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Analysing the Driving Forces of Carbon Stock Change for Climate Change Mitigation

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ABSTRACT

The management of land use is a significant factor in maintaining the equilibrium of carbon stocks. However, the expansion of infrastructure, mining, industry, trade, economic activity and population has resulted in significant changes to land use, which have led to a reduction in carbon stock reserves. The objective of this study was to map the level of carbon stock reserves and to analyse the variable driving forces of carbon stock change. The variables used in this study encompass 21 distinct types, including: socio-economic, physical, locational, land and spatial planning aspects. The dependent variable comprises the level of carbon stock by land use type in 2014, 2018, and 2022. Spatial regression analysis was employed to ascertain the driving forces that exert a predominant influence on alterations in carbon stock reserves. The results of the spatial regression analysis between the dependent and independent variables yielded a highly significant correlation, as indicated by the R-square value exceeding 0.09. This condition is influenced by the use of complex and comprehensive variables, as well as the use of spatial regression which is able to analyse between variables by considering spatial aspects. The results of the analysis demonstrate that location variables (city centre, airport and road accessibility), physical variables (relative relief) and land variables (land title status) are the most dominant variables. The analysis of the driving force of carbon stock change represents a crucial aspect of land use management and the control of land use change from areas with high to low carbon stock. In order to maintain the balance of carbon stock reserves, it is essential to optimise mangrove areas and implement reforestation initiatives in forest areas.

Keywords: carbon stock, climate change, land use, driving forces.

INTRODUCTION

Land use change from vegetated land (forests, mangroves, community plantations, mixed gardens, etc.) to developed land, infrastructure, open land, and ponds further reduces carbon stocks (Nave et al., 2024; Utami et al., 2024; Weindl et al., 2017). The impact of carbon stock depletion is fuelling the rise in climate change disasters (Melvin et al., 2017), including: floods, landslides, tidal floods, droughts, fires, abrasion, tidal waves, etc (Anand and Oinam, 2019; Laino and Iglesias, 2023; Sutrisno et al., 2021). The effects of climate change disasters can lead to disruption of livelihoods, reduced food production, loss of jobs, loss of biodiversity, sinking of islands and threaten the sustainability of livelihoods (Hassan et al., 2022; Nichols, 2019; Thagunna et al., 2022). Various studies show that the impact of climate change disasters also leads to a decline in physical and human capital, natural, social, financial resulting in vulnerability in all aspects of life (Chuong et al., 2024; Obahoundje and Diedhiou, 2022). In a developing country, the pursuit of carbon emission control and economic growth are often inextricably linked (Segundo et al., 2021). Demands for increased economic growth, poverty alleviation, equitable development, and prosperity must be supported by accelerated infrastructure development, increased development of industrial, commercial and mining areas (Verma et al., 2020). These efforts have the potential to stimulate accelerated economic growth; however, they also have the capacity to precipitate environmental degradation and imbalances in carbon stocks (Gençay and Durkaya, 2023; Varamesh et al., 2014). The implications of massive development and economic growth for land use change are significant, with the majority of affected land comprising the areas of high vegetation density that are capable of absorbing carbon (Bakute et al., 2021; Liu et al., 2023; Xu et al., 2023). In addition to the impact on land use change, a range of economic, industrial, and mining activities also necessitate energy, the majority of which is derived from the combustion of fossil raw materials. This has ramifications for the rising levels of CO_2 in the atmosphere (Gençay and Durkaya, 2023; Hayes et al., 2023). The extensive clearance of land and combustion of fossil fuels represent a significant contributor to the observed increase in carbon emissions, particularly in developing countries striving to enhance their gross domestic product/GDP (Balch et al., 2016; Sovacool et al., 2023; Ziaul Hoque et al., 2022).

In order to mitigate the adverse effects of climate change on a global scale, a number of countries entered into an agreement, as set forth in the Paris Agreement. In order to facilitate the implementation of the agreement, the Indonesian government enacted Law Number 16 of 2016 concerning the ratification of the Paris Agrrement to the United Nations Framework Convention on Climate Change, The aforementioned Presidential Regulation No. 98 of 2021, in conjunction with its subsequent derivative regulations, specifically Law No. 16 of 2016 and Presidential Regulation 98 of 2021. At the climate change conference held in Copenhagen, Indonesia committed to reducing carbon emissions by 29% to 41% from business as usual (Presidential Regulation No. 98 of 2021), in accordance with policies set by the government. Adaptation and mitigation strategies to address climate change are of paramount importance for all countries, as they can significantly reduce the risk of disasters (Alexandri et al., 2024; Feng et al., 2023; Salminah et al., 2020; Soboka and Yimer, 2022). A number of technologies are being developed by various countries with the objective of optimising the role of renewable energy in order to mitigate the energy crisis (Chu et al., 2023; Gabriele et al., 2023). It is imperative that strategies and actions to reduce carbon emissions be implemented concurrently by the government, stakeholders, and most importantly, with the active involvement of the community.

In accordance with Presidential Regulation No. 98 of 2021, mitigation action plans may be implemented through a number of avenues, including the initiation of the greenhouse gas emission inventory stage, which encompasses such activities as monitoring, collection, and calculation (Presidential Regulation No. 98 of 2021). Carbon stock monitoring represents one of the key mechanisms through which the level of carbon emissions can be ascertained and the level of carbon stock reserves stored in a given area can be determined on a periodic basis (Utami et al., 2024; Presidential Regulation No. 98 of 2021), as a basis for formulating policies to combat climate change. In addition to monitoring, several studies have also analysed driving forces to determine the variables that affect carbon stock changes and developed carbon stock prediction models to determine the level of carbon stock reserves in the future as an important part of climate change mitigation (Hortay and Pálvölgyi, 2022; Huang, 2018).

Monitoring and analysing the drivers of carbon stocks can be done through several mechanisms, one of which is the calculation of terrestrial carbon stock reserves based on land use (Anindita et al., 2022; Nave et al., 2022; Weindl et al., 2017). Research on terrestrial carbon stock calculations and drivers has been carried out by Fadhli et al., (2021); Feng et al., (2024), nevertheless, the study is constrained by the use of a low-resolution satellite imagery as the source map. Huang (2018); Wu et al., (2024) also conducted research related to the analysis of the driving forces that affect changes in carbon stock reserves; however, the study was limited by the use of a restricted set of variables, which is not comprehensive. The lack of detailed data sources and the lack of comprehensive variables used are feared to have implications for the inaccuracy of climate change mitigation actions. In this case, the use of detailed data sources and comprehensive driving force variables is needed so that the variables that have a significant effect can be formulated appropriately (Mekonnen et al., 2022; Zhou et al., 2020). This study aimed to address the shortcomings of previous research by providing a more detailed analysis of the level of carbon stock by land use type and identifying the driving forces and variables that significantly affect the level of carbon stock.

METHODOLOGY

Study area

This research was conducted in Temon District (15 villages), Wates District (8 villages) and parts of Panjatan District (3 villages), Kulon Progo Regency, Yogyakarta, Indonesia. The unit of analysis was the village level, consisting of 26 villages. The selection of locations was based on several aspects: (1) there is a large infrastructure development, namely the Yogyakarta International Airport; (2) there is a mangrove area as a blue carbon ecosystem; (3) land conversion is massive. The research site can be explained as shown in Figure 1.

Data, sources, and method

The data set employed in this study comprises dependent data, which can be broken down as follows: the land use maps for the years 2014, 2018, and 2022 were obtained through the visual interpretation of Pleiades imagery with a spatial resolution of 0.5 meters. The carbon stock reserve levels were reclassified based on the land use types in accordance with the Greenhouse Gas (GHG) coefficient, as outlined by the International Council for Local Environmental Initiatives/ ICLEI. The classification system is presented in Table 1 below.

