RESEARCH PAPER

MODELING FUTURE CARBON STOCK PREDICTIONS BASED ON LAND USE

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ABSTRACT. The considerable influence of extensive land use change on the increasing levels of carbon emissions has significant implications for the occurrence of a multitude of disasters. The objective of this research is to develop a predictive model of future carbon stocks based on land use type. The data set includes land use maps from 2014, 2018, and 2022, obtained through visual interpretation of Pleiades data and associated driving variables, including socio-economic, locational, physical, land, and spatial planning factors. To predict land use in relation to future carbon stock values, the Multilayer Perceptron Neural Network Markov Chain (MLPNN-MC) algorithm was employed. Research related to this modeling is capable of producing an accuracy rate of 98%. The results of the prediction demonstrate that by 2034, there will be a reduction in the area of land used with high to low carbon stock, with a decrease of 153.2 ha, which equates to a reduction in carbon stock of 9,050 tonnes C/ha. To reduce carbon emissions, it is essential to implement policies that regulate land use change, optimize forest management, and conserve mangrove ecosystems. The monitoring and prediction of future carbon stocks plays a pivotal role in climate change mitigation, enabling more targeted and measurable actions to be taken.

KEYWORDS: carbon stock, climate change, land use, built-up expansion, machine learning, prediction modeling

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INTRODUCTION

The occurrence of climate change disasters on a massive scale in various countries represents a significant threat to the sustainability of human life and the realization of sustainable development (Gao et al. 2024; Lin et al. 2024). The impact of global warming, exemplified by the occurrence of extreme temperatures from 2023 to 2024 in Southeast Asia and South Asia, has implications for the cessation and disruption of various community activities. The occurrence of temperatures reaching 44°C in India and up to 37°C in parts of Indonesia is a detrimental impact of global warming (Meteorological Climatological and Geophysical Agency/MCGA 2024). The World Meteorological Organization (WMO) and the MCGA have identified Asia, including Indonesia, as a region that is likely to experience a significant increase in the frequency and intensity of disasters associated with global warming (Dong et al. 2021). In addition to the effects of extreme temperatures, the consequences of climate change include the loss of land, the disappearance of small islands, an increase in the frequency of hydrometeorological disasters, the decline of biodiversity, an expansion of the range of diseases, the disruption of social, economic, cultural activities, and an intensification of ecosystem damage (Sutrisno et al. 2021; Abbass et al. 2022; Laino and Iglesias 2023; Kim et al. 2024).

A number of previous studies have demonstrated that massively occurring climate change disasters in various countries are significantly influenced by alterations in the value of terrestrial carbon (Liu et al., 2023; Zhang et al., 2024) and the combustion of energy and fuel derived from fossils (Hu et al., 2024; Zhang et al., 2024). The study conducted by Achmad et al. (2024); Nakakaawa et al. (2011) explained that forest ecosystems/vegetation in various countries have an important role in maintaining the global carbon (C) balance, which is estimated at 80% of aboveground C stocks and 20% of belowground C stocks. In this context, it is crucial to assess and monitor the availability of terrestrial carbon stock through land use data, as well as to assess and analyze the relationship between land use patterns and carbon stock (Liu et al., 2023; Wu et al., 2024). In addition, further research is required on the modeling of future carbon stock predictions, as a basis for estimating the amount of carbon stock lost. A measured approach to the amount of carbon stocks in the future is an important part of formulating various targeted and appropriate mitigation policies to reduce the adverse effects of climate change disasters.

The high rate of land use change, particularly the reduction of vegetation cover, the decline of forest areas and mangroves, has significant implications for the increase in carbon emissions released into the atmosphere (Zhang et al., 2023; Chinembiri et al., 2023; Halim et al., 2023). The increasing demand for land for development and to fulfil socio-economic needs has implications for declining levels of carbon stock (Raqeeb et al., 2024). Furthermore, government initiatives to stimulate economic expansion through the expansion of mining, industrial, trade, and service areas, as well as accelerated infrastructure development, have also precipitated increased land use change, decreased vegetation cover, and resulted in reduced forest and mangrove areas in various countries (Cortés Arbués et al., 2024; Wu et al., 2024; Yusuf, 2021). Such alterations in land use have a direct impact on the carbon storage capacity of vegetation and plants, resulting in shifts in ecosystem functionality and alterations in soil carbon storage (Aneva et al., 2020; Segura et al., 2024).

Land use is not only related to economic conditions, but also plays an important role in social and environmental sustainability (Luo et al., 2024). Monitoring of land use change and land use prediction modeling are very important for determining global carbon stocks, providing land use restrictions and guidance for land use planning to maintain carbon stock balance (Dong, 2024; Huang et al., 2024; Zhang et al., 2024). However, based on previous literature review, studies on predicting future carbon stocks are still limited. So far, prediction analysis has been reviewed by Alam et al. (2021); Dey et al. (2021); Girma et al. (2022), who discuss predictions of built-up and non-built-up land use in relation to urban sprawl. While several studies analyzing carbon stock predictions based on land use, such as Dong (2024), were conducted without the use of driving force variables, the study by Wu et al. (2024) was limited to the use of economic and geographic variables, and the study by Shao et al. (2023) was limited to the use of physical and socio-economic factors. In addition to the limited use of drivers, several previous studies, namely Xu et al. (2024); Shao et al. (2023), still used medium resolution (Landsat) and low resolution (NOAA) satellite imagery as data sources. The use of limited driving forces, data sources from low-resolution satellite imagery, and the use of inappropriate algorithms may have implications for the inaccuracy of carbon stock prediction (Almubaidin et al., 2024; Bao et al., 2021; Jakariya et al., 2020; Ma et al., 2024; Meliho et al., 2023). The limitations and inaccuracies of predictive data are feared to lead to inaccurate policy-making in climate change mitigation. This research aims to address the existing gap in modeling future carbon stock predictions using more accurate and detailed data sources, comprehensive driving factors, and compatible algorithms through the implementation of the Multilayer Perceptron Neural Network Markov Chain (MLPNN-MC) algorithm. The MLPNN-MC algorithm represents the latest hybrid model/model development that is capable of generalizing each simulation and modeling multiple transitions simultaneously due to its three-layer structure comprising the input, output, and hidden layers (Mishra et al., 2014). The utilization of this algorithm has been demonstrated to yield highly accurate results, with accuracies ranging from 85% to 93%, as evidenced in several studies conducted Girma et al. (2022); Mishra and Rai (2016); Soni et al. (2022).

