Simulating Land Use Change in Ilagan, Isabela using Markov Chains and Cellular Automata

Arnel Malubay
Department of Information Systems and Computer Science
Ateneo de Manila University
Quezon City, Philippines
arnel.malubay@obf.ateneo.edu

Patricia Angela Abu, PhD
Department of Information Systems and Computer Science
Ateneo de Manila University
Quezon City, Philippines
pabu@ateneo.edu

Raphael Alampay, PhD
Department of Information Systems and Computer Science
Ateneo de Manila University
Quezon City, Philippines
ralampay@ateneo.edu

Christian Paul Chan Shio, PhD
Department of Mathematics
Ateneo de Manila University
Quezon City, Philippines
cchanshio@ateneo.edu

***Abstract*—The loss of vegetation and forestland has been an ever-present concern in our rapidly urbanizing society. Coupled with the looming threat of climate change, this presents challenges to the economy, food sustainability, wildlife preservation, and disaster management. As such, efforts to model land use change are utilized to better enable policymakers and relevant stakeholders in strategic planning of urban landscapes.**

In this project, a Markov chain cellular automata model will be used to simulate the land use change in Ilagan City, Isabela, a highly forested city in the Philippines over a span of 50 years . An open source land use map for 2020 will be used as the initial configuration for the cellular automata. Three transition matrices will be utilized, all of which are derived from historical data on land use change in select areas in the country. Results suggest a general trend of decrease in agricultural open land and significant increase in built-up urban area, with results showing up to 57.42% increase in land cover for built-up surfaces over a span of 50 years. Surprisingly, results also show an increase in forestland, which suggests either an expected preservation of forestland in the coming decades, or a limitation of the neighborhood-based simulation in a majorly forested area.

***Index Terms*—cellular automata, Markov chains, land use change, urbanization, deforestation**

I. Introduction

Deforestation has been a major concern to the global community in the past two decades, as the world experienced a net loss of 101 Megahectares of tree cover from 2000 to 2020 [1]. Within the South and Southeast Asian region in particular, a long running-relationship between deforestation, urbanization, economic growth, and carbon dioxide emissions have been established, with results further suggesting the aggravation of environmental pollution associated due to deforestation and urbanization [2]. As such, modeling of land use and forest cover change have been explored deeply in the past few years in hopes of enabling better and calculated urban planning.

As a third-world country surrounded by several coastlines, the Philippines faces a looming and ever-present threat brought about by climate change. Unfortunately, the country has also been experiencing a constant and steady decline in forest cover, losing around 77 kilohectares of forest cover from 1990 to 2021 [3]. In line with this, the goal of this paper is to simulate the land use change in Ilagan City, the capital and largest city of Isabela, which is the province with the fourth highest forest cover in the country as of 2021 [3]. In particular, several scenarios represented by different Markov chain transition matrices will be incorporated with cellular automata in order to see the possible trends in land use change that Ilagan, Isabela may experience in the coming years.

II. Review of Related Literature

The use of cellular automata in modelling the dynamics of land use have been commonplace in the last two decades. As early as 2004, cellular automata was coupled with fuzzy sets theory in order to improve GIS-based land use change modelling [4]. In the same year, system dynamics was also integrated into cellular automata in order to create a land use scenario dynamics model [5].

Eventually, the integration of artificial intelligence techniques in cellular automata-based land use change modelling will be explored. Okwuashi et al. used support vector machines in order to create nonlinear cellular automata transition rules in a land use change model [6]. A similar approach was done by Wu and Hong using logistic regression modelling [7] and by Qin and Fu using random forests [8]. The use of agents and reinforcement learning was also explored by Ettabaa et al. [9] and Sfa et al. [10] respectively.

Another common approach is the use of Markov chains in order to utilize historical land transition data in creating the transition rules for a cellular automata in a land use change model. This particular approach was done in the case of Changping District [11], Nansi Lake [12], Qingdao [13], Beijing [14], Prayagraj [15], and Kyiv [16].

