Remote sensing and geographic information systems technics for spatial-based development planning and policy

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ABSTRACT

Indonesia's land-use and land-cover change (LULCC) is a global concern. The relocation plan of the capital city of Indonesia to East Kalimantan will be becoming an environmental issue. Knowing the latest land cover change modeling and prediction research is essential for fundamental knowledge in spatial planning and policies for regional development. Five articles related to integrated technology of geographic information systems (GIS) and remote sensing for spatial modeling were reviewed and compared using nine variables: title, journal (ranks), keywords, objectives, data sources, variables, location, method, and main findings. The results show that the variables that significantly affect LULCC are height, slope, distance from the road, and distance from the built-up area. The artificial neural network-based cellular automata (ANN-CA) method could be the best approach to model the LULCC. Furthermore, by the current availability of global multi-temporal and multi-sensor remote sensing data, the LULCC modeling study can be limitless.

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1. INTRODUCTION

The government needs to control deforestation in Indonesia. Between 2001 and 2016, 40% of massive land conversion for oil palm and timber plantations caused deforestation in Indonesia [1], [2]. This agroindustry activity is one of the main driving factors for deforestation [3], [4]. It happens in Sumatera [5], [6], Java [7], Papua [8], dan Kalimantan [9]. Government policies and rapid development are the main subjects causing deforestation in Indonesia and have become global concerns [10]–[12].

The current government policy was the relocation plan of the capital city of Indonesia from Jakarta to East Kalimantan. This policy will probably relocate the severe deforestation problem in Java to Kalimantan and cause new environmental problems [11], [13]. Therefore, this policy requires a strong commitment from the government and collaboration from multi-stakeholders. Otherwise, this policy will lead to environmental degradation like land conversion and excessive deforestation [14], threaten the 0.3 million ha peat ecosystems [15], and cause biodiversity disasters [11].

Environmental degradation, a form of land conversion caused by development, was a concern for a long time [16], [17]. To overcome this problem, the concept of sustainable development emerged [18], [19]. For implementing the sustainable development concept, the capital city relocation plan then carries the idea of forest city, ecology, and conservation with the theme "*Negara Rimba Nusa*" (Island Forest Country) [14], [20]. However, even though a transformation has begun with careful planning, the results within decades may not be what was expected [21], [22]. Therefore, it is essential to conduct a land-used and land-cover change (LULCC) study to monitor changes and the impact of each spatial policy on the environment.

Meanwhile, the current evolution of remote sensing technology allowed users to choose various global data sources that can be easily accessed [23], [24]. The integration of remote sensing (RS) and geographic information systems (GIS) provides spatial data processing capabilities for the identification, monitoring, and evaluation of an area [25], [26]. This integration was widely used for environmental protection [27], [28], land use management [29], [30], environmental carrying capacity analysis [31], and deforestation monitoring [32]–[35]. This knowledge plays an important role in the decision-making process [36], [37] and is fundamental knowledge for regional spatial planning and policy [38], [39]. However, to the best of the author's knowledge, there have been no studies on LULCC monitoring to support the relocation plan of the capital city. Therefore, this study aims to determine the current developments in integrating GIS and RS technology (spatial modeling) for monitoring and controlling LULCC by conducting a literature review from indexed and reputable journals to see the similarities, differences, and the latest technological approaches. The results of this study can be helpful as an initial reference for sustainable development planning and LULCC monitoring in the new capital city.

2. METHOD

Several studies conduct a literature review to identify the ability of remote sensing and GIS technic for many purposes. In [40] comparing strengths and weaknesses of five articles on monitoring drought vulnerability in several locations in Indonesia using remote sensing data. While [41] formed a concept matrix in Microsoft Excel to compare 57 article titles, years, authors, journal, keyword, purpose, data source, sample country, methodology, theme, and main findings of coronavirus disease (COVID-19) studies and its connection to the environment. Furthermore, [42] conduct a comprehensive study to identify big-data remote sensing and cloud computing GIS applications.