This carbon stock prediction modeling was conducted in a rural area affected by the national strategic project of constructing Yogyakarta International Airport (YIA). Initially, the area exhibited a high degree of dense vegetation cover, resulting in substantial carbon stock accumulation. However, substantial infrastructure development has led to significant alterations in land use and carbon storage. To date, there has been a paucity of research examining the relationship between infrastructure development, land use changes, carbon stock storage, and the modeling of future carbon stock predictions. The present study aims to address this research gap by employing advanced data analysis techniques, namely remote sensing satellite imagery and machine learning algorithms, to develop a more sophisticated and precise prediction model. The objective of this study is to formulate a prediction model for future land use in relation to carbon stocks in areas affected by the construction of YIA. To this end, the study will utilize more detailed data sources, more comprehensive driving variables, and the apply the MLPNN-MC algorithm to produce more accurate land use predictions to carbon stocks.

MATERIALS AND METHODS

Study Area

The research was conducted in the area affected by the construction of the YIA. The research methods employed included the modeling of predicted changes in carbon stock in 2026, 2030, and 2034. The construction of this infrastructure development project, which encompasses an area of approximately ±587 ha, has the potential to result in increased land use change. The research site encompasses 26 villages situated within Kulon Progo Regency, Yogyakarta, Indonesia. The study area encompasses Temon subdistrict (15 villages), Wates subdistrict (8 villages), and parts of Panjatan subdistrict (which includes 3 villages). The spatial distribution of the study area is illustrated in Fig. 1.

Data and data sources

The data presented in this study encompasses both dependent data, which pertains to multitemporal land use, and independent data, which encompasses driving forces. Multitemporal land use maps were obtained from Pleiades, a 0.5 m very high resolution satellite (Melis et al., 2021) in 2014, 2018 and 2022. The selection of images was based on the development process of the YIA, with 2014 being the initial state before the airport was built, 2018 being the land clearing/initial development stage, and 2022 being the post-development stage when the airport was operational. In addition to the consideration of the airport development process, the selection of satellite imagery with a 4-year/short period is capable of representing changing conditions with greater detail and of reflecting very dynamic driving forces. This will have a significant effect on the quality and accuracy of carbon stock prediction modelling. Image interpretation was carried out visually, as this method can provide a higher level of accuracy compared to maximum likelihood, random forest or other methods (Schepaschenko et al., 2019). The land use classification is divided into 2 (two), namely 1) high carbon stock reserve land consisting of mangroves, plantation, green belts, mixed gardens and dry land/rice fields; 2) low carbon stock land consisting of water bodies, infrastructure, rice fields, open land and built-up land. In order to determine the level of accuracy of land use, a sampling test was conducted where the number

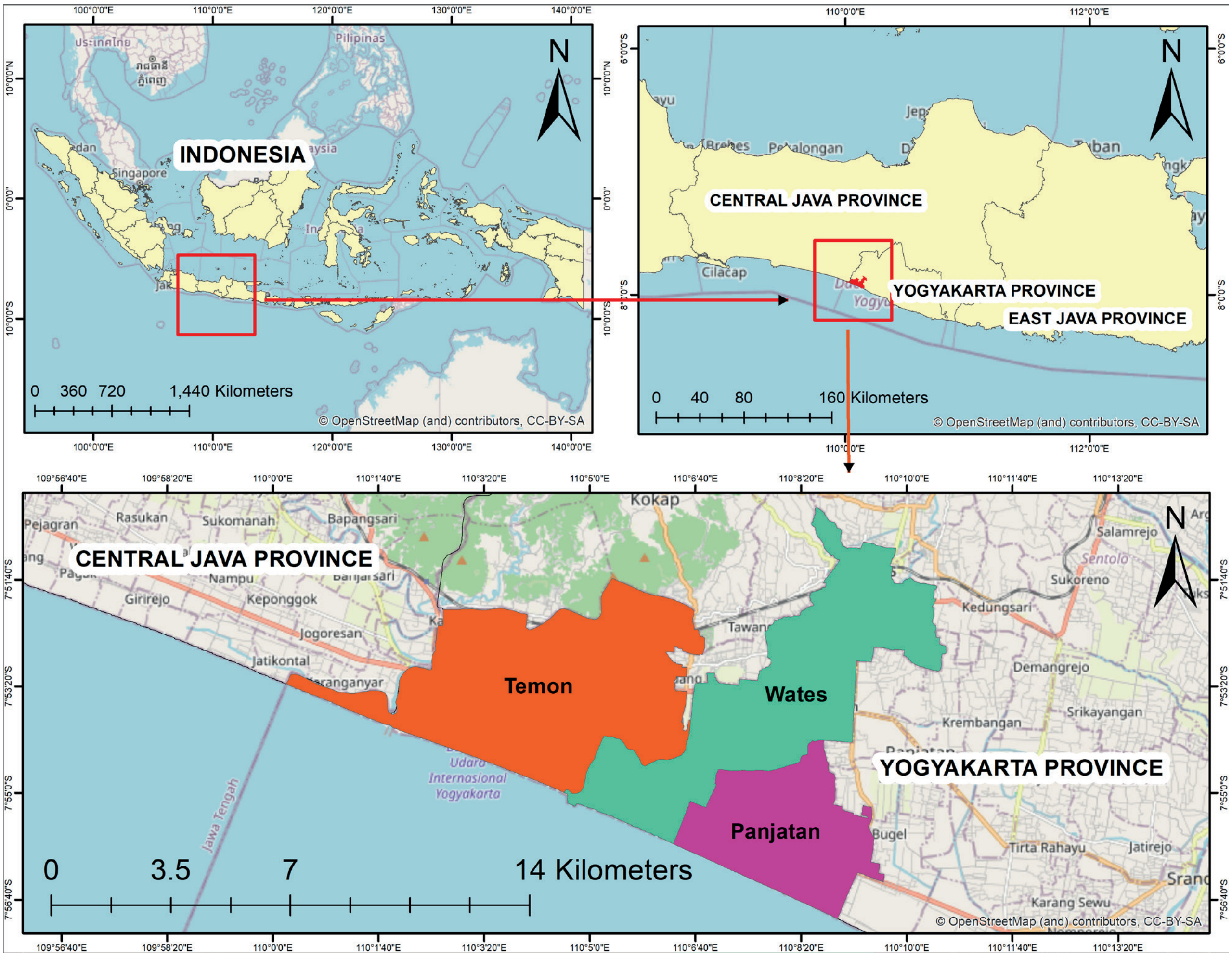

Fig. 1. Study area

of samples was determined using the Slovin formula with stratified random sampling. The number of land use samples in this study was 441 points, and from the results of the accuracy test in the field, there were 33 sample points that were less appropriate. Therefore, the accuracy test for land use can be formulated as follows (Eq. 1):

$$Accuracy\ value = \frac{Number\ of\ Correct\ Land\ Use\ Samples}{Total\ Land\ Use\ Samples} \times 100\% \quad (1)$$

Based on these calculations, the results of land use interpretation through Pleiades are able to produce a very high accuracy of 92%, so this data is eligible for further analysis. To determine the level of carbon stock by land use type, this study refers to the International Council for Local Environmental Initiative (ICLEI 2022) guidelines as described in Table 1. Based on Table 1, mangroves have the highest carbon sequestration capacity of 120, while the lowest are water bodies and infrastructure with a carbon sequestration value of 0.