Meanwhile, the independent data consisted of 4 aspects with a total of 21 variables, including: physical aspects (relative relief, landslide, flood, tsunami and drought vulnerability); socio-economic aspects (population, agricultural employment, village income and tax/revenue sharing); location aspects (road accessibility, city centre, number of hospitals, number of health centres/

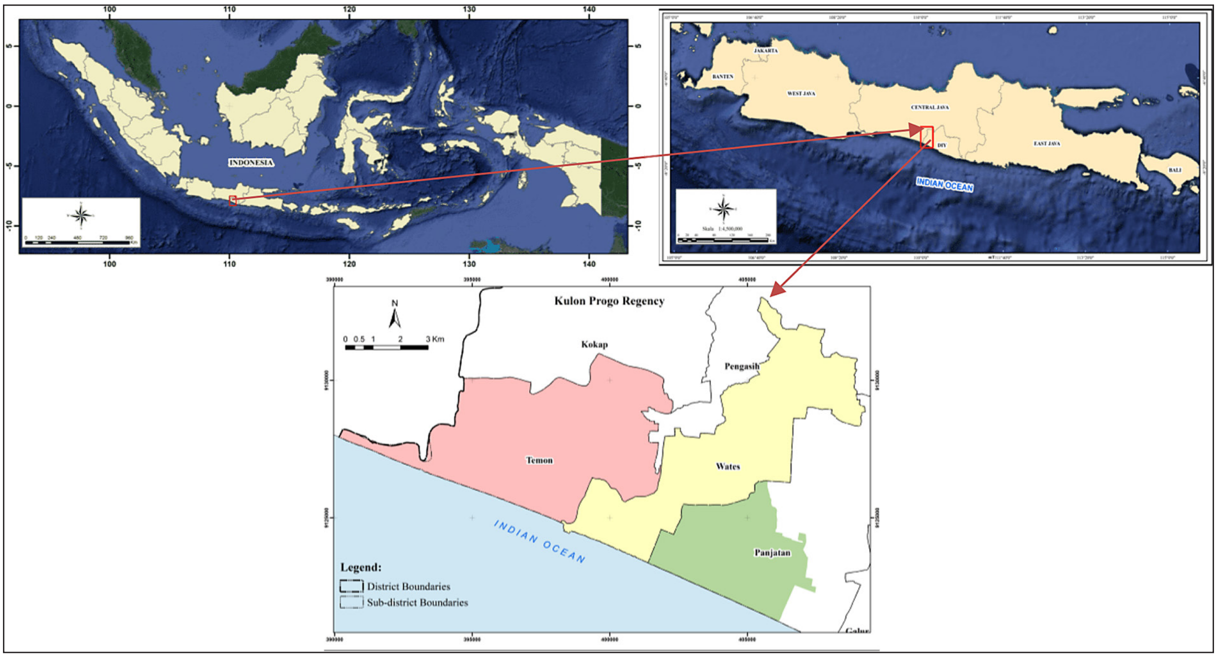

Figure 1. Study area

Table 1. Land use reclassification based on greenhouse gas (GHG) coefficient

Land use	GHG	Class	Land use	GHG	Class
Infrastructure, water body	0		Dryland farming/fields	10	
Rice fields	2	Low	Greenspace/shrub	30	High
Open field	2,5		Plantation/Mixed gardens	63	

Note: source: ICLEI, 2022.

clinics, universities, secondary schools, number of industries and airports); land and spatial planning aspects (land value zone, land title status, protected areas, and agricultural cultivation areas). The research flowchart can be explained as Figure 2.

Spatial regression is used to analyse the relationship between the dependent variable and the independent variable. The software used in this spatial regression analysis is Geoda, which is obtained from the website https://geodacenter.github.io/download.html. This regression has the advantage of being able to take into account location factors, so that there is a spatial weight in it (Caraka and Yasin, 2017; Hasbi et al., 2014). Anselin (1998) explained that taking into account location effects is important, because something that is close has a greater impact than something that is far away. The spatial regression formula can be explained as follow

$$y = \rho W_1 y + X\beta + u \quad (1)$$

$$u = \lambda W_2 u + \varepsilon \quad (2)$$

where: y – Vector of dependent variables with size $n \times 1$, X – matrix of independent variables with size $n \times (p + 1)$, β – vector of regression coefficient parameters of size $(p + 1) \times 1$, ρ – spatial lag coefficient parameter of the dependent variable, λ – the spatial lag coefficient parameter on the error is $\lambda < 1$, W_1 and W_2 – spatial weight matrix of size $n \times n$, ε – error vector of size $n \times 1$ with distribution IIDN.

The stages performed in spatial regression in this study include:

1. Conduct a spatial dependency test using Moran's I with the following hypothesis:
- $H_0 : I = 0$ (no dependencies between locations)
- $H_1 : I \neq 0$ (there are dependencies between locations)

The test statistic is expressed in the following equation.

$$Z_{count} = \frac{\hat{I} - \hat{I}_0}{\sqrt{\widehat{var}(\hat{I})}} \quad (3)$$

with

$$\hat{I} = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, \hat{I}_0 = -\frac{1}{n-1} \quad (4)$$

$$\widehat{var}(\hat{I}) = \frac{n^2(n-1)S_1 - n(n-1)S_2 - 2S_0^2}{(n^2-1)S_0^2} \quad (5)$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}, \quad S_1 = \frac{1}{2}\sum_{i \neq j}^{n}\left(w_{ij} + w_{ij}\right)^2, \quad S_2 = \sum_{i=1}^{n}(w_{i.} + w_{.i})^2 \quad (6)$$

$$w_{i.} = \sum_{j=1}^{n} w_{ij}, w_{.i} = \sum_{j=1}^{n} w_{ji} \quad (7)$$

where: x_i – data to-i (i = 1, 2, …, n), x_j – data to-j (j = 1, 2, …, n), $\bar{x}$ – average of observation data, w_{ij} – element of spatial weight matrix row to -i column to-j.

Decision making H_0 rejected if the value |Zcount| > Zα/2.

2. Perform the Lagrange Multiplier test to determine whether a model has spatial effects or not.

a) Lagrange Multiplier *Lag* (LM_{lag}) – the statistical procedure for Lagrange Multiplier Lag testing (LM_{lag}) is as follows:

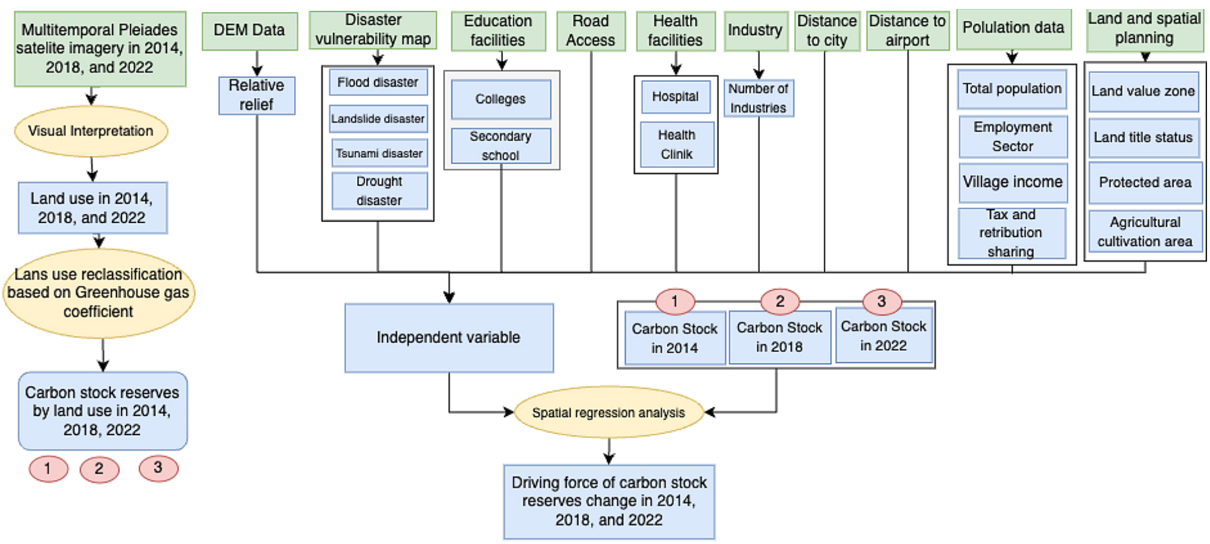

Figure 2. Research flow chart

Hypothesis:
- $H_0 : \rho$ (No spatial lag dependencies)
- $H_1 : \rho$ (There is spatial lag dependency)

Test statistics:

$$LM_{lag} = \frac{\left[\frac{\boldsymbol{\varepsilon^T W_1 y}}{\boldsymbol{s^2}}\right]^2}{\frac{\boldsymbol{(W_1 X\beta)^T M W_1 X\beta}}{\boldsymbol{s^2}} + \boldsymbol{T}} \quad (8)$$

with

$$s^2 = \frac{\varepsilon^T \varepsilon}{n}, M = I - X(X^T X)^{-1} X^T$$
$$T = tr(W_1^T W_1 + W_1^2) \quad (9)$$

where: X – matrix of independent variables with size $n \times k$, W_1 – the standardised resultant spatial weight matrix of size $n \times n$, ε – error vector, y – vector of observation values of the dependent variable of size n × 1.

