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Artificial intelligence in land use prediction modeling: a review

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ABSTRACT

This study aims to review methods of artificial intelligence (AI) in land use modelling. Data were extracted from journals in the Scopus and Google Scholar databases using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) method. The review demonstrates that modelling land use predictions is a complex matter that involves land use maps and driving forces. AI technology can support land use forecasting by interpreting land use data, analyzing drivers, and modeling. However, AI has limitations in terms of broad contextual understanding and algorithmic errors. To anticipate this, it is necessary to select the appropriate image resolution and interpretation method in accordance with digital data segmentation. It is also recommended to use spatial regression methods to determine the driving forces that affect land use. Hybrid models such as multilayer perceptron neural network Markov chain (MLPNN-MC), random forest algorithm (RFA), and cellular automata (CA)-Markov chain (MC) are recommended for modelling. The selection of a model should be based on the data's characteristics and tested for accuracy. The use of AI for land use prediction modelling is expected to provide accurate predictions that can be used as a basis for land use policy.

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1. INTRODUCTION

Economic growth and population increase are frequently the main drivers of land use change [1], [2]. Increased mining, industrial, plantation, and infrastructure development activities in various countries often cause a decline in forest areas, reduced vegetation cover and agricultural land [3], [4]. This condition has a negative impact on biodiversity, causing ecosystem damage, reduced food security, environmental degradation, increased carbon emissions, and various disasters such as floods, landslides, and droughts [5]-[7]. To control excessive land conversion, the government has implemented various regulations, rehabilitated forest areas, established regional spatial plans, and protected agricultural land. However, these efforts have not been entirely successful in controlling land conversion. As a result, the damage and carbon emissions caused by land use change remain high, which could threaten the lives of people now and in the future.

In this context, monitoring and evaluation efforts, as well as predictions of future land use, are crucial for understanding future land use patterns. Land use prediction is an essential database for formulating policies [8] and serves as a basis for early damage mitigation [9], [10]. Otherwise, the results of land use prediction modeling are also an important tool in formulating regional spatial planning policies and formulating development policies. The rapid development of artificial intelligence (AI) technology has enabled more effective and efficient land use prediction modelling. Currently, various methods, models, and software can be used to facilitate land use prediction. However, AI technology has several limitations, including the requirement for representative data, comprehensive variables, and accurate data. AI also has limitations in understanding complex contexts and variables, which can result in biased and inaccurate land use prediction data.

Based on the limitations, land use prediction modelling using AI needs to consider various aspects including appropriate and representative data sources, accurate data, variables of the driving forces being modelled, and appropriate methods so that the results are more accurate [11]. Rani *et al*. [12] stated that compiling land use prediction models involves complex aspects. Zhao *et al*. [13] also explained that it is necessary to test the influence of the most dominant driving factors and the accuracy of the results with existing land use before making predictions for the future. Based on the problems, this systematic literature review purpose to analyse the various research that has been conducted on land use prediction modelling, both in terms of data sources, driving force variables, methods used, and the resulting level of accuracy. Through this research, it is hoped that future research can select the right data, variables, and models so that the resulting land use predictions have a high level of accuracy and can be used in formulating various sustainable land use management policies.

2. RELATED WORK

This sub-section discusses the use of AI in land use monitoring, evaluation, and prediction modelling. The first subsection discusses the application of AI in analyzing land use map data sources, as well as AI in analyzing driving forces. In the second subsection, discusses AI in land use prediction modelling.

2.1. Artificial intelligence for land use data interpretation

The rapid development of technology has made it easier to produce maps of land use. Remote sensing data is particularly useful due to its ability to cover large areas, relatively low cost, and varying levels of accuracy from low to very high. Interpretation is required to produce a land use classification from the image data stored in each pixel. Machine learning and deep learning provides a quick solution for digital classification of remote sensing data. Several researchers argue that each machine learning and deep learning method has various advantages and disadvantages, where these conditions are determined by the dataset and the user's ability to understand the data [14], [15]. Previous research shows that various machine learning and deep learning methods for land use data interpretation can use various models. In this case, it is important to analyse the data sources, methods used, and test the accuracy of the interpretation results through machine learning or deep learning.