Some studies also focus on integrating certain socioeconomic and environmental aspects in the analysis of land use change models. Pei et al. utilized economic data in modelling the land use change in Jinzhou [17]. On the other hand, Kang and Kim simulated land use change in the context of autonomous vehicles [18]. On the environmental side, Capetillo and Medina integrated tree growth temporal dynamics in modelling land use change and reforestation in Mexico [19]. Similarly, both Pinheiro et al. [20] and Putri et al. [21] utilized a multitude of variables in analyzing and creating the transition rules for their land use change models.

In the context of the Philippines, certain studies utilizing cellular automata in modelling natural phenomena has been done as well. Tan and Vicente used cellular automata to simulate fire spread in urban settlements [22]. On the other hand, Beltran and David used Markov chains and cellular automata to model the land use change in Camiguin [23]. The methodology followed by the latter study will be the basis for the methodology that will be used in this project.

III. Methodology

Fig. 1 outlines the methodological framework to be used in this project.

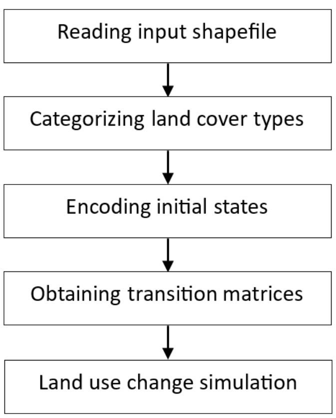

Fig. 1. Methodological Framework

A. Reading input shapefile

The data that will be used for this project is a shapefile of Ilagan City, Isabela that captures the land use status of the city in 2020 that was sourced from the Isabela Land Cover Assessment (ILCA) project of the Institute of Environmental Science for Social Change (ESSC) [24]. This dataset contains 19 land cover classes, which are as follows:

Banana, Coconut, Primary Forest, Secondary Forest, Ultramafic Forest, Mangrove, Cassava, Mossy Forest, Shrubland, Sugarcane, Land with tree cover, Built-up surfaces, Water, Bare soil/sediment, Grassland, Corn, Calamansi, Limestone Forest, and Rice

The shapefile provided encodes a rectangular map that does not show the borders of Ilagan City, as shown in Fig. 2. In order to reflect the city borders, a shapefile of Philippine municipalities obtained from [25] was used to overlay the borders of Ilagan City to the land cover map, as shown in Fig. 3.

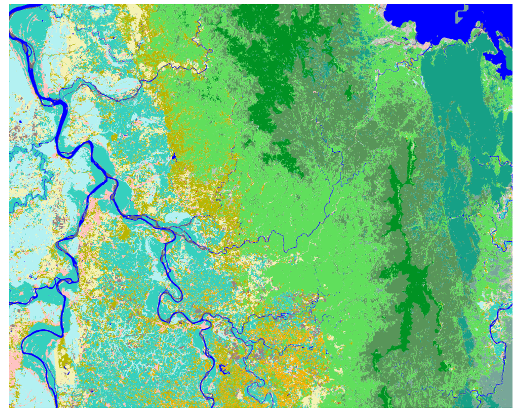

Fig. 2. Land Cover Map of Ilagan City in 2020

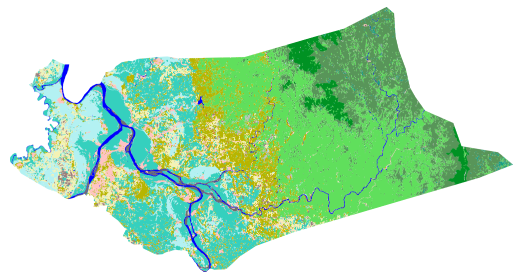

Fig. 3. Land Cover Map of Ilagan City in 2020 with city borders reflected

B. Categorizing land cover types

In order to proceed with land use change simulation using cellular automata, the states of the cellular automata must first be defined. Although the provided land cover types could be used as states of the cellular automata, doing so would imply a total of 19 states, which requires the creation of a 19 x 19 transition matrix. In order to simplify the simulation, a total of 4 states will be used, which follows the states used in [23]. These states correspond to groups of land cover types provided in the dataset, as shown below.