Rejection area:

Reject H_0 when $LM_{lag} > \chi^2(\alpha,1)$, which leads to the conclusion that there is spatial lag dependence.

b) Robust Lagrange Multiplier *Lag* (RLM_{lag}) – here is the statistical procedure for Robust Lagrange Multiplier Lag testing (LM_{lag})

Hypothesis:
- $H_0 : \rho = 0$ (No spatial lag dependencies)
- $H_1 : \rho \neq 0$ (There is spatial lag dependence)

Test statistics:

$$RLM_{lag} = \frac{\left(\frac{\varepsilon^T W y}{\sigma^2} - \frac{\varepsilon^T W \varepsilon}{\sigma^2}\right)^2}{\sigma^{-2} D - T} \quad (10)$$

Rejection area:

Reject H_0 when $RLM_{lag} > \chi^2_{(\alpha,1)}$ or *p-value* $< \alpha$ which leads to the conclusion that there is spatial lag dependency.

c) Lagrange Multiplier *Error* (LM_{lag}) – here is the statistical procedure for Lagrange Multiplier Error testing (LM_{error})

Hypothesis:
- $H_0 : \lambda = 0$ (No spatial dependency of errors)
- $H_1 : \lambda \neq 0$ (There is spatial dependency of errors)

Test statistics:

$$LM_{error} = \frac{\left[\frac{\boldsymbol{\varepsilon^T W_2 \varepsilon}}{\boldsymbol{s^2}}\right]^2}{\boldsymbol{T}} \quad (11)$$

with:

$$s^2 = \frac{\varepsilon^T \varepsilon}{n}, T = tr(W_2^T W_2 + W_2^2) \quad (12)$$

where: W_2 – the standardised resultant spatial weight matrix of size n × n, ε– error vector, y – vector of observation values of the dependent variable of size n × 1.

Rejection area:

Reject H_0 when $LM_{error} > \chi^2_{(\alpha,1)}$, which leads to the conclusion that there is spatial dependency of the errors.

d) Robust Lagrange Multiplier Error (RLM_{lag})

Here is the statistical procedure for Robust Lagrange Multiplier Error testing (RLM_{error})

Hypothesis:
- $H_0 : \lambda = 0$ (No spatial dependency of errors)
- $H_1 : \lambda \neq 0$ (There is spatial dependency of errors)

Test Statistics:

$$\mathrm{RLM_{error}} = \frac{\left(\frac{\varepsilon^T W \varepsilon}{\sigma^2} - T\sigma^2 D^{-1} \frac{\varepsilon^T W y}{\sigma^2}\right)^2}{T - T^2 \sigma^2 D^{-1}} \quad (13)$$

Rejection area:

Reject H_0 when $RLM_{error} > \chi 2_{(\alpha,1)}$, which gives the conclusion that there is spatial dependency of errors.

3. Calculating the parameter estimation value of the SAR model

a) Perform parameter significance test for SAR model using Wald test.

1) Wald test Parameters ρ

Hypothesis:
- $H_0 : \rho = 0$ (There are no lag dependencies on the dependent variable)
- $H_1 : \rho \neq 0$ (there are lag dependencies on the dependent variable)

Test Statistics:

$$Wald = \left(\frac{\hat{\rho}^2}{var(\hat{\rho})}\right) \quad (14)$$

where: $\hat{\boldsymbol{\rho}}$ – parameter estimation ρ, var($\hat{\boldsymbol{\rho}}$) – variance of parameter estimates.

Rejection area – Reject H_0 when Wald test > $\chi^2_{\alpha,1}$ which gives the conclusion that the tested parameter is significant.

2) Parameter β

Hypothesis:
- $H_0 : \beta k = 0$ (Regression coefficient has no effect)
- $H_1 \; \beta k \neq 0, k = 1,2,...,n$ (Regression coefficient has an effect)

Test statistics

$$Wald = \left(\frac{\hat{\beta}_k^2}{var(\hat{\beta}_k)}\right) \quad (15)$$

where: $\hat{\beta}_k$ – parameter estimation β to-k, var($\hat{\beta}$) – variance of parameter estimates β to-k.

Rejection area:

Reject H_0 when Wald test > $\chi^2\alpha,1$ which gives the conclusion that the tested parameter is significant.

4. Calculating the parameter estimation value of the SEM model.

a) Conduct parameter significance test for SEM model using Wald test.

1) Parameter λ

Hypothesis:

H_0 : $\lambda = 0$ (No spatial dependency of errors)

H_1 : $\lambda \neq 0$ (there is spatial dependency of errors)

Test statistics:

$$Wald = \left(\frac{\hat{\lambda}^2}{var(\hat{\lambda})}\right) \tag{16}$$

where: $\hat{\lambda}$ – parameter estimation λ, var($\hat{\lambda}$) – the diagonal element of the variance matrix that corresponds to λ.

Rejection area:

Reject H_0 when Wald test value > $\chi^2_{\alpha,1}$ which concludes that the parameter λ is significant.

Parameter β

Hypothesis:

H_0 : $\beta_k = 0$ (Regression coefficient has no effect)

H_1 : $\beta_k \neq 0$, k = 1,2,...,n (Regression coefficient has an effect)

Test statistics:

$$Wald = \left(\frac{\hat{\beta}_k^2}{var(\hat{\beta}_k)}\right) \tag{17}$$

where: $\hat{\beta}_k$ – parameter estimation β to-k, $var(\hat{\beta}_k)$ – variance of parameter estimates β to-k.

Rejection area – reject H_0 when Wald test > $\chi^2_{\alpha,1}$ which gives the conclusion that the tested parameter is significant.

In spatial regression analysis, the R-square value indicates the degree of significance between the dependent and independent variables. Additionally, the Akaike information criterion (AIC) provides a measure of model fit. The most appropriate model is determined based on the highest R-square value and the lowest AIC value. The AIC and R-squared formulas are presented below:

$$R\text{-}squared = \frac{SS_{regression}}{SS_{total}} \tag{18}$$

where: $SS_{Regression}$ – regression effect sum of squares, SS_{Total} – total number of squares.

$$AIC = AIC = -2Lm + 2m \tag{19}$$

where: Lm – maximum log – likelihood, m – number of parameters in the model.

The results of spatial regression analysis can demonstrate the significance value between variables. In this context, a higher significance value indicates that the independent variable exerts a greater influence on the dependent variable. This significance value can be shown from the probability value indicator. This value indicates a measure that determines the amount of evidence that must be shown in the sample before rejecting the null hypothesis and declaring the effect statistically significant. In addition to the probability value, the influence between variables can also be indicated by the z-value. The formula for z-value is:

$$Z = \left(\frac{x-\mu}{\sigma}\right) \tag{20}$$

where: x – the value of the data point, μ – the average of the sample or data set, σ – the standard deviation.

RESULT AND DISCUSSION

Dependent variable carbon stock reserve by land use

The analysis of variables that affect carbon stocks in a multitemporal manner represents a crucial aspect of regional carbon emission control. In order to ascertain the underlying driving forces, it is necessary to analyse the dependent data pertaining to the level of carbon stock reserves, with a view to assess land cover based on greenhouse gas coefficient. In this analysis, the level of carbon stock reserve is classified into two categories: high and low carbon stock reserve. To obtain this data, several processes were undertaken, including the reclassification of land use from eight categories into two classes: land use with high carbon stock value (mangroves, greenspace, fields, and smallholder plantations) and land use with low carbon stock value (infrastructure, water bodies, rice fields, built-up land, and open land). The data on carbon stock reserve levels by land use type in 2014 can be found in Figure 3.

