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Local-Scale Carbon Sink Determinants and Spatial Heterogeneity in a Rapidly Urbanizing Coastal Metropolitan Region of Indonesia

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ABSTRACT

Understanding carbon sink dynamics at local administrative scales is essential for developing effective climate mitigation and urban planning strategies in rapidly urbanizing coastal regions. However, existing studies have largely focused on broader regional scales, providing limited insights into local spatial heterogeneity and governance-relevant carbon management. This study investigates carbon sink profiles and their determinants in the Samarinda Metropolitan Area (SMA), Indonesia, using 34 sub-districts and 289 urban villages as analytical units. Carbon sinks were estimated using Net Primary Production (NPP) data, while Ordinary Least Squares (OLS), Spatial Lag Model (SLM), and Geographically Weighted Regression (GWR) were applied to examine global and local spatial relationships. The results reveal significant spatial clustering of carbon sinks at both sub-district (Moran's I = 0.277, p = 0.003) and urban village levels (Moran's I = 0.099, p < 0.001). The urban village model demonstrated superior performance (R^2 = 0.669) compared with the sub-district model (R^2 = 0.526). Forest cover (β = 1.020) and wetness (β = 0.225) positively influenced carbon sinks, whereas elevation (β = −0.112) and NDVI (β = −0.131) exhibited negative effects. GWR results identified forest as the strongest determinant (R^2 = 0.949). Effective local carbon management can enhance ecosystem services, strengthen environmental resilience, reduce climate-related economic risks, and support sustainable urban economic development. These findings support spatially targeted planning interventions, including forest conservation, wetland restoration, and blue carbon governance in coastal metropolitan regions.

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Highlights:	**Contribution to the field statement:**
- Carbon sink and its determinants were examined at local scales in SMA (Samarinda Metropolitan Area). - NPP, OLS, SLM, and GWR were integrated to identify the spatial patterns and local scale mechanisms of carbon sinks. - Forest and wetness positively influence carbon sinks with spatially differentiated effects. - Urban village level provide better performance for supporting localized carbon management and planning interventions.	This study advances urban carbon sink research by examining determinants at the smallest administrative units and revealing local spatial heterogeneity through multiscale spatial analysis. The findings support localized climate governance, low-carbon urban development, and sustainable urban economic resilience by enhancing ecosystem services, reducing environmental risks, and informing place-based planning strategies.

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1. Introduction

Climate change has affected human activities in multiple aspects (Kabir et al., 2023). As urbanization continues to intensify, cities have become major contributors to global carbon emissions while simultaneously experiencing increasing pressure on ecological systems. Consequently, carbon sinks have received growing attention because of their critical role in climate mitigation (Huang et al., 2020). In urban settings, the capacity to control and increase carbon sink becomes critical as cities expand and contribute to carbon emissions (Kinnunen et al., 2022). Carbon sinks in urban areas are influenced by various factors that differ considerably across geographical scales (Bordoloi et al., 2022; Dong et al., 2024; Wei et al., 2022). Additionally, carbon sink is strongly influenced by land cover transformation, urban expansion, environmental conditions, and human activities. Previous study further demonstrate that urbanization and urban population can significantly influence carbon outcomes, especially carbon emissions (Somoye & Akinwande, 2023). In parallel, urban green infrastructure and accessible green spaces have been recognized as important mechanisms for supporting sustainable low carbon development (Benameur et al., 2024; Salimi et al., 2025). Therefore, understanding how carbon sink mechanisms vary across urban settings has become increasingly important for contemporary urban planning and climate governance.