1) State 0 : Forests and Wooded Land:
   Primary Forest, Secondary Forest, Ultramafic Forest, Mossy Forest, Land with tree cover, and Limestone Forest
2) State 1 : Open Land:
   Banana, Coconut, Cassava, Shrubland, Sugarcane, Bare soil/sediment, Grassland, Corn, Calamansi, and Rice
3) State 2 : Built-up Areas:
   Built-up surfaces
4) State 3 : Water:
   Water and Mangrove

Upon classifying the states, the resulting map is shown in Fig. 4.

C. Encoding initial states

The resulting map reflecting the states defined previously was then saved as a PNG image and loaded as a two-dimensional array where each entry corresponds to a state

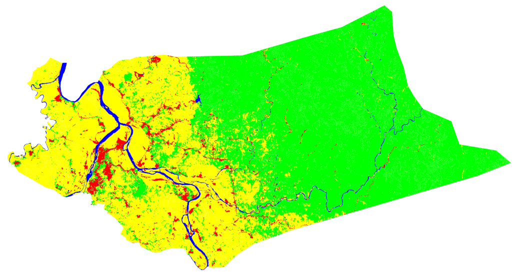

Fig. 4. Land Use States of Ilagan City (Forest and Wooded Land is colored green, Open Land is yellow, Built-up Areas is red, and Water is blue)

based on the pixel color. This was done since the original shapefile file format can not be directly represented in a pixel-wise manner. The array of initial states has shape $1,498$ x 787, equating to $1,178,926$ pixels, $551,567$ of which corresponds to pixels outside the city borders (colored white) and were assumed to be constant throughout the entire simulation, i.e. city territory is assumed to be constant. The remaining $627,359$ pixels correspond to $1,131.87$ km^2 of land area [24], which means each pixel covers $1,804.18$ m^2. The land cover for each state in the initial configuration is given in Table I.

TABLE I
INITIAL LAND COVER

State	Pixel Count	Percentage	Land Cover
Forests and Wooded Land	358,604	57.16	646.99 km^2
Open Land	232,253	37.02	419.03 km^2
Built-up Areas	22,853	3.64	41.23 km^2
Water	13,649	2.18	24.63 km^2

D. Obtaining transition matrices

For this project, three setups of transition matrices will be considered. These matrices were obtained from existing literature of land use change in select areas in the Philippines, namely: Mactan Island [26], Laguna de Bay [27], and Baroro Watershed (in La Union) [28]. Similar to [23], a major assumption for this simulation is that the transitions between different land use states are dependent on the area's population growth rate. As such, the transition matrices will be adjusted based on the area's population growth rate as well as Ilagan's growth rate. All growth rate data are obtained from the latest census of the Philippine Statistics Authority's official website [29].

For the adjustment of the transition matrices, the methodology from [23] will also be adopted. Consider the land use transition matrix $T^{A,t}$ of location A over a span of t years, where $T^{A,t}_{i,j}$ describes the percentage change of land use state i to land use state j in A over t years. Suppose location A has a population growth rate of g_a, and location B has a population growth rate of g_b. It follows that the adjusted annual transition matrix for location B, which we denote as $T^{B,1}$, is defined as follows:

$$T^{B,1} = \exp\left(\frac{\log\left(T^{A,t}\right)}{\left\lfloor \frac{tg_a}{g_b} \right\rfloor}\right) \tag{1}$$

where $\exp$ and $\log$ denote matrix exponentiation and matrix logarithm respectively. It should be noted that this particular approach in deriving annual transition matrices can yield negative matrix entries, which are not suitable for simulation purposes [30]. However, in the case of this project, as well as that of [23], all derived transition matrices have nonnegative entries.