This study's literature review uses a simple systematic review by forming a matrix table to compare and analyze the articles [40], [41]. We use Elsevier's Scopus database to perform a meta-analysis because it is the largest abstract and citation database [42]. We searched the article on October 21, 2020, with the query shown in Table 1. First, we search the articles using the advanced document search tool using "land cover change" and "prediction" keywords. The result was 531 documents. Second, the articles were filtered by year (the last four years) and obtained 243 documents. After that, the articles were limited to the document type (articles only) to shorten the list and focus on the high-quality academic level and obtain 198 documents.

After running a meta-analysis, we select the appropriate articles by a manual approach using a sorting tool. The papers were sorted by the number of citations then validated by titles and abstracts. The studies should be related to land cover change monitoring and management using remote sensing technology and GIS technic. Then, we found four articles. Another article was added based on country filters to complete the analysis with current research related to the study case in Indonesia. Unlike [40] and [41] research, we synthesize five selected articles using nine variables in matrix tables. The variables studied included: title, journal (rank), keywords, objectives, data sources, variables, location, methods, and main findings.

Table 1. Articles search keyword and query

Stages	Query	#Articles
1	TITLE-ABS-KEY ("land cover change" AND "prediction")	531
2	AND (LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017))	243
3	AND (LIMIT-TO (DOCTYPE, "ar"))	198
4	Manual search: sorted by number of citations	4
5	AND (LIMIT-TO (AFFILCOUNTRY, "Indonesia"))	7
6	Manual search: based on associated with the previous four selected articles	1

3. RESULTS AND DISCUSSION

This section consists of two-part. We first discussed the current land cover change modeling and prediction research in Indonesia using the GIS technic and remote sensing data. The second part was a comparative study, comparing the current research in Indonesia and other related research to find the weakness and novelty for further future studies.

3.1. Land cover change modeling study in Indonesia

In [6] research with the title “Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton” was discussed in this section. This article represents the current research that applies LULCC monitoring in Indonesia using remote sensing technology, advanced GIS, and an artificial neural network (ANN) approach. MDPI AG publishes this article in the sustainability journal with Q1 Scimago Journal rank and ISSN 2071-1050.

3.1.1. Regional problem and spatial approach

In [6] started their research by hypothesizing that LULCC is an instrument to help develop land conservation strategies, monitor land use, and control land-use change due to development. LULCC is a spatial and temporal model, which means the changes can be monitored over time and even predict the LULCC in the future based on the changes in the past and driving variables that have a high correlation to these changes. According to [6], cellular automata (CA) was commonly used to simulate LULCC by estimating a pixel value based on its initial value, neighborhood effect, and transition rules. Of the several methods mentioned, they chose the artificial neural network-based cellular automata (ANN-CA) method for their research. By considering various factors that might influence the changes, this approach can determine changes in LULC [43], [44]. However, they did not explain why they chose the ANN-CA method over the other methods.

The land conversion and deforestation in North Sumatra were the triggers for determining research locations and objectives. Therefore, his research aimed to monitor the land-use change transition between 1990 and 2000 in North Sumatra. The second objective was to predict the change in land use using the ANN-CA approach in 2050 and 2070. The research results were promising as instruments for planning forest conservation, managing land use, and managing species distribution in the future.

This study objective was noticeable and very typical for similar research, which analyzed the changes of LULC in the past to predict the LULC in the future [45]–[47]. They have a transparent and robust background to determine the study area. In this case, three decades of massive development in North Sumatra increased population, and land allocation for plantations resulted in uncontrolled land-use change.

The background of LULC's problems tends to be specific and unique. We can see in another research background, which clearly emphasizes the effect of LULCC on the Chunati Wildlife Reserve [48], [46], who pay special attention to land-cover changes for shrimp ponds are also an example of a strong background link to study area selection. The context of the location in LULCC research was critical to emphasize because the research location relates to a conclusion or theory produced in a study.

Different areas require different approaches. In spatial planning and policy, location definition was essential. Transformation theory summarizes that we cannot generally apply a change in a location to another location [49]. Furthermore, the study [50] also explains that a particular time and place metaphor would not suit other times and places. Therefore, the development background in a specific area defines how that local government develops its policy. With explicit spatial modeling in each region, they could formulate the spatial policies more accurately. Moreover, remote sensing data in spatial modeling is beneficial and fundamental data to support regional analysis [51]. The current availability of multi types and multi-temporal remote sensing data will provide a limitless application in spatial modeling and analysis [23], [24], [42].

