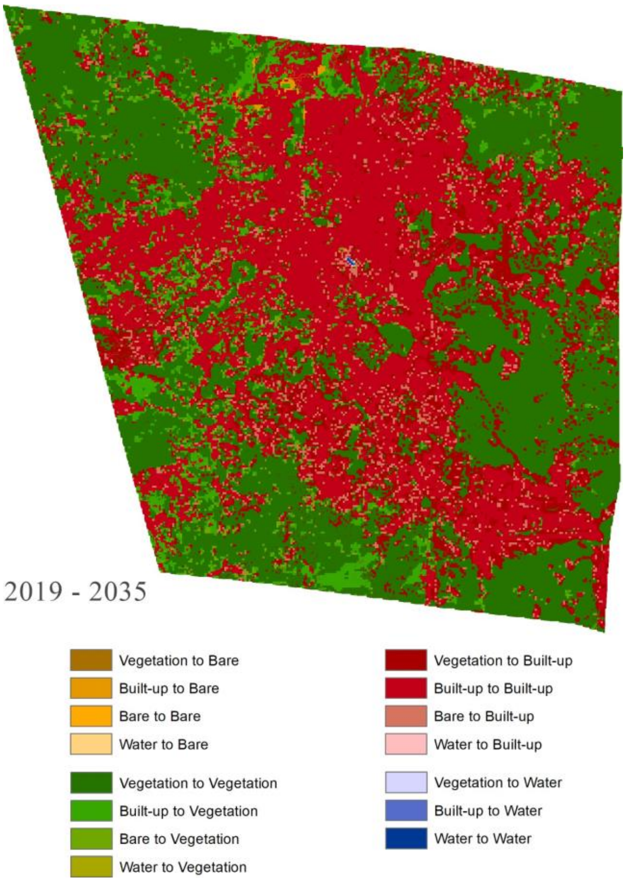

Figure 5. The predicted LULC change in Baguio City from 2019 to 2035

The greatest contributor to the increase of built-up areas by 2035 is the vegetation class, with a total of 1880.66 hectares converted to built-up areas, as shown in Table 6. These are concentrated in Brgy. Asin Rd, Brgy. Santo Tomas Proper, Brgy. Camp 7, Brgy. Liwanag-Loakan, Loakan Proper, Trancoville, and Camp John Hay. These are areas that are found alongside roads and/or are continuations of expanding built-up features from the previous years.

A common characteristic among the barangays mentioned above is that built-up developments, specifically residential developments, tend to form close to each other. These expansions of built-up areas tend to concentrate on one section of the barangay, leaving the other parts of the barangay vegetated. This phenomenon is most predominantly seen in barangays with large land areas such as Irisan and Asin Rd.

In the Central Business District, barely any vegetated areas were converted to built-up. This is expected as the already congested CBD has little to no vegetation to convert into built-up. Furthermore, this properly reflects the pattern of land cover change within the CBD during the training years of 2003 to 2011.

In an interview with the head of the City Planning and Development Office (CPDO) of Baguio City, it was mentioned that the areas near the vicinity of sinkholes (in Figure 6) are not expected to have large amounts of built-up developments in the future. In 2035, the simulation predicted that there would be minimal built-up developments formed near sinkholes. However, imagery from Google Earth showed that there were already built-up developments near sinkholes in the year 2019. These are residential areas located at Brgy Irisan, Pinsao Proper, Asin Rd, San Luis Village, Dominican Hill-Mirador, Bakakeng Central, and Dontogan.

		TO			
		Vegetation	**Built-up**	**Bare**	**Water**
FROM	Vegetation	2483.993	878.168	2.055	0.105
	Built-up	387.900	1880.663	11.758	0.350
	Bare	144.770	282.248	0.658	0.058
	Water	0.018	0.380	0.000	0.383

Table 6. A transition matrix showing the land areas (hectares) that transitioned from each land cover class to another from 2019 to the 2035 prediction

Figure 6. Sinkholes located in existing residential areas (Base map source: Google Earth, 2020)

The CPDO also expects that the development of built-up areas will only occur in Alienable and Disposable Lands. On the other hand, vacant forests and forest reserves shall have minimal to no development. The 2035 prediction reflects this well, as shown in Figure 7, as developments in built-up areas would occur on Alienable and Disposable lands but will be minimal on the vacant forests. Development inside forest reserve areas is still possible by 2035, however, as a noticeable amount of vegetated areas were converted to built-up areas inside Camp John Hay. These changes came from the expansion of existing built-up areas inside the said camp.

The overall accuracy of 72.80% and kappa value of 0.61 achieved by this simulation are comparable to those yielded by related simulation studies (summarized in Table 7) using CA-

ANN in MOLUSCE. This shows that the model is capable of predicting future land cover change and may serve as a viable guide for future land use development plans.

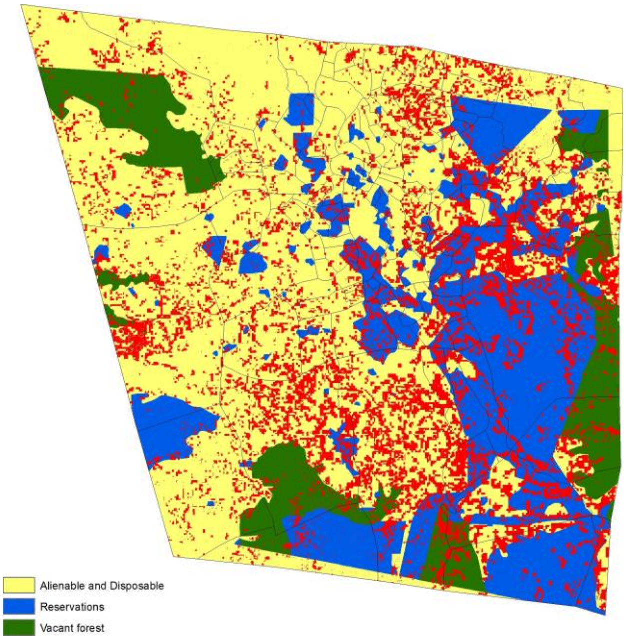

Figure 7. Predicted built-up expansion by 2035 (red pixels).

Authors	Year of Study	Percent Correctness
M. Tauhid Ur Rahman et al	2017	70.20
Alexander Mkrtchian & Daria Svidzinska	2015	71.10
B. Aneesha Satya et al	2000	76.23

Table 7. Accuracy of other Simulation studies using CA-ANN in MOLUSCE

4. CONCLUSION

In conclusion, the prediction results align with the city's urban planning expectations as outlined in their Comprehensive Land Use Plan (CLUP). The model predicts the expansion of new built-up areas away from the Central Business District, in line with the city's efforts to alleviate congestion. Furthermore, future urban development is expected mostly in Alienable and Disposable lands, while minimal built-up expansion is anticipated in forest reservations.

The city's plan of avoiding development near hazardous sinkholes was also reflected in the model. However, the study also found that several residential areas already exist near sinkholes. This is a concern that the city government must monitor and address moving forward.

With an overall accuracy of 72.80, comparable to the accuracy achieved by related studies, it can be concluded that this model is a viable tool for predicting future land use and land cover change and may serve as a guide for the creation of land use development plans.

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