E. Land use change simulation

The simulation process to be used in this project is based on [23]. A transition matrix T will first be derived (as shown in the previous section), where $T_{i,j}$ represents the annual rate of change from state i to state j based on previous historical data. In this project, a series of transition matrices T will be used, with each representing a certain trend in land use change.

For this simulation, the neighborhood of each cell/pixel is a 7 x 7 Moore neighborhood around the cell, consisting of 48 neighbors in total. The transition rule to be used will not be deterministic but is instead a probabilistic one. Given a cell with current state i, let $p_{i,j}$ be the probability that the cell transitions to state j in the current timestep. This probability is then defined by (2).

$$p_{i,j} = \frac{w_j T_{i,j}}{\sum_{k=0}^{3} w_k T_{i,k}} \tag{2}$$

where w_j is the number of neighboring cells in state j. This particular formulation assumes that cell transitions are dictated by the transition matrix T and the immediate neighborhood of the given cell.

As mentioned previously, all white pixels are not considered for the simulation and as such, only the four states defined previously are considered in the transition matrix T.

Finally, since the cellular automata is stochastic, several runs of the simulation will be done for each transition matrix. From this, summary results will then be obtained and analyzed.

IV. Results and Discussions

For each of the three setups that will be considered, a simulation of the land use change will be done over a span of 50 years. After which, 5 runs of each setup will also be done in order to analyze the terminal land use percentages across multiple runs.

A. Setup 1: Mactan Island

The following land use transition matrix of Mactan Island over a span of 18 years $(2000-2018)$ was obtained from [26].

$$\begin{pmatrix} 0.538 & 0.062 & 0.396 & 0.004 \\ 0.359 & 0.256 & 0.369 & 0.017 \\ 0.208 & 0.075 & 0.715 & 0.003 \\ 0.202 & 0.110 & 0.158 & 0.530 \end{pmatrix}$$

From this, an annual transition matrix for Ilagan City was derived, using the methods described earlier. This matrix, which we denote as T_1, is shown below:

$$T_1 = \begin{pmatrix} 0.982 & 0.003 & 0.015 & 0.000 \\ 0.021 & 0.965 & 0.013 & 0.001 \\ 0.007 & 0.004 & 0.989 & 0.000 \\ 0.006 & 0.006 & 0.002 & 0.985 \end{pmatrix}$$

After running a simulation using T_1 over 50 timesteps, the resulting land use stackplot is shown in Fig. 5. The terminal land use percentages are summarized in Table II. From these figures, we see an increase in both forests and wooded land and built-up areas, accompanied by decreases in open land and water. Although the increase in built-up areas seems quite small, it is worth noting that its initial land cover is minimal. As such, the increase from 3.64% to 4.48% actually equates to around a 23.08% increase in land cover over 50 years. Similarly, the decrease in water is around 38.53%.

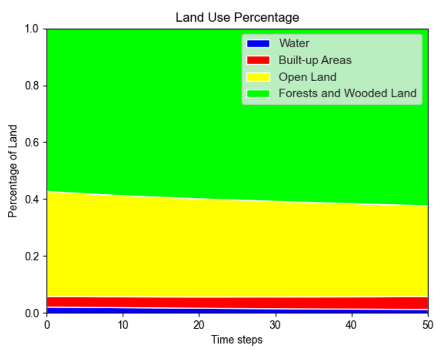

Fig. 5. Land Use Stackplot for T_1

TABLE II
TERMINAL LAND COVER PERCENTAGES OVER 50 YEARS FOR T_1

State	Initial	Terminal	Net Change
Forests and Wooded Land	57.16	62.23	+5.07
Open Land	37.02	31.96	-5.06
Built-up Areas	3.64	4.48	+0.84
Water	2.18	1.34	-0.84

Running the simulation 5 times shows that the terminal percentages across the runs are quite similar, with only minute differences, as shown in Fig. 6. This verifies the trend that was established earlier.