3.1.2. Lack of the standard of remote sensing data acquisition and extraction

The challenges of LULCC modeling commonly start with the availability of remote sensing data with sufficient temporal. It was necessary to build an optimal model. Due to the limited data, the study [48] digitized the Google Earth imagery to complete the variable required. This situation was undoubtedly not recommended unless the researcher could explain the data extraction method and its validation to produce sufficient accuracy and quality data for modeling. On the other hand, cloud-based computing technology (Google Earth Engine) became a trend to provide multi-sensor and multi-temporal remote sensing data and conduct spatial analysis [24], [42]. This technology could solve the classic problem of providing multi-temporal remote sensing data.

In work [6], data for spatial modeling was very well explained both for data sources and data quality, such as Advanced Spaceborne Thermal Emission and Reflection-Global Digital Elevation Model (ASTER GDEM) 2017 from United States Geological Survey (USGS) (30 arc-sec resolution); Main road network map, published in 2000 by the Ministry of Environment and Forestry (MEF); Map of Soil type from Food and Agriculture Organization (FAO), published in 2000 and LULC maps, published in 1990, 2000, and 2010 from MEF based on Landsat imagery.

The LULCC simulation to be modeled by [6] has three LULC maps as a dependent variable. For the independent variables that drive and influence the change in LULC, there were height values, slope, and slope directions obtained from ASTER GDEM. They also calculated the distance from the road network map. The last independent variable was soil types based on the soil type map. An interesting thing from [6] research was that the LULC classification class was a lot (12 categories) compared to the other four studies, with only seven types on average. They include the airport as a unique class because they argue that the airport land use would not change in a long time. This argument was quite interesting to discuss. The assumptions seem strong, but they did not apply them to other land use classes even though government offices, ferry ports, and other public facilities have remained unchanged for a long time. Eventually, they divide LULC in urban areas into only two classifications for simplification reasons: urban and non-urban. If so, the reasons for the classification of LULC into 12 classes previously described are no longer relevant and make this study inconsistent. Several studies proved that reclassification and generalization could improve classification accuracy [52], [53]. Therefore, they should be kept the LULC classification as simple as possible.

3.1.3. How the LULCC spatial modeling work

In work [6], the simulation of LULC change starts by defining the input data. The LULC 1990 is the initial land cover condition, and the LULC 2000 is the final land cover condition. Five variable maps such as elevation, slope, slope direction, distance from the main road, and soil type are the explanatory variables that drive LULCC. Then, we can obtain the transition matrix by calculating the LULCC in 1990-2000. LULCC model carried out using ANN in the MOLUSCE module in QGIS, based on 17 spatial variables. The result was a transition probability model. This model shows the possibility of a pixel changing its value to another land-use class based on the correlation to the explanatory variable.

The study [6] very well explains each stage of spatial modeling using the ANN-CA method. Referring to previous research [54], they chose to use 12 neural networks (2n/3) because they could produce the same accuracy as recommended (2n+1) with a faster learning time. This network consists of the input, hidden, and output layers as shown in Figure 1. By sending the threshold by the backpropagation mechanism, the ANN will provide a weight of transition probability. After that, they use the CA approach to simulate the LULCC in the future. They did not clearly explain why they chose the integration ANN and CA method in their study. However, in another study, researchers describe that ANN could achieve a high level of accuracy in LULCC simulations because it can detect potential nonlinear relationships between implied driving factors and the LULCC phenomenon [44], [55].

To determine the significance of the driving variable, they performed several simulations with a combination of different driving variables. This step was excellent to explain which variables have the most influence so that it can produce the optimal model. After validating the LULC 2010 prediction with its reference map, they believe that the variables of height and distance from the road have a more significant impact on changes in LULC than other variables. This stage was important for similar studies in the future to determine what variables may more drive LULCC. Simulations of several combination variables can be an excellent step in any research to produce an optimal model. This step becomes essential considering that every location has different characteristics, and it may be the most influential variable in one place, but in another area would be different.

