# In Land Change Modelling: Design Cognition and Machine Learning

Medria Shekar Rani[1,*], Wiwik Dwi Pratiwi[1]

[1] *School of Architecture, Planning and Policy Development, Institut Teknologi Bandung, Indonesia*
[*]*Corresponding author. Email: medria.shekar@gmail.com; medriasr@ar.itb.ac.id*

**ABSTRACT**
The landscape is continuously changing due to natural disturbances and anthropogenic activities. The alteration can and simulated using models continuously being developed with different approaches, such as Machine learning and Cellular. This paper explores the use of Multi-layer perceptron (MLP) integrated with the Cellular Automata-Markov (CA-Markov) model to simulate the future land cover change based on development planning scenarios. An example of model applications and the potential elaboration using free online spatial datasets in Jakarta is also presented. The paper shows how different spatial policies and guidelines can be incorporated into the modeling process, allowing users to assign areas where new developments can occur in the future. It is argued that the generation of spatial plan alternatives and the possibility of including sketching as a tool in the activity is similar to design cognition.

***Keywords:*** *Land change modeling, Machine learning, Design cognition.*

## 1. INTRODUCTION

Modeling is developed to assess the land cover change and project the alteration based on scenarios. Six categories of land change modeling approaches include the machine-learning and statistical, cellular, agent-based, sector-based economic, spatially disaggregated economic, and hybrid methods [1]. Land change is a complex process; thus, the integration of different models, which combines each modeling technique's strength, is required to simulate the alteration [2] successfully. Examples of the hybrid approaches include the integration of Multi-layer perceptron (MLP) with other models, such as Cellular Automata (CA) [3] and Cellular Automata-Markov (CA-Markov) [4].

MLP is one of the Artificial Neural Networks (ANNs) used in machine learning [5]. According to Brown et al. [1], machine learning imitates natural learning systems using artificial intelligence tools. The algorithms can be used to detect the patterns in a dataset, connect the input and output data, and map their interactions to other datasets. Land change models have been widely used, including models that apply a combined MLP with CA [3,6] and MLP with CA-Markov [7-8]. One of the MLP-CA-Markov models (i.e., the Land Change Modeler (LCM) module from Terrset) allows users to allocate specific areas where the land change is prohibited in the future. Thus, it provides an opportunity to investigate the effects of policies on land change [9]. A study [10] has been done to demonstrate architects and landscape architects' involvement in the modeling process. However, the participants' cognitive function in the land change modeling has not been further discussed.

The use of computers for problem-solving in a creative process had become a concept known before the term 'artificial intelligence' was first introduced in 1956 (McCorduck 2004, cited in Steenson [11]). A study from Steenson [11] studied how architects explore cybernetics and artificial intelligence on buildings and the built environment. Negroponte from the MIT Architecture Machine Group stated that an architecture machine should employ sensing capabilities and immerse with the environment similar to what designers would do; formulating and solving appropriate problems [11,12]. The process is influenced by the designers' education and experiences, including attachment to a single design concept.

This paper presents the integrated MLP-CA-Markov model's potential to simulate the land cover change in Jakarta and the surrounding area (1989-2019). The study also describes the use of machine learning and development scenarios in the simulations, including the user's cognitive process in land change modeling. While most of the land change modeling studies focus on predicting land use and land cover changes, user involvement in the modeling optimization still becomes a challenge [1]; thus, further research on this topic is required.

## 2. DATA AND METHODS

The case study area is located in Jakarta and the surrounding area in Indonesia. Maps showing the developed and the undeveloped regions were generated from Landsat imagery (USGS/ United States Geological Survey) taken on 6 July 1989 and 11 September 2019 (Figure 1). The developed areas include settlements, public facilities, streets, and other impervious surfaces. On the other hand, undeveloped areas comprise natural landscapes, agricultural fields, and other areas covered by vegetation. The two land cover types were identified using the unsupervised image classification in ArcGIS. The image accuracy of the 2019 developed map was assessed using a confusion matrix.