2.2. Artificial intelligence for land use driving forces land use prediction modelling analysis

The land use that takes place in each region is influenced by various aspects that are very complex. In order to make predictions of land use change, at least a multi-temporal land use map and comprehensive driving force variables are needed. Multiple linear regression, spatial regression or other statistical analyses can be used to identify the driving forces that have a dominant influence on land use. Machine learning and deep learning have an important role to play in addressing this problem, but user understanding and interpretation, as well as the significance of the results, must of course be considered [16]. Land use prediction modelling has undergone various AI methods. AI makes it easy to obtain results, but users must pay attention to modelling accuracy and logical analysis of field conditions.

3. METHOD

The study of land use modeling and analysis land use includes a variety of research conducted around the world. The mechanism of data search carried out without limitations is intended to determine the trends of the study and obtain the complete literature. The reviewed literature collection was carried out through Scopus and Google Scholar using several keywords: ("landuse" or "landusechange" or "landuse dynamic"), ("modeling" or "predicting"), and ("driving force"). The review was completed by using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) mechanism. Based on the literature collection through Scopus and Google Scholar, 237 journals were obtained. To obtain journals relevant to the topic of the study, researchers screened the titles and abstracts of 237 journals and selected 57 journals. Furthermore, the researchers reviewed the relevant journal manuscripts using the indicators specified. Out of the 57 journals, researchers thoroughly reviewed those related to the objectives, methods, results, and discussions. From this process, 33 papers were found to be relevant to the theme of land use prediction modelling and research related to monitoring land use using AI.

The researcher's process of collecting, reviewing, analysing, and selecting literature relevant to the research objectives is illustrated in Figure 1. Subsequently, an in-depth analysis of 33 journals was conducted to map the development trend of land use studies. The analysis included an examination of data sources, data interpretation, variables and methods of driving factors, and methods and accuracy of land use prediction using AI.

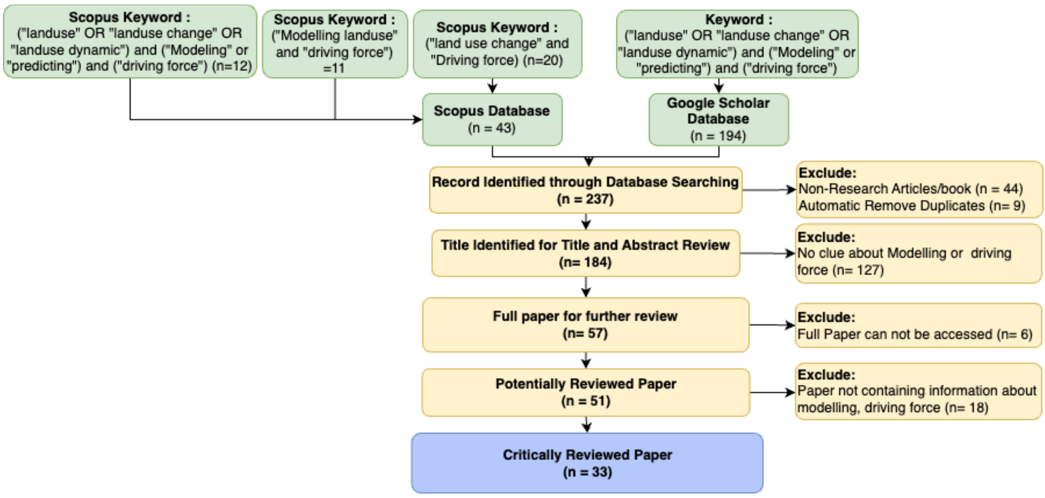

Figure 1. Diagram of article review selection process

4. RESULTS AND DISCUSSION

4.1. Land use reasearch themes

Land management studies are continuously evolving in response to the increasing negative impact of land use change [17], [18]. Land use-related publications mostly discuss patterns of change in the context of land use monitoring, while only a few publications discuss separately the analysis of the driving forces that cause changes and modeling. Based on the analysis, there is only a small number that analyze driving forces and land use modeling simultaneously and in-depth. Figure 2 explains the study of multitemporal land use change patterns as a fundamental analysis in land-use stewardship.