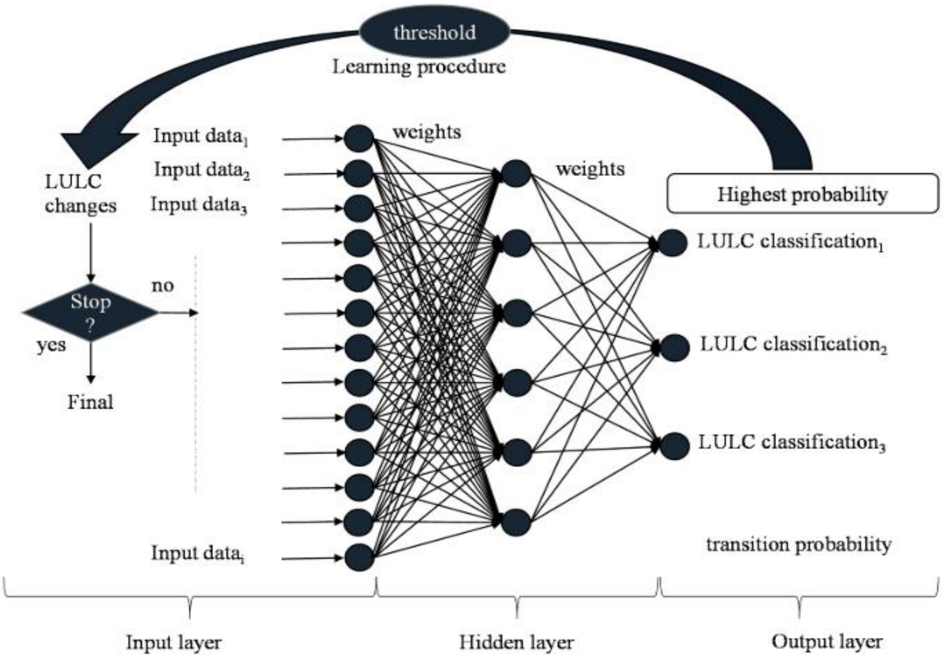

Figure 1. The model structure of the ANN-CA method [6]

After determining the most influential variables and obtaining the optimal model with an acceptable kappa value, we can conduct the predictions of LULC in 2050 and 2070. The author did not explain why they ran the LULCC forecasts up to 50 years and 70 years into the future. Meanwhile, the data input for modeling was only 10-year LULC change data (1990-2000) and then predicted the LULC 10 years later (2010) to validate the model with the available reference map.

In the MOLUSCE module in quantum GIS (QGIS), the prediction time length was calculated based on (1), wherein [6] resulted in predictions of changes in LULC for 2010.

$$Prediction\ time\ lenght = t1 + (t1 - t0) = 2000 + (2000 - 1990) = 2010 \quad (1)$$

It would make sense if the projections were made up to 2,030 (predicting LULCC for 20 years), considering the data used was from 20 years ago. If they want to predict by 2,050 (40 years later), it is possible to increase the number of simulations to 5 iterations. However, the use of data from 40 years ago would be better because the longer calibration interval of the model can better describe the overall LULCC [44].

Furthermore, there is another suitable target for LULC management and sustainable development. The implementation and achievement target of sustainable development goals (SDGs) will be in 2030 [19], [56]. This consensus could also be considered a reference to determining the length of the prediction time. So, the result of the LULCC model will have a more measurable benefit value.

3.2. The comparative studied

Five articles were reviewed and compared by nine variables: title, journal (ranks), keywords, objectives, data sources, variables, location, method, and main findings. Three comparisons matrices are presented in the recapitulation table, divided into three groups as shown in Tables 2-4.

3.2.1. The reference

The researcher publishes their paper in five different journals within two Scimago Journal ranks. There are three articles in the Q1 journal category (Ecological indicators, ISPRS International Journal of Geo-Information and Sustainability) and two in the Q2 journal category (Arabian Journal of Geosciences and Environmental Monitoring and Assessment). All the article titles represent the correlation of the study theme according to the main keywords "modeling" and "prediction" as shown in Table 2. Based on the keywords or objects studied, the five articles conducted studies related to the CA method for predicting LULCC with two different approaches. Two papers examine the CA-Markov method, while the other uses the ANN-CA approach.