B. Setup 2: Laguna de Bay

For our second setup, the following land use transition matrix of the Laguna de Bay area over a span of 15 years ($2015 - 2030$) was obtained from [27]. It is worth noting that the matrix below is also a derived one, which [27] based on previous land use data as well, thereby allowing it to include further years. Unfortunately, the data that this matrix was based on is not readily available.

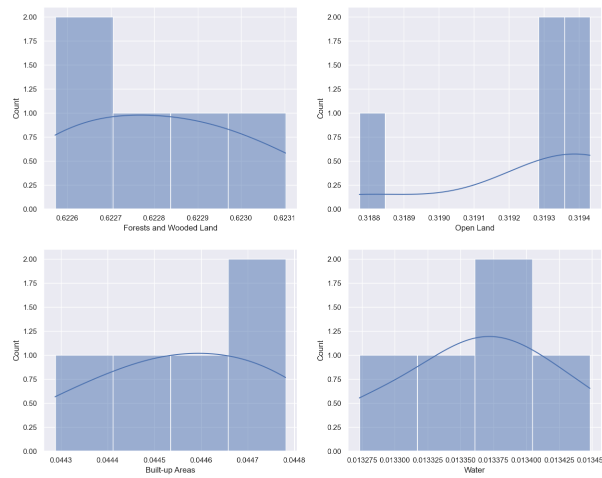

Fig. 6. Terminal Land Use Percentages across 5 runs for T_1

$$\begin{pmatrix} 0.742 & 0.237 & 0.021 & 0.000 \\ 0.312 & 0.575 & 0.114 & 0.000 \\ 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{pmatrix}$$

From this, the following matrix is derived, which we denote as T_2.

$$T_2 = \begin{pmatrix} 0.980 & 0.020 & 0.000 & 0.000 \\ 0.026 & 0.966 & 0.008 & 0.000 \\ 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{pmatrix}$$

The resulting land use stackplot after 50 timesteps of simulation is shown in Fig. 7 while the terminal land use percentages are summarized in Table III. From these figures, we see a very slight increase in forests and wooded land and a slight decrease in open land. Similar to the previous setup, the increase in built-up areas is quite significant, amounting to 26.10% increase in land cover over 50 years. Water area on the other hand, is unchanged, which is to be expected from T_2.

TABLE III
TERMINAL LAND COVER PERCENTAGES OVER 50 YEARS FOR T_2

State	Initial	Terminal	Net Change
Forests and Wooded Land	57.16	57.45	+0.29
Open Land	37.02	35.78	-1.24
Built-up Areas	3.64	4.59	+0.95
Water	2.18	2.18	0.00

Running the simulation 5 times once again shows that the terminal percentages across the runs are similar, as shown in Fig. 8.