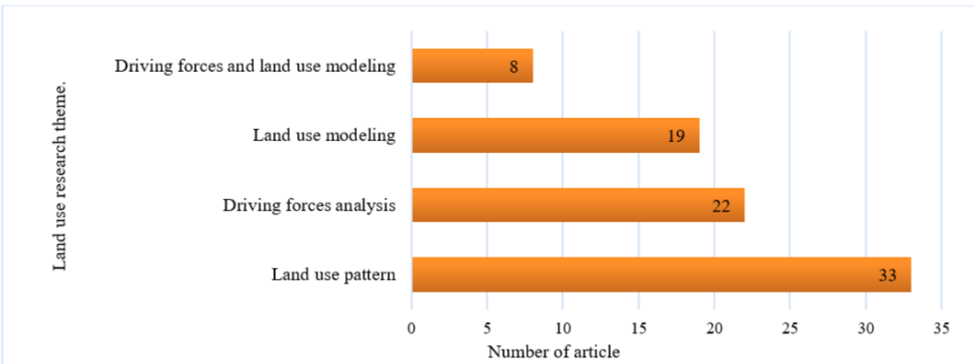

Figure 2. Land use study classification (n=33)

This analysis becomes material in monitoring land use as a basis for formulating policies. However, the study has limitations, as it does not identify what factors are driving land use changes. Furthermore, several researchers developed an analysis of land use change and its driving forces as a basis for formulating land use prediction models that are able to provide information to the authority to formulate policies in spatial planning and sustainable land management. The development of research themes related to land use is necessary, particularly in the area of comprehensive land use prediction modelling.

4.2. Land use map data sources

The sources of data used to create land use maps are primarily derived from the interpretation of satellite imagery and unmanned aerial vehicle (UAV) [19], [20]. Remote sensing images offer several advantages, including the ability to present land cover data from both the past and present, record areas that are difficult to access, and cover a wide area [21], [22]. Satellite images have varying spatial, temporal, spectral, and radiometric resolution characteristics, each with its own advantages and limitations [23]. The selection of satellite imagery can be adjusted to the mapping objectives, area, map scale, and land use classification. Remote sensing image interpretation methods for land use classification are primarily conducted digitally. The most commonly used methods include maximum likelihood [24], [25], support vector machine (SVM) [26], artificial neural network (ANN) [27], and nearest neighbor classifier. Maximum likelihood is widely used due to its simplicity and high accuracy [28]. However, visual analysis may be recommended for interpreting SPOT and Peliades imagery [29]. The process of classifying digital interpretations can be completed more quickly, but the resulting interpretations may be less detailed and have relatively lower accuracy [30]. On the other hand, visual interpretation takes longer but can produce a more detailed and accurate land use classification [31], [32]. It is important to consider the accuracy of the interpretation results as the land use map data source is the main basis for land use prediction.

4.3. Driving force variables in land use change

Changes in land use that occur massively in each region are influenced by very varied driving forces from physical/environmental, social, economic, and policy aspects. The driving force of land use change that is dominant will have a very large influence on the conversion of land functions in an area [33]. Driving forces such as the existence of industry, distance from the city center [34], and population growth [35] are factors that often affect land use. Studies on the driving forces analysis with land use changes can also be used as material for mitigating land management. Based on the review of 22 journals that analyze driving forces, several types of driving force variables are presented as shown in Figure 3.