Table 2. Source of reference

No.	Title	Journal (Ranks)	Keywords	Reference
1	Modeling land-use change using cellular automata and artificial neural network: The case of Chunati Wildlife Sanctuary, Bangladesh	Ecological indicators (Q1)	Chunati Wildlife Sanctuary; Markov chain; cellular automata; artificial neural network; binary logistic regression; land use and land cover change	[48]
2	Monitoring and prediction of land use/land cover changes using CA-Markov model: a case study of Ravansar County in Iran	Arabian Journal of Geosciences (Q2)	Land use/land cover; Remote sensing; CA-Markov; Iran	[45]
3	Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for southwestern coastal Bangladesh.	Environmental monitoring and assessment (Q2)	Assasuni; Shrimp farm; Bare lands; CA-ANN model; Migration; MOLUSCE	[46]
4	Monitoring and modeling of Spatiotemporal urban expansion and land-use/Land-cover change using integrated Markov chain cellular automata model	ISPRS International Journal of Geo-Information (Q1)	land-use/land-cover change; urbanization; CA–Markov; Nepal; remote sensing	[47]
5	Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton	Sustainability (Q1)	land use; land cover; cellular automata; artificial neural network; LULC prediction; North Sumatra; Indonesia	[6]

3.2.2. The objective and the resources of the studies

In general, all articles share a common objective, to analyze LULCC through observation and predict LULCC in the future as shown in Table 3. In [48] put particular emphasis on LULCC at the Chunati Wildlife Sanctuary (CWS). Meanwhile, [46] tried to figure out the effect of LULCC on future land use management systems in the southwestern coastal region of Bangladesh. In contrast to the other four articles, the analysis of changes in LULC by [46] emphasizes the development of urban areas and calculates the rate of the urban region's expansion. The objective of the LULCC study and LULCC predictions was typically similar and straightforward. So, this type of study was easy to replicate in different locations but challenging to have a novelty unless inventing significant method modifications.

Table 3. Objective, data source and variable comparation

No	Objectives	Data Sources	Variables	Location	Reference
1	(a) Predict the LULC scenario of CWS in 2020 and 2025. (b) Determine the influence of the driving factors for LULCC in CWS.	Landsat TM and Landsat OLI / TIRS imagery resampled to 30 m resolution (2005, 2010, and 2015). SRTM DEM 30 m resolution. Road's network, excavated areas, and water sources from Google Earth imagery converted to raster.	Independent variables (IV): slope, height, distance to the excavated area, distance to the highway, distance to local roads, distance to natural water sources. dependent variables (DV): vegetation, agricultural, and bare land	CWS in Southeastern Bangladesh	[48]
2	(a) Investigating LULCC (1992-2015). (b) Modeling and predicting LULCC for 2030.	Landsat 5 and 8 imagery (1992 and 2015). Google Earth imagery. Aerial photo and 1:50,000 topographic maps. DEM (30 m). Field survey for accuracy assessment. Demographic data.	DV: wetland agriculture, dryland farming, garden, bare land, field, and built-up area	Ravansar area in western Iran.	[45]
3	(a) Analyzed LULCC in Assasuni Upazila, Satkhira District (1989-2015). (b) Predict the LULC in 2028 by CA-ANN model (c) Illustrate the effect of LULCC and land use management systems in the future.	Field survey data (2015) to assess the accuracy of LULC classification. FGD data related to the socio-economic conditions of the local community. Questionnaire survey (2017) regarding changes in employment and immigration status. Landsat TM 30 m image (1989) corrected with 1:50,000 topographic maps (1990). Landsat ETM image (2002) and Landsat oil image (2015) was corrected with the 1989 Landsat image and resampled to 30 m resolution.	IV: elevation and distance from the main road DV: settlement, vegetation, bare land, and wetlands/ponds	Assasuni Upazila, Satkhira District, Bangladesh.	[46]
4	(a) Analyzed LULCC (1989-2016). (b) Evaluating the ratio of urban expansion and spatial-temporal change. (c) Predict LULCC in 2026 and 2036 by CA-Markov model.	Landsat 5 imagery (1989, 1996, 2006, 2011), Landsat 7 (2001), and Landsat 8 (2016). 1: 25,000 topographic maps (1995) provided by Nepal's Survey Department to validate results. Field survey and Google Earth imagery for accuracy assessment.	IV: slope, distance to the main road, distance to water bodies, and distance to the built-up area DV: built-up area, agricultural, forest, shrubs, sand, waterbody, and tea plantation	Jhapa district in southern Nepal.	[47]
5	(a) Determine the transition of LULCC in North Sumatra between 1990 and 2000. (b) Predict and demonstrate LULCC in 2050 and 2070 by the ANN-CA approach.	ASTER GDEM (2017) with 30 arc-sec resolution from USGS. Map of the main-road network (2000) provided by the Ministry of Environment and Forestry. A soil type map (2000) from FAO. LULC maps (1990, 2000, and 2010) provided by the MEF based on Landsat imagery data.	IV: altitude, slope, slope direction, distance from the road, and type of soil DV: airport, mixed vegetation, forest, lake, mangrove, bare land, moor, plantation, pond, settlement, scrub, and swamp	North Sumatra Province, Indonesia.	[6]