Urban scaling is an evolving notion that is used in the context of climate change mitigation, where administrative levels serve as one of the scaling regimes (Hong et al., 2022; Yang & Zhao, 2023). This theory suggests that urban environmental processes operate differently across governance and administrative scales, resulting in heterogeneous ecological outcomes. Especially when implementing climate policies and initiatives, it is imperative to categorize urban areas according to administrative levels (Landauer et al., 2019; Yu & Zhou, 2023). Also, from a governance perspective, administrative scales influence how environmental policies are implemented, monitored, and translated into land-use outcomes. Moreover, these governance processes are closely associated with the socio-economic dimensions of contemporary urbanization, as land-use decisions, ecological resource allocation, and urban development priorities may shape long-term urban sustainability. Carbon sink therefore cannot be understood solely through ecological indicators but must also be interpreted through governance structures that shape land-use allocation, development intensity, and ecosystem management. Recent studies indicate that urban development patterns, including metropolitan expansion and new-town development, may substantially alter carbon sink capacity through land-cover change and ecological restructuring (Han et al., 2024). Similarly, urban green accessibility, distribution and spatial configuration have been shown to influence environmental sustainability outcomes (Benameur et al., 2024). This perspective highlights the need to connect urban governance, land cover, and carbon sink mechanisms within a unified analytical framework.

Although carbon sink research has expanded rapidly, several limitations remain. Existing studies often emphasize either spatial–temporal changes of carbon sinks (Zhang & Deng, 2022), the driving forces (Dong et al., 2024), or urban ecological interventions (Salimi et al., 2025), but rarely integrate governance scale with carbon sink mechanisms. Most studies also focus on national, regional, or metropolitan levels, limiting understanding of how carbon sink processes vary across local administrative units. Furthermore, local-scale carbon management has frequently been discussed as a policy objective without being operationalized through urban planning mechanisms or linked to spatial heterogeneity. These limitations reduce the ability of urban planners to identify targeted interventions and weaken the applicability of findings for local climate governance.

To address these limitations, this study investigates carbon sink profiles and their influencing factors across local administrative scales in the Samarinda Metropolitan Area (SMA), Indonesia. By focusing on sub-districts and urban villages as governance units, this study examines how land use–land cover, environmental conditions, and socio-environmental indicators interact with carbon sinks at the local scale. Unlike previous studies that primarily evaluate carbon sinks at broader scales, this study combines spatial pattern analysis and multiscale spatial modelling to reveal local spatial differentiation and governance relevance. This study also leverages NPP-based carbon sink estimation combined with multiscale spatial modelling to identify local variations in carbon sink mechanisms, advancing beyond previous studies that predominantly focus on broader regional scales or single analytical approaches. The findings contribute academically by extending discussions on urban scaling and carbon sink mechanisms and practically by providing evidence for scale-sensitive urban planning and localized climate mitigation strategies in coastal metropolitan regions. Although the study is conducted in SMA, the analytical framework may also provide transferable insights for other rapidly urbanizing coastal metropolitan regions facing similar ecological and governance challenges. This study will incorporate several factors like population, land use-land cover, climate, and environmental factors. Additionally, a set of remote sensing-based eco-environmental indicators will be included based on a previous study that demonstrated the close relationship between carbon sinks and environmental quality (Hasanah & Wu, 2024).

The purposes of this study are: (1) to understand carbon sink profiles and their spatial patterns across local scales; and (2) to understand the influence of various factors on carbon sinks at local scales and the spatial differentiation of these relationships. The findings are expected to support evidence-based urban planning and contribute to climate-sensitive governance and sustainable development. The paper's structure is presented in Figure 1.