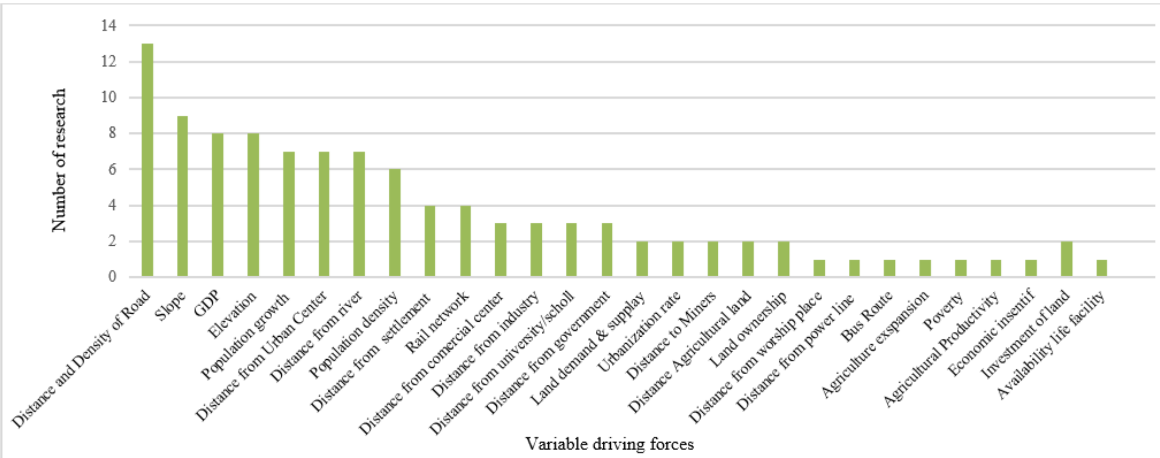

Figure 3. Diagram of driving force variables in land use (n=22)

The variables affecting land use in each region as shown in Figure 3 are complex. Choosing the right variables that represent physical, social, economic, cultural, regulatory, policy, location, and spatial aspects is an important part of developing land use predictions. Ignoring the variables will result in less accurate and biased land use prediction data.

4.4. Methods of analysis of driving forces for land use change

The development of technology and software for statistical data and spatial data analyses increasingly makes it easier to analyze the relationship between driving forces and land use. Regression analysis is one of the methods that many researchers use to find out the most dominant factors for land use. Figure 4 shows the statistics analysis and methode that can be performed through machine learning and deep learning.

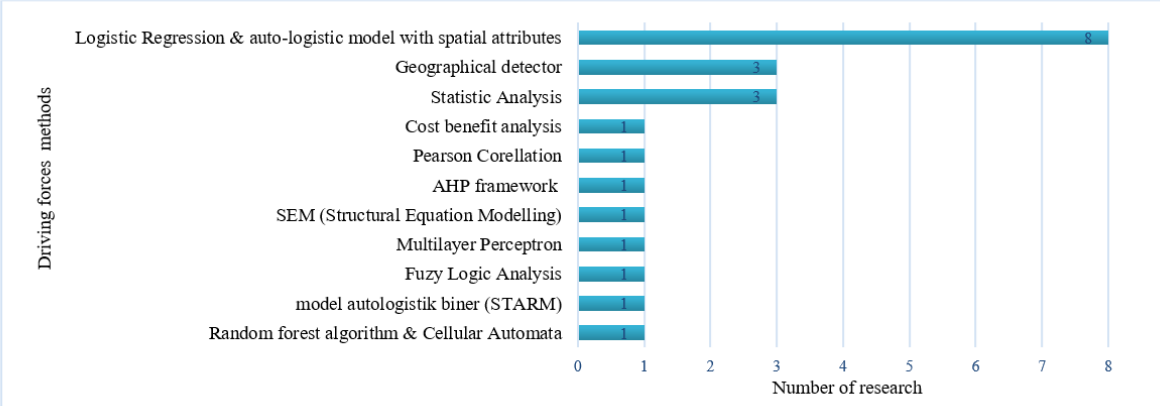

Figure 4. Methods of analysis of the relationship between driving forces and land use (n=22)