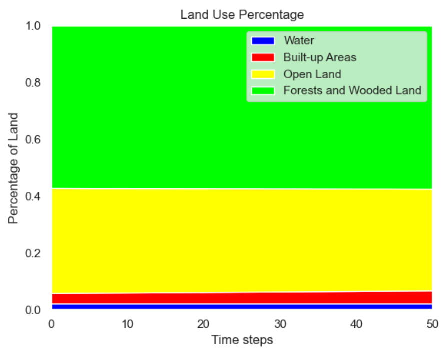

Fig. 7. Land Use Stackplot for T_2

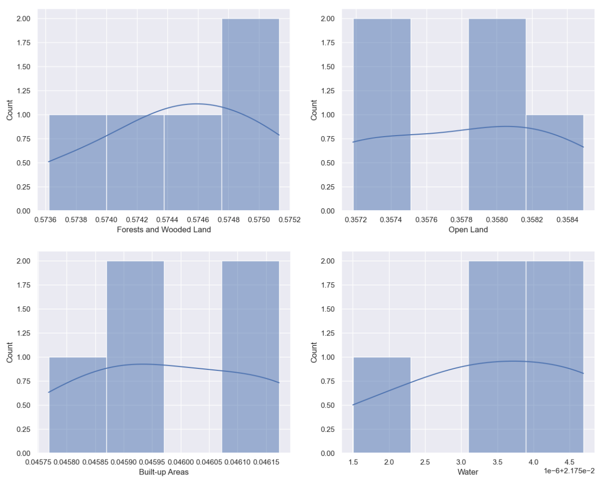

Fig. 8. Terminal Land Use Percentages across 5 runs for T_2

C. *Setup 3: Baroro Watershed*

For our last setup, the following transition matrix of Baroro Watershed in La Union over 12 years $(2003 - 2015)$ was obtained from [28].

$$\begin{pmatrix} 0.759 & 0.230 & 0.011 & 0.000 \\ 0.353 & 0.576 & 0.072 & 0.000 \\ 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{pmatrix}$$

The derived transition matrix, which we denote as T_3, is shown below.

$$T_3 = \begin{pmatrix} 0.943 & 0.057 & 0.000 & 0.000 \\ 0.087 & 0.898 & 0.015 & 0.000 \\ 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{pmatrix}$$

After running a simulation using T_3 over 50 timesteps, the resulting land use stackplot is shown in Fig. 9, while the terminal land use percentages are summarized in Table IV. From these figures, we once again see an increase in both forests and wooded land and built-up areas and a decrease in open land. The increase in built-up areas in this setup is by far the highest one, rising from 3.64% to 5.73% for a percentage increase of around 57.42%.

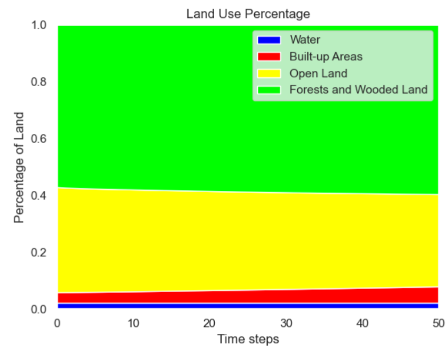

Fig. 9. Land Use Stackplot for T_3

TABLE IV
TERMINAL LAND COVER PERCENTAGES OVER 50 YEARS FOR T_3

State	Initial	Terminal	Net Change
Forests and Wooded Land	57.16	59.62	+2.46
Open Land	37.02	32.48	-4.54
Built-up Areas	3.64	5.73	+2.09
Water	2.18	2.18	0.00

Finally, running the simulation 5 times once again shows that the terminal percentages across the runs are similar, as shown in Fig. 10.

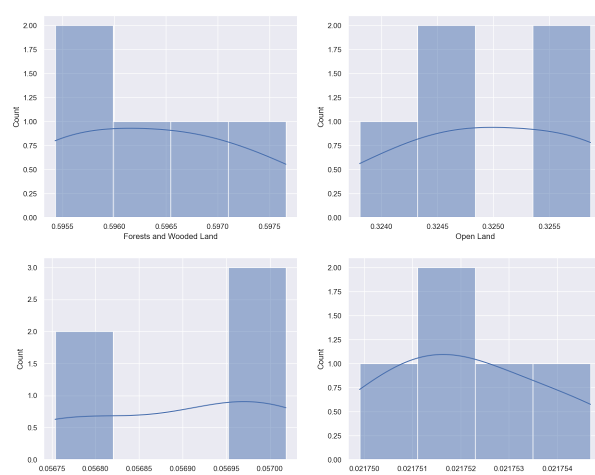

Fig. 10. Terminal Land Use Percentages across 5 runs for T_3

V. Conclusions and Recommendations

A common trend across all setups presented thus far is the increase in both forests and wooded land and moreso in built-up areas, accompanied by a decrease in open land. Water area experienced negligible changes across most setups, except for that of Mactan. As such, if these trends are what Ilagan City will follow for the next 50 years, then the the conversion of agrarian open land into built-up areas is to be expected. This particular trend may result into lower agricultural output and threats to both the food sustainability and economy of Ilagan. Surprisingly, forest area is also expected to be preserved and even expected to increase in land cover.