Figure 2 shows the generated 1989 and 2019 land cover maps with an overall accuracy of 84.40% for the latter map. Both maps were then used to simulate the land cover change in the area (1989-2019) using the Land Change Modeler (LCM) module from Terrset, which applies the CA-Markov-MLP model. CA simulates the land change based on the previous state of cells and the condition of their surrounding [6], whereas Markov models the transition probabilities of land cover change [13].

MLP comprises three layers; input layer, hidden layer, and output layer [14] (Figure 3). MLP uses the information on the maps of land cover change (i.e., explanatory variables or elements that cause the alteration) as the input layer to develop their relationships with land cover patterns in an iterative process [15]. The number of hidden nodes affects the accuracy level and training time. The output layer of MLP is the probability of conversion from one land cover type to another [14].

Five potential explanatory variables of land cover change (e.g., elevation, slopes, proximity to rivers, population density, and the likelihood of land cover to change to another), as the input layers, are modeled at once in the MLP. In this study, the raw data to develop the land change driver maps (Figure 4) were retrieved from various datasets. The elevation and slope maps were generated from the digital elevation model (DEM) from the BIG/ Indonesian Geospatial Agency. A map showing the proximity to rivers was developed from the river network data retrieved from BIG. The population density map was downloaded from WorldPop [17]. MLP works iteratively using the maps of drivers as the input data to model the transition potential from one land cover type to another [4]. LCM, then, uses the MLP outcomes to simulate the future land cover based on scenarios.