This study formulates independent data in the form of driving forces, drawing from previous literature reviews and pre-field studies. These studies analyze the physical aspects, policies, land conditions, and socio-economic aspects of the community to derive more comprehensive driving forces. The driving forces used include socio-economic aspects, including population, type of work, original village income, and tax/levy sharing. Furthermore, the analysis encompasses physical aspects such as relative relief, flood vulnerability, landslides, drought, and tsunami vulnerability. Location-specific variables include city centers, airports, roads, industry, educational facilities, and health centers. This study also uses land and spatial planning aspects, including land value zones, land rights status, protected areas, and agricultural cultivation areas. Driving forces factors and data sources can be described in Table 2.

Methods

Driving Forces Analysis Through Spatial Regression

The driving forces variables utilized in this study encompass 21 variables, with the objective of ascertaining

Table 1. Land use reclassification based on Greenhouse Gas (GHG) Coefficient

Land Use	GHG	Class	Land Use	GHG	Class
Infrastructure, water body	0	Low	Dryland farming/fields	10	High
Rice fields	2		Green space/shrub	30	
Open fields	2.5		Plantation/Mixed garden	63	
			Mangrove	120	

Sources: International Council for Local Environmental Initiatives/ICLEI 2022

Table 2. Data and Data Sources of Driving Forces

Variables	Data Sources	Variables	Data Sources
Population, type of work, original village income, and tax/levy sharing	Secondary data from 26 villages/ sub-districts	Land value zones, land rights status,	Land Office data
Flood vulnerability, landslides, drought, and tsunami vulnerability	Data the Regional Disaster Management Agency in 2022	City centers, roads, airports, industry, educational facilities, and health centers	Pleiades imagery & Local Government
Relative Relief	National Digital Elevation Model	Protected areas, and agricultural cultivation areas	Detailed Spatial Planning Map

Sources: Data Analysis 2024

the driving forces that exert a substantial influence. These variables are subjected to spatial regression analysis, a method that has been selected on the basis of its capacity to accommodate spatial weight, thereby ensuring a more accurate representation of the prevailing conditions of dependent and independent data in the field (Caraka and Yasin 2017; Hasbi, et al. 2014). The determination of significant driving forces at the initial stage is of paramount importance to ensure the modeling results attain optimal accuracy. The Eq. 2 for determining spatial regression is outlined below.

$$Y = a + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_n x_n + \beta_{n+1} autocov \quad (2)$$

where x_i *(i= 1,2,3,…, n)* - driving forces, $\beta_{i\ (i=1,2,3,\ldots,n)}$ - regression coefficient, n - amount of data, Y - dependent variable, $x_{1,\ldots,n}$ - independent variable.

Scenario Carbon Stock Prediction

The modeling of carbon stock prediction is based on land use type and utilizes the MLPNN-MC algorithm. The MLPNN-MC algorithm was selected due to its capacity to analyze very complex data sets (Soni et al., 2022). A key element of this modeling is change analysis, which involves the identification of areas that undergo change and remain constant over a specified time period. In the subsequent stage, the driving forces factors are processed through the Land Change Modeler (LCM) multilayer perceptron to generate a potential transition map and to identify the relevant driving forces. In the subsequent stage, the Markov chain is utilized to predict future changes based on previous changes. The Markov chain process according to Memarian et al. (2012) can be explained in the Eq. 3.

$$F_x\left(X\left(t_{n+1}\right) \le \{X_{n+1} \middle| X\left(t_n\right)\} = X_n, X\left(t_{n-1}\right) = x_{n-1}, \ldots, X\left(t_1\right) = x_1\right) = \left(X\left(t_{n+1}\right) \le \left(x_{n+1} \middle| X t_n\right)\right) = x_n \quad (3)$$

where *X(t)* signifies with the marcov chain process at time *(t)*, t_n is the current time period, (t_{n-1}) defines the previous time periode, and (t_{n+1}) represent the future periode. The transition probability from one state *(i)* to another *(j)* by Memarian et al. (2012) can be explained the Eq. 4.

$$P_{i,j} = P_r(X[k+1] = \{j | X[k]\} = i) \quad (4)$$

where *X[k]* denotes the states *{x1,x2,x3,....}* between *i* and *j*. With these conditions, the probability matrix according to Memarian et al. (2012) is formulated as follows (Eq. 5):

$$\begin{bmatrix} P_{1,1}\ P_{1,2} \ldots P_{1,n} \\ P_{2,1}\ P_{2,2} \ldots P_{2,n} \\ \ldots \\ \ldots \\ P_{n,1}\ P_{n,2} \ldots P_{n,n} \end{bmatrix} \quad (5)$$

In this study, the independent variable of the carbon stock level is based on the type of land use over a 4-year period (2014, 2018, and 2022) with the consideration that the resulting change matrix is more detailed. The accuracy and validation tests in this study were carried out by creating a simulation of carbon stock predictions in 2022 based on the 2014 and 2018 maps and key drivers. The predicted carbon stock based on land use type in 2022 was then compared and analyzed with the carbon stock based on land use type in 2022. The Eq. 6 for determining the accuracy test is as follows:

$$AccuracyTestof\,CarbonStockPrediction = \frac{Value\ of\ existing\ in\ 2022}{Value\ of\ Prediction\ in\ 2022} \times 100\% \quad 6)$$

This modeling prediction accuracy test is very important to ensure that the data, algorithms, and processes carried out meet accuracy standards. The prototype model that has passed the accuracy test is utilized as a foundation for the compilation of predictions concerning carbon stock levels in 2026, employing the 2018 and 2022 maps and driving forces factors. Furthermore, to produce predictions for 2030, data from 2022 and 2026 are utilized, and the same process is repeated to produce predictions for 2034, 2026 and 2030. Additionally, the study considers relevant driving forces. For a more detailed understanding of the research stages, refer to the research flow chart illustrated in Fig. 2.

RESULTS AND DISCUSSION

Multitemporal Land Use Map Database

Pleiades image interpretation results show that the most dominant land use type in 2018 and 2022 in the study area is in the form of: rice fields and built-up land, where both types of land use have very low carbon stock content (Singh et al., 2024). Conversely, land use in the form of mixed gardens and mangrove forests, which possess a high carbon stock capability, is only found in a very small area. The spatial distribution of land use data in 2018 can be explained in Fig. 3a, while in 2022 in Fig. 3b.