Based on Figure 4, it shows that regression analysis is widely chosen because it is able to show the value of the coefficient between the independent variable and the dependent variable [36]. With logistic regression, the value of the effect of land use change can be visible so that it can be determined which variables have a dominant effect and which ones have a low effect [37]. Some of the advantages of using logistic regression analysis according to Li *et al.* [38] include being able to handle binary dependent variables and the normality assumption requirement being more flexible. However, a study conducted by Deng *et al.* [39] showed that this logistic regression model has not been able to show the driving forces brought by spatial expansion and some geographical elements. Therefore, this method was developed by combining spatial attributes, namely by establishing the function of spatial autocorrelation weights [40]. Although logistic regression has not been able to show spatial attributes, in a study conducted by Bamrungkhul and Tanaka [41], this analysis was able to achieve an accuracy rate of up to 96.7%, so this model could be used to analyze the relationship between driving forces and land use. The use of logistic regression models can utilize the binary logistic regression model (BLRM) that is suitable for binary dependent variables or can also utilize multinomial logistic regression that is more suitable for multivariate dependent variables.

Geographical detector model (GDM) is one of the models that is widely used. This model is one of the statistical models used to detect the heterogeneity of spatial objects. This model is, in addition to being used to analyze social, economic, and environmental conditions also used to analyze the driving forces of land use. The geographic detector model is able to reveal the importance of explanatory variables and the driving force identity of geographic phenomena based on the spatial variance between layers. GDM includes several factors: risk detection, factor detection, interaction detection, and ecological detection [42]. The use of GDM is effectively able to determine the relationship between many factors, to be independent or interactive, to find out whether these factors are mutually reinforcing or actually weakening, and to know whether these variables have a linear or non-linear relationship. In addition to the two analyses, the development of various methods to determine the relationship between driving forces and land use has been widely developed, including using structural equation modeling (SEM). This model uses a logical approach with statistical methods, where analysis is carried out by building multivariate causal relationships and using structural equations and measurement models [43]. Previous research suggests that to analyse the relationship between dependent and independent variables related to spatial aspects, it is advisable to use spatial regression analysis. Including weighting factors based on regional correlation will produce a more accurate correlation value and describe the actual conditions in the field.

4.5. Modeling methods for land use predictions

Modeling of land use predictions can be done with various methods and various types of software (Idrisi TerrSet, QGIS, and LanduseSim). In its development, hybrid modeling methods have been produced and implemented to improve the representation of dynamic processes and enhance the prediction of highly complex land use [44]. One method that is often used is the Markov chain (MC), which is integrated with various methods into cellular automata (CA)-MC [45], multilayer perceptron-Markov chain (MLP-MC), multilayer perceptron neural network (MLP-NN)-MC [46], stochastic Markov chain (ST-MC), and clues model-MC. The CA-MC model is one of the most widely used methods for predicting land use [47]. The CA-MC method is the result of combining CA and transition matrix probability of land use change data. The

MC is a simulation technique for predicting stochastic models and illustrating the likelihood of change from one state to another. In using the MC, there must be data on the multitemporal land use probability transition matrix so that it can be used to compile land use prediction simulations [48]. The use of CA-MC becomes a unity where CA function to detect spatial changes in land use, while the MC serves to predict spatial-temporal changes in the future [49].

The MLP-NN-MC method is one of the methods that researchers have recently developed to predict land use. MLP-NN is an effective approach in predicting land use, where this method is able to predict geospatial changes with the help of existing change data. MLP-NN has the highest power to generalize transitions through a supervised backpropagation (an algorithm to carry out a supervised learning process on an ANN (supervised learning) to simulate changes in land use. MLP-NN is also able to provide the best generalizations for each of the land use simulations [50]. Meanwhile, the MC approach plays a role in determining land transition areas to predict the dynamics of changes that will occur [51]. This MLP-NN and MC approach is able to provide future land use change scenarios more accurately.