It is worth noting though that the increase in forest area may be a byproduct of the assumptions of the simulation process. In particular, (2) assumes that the transition probability is dictated by both the transition probability matrix as well as the immediate neighborhood of a given cell. Even though the initial land cover of built-up areas is rather small, all setups reported an increase in land cover for this land use state, which is certainly a result of the transition matrices favoring the transition to built-up areas. On the other hand, the increase in forest area may perhaps be attributed to the fact that Ilagan is majorly covered by forestland, thereby dominating the w_j terms in (2).

Due to this, a possible recommendation for future studies is the use of an alternative transition rule for the cellular automata simulation that places more weight on the transition matrix as compared to the immediate neighborhood, allowing for transitions to more closely mirror the historical data of land use.

Finally, if land use maps from previous years are also made available, another possible approach that can be explored is the use of supervised machine learning in the transition rule, as evidenced by the works of [6], [7], and [8].

References

[1] Global Forest Watch, "Forest Monitoring Designed for Action," globalforestwatch.org. https://www.globalforestwatch.org/dashboards/global (accessed Mar. 27, 2023).

[2] Z. Arshad, M. Robaina, M. Shahbaz, and A. B. Veloso, "The effects of deforestation and urbanization on sustainable growth in Asian countries," Environmental Science and Pollution Research, vol. 27, no. 9, pp. 10065–10086, 2020.

[3] Department of Environment and Natural Resources - Forest Management Bureau, "Philippine Forestry Statistics," https://forestry.denr.gov.ph/. https://forestry.denr.gov.ph/index.php/statistics/philippines-forestry-statistics (accessed Apr. 7, 2023).

[4] S. Dragicevic, "Coupling fuzzy sets theory and GIS-based cellular automata for land-use change modeling," IEEE Annual Meeting of the Fuzzy Information, 2004. Processing NAFIPS '04., 2004.

[5] He et al., "Developing land use scenario dynamics model by the integration of system dynamics model and cellular automata model," IEEE International Geoscience and Remote Sensing Symposium, 2004. IGARSS '04. Proceedings. 2004.

[6] O. Okwuashi, P. Nwilo, J. McConchie, and E. Eyo, "Enhancing a GIS cellular automata model of land use change using support vector machine," 2009 17th International Conference on Geoinformatics, 2009.

[7] T.-chu Wu and B.-yi Hong, "Simulation of urban land development and land use change employing GIS with cellular automata," 2010 Second International Conference on Computer Modeling and Simulation, 2010.

[8] X. Qin and B. Fu, "Assessing and predicting changes of the ecosystem service values based on land use/land cover changes with a random forest-cellular automata model in Qingdao Metropolitan Region, China," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 6484–6494, 2020.

[9] K. S. Ettabaa, I. R. Farah, and M. B. Ahmed, "Towards an intelligent approach based on multi-agent system and cellular automata for Modeling Land Use Change," 2006 2nd International Conference on Information & Communication Technologies. 2006.

[10] F. E. Sfa, M. Nemiche, and R. P. Lopez, "A generic model of reinforcement learning combined with macroscopic cellular automata to Simulate Land Use Change," 2019 4th World Conference on Complex Systems (WCCS), 2019.

[11] S. Wang, X. Zheng, L. Wang, and X. Zang, "Simulation of precise scale land use change based on the Markov-Cellular Automata Model," 2010 18th International Conference on Geoinformatics, 2010.

[12] Y. Zhang, J. Zhao, J. Zhang, and D. Song, "Land use pattern evolution and trend simulation in Nansi Lake," 2018 7th International Conference on Agro-geoinformatics (Agro-geoinformatics), 2018.

[13] X. Qin and B. Fu, "Assessing and predicting changes of the ecosystem service values based on land use/land cover changes in Qingdao, China," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, 2019.