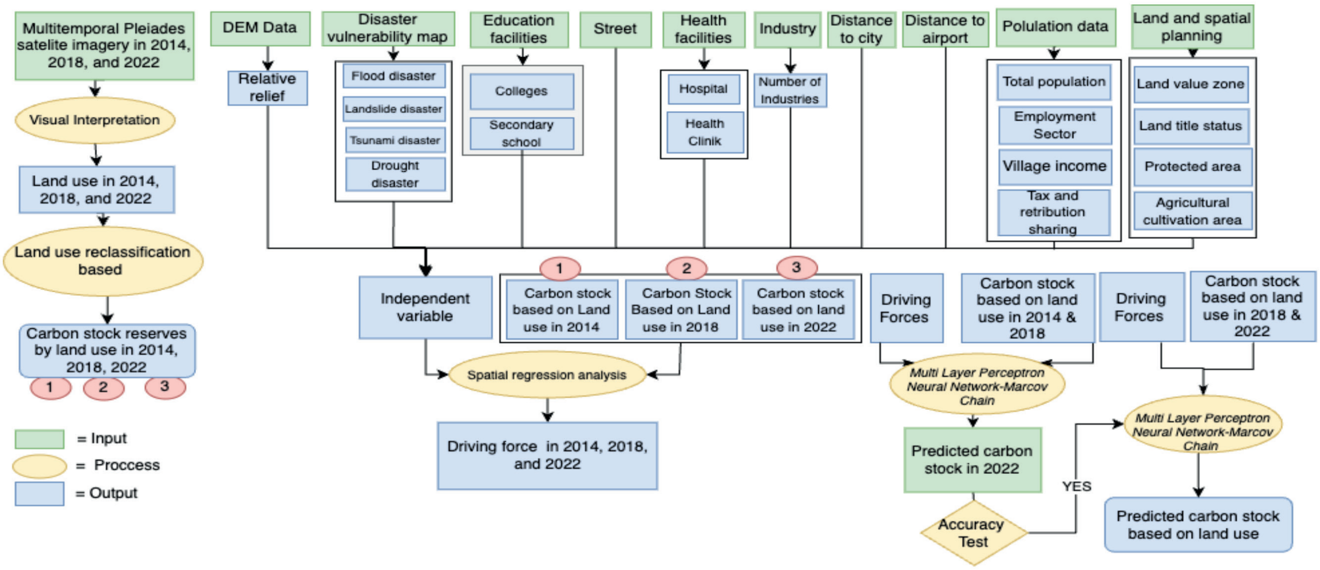

Fig. 2. Research flowchart

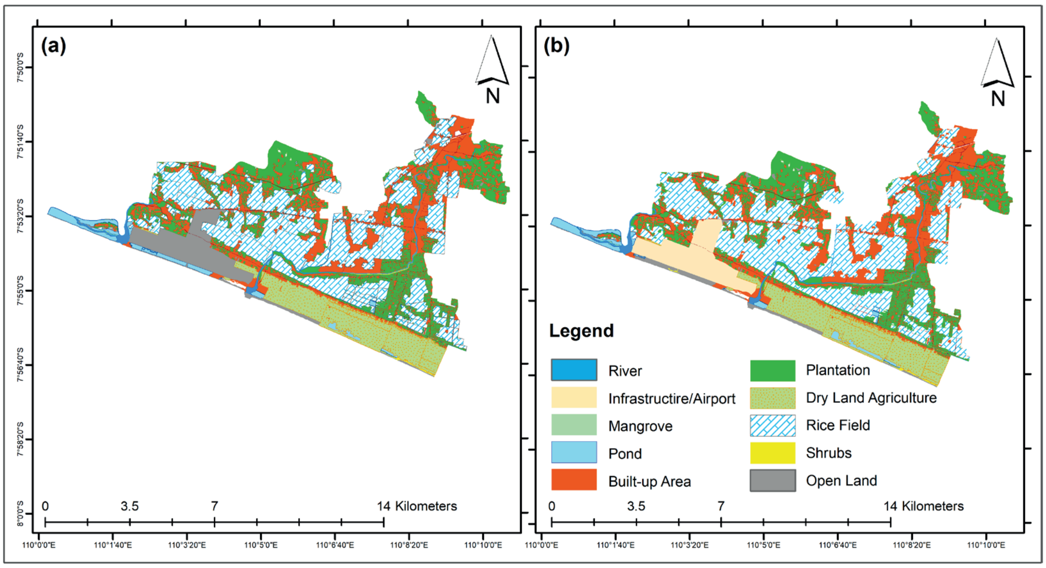

Fig. 3. (a) Land Use Map 2018; (b) Land Use Map 2022

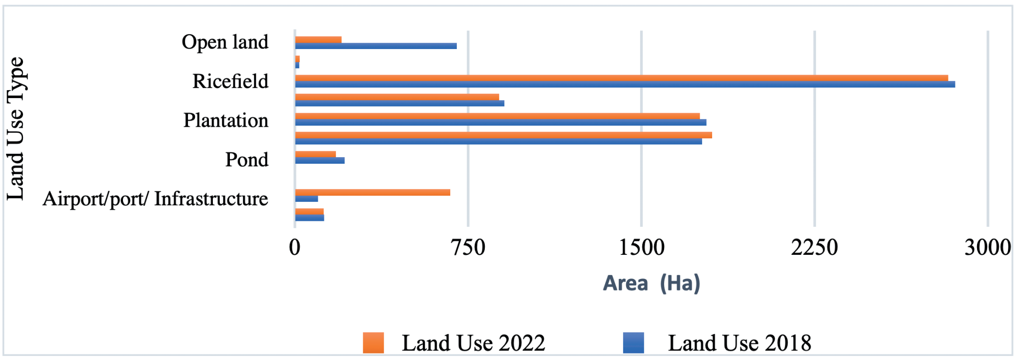

Fig. 4. Land Use Area in 2018 and 2022 (Source: data analysis 2024)

Based on Fig. 3, it shows that the development of YIA is one of the triggers for the increase in land use change. Airport development not only changes the land used for airports but also has implications for changing land for infrastructure development to support airports, land for settlements, and economic activities. Data on changes in land use areas from 2018 to 2022 can be explained in Fig. 4.