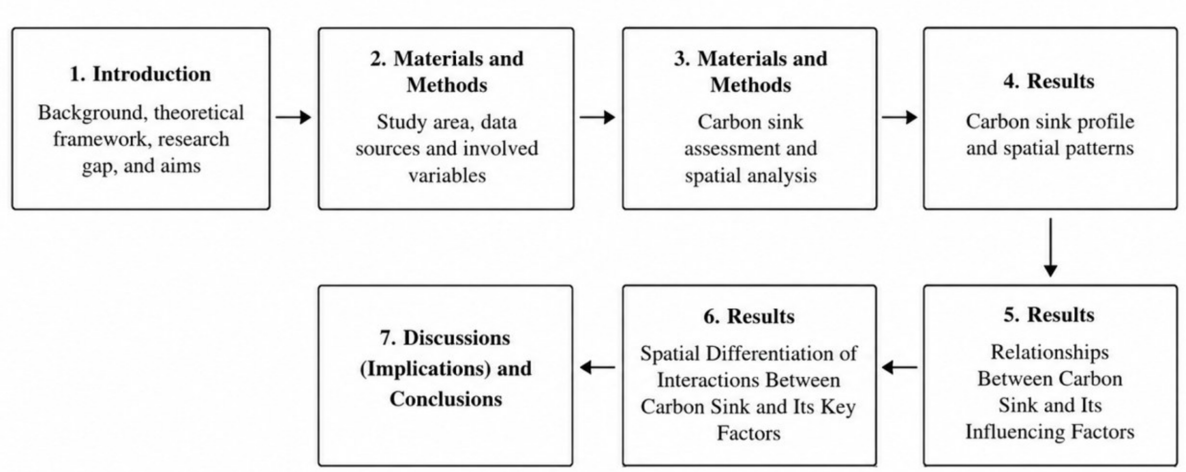


Figure 1. The Paper's Structure.

2. Methodology

2.1 Study Scope

The study covers the Samarinda Metropolitan Area (SMA), located in East Kalimantan province, Indonesia. The area is pivotal in supporting the new capital, Nusantara, and is also connected to the National Strategic Plan. As a rapidly urbanizing coastal metropolitan region, SMA serves as an important economic hub characterized by interactions among urban expansion, ecological resources, and coastal environmental systems. The region includes a combination of inland and coastal landscapes, creating heterogeneous environmental conditions that may influence carbon sink distribution through variations in land cover, ecosystem functions, and development intensity. Using 34 sub-districts and 289 urban villages in the SMA as local-scale study samples, this study focuses on the year 2021 as the basis for data collection. The selection of 2021 was intended to represent the baseline of carbon sinks and their influencing factors prior to the official commencement of major development activities associated with the new national capital. As the main purpose of this study is to examine the spatial distribution of carbon sinks and their influencing factors across local administrative scales rather than temporal dynamics, a cross-sectional approach was considered appropriate. The map of the study scope and the study samples are shown in Figure 2.