Figure 3 shows the carbon stock reserve level of the study area before the implementation of the National Strategic Project of Yogyakarta International Airport Development. The spatial distribution of the high level of carbon stock reserve is elongated on the south and north sides of the study area. The high level of carbon stock reserve in 2014 was influenced by the extensive land use in the form of fields, mixed gardens, smallholder

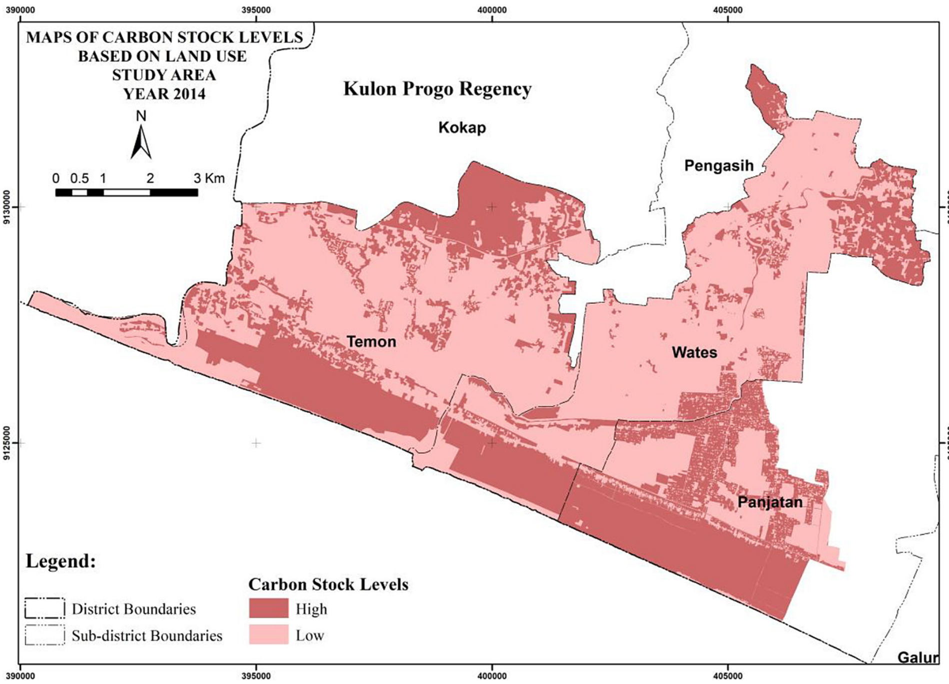

Figure 3. Map of carbon stock reserve levels in 2014

plantations, and the presence of mangroves. The results of the analysis show that the level of carbon stock reserves in 2014 was still very high at 150,286.57 Tonnes C/Ha.

However, the process of land acquisition and land clearing that will take place from 2015 to 2018, as well as increased economic activities, have implications for massive land use changes. The results of the analysis show that in the period from 2014 to 2018 there was a decrease in land use with high carbon stock reserves, namely moorland and mixed gardens, where an area of ± 1.957 Ha in 2014 became ± 1.810 Ha in 2018 (a decrease of ± 147 Ha), in addition there was also a decrease in fields from an area of ± 1.320.8 Ha in 2014 to ± 907 Ha in 2018 (a decrease of ± 413 Ha). In addition to the decrease in the area of land use with the capacity to absorb carbon stocks, the area of land use with the capacity to store low carbon stocks also increased in the study area, built-up areas increased by 78 Ha and infrastructure and ponds by 60 Ha. The spatial distribution of carbon stocks in 2018 is shown in Figure 4.

Figure 4 illustrates a significant decline in the level of carbon stock reserves in 2018, particularly at the YIA airport construction site (Jangkaran, Sindutan, Palihan, Kebonrejo, and Glagah Villages). The results of the analysis demonstrate that in 2018, the level of carbon stock reserves was 138,351.21 ± 11,935.36 Tonnes C/Ha, representing a decrease of 11,935.36 ± 138.35 Tonnes C/Ha. One of the primary factors contributing to this reduction in carbon stock reserves is the development of the airport, which has resulted in a decline in land use, particularly in the form of mixed gardens and fields.

Following the construction of the YIA airport in 2022, the rate of decline in land use that can store carbon stock reserves persisted. However, when compared to the 2014–2018 period, the decline rate was relatively lower during the 2018–2022 period. The spatial distribution of carbon stock reserve levels in 2022 can be elucidated by referring to Figure 5.

Figure 5 illustrates that there has been a significant transformation in land use from the areas with high carbon stock reserves to the land use types with low carbon stock in the villages of Garongan, Pleret, and Kaligintung. The result of the carbon stock reserve calculation analysis based on land use type in 2022 is 135,257.5 Tonnes C/Ha (a reduction of 3.094 Tonnes C/Ha from 2018). The data on the land use areas with high carbon stock reserve values per village in 2014, 2018, and 2022 are presented in Figure 6. A review of maps 3, 4, and 5, as well as figure 6, indicates a reduction in land use with high carbon stock levels across all villages. The villages that experienced the most significant reduction in land use with high carbon stock reserves from 2014 to