This type of research was suitable for case studies related to a specific and local environmental problem. Each region across the world certainly has its unique landscape and ecological issues. That was why the research about LULCC and predictions was a local and regional study [57]. Therefore, the definition of the research area was necessary. The research background should describe why they should study a LULC phenomenon in that area.

Studies related to the LULCC predictions using the CA method approach require input data in a raster format. If the data source like the LULC map obtained from a particular institution was in vector format, we need to convert it to raster format. The input of raster data must be in the exact resolution and extent [53], [57]. In addition, the coordinate system and accuracy of input data were also important [45]–[47]. [46] specifically conducted a field survey to verify the results of a land cover classification in 2015. This stage makes the input data in his research much more valid than in the other four articles.

The use of Google Earth imagery to verify LULC classification results was one of the semblances in these studies [45], [47]. Due to the easy access to image data on Google Earth, which was available with an excellent level of temporal resolution [58]. The verification method of LULC classification results by Google Earth imagery may be an alternative solution for the efficiency and effectiveness of the research timeline. However, based on the [46] study, we recommend using primary data to validate the LULC classification accuracy to ensure the quality of data input.

Landsat imagery was the most frequent data for LULC classification and LULC map production. Landsat data provides 40 years of continuous earth observation data with relatively high spatial resolution and is freely available, covering most of the earth's surface [59], [60]. Whereas the SRTM digital elevation model (DEM) [48], topographic maps [45]–[47] or ASTER GDEM [6] were three of the most data to obtain height and slope variables. Most researchers used secondary data from government institutions to get other driving variables. Due to data limitations, the study [48] complemented the variable by extracting it from Google Earth imagery.

In Indonesia, under the one data policy (Presidential Decree No.39 of 2019), researchers could easily access secondary data from related government agencies [61]. For example, the study [6] uses the Ministry of Environment and Forestry data as secondary spatial data in their research. Moreover, for further study, secondary spatial data was recommended to be obtained from corresponding government agencies under the Presidential Decree No. 27 of 2014 concerning the National Geospatial Information Network [62].

Modeling of future LULCC scenarios requires a driving variable (independent variables) as a determining factor for land-use change. Most researchers commonly use slope and distance from the road [6], [47], [48] as driving variables and then supplement them with other variables such as distance from water sources, distance from the settlement, or type of soil. Meanwhile, [46] only used two types of driving variables, namely elevation, and distance from the main road. Of the five articles, the only article that did not explain or review the driving factors for land-use change was [45].

The dependent variable or the variable influenced by the driving variable was the LULC class. Each study has its considerations for determining the type and number of LULC classes according to their research objectives. The study [46] pay attention to shrimp pond land cover while [47] separate tea plantation land into a unique category. The most numerous and complex classifications were on [6] study with 12 classes LULC. In contrast, [48] divides LULC types into only three classification categories: vegetation, agricultural areas, and bare land. Reclassification and simple classification categories could improve the accuracy of LULC maps classification results [52], [53].