As illustrated in Fig. 4, there has been a notable decline in land use from areas with high carbon stock. This is evidenced by a reduction in plantations by 28 ha and dryland farming by 23 ha. During this period, there was also an increase in land use with low carbon stock value, namely 272 ha of infrastructure and 43 ha of built-up area. The decrease in land with high carbon stock and the increase in land use with low carbon stock will undoubtedly further contribute to the emission of carbon. This research reinforces the findings of Verma et al. (2020) that development tends to convert land from high carbon stock to low carbon stock land, a condition that certainly contributes to increasing carbon emissions.

Driving Forces Variables

The process of carbon stock alteration in response to land use in a given area is influenced by a multitude of complex and dynamic variables. It is imperative to ascertain the most significant driving forces to ensure the accuracy of the resulting prediction model. To this end, spatial regression is employed to verify the impact of these driving factors on land use changes. The outcomes of the spatial regression accuracy test, which delineate the relationship between driving forces and carbon stock changes based on land use types, are delineated in Table 3.

The findings of the spatial regression analysis in Table 3 demonstrate that the driving forces factor employed exerts a profound influence on alterations in land utilization in relation to carbon values, as evidenced by the R-square value of 0.83 or 83%. Moreover, the analysis reveals that the most suitable model, as indicated by the highest R-square value and the lowest Akaike Information Criterion (AIC) value, is the spatial lag model. The distribution of significance values between variables is elucidated in Table 4.

The findings of the analysis demonstrate that the presence of driving factors with a probability value of less than 0.05 is indicated, including city centers, airports, roads, industries, and relative relief. These driving factors are associated with a decrease in carbon stocks. The resultant increase in land conversion is from mixed gardens/plantations and dry land agriculture to built-up land and infrastructure. The closer an area is to these factors (airport, city centers, roads and industries), the higher the carbon stock decline. Conversely, the relative relief factor is one of the factors that can suppress the reduction of carbon stocks. Areas with high relative relief tend not to have massive land use change, which correlates with the high level of carbon stock in the area. And vice versa: the flatter the relative relief, the greater the tendency for the carbon stock to decrease. The findings of this study support previous research that the variables influencing land use change are complex and highly dynamic (Long and Yan, 2012; Mekonnen et al., 2022). This study also supports research by Rani et al. (2023); Xu et al. (2024) that the use of comprehensive variables that have a large influence on the rate of land use change is very important in developing land use forecasts. The limitations of the driving forces variables used and their lack of influence have implications for the inaccuracy of carbon stock predictions. The spatial distribution of driving force variables in this study is illustrated in Fig. 5.

Transition Potential Modelling

The training of the machine learning (MLP) network model was conducted using the Land Change Modeler, with the land use change triggers consisting of five variables and land use maps from 2014 and 2018. The results of the model sensitivity analysis are presented in Table 5. During the specified period, the model demonstrated a high level of accuracy with all variables, reaching an accuracy of 87.9%. The results of the sensitivity analysis, as elucidated in Table 5, demonstrate that the predominant driving forces are airports, while relative relief is the least significant.

Table 3. Spatial Regression Accuracy Test of Carbon Stock Reserve Variables in 2018

Model	R-square	AIC	Moran	Lagrange Lag	Lag error	Lag	Heteroke dasticity	Spatial Dependency
Classic	0.760553	311.175	0.00854	0.04880	0.29756	SARMA		
Spatial Error	0.827054	307.582				0.03642	0.02661	0.05802
Spatial Lag	0.834779	306.889					0.21018	0.01216

Source: Data Analysis, 2024

Table 4. Spatial Regression Analysis of Carbon Stock Reserve Variables in 2022

Variable	Coefficient	Std.Error	z-value	Probability
W_KRB.	0.622324	0.148483	4.19123	0.00003
CONSTANT	-542.544	148.27	-3.65915	0.00025
Protected	0.214102	1.4342	0.149283	0.88133
Agriculture	-0.737243	0.952464	-0.774038	0.43891
Road access	-0.00590488	0.00406924	-1.4511	0.14675
Flood	-0.294431	0.294713	-0.999045	0.31777
Land title	-9.38065	9.31859	-1.00666	0.31410
Relief	0.593635	0.273385	2.17143	0.02990
Land val_	2.32608e-05	6.50807e-05	0.357415	0.72078
City	36.9229	11.2262	3.28899	0.00101
Industry	104.1	71.4647	1.45667	0.05021
Airport.	31.4277	16.3897	1.91752	0.05017
Employment	5.29773	2.14639	2.46821	0.0135
Population	0.0193318	0.0168305	1.14861	0.25072