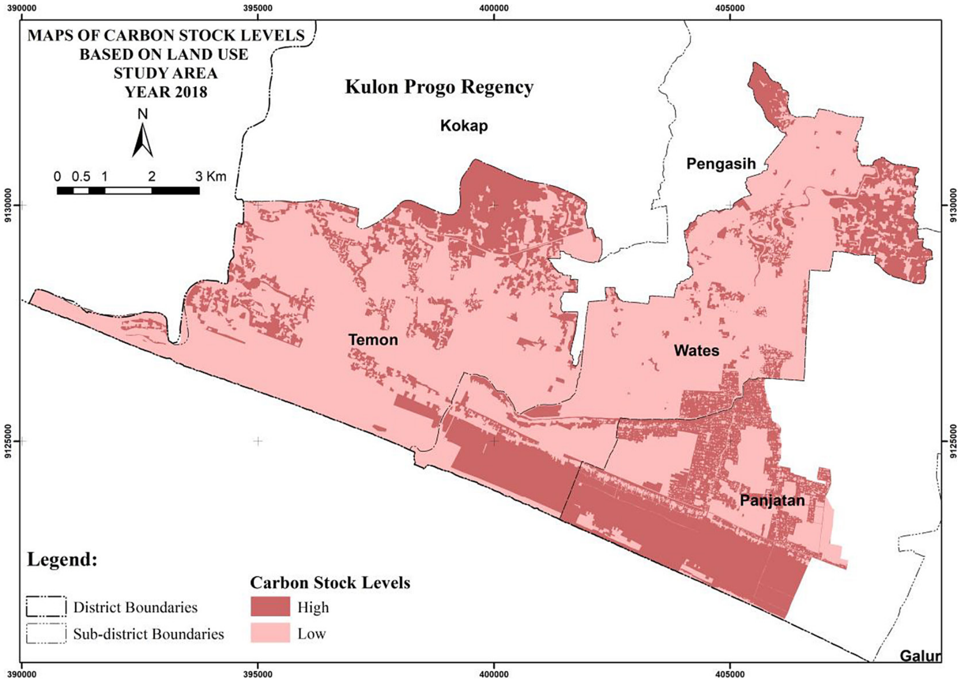

Figure 4. Map of carbon stock reserve levels in 2018

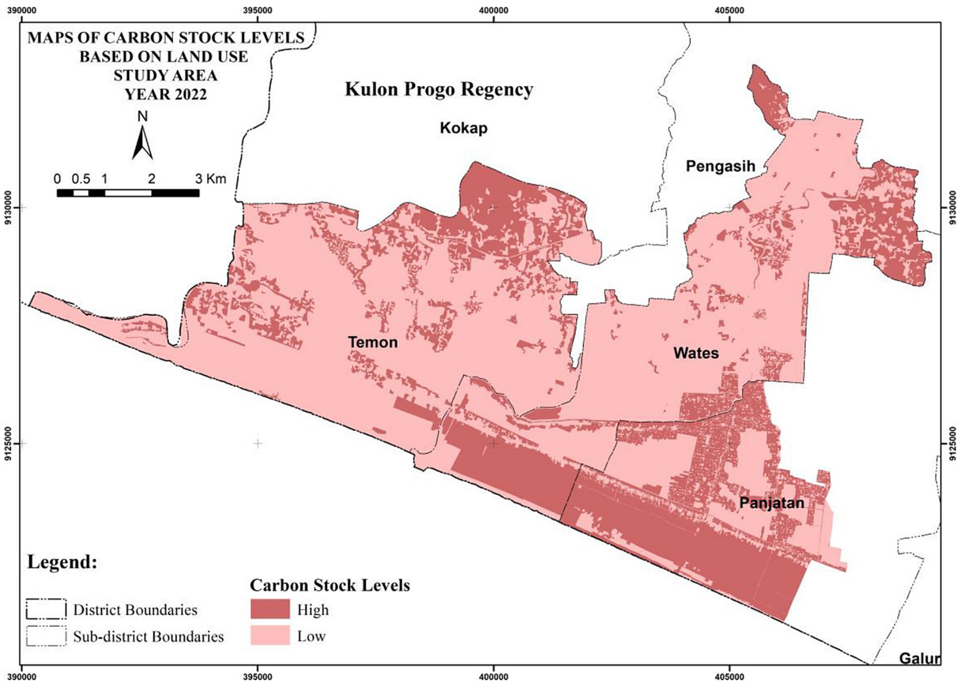

Figure 5. Map of carbon stock reserve levels in 2022

2022 are as follows: Glagah, Palihan, Jangkaran and Sindutan. The reduction of mixed gardens and fields as land use with the ability to store high carbon stock reserves has been transformed into an airport area, which has contributed to the decline in carbon stocks. Figure 6 demonstrates that some villages with land use capable of storing high carbon stocks are limited to Garongan, Pleret, and Karangwuni villages.

This research demonstrates that the large-scale infrastructure development of Yogyakarta International Airport, while facilitating transportation and stimulating economic growth, also has the unintended consequence of accelerating land

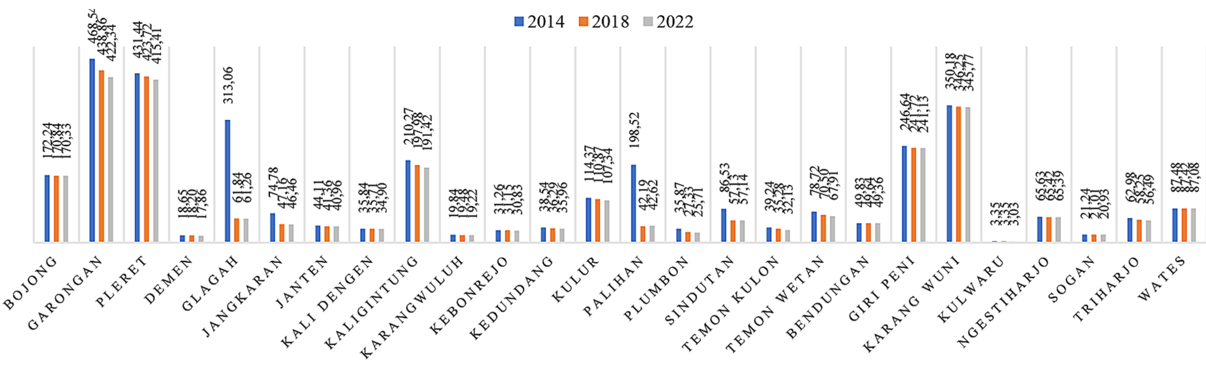

Figure 6. Area of land use with high carbon stock value per village in 2014, 2018, 2022

use change and reducing carbon stock reserves. The monitoring of changes in carbon stock levels based on multitemporal land use maps represents a crucial aspect of understanding the rate of carbon emissions, thereby facilitating the development of climate change mitigation strategies (Stagakis et al., 2023).

Variable driving forces of carbon stock reserve by land use

The variables employed in this study are of a considerable complexity, encompassing socio-economic, locational, physical, land and spatial elements. The statistical analysis of the independent variables utilized in this study is elucidated in Table 2. To determine the relationship between several dependent and independent variables can be illustrated by using a scatter plot, as exemplified in the following figure. The variables employed to ascertain the extent of change in the level of carbon stock reserves in this study encompass socio-economic aspects, including population variables, the percentage of employment in the agricultural sector, village original income (PAD), and revenue sharing (taxes and levies). The total population data, with the corresponding analysis units per village, for the years 2014, 2022, and 2022 are presented in Figure 8.

Figure 8 illustrates that the highest population density is observed in Wates, Giripeni, and Triharjo, which is influenced by the city centre and the presence of industrial activities.

In this study, the location variables employed include the distance to the city centre, airport, roads accessibility, industrial areas, hospitals, health clinics, universities, and secondary schools. The results of the analysis indicate that the areas with the highest road access are located in the Wates subdistrict, Triharjo, Bendungan, and Palihan villages. These villages not only have excellent road access but also proximity to the city centre. The

Table 2. Statistical description of research variables

No	Variabel	2022			2018			2014		
		Mean	Maximum	Minimum	Mean	Maximum	Minimum	Mean	Maximum	Minimum
1	Protected area (Ha)	8.5	39.43	1.6	117.7	54.2	0	117.7	54.2	0
2	Agricultural cultivation area (Ha)	39.2	67.42	157.8	83.64	0	7.7	157.8	83.64	0
3	Road accesibility (m)	1237.2	5000.6	0	1237.2	5000.6	0	1237.2	5000.6	0
4	Flood disaster (Ha)	120.37	238.3	13.7	120.37	238.3	13.7	120.37	238.3	13.7
5	Land title status	2.9	14	0.41	2.9	14	0.41	2.9	14	0.41
6	Relative relief (Ha)	47.8	350	0	47.8	350	0	47.8	350	0
7	Land value zone (Rp)	1032680.9	2891410	300978	776196.7	2215552	201658	100577.4	361667	46830
8	Distance to city (Km)	7.7	13.33	0.28	7.7	13.33	0.28	7.7	13.33	0.28
9	Distance to airport	5.1	11.25	0.69	5.1	11.25	0.69	5.1	11.25	0.69
10	Industry	0.1	1	0	0.1	1	0	0.1	1	0
11	Employment in the agricultural (%)	26.6	45.14	2.37	37.67231	60.68	3.85	42.071538	66.3	4.59
12	Population (person)	3540	13942	1071	3496	14241	1076	3220	13512	960

Note: source: data analysis, 2024.