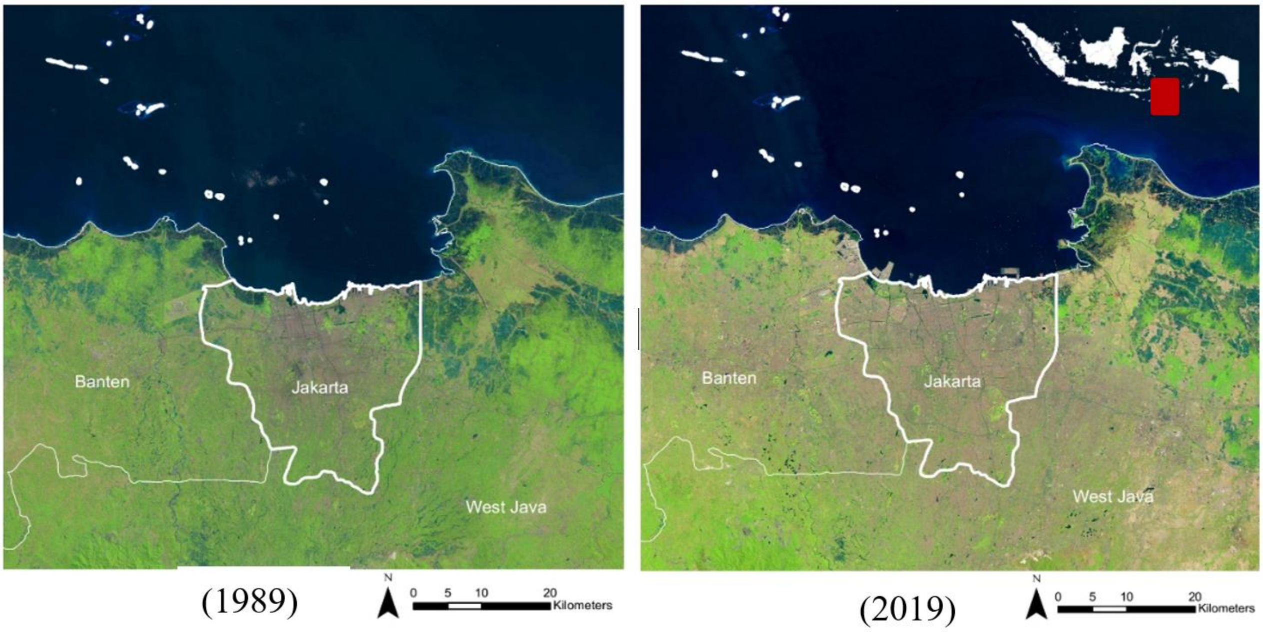



**Figure 1** Natural color of Landsat imagery in 1989 and 2019. Source: [16]

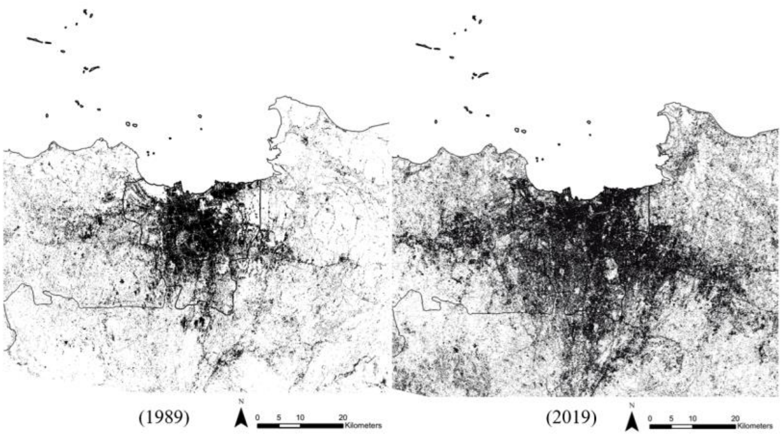



**Figure 2** Developed areas (black color) in Jakarta and its surrounding area identified using the unsupervised classification

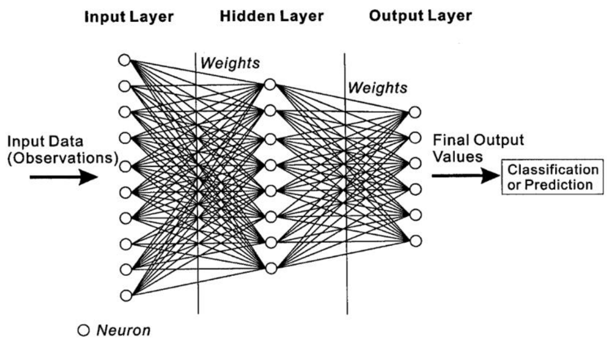
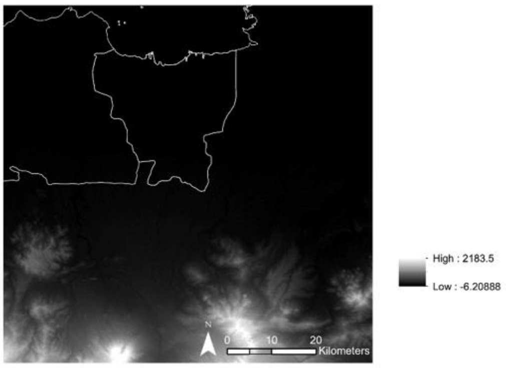
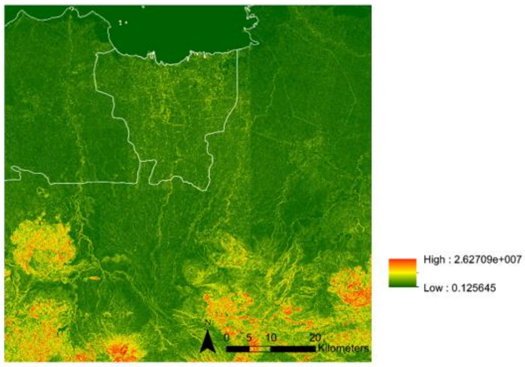



**Figure 3** An artificial neural network structure. Source: [6]




(a)

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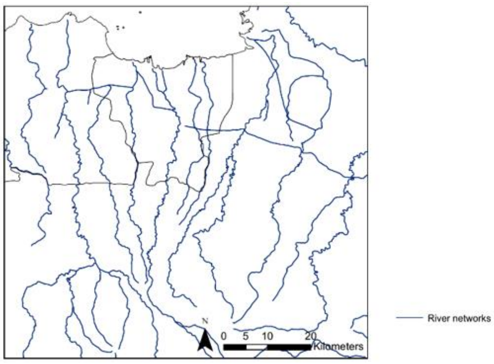


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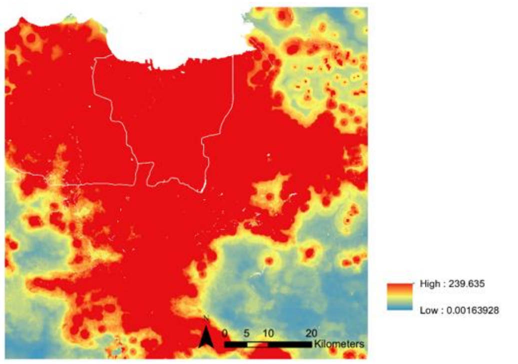