3.2.3. LULCC modeling method development

Of the five articles, three articles use the ANN-CA approach [6], [46], [48] while two articles use the CA-Markov approach [45], [47] to model LULCC. Only study [47] analyzed urban area expansion using the ring-based buffer analysis. Based on his study, the distance from the built-up area has an essential role in urban development. In other words, the variable distance from the built-up area could be one of the driving variables affecting land-use change.

Meanwhile, to produce a potential map of transition, the study [47] used the multi-criteria evaluation (MCE) method, weighted by the analytic hierarchy process (AHP). SMCE was the process of aggregating some geographic data into a decision result, and AHP was one of the most common multi-criteria decision-making techniques for GIS-based suitability procedures [63]. However, according to [6], the ANN-CA method may be better and more reliable in terms of objectivity to produce a transition probability model than the AHP method, which involves subjectivity from experts. Another study agrees that ANN is more objective in modeling the nonlinear correlation between LULCC and the driving variable [44], [55].

In [46] present a very well and complete explanation for each method required in every stage of their work as shown in Table 4. While the other [6], [45], [48] lack detail in the description of how to prepare each variable. [46] explained that he used the first-order polynomial fit method for image correction. Then for the LULC classification, he used the maximum likelihood classification (MLC) algorithm. In contrast, several studies recommend machine learning methods such as support vector machine (SVM) and random forest (RF) for LULC classification than the MLC algorithm [64], [65]. Furthermore, the inverse distance weighted (IDW) method generates the elevation model. The distance variable from the main road calculates using the Euclidean distance method. ANN-CA for LULC prediction and finally for accuracy assessment, 200 control points were measured by stratified random sampling. All those stages indeed depend on the availability and completeness of the data. If all the data was available with sufficient accuracy, the research could immediately focus on modeling the LULCC and finding the most influential driving variables. The other study also suggests that data preparation stages in the LULCC study are crucial [32].

Two of the five articles discuss which variables have the most influence in modeling the LULCC. The research [48] were assessing the significance of independent variables using the binary logistic regression method. As a result, he concluded that height, slope, and distance from the road were the variables that had a significant influence in predicting the vegetation cover. Meanwhile, the study [6] conducted several simulations combining different driving variables. He makes seven variable combinations simulations. The accuracy was not much different. However, based on the best accuracy, they concluded that the variable height and distance from the road have a more significant impact on changes in LULC than the other variables.