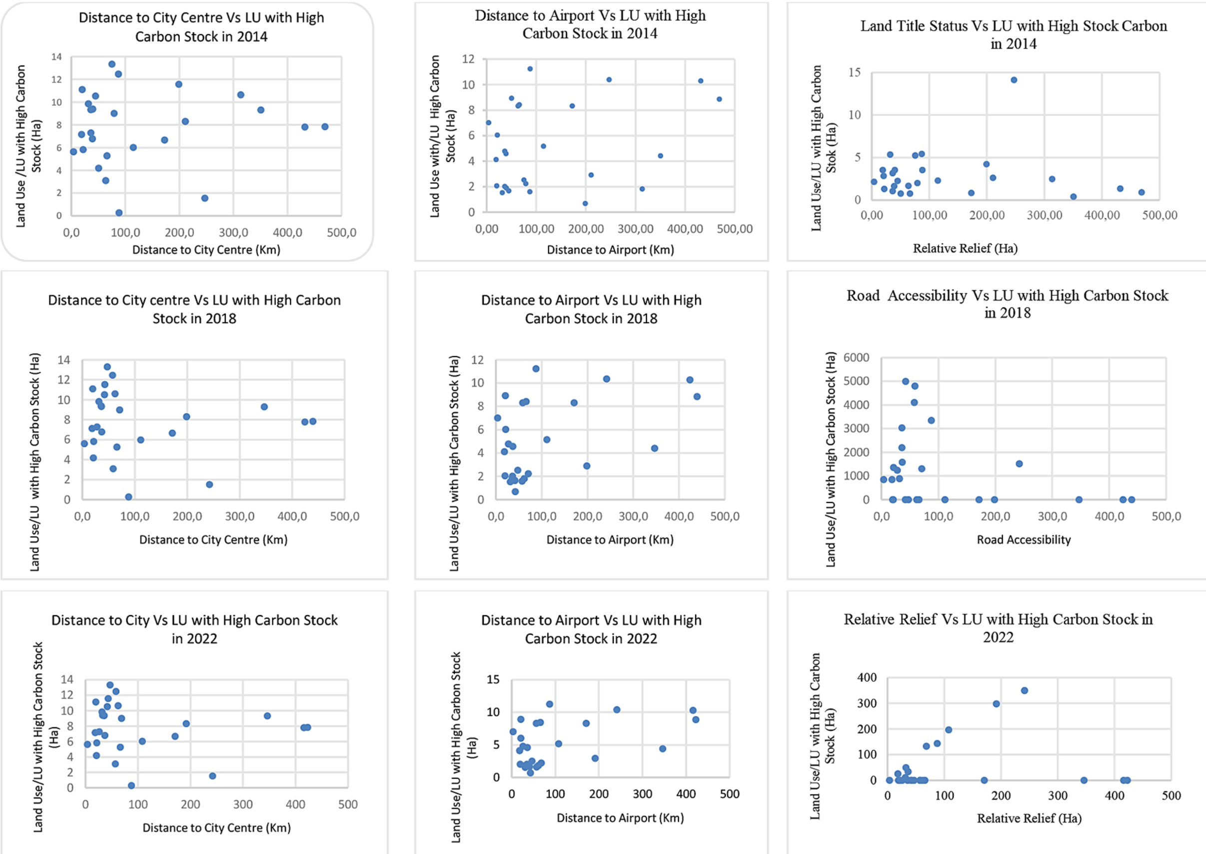

Figure 7. Scatter plot diagram of the relationship between independent and dependent variables

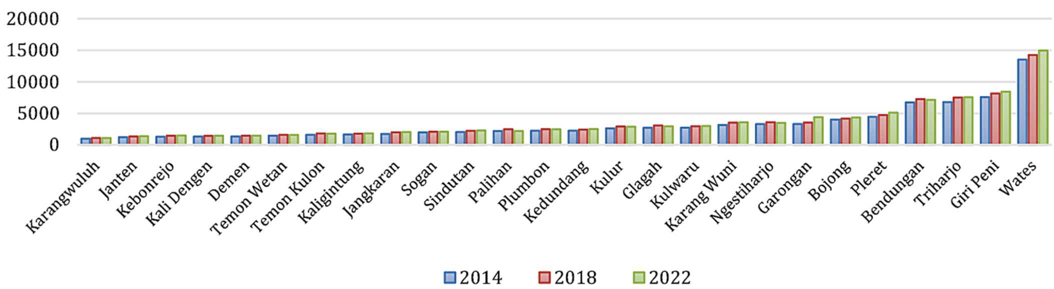

Figure 8. Total population of 26 villages in 2014, 2018, and 2022 (Source: BPS Kulon Progo, 2023)

spatial distribution of the variables of distance to the city centre and distance to the airport can be observed in Figures 9a and 9b, respectively.

The data presented in Figures 9 (a) and (b) illustrate that the geographical separation between the airport and the city centre is considerable. Furthermore, the proximity of villages to the city centre is not reflected in their proximity to the airport, and vice versa. In addition to the aforementioned variables, this study incorporated a range of physical aspects, including the relative relief variable, landslide, flood, drought and tsunami vulnerability. The spatial distribution of relative relief variables can be elucidated through the use of Figure 10.

The results of the analysis indicate that the majority of the study area is characterised by relatively flat topography, with areas of slightly elevated to high relief observed in Giripeni, Kaligintung, and Kulur villages. In terms of land and spatial aspects, the variables employed are as follows: the land title status, land value zones, protected areas, and cultivated areas. These variables were subsequently analysed in order to ascertain their relationship with the dependent variable through the use of spatial regression analysis. This approach offers a number of advantages over non-spatial regression, primarily due to the incorporation

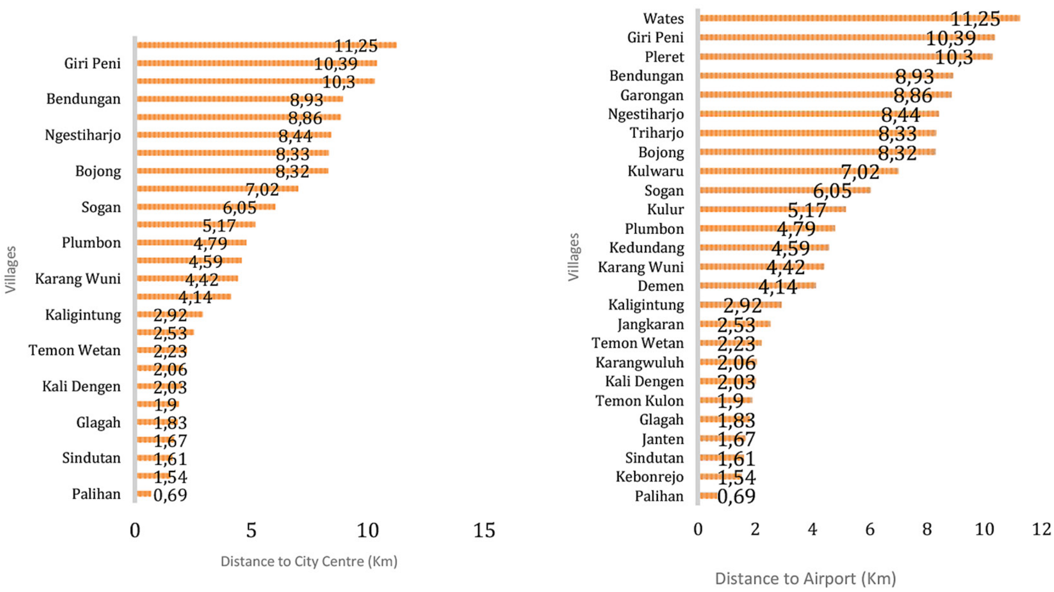

Figure 9. (a) distance of the sub-village to the city centre; (b) distance of the sub-village to the airport

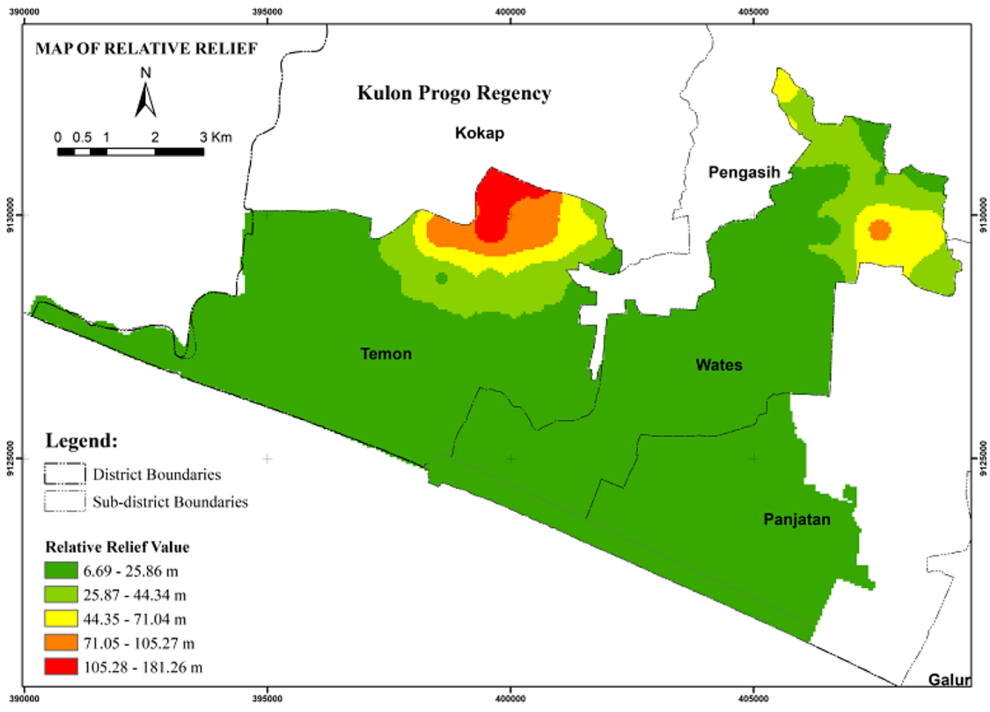

Figure 10. Relative relief map

of spatial weighting and connectivity relationships between analysis units.