Some other models in addition to using the methods are land transformation model (LTM) as a method of predicting land use using ANN. In LTM, there are six components: i) data sets and procedures in geographic information system (GIS); ii) pattern recognition that allows ANN to recognize the existence of land use changes; iii) calibration; iv) validation models; v) creation of future scenarios of land use, and vi) model outputs and applications within the framework of GIS [52]. The use of analysis through ANN is also often used because this method is able to adjust, self-organize, and effectively overcome backpropagation method errors. Some of the methods used to compile land use predictions based on the results of the review are presented in Figure 5.

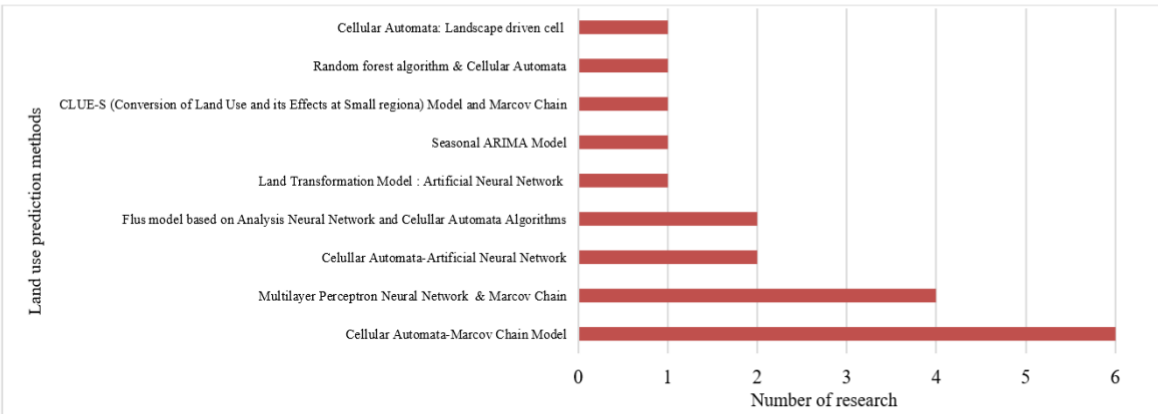

Figure 5. Modeling methods for land use predictions (n=19)

Each modeling method for land use predictions has advantages and limitations. One of them is the ANN-LTM method which has the advantage of being able to work well on data with large inputs and to predict land use quickly. However, this method has limitations, in that it cannot be known to what extent the independent and dependent variables influence each other and if this model does not work properly, a generalization process will appear, and it will affect the level of accuracy. On the other hand, the CA method, one that is most commonly used, has the advantage of being easily integrated with other models and being able to simulate temporal and spatial patterns, the data used is simple and the model is easier to understand. The development of various predictive modeling methods aims to obtain accurate results and to be easy to operate, be able to provide solutions to dynamic and complex land use conditions and be able to process parameters/variables whose amount of data is very large.

The accuracy of land use prediction results becomes an important part of compiling the modeling because it will determine whether the modeling results are valid, less valid, or invalid. Inaccurate land use prediction data in the future will certainly be fatal for formulating land use policies and spatial planning. Some factors that affect the accuracy level of land use prediction results include the data source used, the accuracy level of land use interpretation results, the scale of the resulting map, the driving forces for land use change, the modeling method for land use predictions, and the social/physical conditions of the study area [53]. The accuracy results of several land use prediction models are presented in Table 1.