(d)

**Figure 4** Raw data for the explanatory variables of land cover change; (a) elevation (meter); (b) the percentage of slopes; (c) river networks; (d) population density (number of people per pixel)

## 3. RESULTS AND DISCUSSION

Figure 5 illustrates the land cover change in Jakarta and the surrounding area (1989-2019), modeled in LCM. The land cover alteration from undeveloped to developed areas is indicated by the red color on the map, whereas areas with no change and background (no data) are shown in black. It can be seen that the alteration is mostly located in the eastern, southern, and western parts of Jakarta. These areas are located in the lowland (Figure 4b) inhabited by dense populations (Figure 4d). The change map, which also includes the transition from undeveloped to developed areas (Figure 5), was further processed to generate the likelihood of land cover change in the past thirty years as part of the input datasets in the MLP process.

Figure 6a shows the model panel to run the Transition Sub-Models (i.e., simulates the change from one land cover type to another) using MLP. The network has three hidden layers, or 2n/3, where n is the input layer [18]. The modeling outcomes are the images of transition potential from one land cover to another (Figure 6b and Figure 6c). The model accuracy of 71.85% and the skill measure (i.e., how useful the explanatory variables influenced the land cover alteration in the past) of 0.6246. Each pixel on the output images has a value ranging from 0 to 1, which indicates the likelihood of specific land cover types to change at the end of the simulation.

Open data sources, such as World pop (https://www.worldpop.org/) [17] and OpenStreetMap [19], provide an opportunity for the modeling users to create more maps of land change drivers, thus more input data for MLP to learn. In this study, a raster map showing the population density in 2015 retrieved from Worldpop was used in the modeling (Figure 4d). The raster image (100 m pixel resolution) was generated based on the United Nations' estimated population data. OpenStreetMap offers free shapefiles of streets, trails, and buildings built by mapper communities as contributors.

Potential scenarios for modeling the future land cover in the case study area include a scenario without any development constraints, based on existing spatial policy. That can be developed based on different modeling and maps created by users. LCM uses a list of incentives and restrictions derived from each scenario to model the future land cover map. For example, in the existing policy-based method, the constraint maps, which show the areas restricted to be built, can be generated based on the study area's current spatial plan (Figure 7a). No further development of settlements and other facilities is allowed in the space allocated for conservation, agriculture, and the existing water bodies. In this case, users should extract the information on the spatial plan and the written guidelines for delineating those restricted areas.

Figure 7b shows the identification process of areas allowed to be built in the future from the spatial plan, which has been previously georeferenced. River buffer and other green spaces on the project are identified as undeveloped areas. In contrast, all classes of built-up areas (e.g., settlements, settlements with green open spaces, offices, and retails) are categorized as developed areas. This study is limited to simulating future change from two general land cover types (e.g., developed areas and undeveloped areas) in the case study area. Therefore, MLP projects any transitions from one land cover type to another regardless of the land cover sub-classes' characteristics. For example, the probability of undeveloped areas to change into settlements with green open spaces is similar to that of offices.

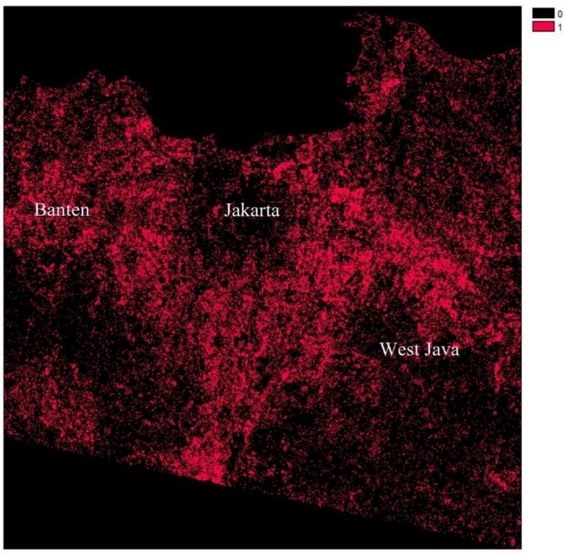


**Figure 5** Transition from undeveloped areas (black color) to developed areas (red) (1989-2019) in the case study area.