Spatial regression analysis of driving force variables

In this study, spatial regression can produce three models in the form of classic/ordinary least squares/OLS, spatial error, and spatial lag models. In order to obtain the most appropriate model, a spatial regression accuracy test is conducted, the results of which can be found in Table 3.

The results of the spatial regression analysis of the dependent and independent variables in 2014 yielded an accuracy test, as illustrated in Table 3. The table demonstrates that the highest R-Square value (0.917881) and the lowest AIC value (297.397) are observed in the spatial

Table 3. Spatial regression accuracy test of carbon stock reserve variables in 2014

Model	R-square	AIC	Moran	Lagrange lag	Lagrange errorr	Lagrange SARMA
Classic	0.839068	305.571	0.00017	0.01817	0.19464	0.02649
Spatial Error	0.917881	297.397				
Spatial Lag	0.906543	316.214				

Note: source: data analysis, 2024.

error model. This R-square value indicates that the model can explain the variation of carbon stock by 91,78 % while 8,22 % is explained by other factors outside the model. On the basis of these two indicators, the most suitable model for analysing the significance value between the dependent and independent variables in 2014 is the spatial error model, as evidenced by the significance value presented in Table 4. The results of the spatial regression analysis indicate that the driving force variables exerting a significant influence on changes in carbon stock reserves by land use type in 2014 are the city centre (z-value: 64.103), the airport (55.1325), relief (0.703214), and land rights status (12.93). Some of these variables exert a significant influence, as indicated by a probability value of less than 0.05. The findings of this research indicate that the distance of an area from the city centre or airport is a significant factor influencing the rate of land conversion from land use with high carbon stock reserves to low. The areas situated farther from these urban centres experience a lower conversion rate. In contrast, the areas with a steep slope are more likely to have a high carbon stock reserve level. With regard to land rights, the status of non-property rights is also a key factor, with high levels of these rights correlating with low land use and high carbon stock reserves. The value of the spatial error coefficient ($\lambda = 0.885$) means that the error value in a village/region increases by 0.885 times the average error of the area that is a direct neighbour to the village/region, assuming other variables are fixed. To find out the driving forces variables that have a dominant effect in 2018, the spatial

$$\begin{aligned} y_{carbon\ stock\ 2014} = & -782{,}954 + 0{,}390 Protected\ area + 0{,}357 Agricultural\ lanc \\ & 0{,}008 Road\ access - 0{,}067 Flood - 12{,}932 Land\ title\ status + 0{,}703 Relief + \\ & 0{,}001 Land\ Value + 64{,}103 City\ centre + 55{,}132 Airport + 166{,}5 Industry + \\ & 0{,}960 Employment - 0{,}033 Population + 0{,}885 \textstyle\sum_{j=1}^{n} w_{ij} \varepsilon_{ij} \end{aligned} \tag{21}$$

Table 4. Variables affecting carbon stock reserves in 2014

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	-782.954	182.503	-4.29008	0.00002
Protected_14	0.389753	1.61245	0.241715	0.80900
Agric_14	0.356689	1.64213	0.217211	0.82804
Road_14	0.00828613	0.00278491	2.97537	0.00293
Flood_14	-0.0673032	0.209622	-0.32107	0.74816
Land title_14	-12.9322	5.99844	-2.15592	0.03109
RELIEF_14	0.703214	0.191101	3.67981	0.00023
Land value_14	0.00107212	0.000303582	3.53158	0.00041
City_14	64.103	14.4316	4.44185	0.00001
Airport_14	55.1325	15.0256	3.66924	0.00024
INDUS_14	166.5	42.394	3.92743	0.00009
Employ_14	0.960197	1.21276	0.791743	0.42851
Population_14	-0.0329937	0.019769	-1.66896	0.09513
LAMBDA	0.885436	0.0629521	14.0652	0.00000

Note: source: data analysis, 2024.

Table 5. Spatial regression accuracy test of carbon stock reserve variables in 2018

Model	R-square	AIC	Moran	Lagrange lag	Lagrange errorr	Lagrange SARMA	Heteroke dasticity	Satial dependency
Classic	0.827958	303.691	0.00224	0.08055	0.34945	0.09157		
Spatial error	0.887936	298.56					0.18138	0.02351
Spatial lag	0.870650	300.838					0.12589	0.02761

Note: source: data analysis, 2024.

regression accuracy test value is explained in Table 5. The results of the accuracy test indicate that the optimal model is the spatial error model, which is evidenced by the highest R-square value of 0.887936 and the lowest AIC value of 298.56. This R-square value indicates that the model can explain the variation of carbon stock by 88.79% while 11.21% is explained by other factors outside the model. The findings of the significance value analysis of the independent variables through the spatial error model are presented in Table 6.

The results of spatial regression analysis of independent and dependent variables in 2018 can be formulated in Equation 22.

The analysis indicates that the key driving forces with a significant impact in 2018 are the city centre (z-value = 75.2635), the airport (*45.0201)*, the road network (- 0.00959056). In 2018, the road variable exerted a more pronounced influence than in 2014. The spatial error coefficient (λ = 0.774) means that the error value in a village/region increases by 0.885 times the average error of the neighbouring villages/regions, assuming other variables are constant

In order to ascertain the relationship between the dependent and independent variables in 2022, the results of the spatial regression accuracy test are presented in Table 7.

The results of the accuracy test indicate that the spatial lag model, which exhibits the highest R-squared value (0.834779) and the lowest AIC value (306.889), is the most accurate spatial regression analysis in 2022. This R-square value indicates that the model can explain the variation of carbon stock by 83.47 % while 16.53 % is explained by other factors outside the model.

$$y_{carbon\ stock\ 2018} = -1145{,}18 + 0{,}220 Protected\ area + 3{,}884 Agricultural\ land - 0{,}009 Road\ access - 0{,}227 Flood - 4{,}348 Land\ title\ status + 0{,}280 Relief + 4{,}937x10^{-5} Land\ Value + 75{,}263 City\ centre + 45{,}020 Airport + 67{,}562 Industry + 1{,}760 Employment + 0{,}051 Population + 0{,}774 \sum_{j=1}^{n} w_{ij}\varepsilon_{ij} \tag{22}$$

Table 6. Spatial regression analysis of carbon stock reserves in 2018

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	-1145.18	184.192	-6.21731	0.00000
Protect area_18	0.219877	1.53909	0.142861	0.88640
Agriculture_18	3.8841	1.50142	2.58695	0.00968
Road_18	-0.00959056	0.00410084	-2.33868	0.01935
Flood_18	-0.226646	0.231923	-0.977248	0.32845
Land title_18	-4.34839	8.10988	-0.536184	0.59183
Relief_18	0.279672	0.211306	1.32354	0.18566
Land value_18	4.93677e-05	6.46873e-05	0.763175	0.44536
City_18	75.2635	14.1161	5.33177	0.00000
Airport_18	45.0201	14.0808	3.19727	0.00139
Industry_18	67.5618	48.0202	1.40694	0.15944
Employment_18	1.75987	1.40502	1.25256	0.21037
Population_18	0.0515088	0.0132141	3.89801	0.00010
LAMBDA	0.774484	0.106641	7.26253	0.00000

Note: source: data analysis, 2024.

Table 7. Spatial regression accuracy test of carbon stock reserve variables in 2018

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

Note: source: data analysis, 2024.

Table 8. Spatial regression analysis of carbon stock reserve variables in 2022

Variable	Coefficient	Std.Error	z-value	Probability
W-KRB_22	0.622324	0.148483	4.19123	0.00003
CONSTANT	-542.544	148.27	-3.65915	0.00025
Protect area_22	0.214102	1.4342	0.149283	0.88133
Agriculture_22	-0.737243	0.952464	-0.774038	0.43891
Road_22	-0.00590488	0.00406924	-1.4511	0.14675
Flood_22	-0.294431	0.294713	-0.999045	0.31777
Land title_22	-9.38065	9.31859	-1.00666	0.31410
Relief_22	0.593635	0.273385	2.17143	0.02990
Land value_22	2.32608e-05	650807e-05	0.357415	0.72078
City_22	36.9229	11.22262	3.28899	0.00101
Industry_22	104.1	71.4647	1.45667	0.14521
Airport_22	31.4277	16.3897	1.91752	0.05517
Employment_22	5.29773	2.14639	2.46821	0.01358
Population_22	0.0193318	0.0168305	1.14861	0.25072

Note: source: data analysis, 2024.