Table 4. Method and main findings comparation

No	Methods	Main Findings	Reference
1	Comparing three models: (a) CA-Markov Model, IDRISI. (b) ANN or Multi-Layer Perceptron (MLP) Model with IDRISI Land Change Modeler (LCM) module. (c) Binary logistic regression model assesses the significant independent variables to predict land cover.	i) The trend is decreased vegetation and increased agricultural land from 2005 to 2015, ii) The ANN model's overall accuracy and kappa index were 0.96 and 0.98, iii) Elevation, slope, and distance from the road were statistically significant in predicting vegetation, iv) Approximately 50% of the total area will be covered by vegetation by 2020 but will decrease to almost 47% by 2025, and v) The CA-Markov model was unsuitable for predicting CWS land use, whereas the ANN model is a good fit to describe future land-use scenarios.	[48]
2	(a) Prediction of land cover change in 2030 by CA-Markov using Landsat 5 and 8 data for 1992 and 2015. (b) Software used are PCIGeomatica10, ENVI 4.7, ArcGIS10, and IDRISI	i) Kappa coefficients of the classification of land use maps for 1992 and 2015 were 0/82 and 0/80, ii) The changes in land use from natural to buildup areas will continue in the future, iii) The built-up area and agriculture will increase, and iv) Fields and bare lands will be converted into built-up areas.	[45]
3	(a) Image correction using 1: 50,000 topographic maps (1990) and 30 GCP, with the first-order polynomial fit method. (b) The MLC technique in the ERDAS IMAGINE software for LULC classification. (c) Creating an elevation model using the IDW method in ArcGIS software. (d) Distance from the main road calculated using the Euclidean distance in ArcGIS software. (e) LULC prediction using the Cellular Automata - Artificial Neural Network (CA-ANN). (f) The accuracy assessment was conducted with 200 control points (50 points for each class) with the stratified random sampling method.	i) The classification accuracy for the 2015 LULC map is 91.5%, with a kappa coefficient of 0.89, ii) Vegetation in agricultural land has increased slightly while bare land has decreased (1989-2015), iii) A sharp increase of wetlands/ponds by 25.9% (1989-2015), iv) Major changes occur between the categories of bare land and shrimp ponds, v) The accuracy of the CA-ANN model is 70.2%, with a kappa value of 0.63, vi) The potential distribution of the LULC class in 2028 shows that the trend of decreasing bare land will continue, and vii) The FGD and questionnaire survey results revealed that LULCC significantly impacted local people's job shifts and migration trends.	[46]
4	(a) The land cover classification uses the MLC method with ENFI software. (b) The LULC classification accuracy-test uses a random sampling method with 210 sample points. (c) Calculate the growth rate of urban expansion using the ring-based buffer analysis method. (d) Analysis of LULC change transition in different years using LCM in TerrSet software. (e) Transition matrix based on the Markov model, which CA-Markov then spatializes. (f) LULC modeling using the CA-Markov method. (g) Evaluation of LULC Modeling with kappa index> 80%.	i) Understanding the LULCC spatial patterns and the dynamics of urban growth over time is essential for effective land management and sustainable urban planning, ii) The level of urban expansion has not been uniform, with the city center as a more intensive area experiencing LULCC, iii) A higher rate of urbanization occurs in former agricultural near the road network, iv) This study shows that "distance from built-up areas" has an essential role in urban development, and v) The CA-Markov model is recommended for further urban and LULC research.	[47]
5	ANN-CA model in the MOLUSCE module in QGIS use to simulate LULCC and predict LULC in the future.	i) Height and distance from the road significantly impact LULCC, ii) 2050 and 2070 LULC predictions show a high increase in the plantation area, iii) The area of forest and mixed vegetation has decreased, indicating the influence of humans on changes in LULC, and iv) Simulation of LULCC using the ANN-CA model can produce reliable predictions for future LULC.	[6]

In general, based on the research results, both the ANN-CA and CA-Markov methods could well model and explain the phenomenon of LULCC in the past and future [6], [47]. All the researchers agree that this time series phenomenon is fundamental knowledge for decision-making and land use planning and management policies because it is a spatially based analysis. Then, the policies made later will be more specific base on the characteristics of each location.

Of the five articles, only one recommends the CA-Markov model as an appropriate tool for further research on cities and LULCC [47]. The other two articles do not provide an opinion on this matter. Meanwhile, the study [48] argues that the CA-Markov model was unsuitable for predicting CWS land use, whereas ANN can better describe future scenarios. This argument was also conveyed by [6] that simulating LULCC using the ANN-CA model can produce reliable predictions for LULC in the future.

4. CONCLUSION

Spatial modeling is one of the integrated remote sensing and GIS-based techniques suitable for LULCC modeling and LULC prediction. The variables that significantly influence LULCC in a particular area are height, slope, distance from the road, and distance from the built-up area. These variables can become fundamental knowledge for determining spatial-based development policies in development planning. In future LULCC research, the researcher can use those four variables as initial references.

The research location has an essential role in conducting the LULCC study. The problem of land-use change in a particular region certainly has unique driving factors and is likely to be different from other regions. So, the research background related to land-use change problems in a specific area was essential to explore. Next, researchers need to carefully consider when determining the related variables that have correlations to the land-use change in that area.

Simulation of LULCC, using either the ANN-CA model or the CA-Markov model, could produce reliable predictions of LULCC for future LULC. However, by considering the objectivity factor in building a transition probability model, the ANN-CA method approach could be the best choice. With the current availability of global remote sensing data, the LULCC modeling study can be limitless explored in other regions. Analysis of LULCC using multi-temporal remote sensing data and GIS provides fundamental knowledge in regional spatial planning.

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