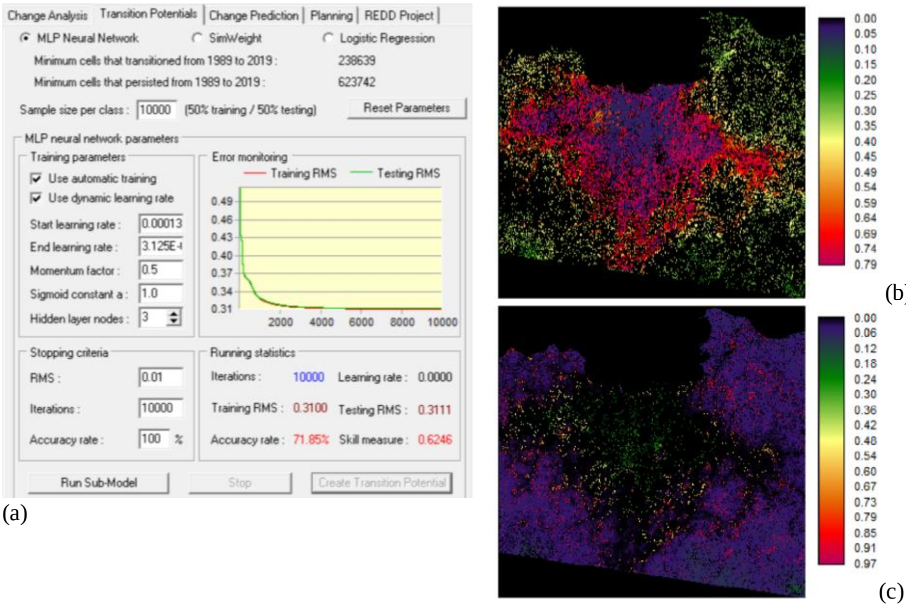


**Figure 6** (a) Transition Potentials panel in LCM; (b) Transition potential from developed areas to undeveloped areas (1989-2019); (c) Transition potential of amorphous regions to developed areas (1989-2019).

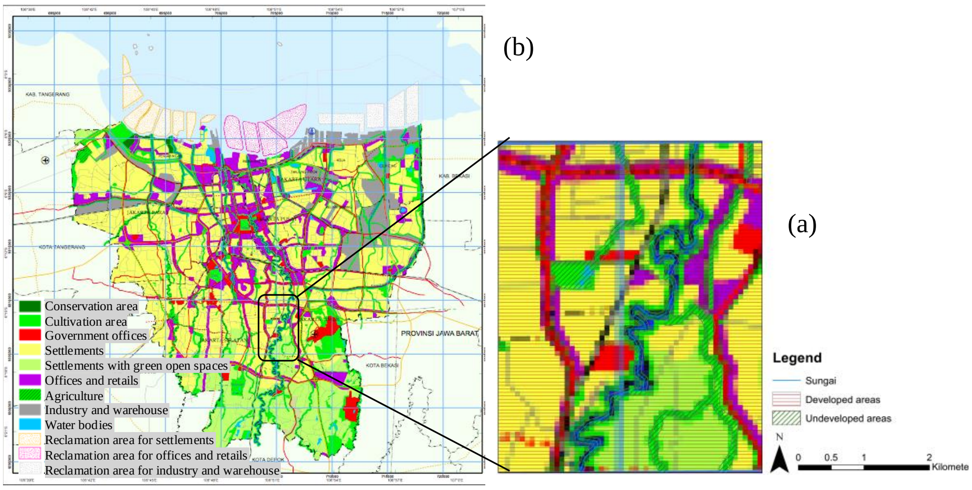


**Figure 7** (a) Transition Potentials panel in LCM; (b) Transition potential from developed areas to undeveloped areas (1989-2019)