The findings of the spatial regression analysis are presented in Table 8. Table 8 illustrates the dependent and independent regression relationship algorithm that affects the level of carbon stock reserve based on land use type. This is expressed in Equation 23.

The results of the spatial regression analysis indicate that the variables representing the city centre and the airport consistently exert a significant influence on the data set from 2014 to 2022. The results of the spatial regression analysis, as presented in Table 8, indicate a correlation between land situated at a distance of 1 km from the city centre and land with high carbon stock levels, amounting to 36.9 Ha. Similarly, 31 Ha of land use with high carbon stock levels is located 1 Km from the airport. This study identified a variable that can inhibit the conversion of land from a high to a low carbon stock, namely relative relief. As illustrated in Table 8, land with a high relief of 1 Ha exhibits a significance of land with a high carbon stock of 0.59 Ha. The value of the spatial lag coefficient (ρ = 0.622) indicates that the value of carbon stock in a given village or region will increase by 0.622 times the average carbon stock of neighbouring or contiguous villages or regions, assuming that all other variables remain constant.

To ascertain the variables that exert dominant influence in 2014, 2018, and 2022, a tabular representation is provided in Table 9 below. Table 9 shows that the variables influencing the level of carbon stocks by land use type in 2014 are different from those in 2018 and 2022. Before the airport was built (2014), the variables city centre, airport, relative relief, and land title status were the variables that significantly affected the decreasing level of carbon stock reserves. In 2018,

$$y_{carbon\ stock\ 2022} = 0{,}622 \sum_{j=1}^{n} w_{ij} y_{carbon\ stock\ 2022} - 542{,}544 + 0{,}214 Protected\ area - 0{,}737 Agricultural\ land - 0{,}006 Road - 0{,}294 Flood - 9{,}381 Land\ title\ status + 0{,}594 Relief + 2{,}326x10^{-5} Land\ Value + 36{,}923 City + 31{,}428 Airport + 104{,}1 Industry + 5{,}298 Employment + 0{,}019 Population \quad (23)$$

Table 9. Variable analysis of carbon stock reserves in 2014, 2018, and 2022

Year	2014	2018	2022
Influential varible	City centre	City centre	City centre
	Airport	Airport	Airport
	Relative relief	Road accessibility	Relative relief
	Land title status		

Note: source: data analysis, 2024.

in addition to city centre and airport, road accessibility is also an influential variable. The findings of this study indicated that the location variable (city centre and airport) is the primary influencing factor and consistently affects land use change in relation to carbon stock across the three time periods under consideration: 2014, 2018 and 2022. This is indicated by the probability value of the two variables, which is less than 0.05. The data from the spatial regression analysis show that the closer to the city centre and airport, the land use in the area tends to have low carbon stock reserves, and vice versa, the areas further away from the city centre and airport have a correlation with land use with high carbon stock reserves. Apart from city centre and airport, the location variable that has a dominant effect is road accessibility. This research showed that the more collector roads, arterial roads and local roads there are, the less high carbon stock land use there is in the area.

In addition to location, physical variables, specifically relief, also affect the level of carbon stock reserves. The areas characterised by high relief morphology exhibit a positive correlation with land use practices conducive to the storage of high carbon stock reserves. In addition, the status of land rights exerts a significant influence on the land aspect. The data indicates that the higher the status of land rights in the form of non-ownership rights (building use rights, use rights, and rental rights), the lower the land use with high carbon stock reserves. This is due to the fact that land parcels with non-owned land status are predominantly utilised as built-up land, resulting in a low level of carbon stock reserves.

As illustrated in Table 9, the results of the spatial regression analysis demonstrate that the variables influencing carbon stock reserves have undergone a transformation. In 2014, the land title status variable was identified as the most influential factor. However, in 2018, road access emerged as the more influential variable. From 2018 onwards, there was a notable increase in land use change in the vicinity of the road network. Since the construction of the airport, the area surrounding arterial and collector roads has become increasingly strategic, with high economic value, and there has been a marked increase in development in the business and service sectors. This has resulted in a significant rate of land conversion around the roads, the majority of which is used for trade and service activities.

Variables affecting carbon stock reserves

The carbon stock value of the study area in 2014, 2018, and 2022 exhibited a notable decline. This phenomenon can be attributed to a shift in land use from the areas with high carbon stock reserve values to those with lower carbon stock values. The decline in the area of land use with high carbon stock reserve values is influenced by a number of factors, including location. In particular, city centres, airports and road variables exert a dominant influence. While the capacity to sustain land use with high carbon stock reserves is contingent upon topography, some locations with pronounced relief do not undergo land use change, which correlates with the presence of high levels of carbon stock reserves.

This research corroborated the findings of Yoo et al. (2024) who asserted that large-scale infrastructure development in developing countries is a key strategy for promoting economic growth. However, the presence of airports has been identified as a significant driver of land use change. The increasing population and anthropogenic activities have implications for increasing carbon emissions, which can trigger various disasters. The analysis of variables that influence changes in carbon stock reserves is an important study in the context of the damage caused by climate change. Wei et al. (2024) explained that the analysis of variables which affect land use change is an important input in formulating policies to mitigate environmental damage and climate change. The empirical findings of this study demonstrated that the driving forces influencing the level of carbon stocks based on land use change are dynamic and complex variables. Theoretically, the findings of this study are in accordance with the research of Xiaoyu et al. (2021); and Mekonnen et al. (2022), which posits that land use change is influenced by fundamental human needs, which are complex and changing. The influence of various factors on land use differs depending on the time period, geographical and environmental location/conditions, society, and policies/regulations in question.

The findings of this study facilitated the simplification of complex and dynamic variables, thereby enhancing their intelligibility and analytical tractability. The spatial regression method with spatial weighting is a statistical analysis that is capable of producing a high degree of accuracy in the interrelationships between variables (98%). The spatial aspect, represented in the form of inter-regional connectivity relationships, is able to generate significance values of the variables affecting land use in relation to carbon values (Wang et al., 2022; Wei et al., 2023; Xie and Zhang, 2023). Theoretically, this study corroborated the findings of Weber (1909), as well as the research conducted by (Tepe and Guldmann, (2020); Xifeng et al., (2023), which indicated that location has a significant impact on land/space use decisions. Strategic locations possess a notable appeal for the establishment of economic areas (trade and services) or settlements. The findings of this study demonstrated that the proximity of city centres, airports, and road access points exerts a significant influence on the rate of land use change, which is associated with a decline in carbon stocks. Furthermore, the results align with those of previous research Mahmoudzadeh & Abedini, (2022); Mariye et al., (2022) which stated that social aspects and physical aspects plays a pivotal role in land use change, with implications for the depletion of carbon stock reserves. The analysis of the variables that affect changes in carbon stocks represents a crucial step in the development of a framework aimed at controlling the rate of land use change. Furthermore, it serves as a fundamental basis for the formulation of climate change strategies and actions (Feng et al., 2024; Fu et al., 2024).

CONCLUSIONS

The transformation of land use exerts a considerable impact on the levels of carbon stored in the environment. The monitoring of carbon stock levels and the analysis of the driving forces that trigger land use change in relation to these levels represent an essential component of climate change mitigation strategies. The development of infrastructure and subsequent economic growth have been identified as factors contributing to the observed decline in carbon stock reserves in the study area, with a reduction of 15,029 tonnes C/ha. The variables that predominantly influence the rate of land use change in relation to carbon stock value from 2014 to 2022 are largely influenced by independent variables in the form of location aspects, namely city centre, airport, and road. In addition to the geographical location of the land in question, the status of land rights also has an impact on the rate of decline in carbon stocks. Conversely, the physical aspect, namely relief, exerts an influence on the rate of decline in land use with high carbon stock reserves. The influence of driving forces in each period results in changes to both the type of variable and the significance value of its influence. The spatial regression analysis employed in this study to analyse the relationship between dependent and independent variables has high accuracy and significance, as evidenced by an R-square value exceeding 90%. The spatial regression analysis is a compatible method as it is capable of analysing the relationship between locations/spatial effects.

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