Source: Data Analysis, 2024

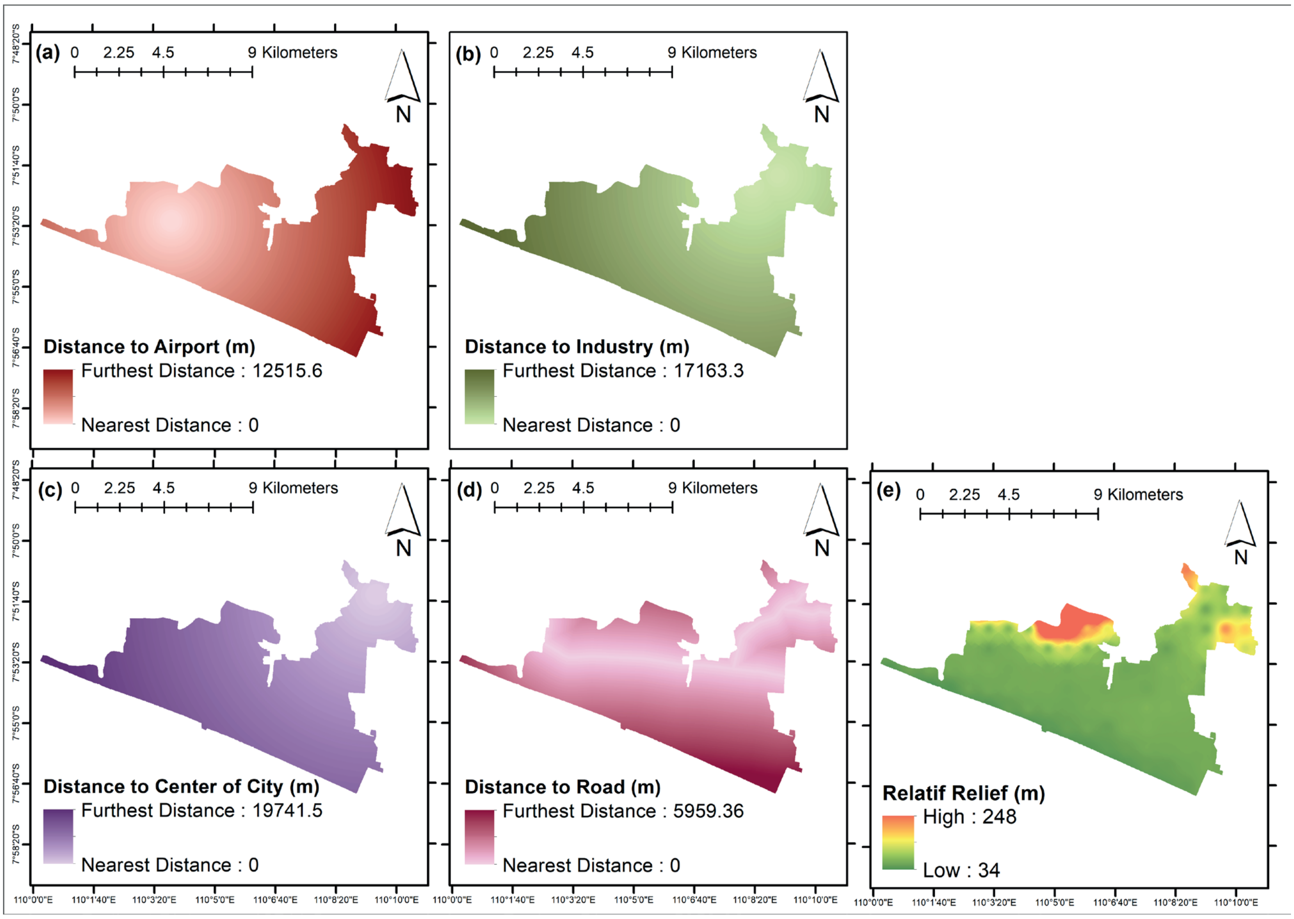

Fig. 5. Maps of drivers of carbon stock change based on land use: (a) distance to airport, (b) distance to industry, (c) distance to city center, (d) distance to road, (e) relative relief

Table 5. Transition sub model: Sensitivity of the model to forcing independent variables to be constant

a. Forcing a single independent variable to be constant			
Model	Accuracy (%)	Skill Measure	Influence Order
With all variables	87.94	0.7588	
Var 1 constant/city center	87.48	0.7496	4
Var 2 constant/airport	68.07	0.3613	1 (most influential)
Var 3 constant/industry	84.96	0.6992	2
Var 4 constant/road access	86.83	0.7366	3
Var 5 constant/relief	88.23	0.7646	5 (least influential)
b. Backwards stepwise constant forcing			
With all variables	87.94	0.7588	
Step 1: var.[5] constant	88.23	0.7646	
Step 2: var.[5,1] constant	88.02	0.7604	
Step 3: var.[5,1,4] constant	87.10	0.7420	
Step 4: var.[5,1,4,3] constant	76.48	0.5296	
c. Model skill breakdown by transition and persistence			
Class		Skill Measure	
Transition: High carbon to low carbon		0.7066	
Persistence: High Carbon		0.8109	

Source: data analysis through land change modeler

Prediction of carbon stock based on land use change and model validation

The validation of the carbon stock level change prediction model was conducted through a comparison of the results of the 2022 carbon stock level prediction with the classified carbon stock map, which underwent a rigorous testing process for accuracy in 2022. The 2022 carbon stock prediction map was derived from the 2014 and 2018 maps, along with the driving forces. The results of the analysis are illustrated in Fig. 6, which presents the findings on the suitability of patterns, spatial distribution, and visualization between the 2022 carbon stock prediction map (Fig. 6a) and the 2022 classified carbon stock map (Fig. 6b).

As demonstrated in Fig. 6, the predicted carbon stock map in 2022 exhibits a comparable pattern, shape, and area to the existing carbon stock map in 2022. The area with high carbon stock predicted was 2,752 ha, which is consistent with the existing carbon stock value of 2,689 ha. Subsequent to this, an accuracy test was conducted utilizing the confusion matrix, yielding an accuracy test result of 98%, signifying very high accuracy. The findings of this accuracy test demonstrate the viability of the algorithm, method, and variables employed in the development of carbon stock predictions in 2022 for application in the prediction of carbon stock based on land use types in 2026, 2030, and 2034. The land use prediction modeling approach utilizing a MLPNN-MC algorithm demonstrated an exceptional degree of accuracy, with an accuracy test reaching 98%. This condition is influenced by the supervised backpropagation, which is capable of more accurately generalizing the transition of land use change. Furthermore, this algorithm has the additional benefit of being able to perform supervised learning transitions in a more directed manner through the artificial neural network in MLPNN. This research corroborates the findings of previous studies on the advantages of MLPNN-MC in analyzing land use prediction modeling (Mirsanjari et al., 2021; Ren et al., 2019; Tariq et al., 2022). The high level of accuracy of land use prediction is also influenced by the data source for preparing detailed land use maps, as well as the use of complex driving forces variables. This research lends support to the assertion that the utilization of precise data sources is a fundamental element in the generation of accurate forecasts (James et al., 2020; Utami et al., 2024a). The Pleiades satellite images, which are capable of very high resolution, are able to produce highly detailed land use data, which in turn enables the generation of accurate predictions (Pu et al. 2018).

Modeling Carbon Stock Prediction Based on Land Use

The uncertainty of future land use represents a significant challenge for land management policy, with the potential for inappropriate policies to result in considerable environmental damage. The environmental damage caused by inappropriate land use is extensive and includes land degradation, water pollution, loss of biodiversity, damage to various ecosystems, and an increase in the frequency of natural disasters such as floods, landslides, droughts, and fires (Karamesouti et al., 2015; Peng et al., 2023). Furthermore, the uncertainty of land use in relation to the condition of carbon stock in the future also has implications for increasing carbon emissions, which have an impact on increasing climate change disasters (Mason et al., 2023; Hayes et al., 2023; Xu et al., 2024; Yan et al., 2024). The analysis of land use predictions in relation to carbon stock is a crucial aspect to consider, given the high level of disaster vulnerability in the study area, as evidenced by the prevalence of floods, landslides, droughts, abrasion, and tidal waves (Kulon Progo Regency, 2023).

A model was constructed to predict land use in relation to carbon stock value in 2026, based on land use maps from 2018 and 2022, as well as variables that trigger land use change. The results of the modeling exercise for the year 2026 are presented in Fig. 7a. The multitemporal land use data from the preceding period and the driving forces variables were then employed to construct a prediction map of land use in relation to carbon stocks for the years 2030 and 2034, as illustrated in Figs. 7b and 7c. In addition, the outcomes of the multitemporal land use prediction modeling can be presented in Fig. 7d.