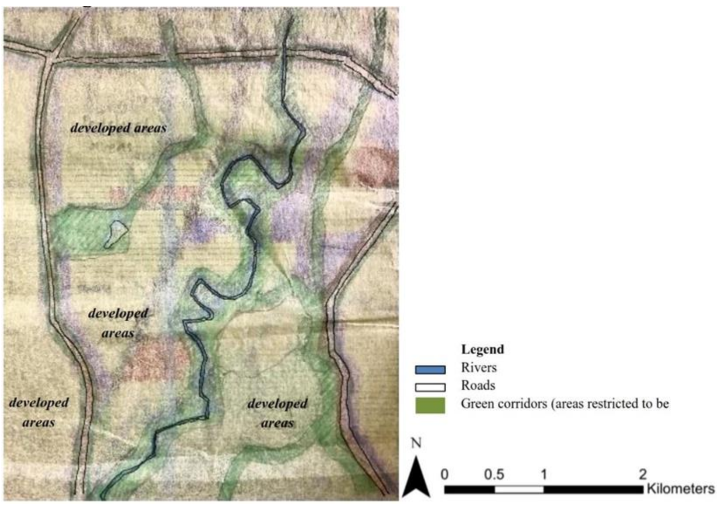


**Figure 8** A sketch to propose the connectivity of green corridors in the case study area.

Users might also generate constraint maps based on on-site analysis and particular design and planning theories. One example is implementing ecological design principles, such as the protection of the river ecosystem, in the development of constraint maps for LCM [10]. It is argued that this process is similar to the aspects of design cognition; problem identification, proposing alternatives to design solutions, and application of design process strategies [12]. It is argued that the application of specific planning guidelines to the modeling requires identifying particular problems on the site, in the same way as the problem framing in the design activity. Constraint maps, then, are generated based on the selected planning guidelines or concepts. As shown on the maps, designers create forms to comply with the design problem (Alexander, 1971, cited in Steenson [11]).

The modeling process can be conducted iteratively to test different sets of spatial planning guidelines. In this case, users are required to develop two or more development scenarios, which are arguably identical to the alternatives of design solution concepts [12]. Sketching can be incorporated into the generation of constraint maps at the preliminary stage of modeling [10]. The sketches are digitized using GIS software before they can be used as constraint maps. Sketching helps designers to think of a general concept and its implementation simultaneously [20].

Figure 8 presents an example of a sketch to propose the connectivity of green corridors along the roads and rivers in the case study area. The width of the green corridors is assigned based on the literature review. The sketch can be overlaid with satellite imagery and the corridor's form based on the existing conditions. Finally, the constraint maps can be generated by digitizing the sketch. Similar to the georeferencing process in the previous scenario (a scenario based on the existing spatial policy), the accuracy relies on the image resolution.

It should be noted that there are at least two limitations of the CA-Markov model; the model stationary and the absence of human decisions in the modeling [21]. The model assumes land change drivers in the past are similar to the factors that cause alteration in the future. However, in reality, the land cover alteration process is not stationary [22], as it is affected by both endogenous and exogenous variables (e.g., natural disturbances and changes in socioeconomic conditions) [15]. Uncertainty is also embedded in the development of base maps from remotely sensed imagery and the land change modeling process [23-24]. Therefore, the modeling outcomes should be interpreted based on these considerations.

## 4. CONCLUSIONS

This study responds to the challenge of integrating land change modeling optimization and user involvement in the process. The results from MLP indicate the future land cover distribution in the case study area, given the current development trends in the area. The research also demonstrates the potential application of the existing spatial policy and other scenarios created by users in the modeling process. The use of MLP in the simulation can assist users or designers in analyzing the potential drivers of land cover alteration. The analysis runs multiple times and produces maps of land cover change probability in the case study area to simulate future land cover maps based on different scenarios.

This study complements the previous research on architects and landscape architects' involvement in the land change modeling process. This paper shows how a decision on the design and planning process for allocating areas for further development can be integrated into the modeling. This process is arguably similar to the design cognition aspects. Users create forms on the constraint maps and benefit from sketching to assist the design cognition. Different development scenarios can be proposed and tested in the model, allowing architects, planners, decision-makers, and other users to visualize the implementation of specific spatial policies and planning guidelines in the future.

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