[14] Q. Zhan, J. Tian, and S. Tian, "Prediction model of land use and land cover changes in Beijing based on ANN and Markov-CA model," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, 2019.

[15] V. K. Mishra and T. Pant, "Mapping and prediction of urban area with Markov-CA model using Landsat-8 images for effective management of urban area in Prayagraj City," 2020 URSI Regional Conference on Radio Science (URSI-RCRS), 2020.

[16] A. Khyzhniak, "Urban modeling based on the data fusion with cellular automata approach," 2020 IEEE 15th International Conference on Computer Sciences and Information Technologies (CSIT), 2020.

[17] L. Pei, X. Ye, and J. Ren, "The research of land use change based on GIS and CA model: Taking the Jinzhou City as an example," 2010 18th International Conference on Geoinformatics, 2010.

[18] N.-Y. Kang and Y. Kim, "Potential of urban land use by autonomous vehicles: Analyzing land use potential in Seoul Capital Area of Korea," IEEE Access, vol. 7, pp. 101915–101927, 2019.

[19] G. M. Ortigoza Capetillo, A. P. Lorandi Medina, and I. Neri, "Modeling and simulating urban afforestation: An alternative for urban climate change mitigation," 2020 IEEE International Conference on Engineering Veracruz (ICEV), 2020.

[20] E. A. Pinheiro, N. A. Camini, M. R. Soares, and S. S. Sumida, "Cellular automata model - landscape dynamics simulation tool in the process of change in land use and cover in the city of Gaúcha Do Norte – MT," 2020 IEEE Latin American GRSS & ISPRS Remote Sensing Conference (LAGIRS), 2020.

[21] M. N. Putri, S. Arfah, Z. D. Permata, L. Sumargana, Y. Anantasena, and H. Sadmono, "Dynamic spatial modelling of land use change in South Kuta, Bali," 2021 IEEE Asia-Pacific Conference on Geoscience, Electronics and Remote Sensing Technology (AGERS), 2021.

[22] E. E. Tan and A. J. Vicente, "Fire spread prediction using probabilistic cellular automata: The case of urban settlements in the Philippines," The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XLII-4/W19, pp. 415–420, 2019.

[23] M. I. Beltran and G. David, "Cellular automata model of urbanization in Camiguin, Philippines," Information and Communication Technology, pp. 29–35, 2014.

[24] Environmental Science for Social Change - Geomatics Unit, (2020). "2020 Isabela Land Cover Map" Ilagan_City.shp. Retrieved from ESSC's Isabela Land Cover Data Portal (https://isabelalandcover2020.essc.org.ph/).

[25] J. Faeldon, "Altcoder/Philippines-PSGC-Shapefiles: High resolution philippine PSGC administrative boundaries," GitHub. https://github.com/altcoder/philippines-psgc-shapefiles (accessed Apr. 15, 2023).

[26] D. Clarin, D. Dy, and A. Diola, "Evaluation of Land Use Land Cover Change due to Urbanization in Mactan Island, Cebu, Using Landsat Data," 2021 Manila Journal of Science 14, 2021.

[27] K. Iizuka et al., "Modeling future urban sprawl and landscape change in the Laguna de Bay Area, Philippines," Land, vol. 6, no. 2, p. 26, 2017. doi:10.3390/land6020026.

[28] J. Encisa-Garcia et al., “Land use/land cover changes assessment and forest fragmentation analysis in the Baroro River watershed, La Union, Philippines,” Journal of Environmental Science and Management, pp. 14–27, 2020. doi:10.47125/jesam/2020_sp2/02.

[29] Philippine Statistics Authority, ”Philippine Statistics Authority,” psa.gov.ph. (accessed Apr. 24, 2023).

[30] S. F. Hasegawa and T. Takada, “Probability of deriving a yearly transition probability matrix for land-use dynamics,” Sustainability, vol. 11, no. 22, p. 6355, 2019. doi:10.3390/su11226355.