The carbon stock prediction modeling as shown in Fig.7a, b, c provides an overview of the carbon stock condition in 2026, 2030, and 2034, which tends to decrease. The decline in carbon stocks is attributable to alterations in land use, with a transition from high carbon stock land in plantation areas and mixed gardens to low carbon stock (built-up land/settlement) in the northern part of the study area. In the southern part of the study area, the shift from dryland farming to ponds led to a reduction in carbon stocks. The findings of the predictive modeling calculation through MLPNN-MC demonstrate that in 2026, the land utilization exhibiting high carbon stock potential (i.e. plantations, dryland farming, green space) amounts to 2,637 ha, representing a decline from 2,689 ha in 2022. The analysis indicates that, by 2026, there will be a decrease in land from high to low carbon stock of 52 Ha, equivalent to

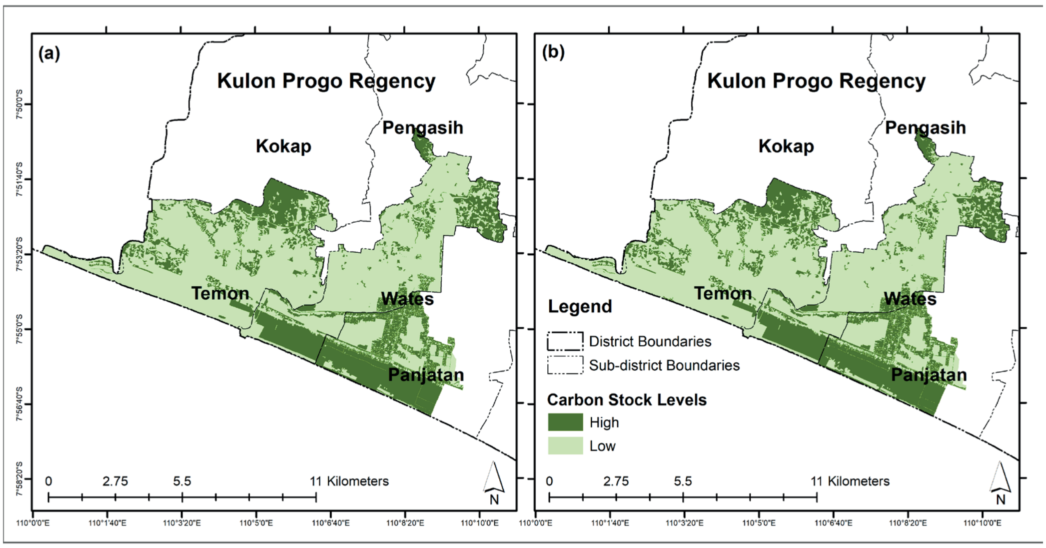

Fig. 6. Comparison of map : (a) Prediction map of carbon stock; (b) Maps of carbon stock level

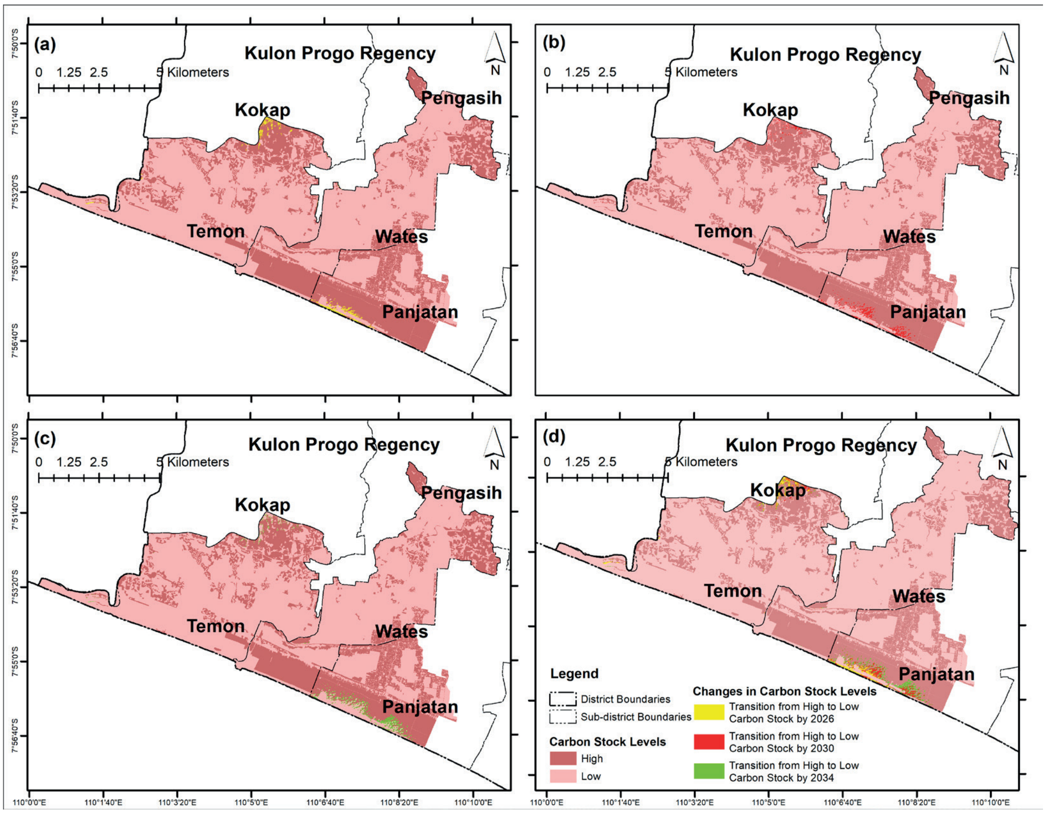

Fig. 7. Map of predicted carbon stock reserve levels by land use year (a) 2026; (b) 2030; (c) 2034; (d) multitemporal

3,050 tonnes C/ha. The reduction of carbon stocks has been demonstrated to result in an increase in carbon emissions, which in turn has been shown to lead to an escalation in climate change disasters. The increase in development and demand for land is undeniable, especially in developing countries, including Indonesia (Li et al., 2023; Liu et al., 2021). Data on the multitemporal decline in the area of high carbon stock land use in the study area are described in Fig. 8.

The findings of this study indicate that the decline in land area with high carbon stock within the study area between 2022 and 2034 is projected to amount to 153.4 Ha. The decline in carbon stock value from 2022 to 2034 is projected to amount to 9,665 tonnes C/ha, in accordance with the greenhouse gas coefficient established by ICLEI (2022). This transformation is primarily driven by the demand for land for airport development and the provision of land to support economic activities (trade and services). Following the development of the airport, a further decline in carbon stocks was observed in the study area. This accumulation of carbon stock decline, if mitigation measures are not implemented, will undoubtedly exacerbate the impact of global warming. The implementation of policies to protect forest areas, mangrove areas, and reforestation policies in green open space areas are crucial elements in maintaining the balance of carbon stocks (van Bijsterveldt et al., 2020; Dajam and Eid, 2024; Raqeeb et al., 2024; Alexandri et al., 2024).