Table 1. The accuracy level of land use prediction modeling

Modeling method	Accuracy (%)	Sources
MLPNN-MC	93.52	[46]
Random forest algorithm (RFA) and CA	93.5	[34]
Future land use simulation (FLUS) model based on ANN-CA	92	[9]
MLPNN-MC	91	[5]
MLP-MC	91	[27]
ANN-CA	90.15	[2]
CA landscape driven cell	88.1	[54]
Land transformation model (ANN)	87.8	[6]
CA-MC	87.6	[29]
CA	87	[55]
Conversion of land use and its effects at small regions model and MC	82	[37]
CA-MC	80	[45]
Land change modeller (LCM): CA, MC, and analysis hierarchy process (AHP)	73	[24]
CA-ANN (Molusce)	67	[44]

Based on 14 studies that present the accuracy level of land use predictions, there are three methods that have a high level of accuracy. The three methods are the MLP-NN-MC method, RFA-CA, and FLUS model based on ANN-CA. The MLP-NN-MC method has the highest level of accuracy because this method is the latest development of existing methods where the use of MLP-NN is able to provide the best generalization for each simulation and to model several transitions at once because there are three layers (input, output, and number of hidden layers) [56]. The high accuracy results from the use of this method for land use predictions were also carried out in [46], [56], where the accuracy results were around 85% to 93%.

The RFA-CA method is one of the models with high-accuracy results. This is because RFA has excellent ability and prediction, has a high tolerance to outliers and noise, and is able to control artificially the root nodes of decision trees. In addition, RFA can combine out-of-bag (OOB) data which functions to calculate the importance of feature variables from very large data. This condition makes RFA able to reveal complex relationships of several feature variables [34]. The accuracy test of the RFA-CA method showing higher results compared to the logistic-CA method., where the accuracy of the RFA-CA was 93.8% while the logistic-CA model was only 89.4%. Meanwhile, the third highest accuracy level is the FLUS model based on ANN-CA. This model is widely used because it has an adaptive inertial mechanism capable of simulating the complexity of social, human, and natural environment variables to identify land use patterns with a high level of accuracy.

The development of AI technology can make complex work easier and faster. However, the most important thing to consider is how AI is able to produce accurate land use predictions. Various previous studies have explained how the AI process works in predicting land use [53] but have not explicitly explained how the data is selected and the methods used to produce accurate data. The findings from this literature review explore that data sources for land use maps, selection of interpretation methods and accuracy testing of interpretation results are very necessary to ensure that the resulting maps are accurate. Comprehensive driving force variables according to regional conditions representing physical, social, economic, location, political, and regulatory aspects also play an important role as triggers for land use change. The spatial regression method by providing spatial weights is a mechanism to explain the relationship between dependent and independent variables. The results of this review also suggest the use of hybrid methods in the development of land use prediction models. Testing the accuracy of land use prediction results is an important tool for predicting future land use. The development of the various methods is carried out so that the results of land use predictions are getting closer to the actual conditions so that the resulting predictions can be used as a basis for formulating various policies.

5. CONCLUSION

Land use plays an important role in controlling environmental damage, disasters, and global warming. The prediction of land use is one of the bases for the formulation of a sustainable spatial planning policy. Therefore, accurate land use prediction results need to be prioritised by researchers. Land use map data sources and driving forces play an important role as dependent and independent variables in modelling. Land use map data sources with high spatial resolution and machine learning/deep learning interpretation methods according to digital data sets are recommended. Driving forces that are comprehensive and representative of regional conditions and spatial regression analysis should be used. The development of AI with hybrid models through various algorithms, including MLPNN-MC method, RFA-CA, and FLUS model based on ANN-CA, offers several advantages. Hybrid methods are able to achieve higher accuracy compared to single methods. When using this hybrid method, it is important for researchers to consider how this algorithm is able to process complex data and model variables to produce accurate predictions. For this reason, an accuracy test with a minimum value of more than 85% is required for each modelling process. The limitation of this research is that the use of various methods in interpreting, analysing driving forces and developing land use prediction modelling methods was not carried out. So, the limitations and advantages of each method from the trial process cannot be formulated in this research. Therefore, future research is needed to test the accuracy of land use modelling results using multiple data sources, multiple driving forces, and multiple methods.

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