The empirical evidence presented in this study indicates that by the year 2034, there will be a notable expansion in built-up land (settlements, trade and services) and a significant increase in the number of ponds in green belt areas, fields, dryland agriculture, plantations, and mixed gardens, with an estimated total area of 153 ha. In this case, efforts to control land use change in order to maintain the balance of carbon stock are required (Dachary-Bernard et al., 2018; Koroso, 2023; O'Driscoll et al., 2023). The empirical evidence presented in this study indicates that by the year 2034, there will be an increase in built-up land, specifically settlements, trade and service areas.

The research demonstrates that the factors influencing land use change are intricate and multifaceted. The utilization of a comprehensive range of variables, and multitemporal land use maps enables the investigation of dynamic land use patterns. The spatial modeling approach utilizing the MLPNN-MC algorithm enables a

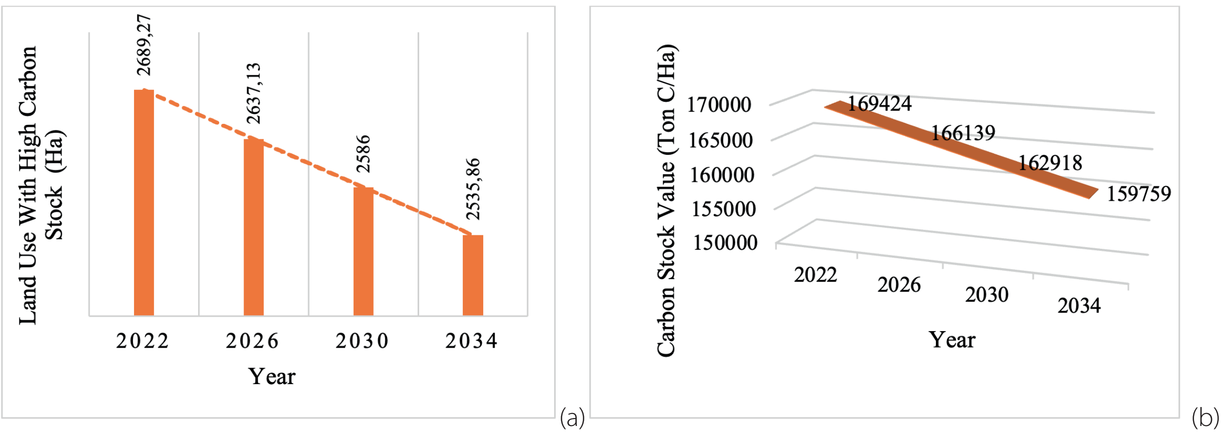

Fig. 8. (a) Area of land use with high carbon stock; (b) Carbon stock levels in 2022, 2026, 2030, and 2034

more comprehensive analysis of the transformation of land use change from one state to another, taking into account the influence of driving variables. The backpropagation technique employed in the MLPNN-MC algorithm enables the minimization of errors in spatial modeling of land use prediction, thereby facilitating the generation of accurate data with a success rate of 98%.

The findings of this study corroborate the previous studies, which indicate that land use has a significant influence on carbon stock changes (Wei et al., 2024; Achmad et al., 2024; Raqeeb et al., 2024). The role of land use in the form of mangroves and forests in absorbing carbon emissions is of great significance. In contrast, the construction of infrastructure, including roads, airports, and harbors, has been identified as a significant contributor to the increase in carbon emissions. The expansion of infrastructure is often accompanied by transportation activities, economic activities, and urbanization, which have implications for increasing energy demand and, consequently, high carbon emissions. Furthermore, these activities have an impact on current and future ecological conditions.

In light of these findings, it is imperative to implement measures to regulate land use in order to maintain equilibrium in carbon stock. This study reinforces the findings of previous research on the significance of land use planning policies based on carbon stock balance (Weindl et al., 2017). Such efforts may be made, for instance, through the optimization of mangrove ecosystems and forest areas through conservation, restoration, or reforestation (Dajam and Eid, 2024; Feller et al., 2017; Utami et al., 2024b). Furthermore, the allocation of land for green open spaces is imperative, given that reduced carbon stocks resulting in increased carbon emissions are a major driver of global warming. Land use predictions pertaining to prospective carbon stock levels furnish spatial data regarding the locations, patterns, and consequences of anticipated land transformations. The prediction carbon stocks represents a crucial aspect in the context of rising carbon emissions (Amadou et al., 2018; Araza et al., 2023). The database and findings presented in this study should serve as the foundation for stakeholders in the formulation of sustainable land management policies, the development of spatial utilization planning and control strategies, and the creation of planning, management, and control frameworks for human activities (social, cultural, and economic) with the aim of mitigating the impact of climate change disasters (Hamad et al., 2018; Ismaili et al., 2023; Xu et al., 2024). The integration of climate change mitigation with land use regulation and control represents a highly effective strategy for maintaining the balance of carbon stock (Xu et al., 2024). This study aims to address the limitations of previous research in carbon stock prediction modeling by enhancing the accuracy of predictions. However, the modeling is constrained to changes in land use types, without conducting a comprehensive assessment of vegetation types or vegetation density levels that may influence carbon values. The study employs a carbon stock scenario in 2034, utilizing driving factors such as social, economic, physical aspects and policies that are currently in effect. It is acknowledged that extreme changes in these factors are possible in the future, and that this has the potential to impact the predicted value of carbon stock. The development of predictive modeling research in the future is expected to further explore the carbon stock prediction modeling approach, with the aim of making it more comprehensive and accurate.

CONCLUSIONS

The impact of land use dynamics on the decline in terrestrial carbon stock levels is significant. Uncertainty in future land use and carbon stock levels can be overcome through modeling to predict land use based on carbon stock levels using the MLPNN-MC Algorithm. This study was able to produce a prediction accuracy rate of 98% for carbon stock levels, thus filling the gaps in previous modeling studies. The high level of accuracy can be attributed to the use of detailed sources for land use map data, comprehensive driving forces factors, and a compatible MLPNN-MC algorithm. The significant driving factors resulting from the spatial regression analysis and land change modeler include airports, city centers, industries, roads, and relative relief. The research findings predict that in 2034, there will be a decrease in land use area from high to low carbon stock of 153 ha, or a decrease in carbon stock levels of 9,665 tonnes C/ha. The modeling provides information on the spatial distribution of land use and carbon stock values that are subject to change. The carbon stock prediction database is an important component in the formulation of land use control policies and climate change mitigation efforts. Although this study was able to produce a high level of accuracy, further research is required to consider vegetation types and calculate all components of carbon stock values more comprehensively.

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