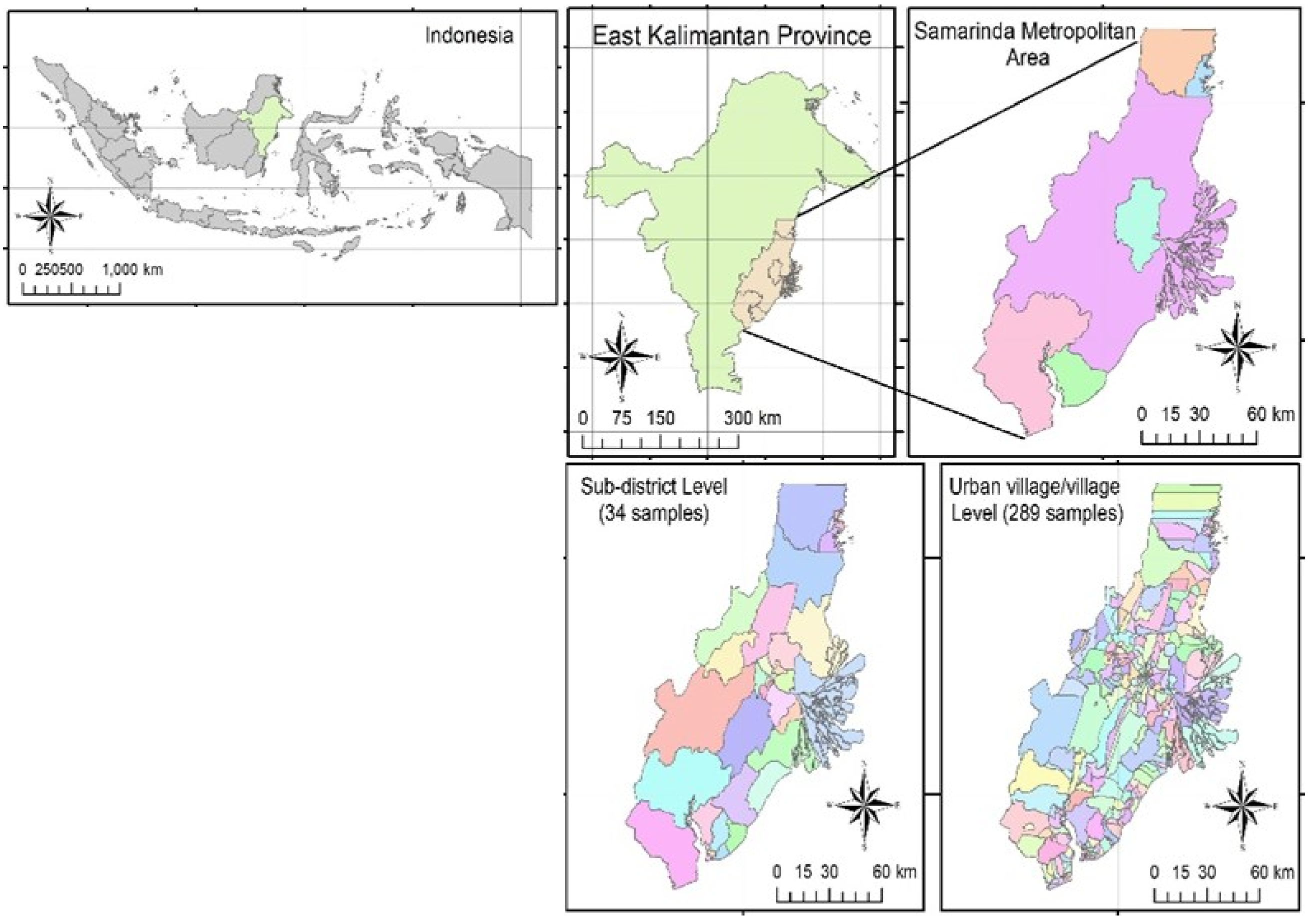


Figure 2. Study Area.

The area covers 12,283.34 km^2. The composition of LULC of the area, including: 76.99% forest, 5.73% shrubland, 4.76% water, 4.55% built-up area, 3.94% wetland, 3.88% crops, and 0.19% other area. This diversified composition highlights substantial ecological and land-use heterogeneity across the metropolitan area and provides a basis for assessing carbon sink. Particularly, the coexistence of forest, wetland, water, and urbanized areas reflects the characteristics of a coastal metropolitan landscape, where terrestrial and water-associated ecosystems jointly contribute to carbon sequestration processes and interact with urban development pressures.

2.2 Descriptions of Data and Involved Variables

The selection of explanatory variables was guided by the theoretical understanding that urban carbon sinks are jointly influenced by anthropogenic activities, land-use characteristics, ecological conditions, and climatic factors. Previous studies have demonstrated that population concentration, urban development intensity, vegetation conditions, hydrological environments, topographic characteristics, and climate variability can significantly influence the distribution of carbon sink capacity. Therefore, this research incorporated various variables representing four major dimensions: (1) anthropogenic factors, (2) land-use and land-cover characteristics, (3) eco-environmental indicators, and (4) natural-climatic factors. Carbon sink serves as the dependent variable, while fourteen influencing factors serve as independent variables. This multidimensional framework enables a comprehensive examination of the mechanisms influencing carbon sink distribution at local scales. Table 1 shows the involved variables, descriptions, and data sources.

Table 1: Data and Involved Variables.

Role	Indicator	Descriptions and source
Dependent variable	Carbon sink-NPP	MOD17A3HGF v061 (500 m)
Independent variable	Population	Extrapolation from WorldPop 2000-2020 data (1 km)
	Built-up area Water Crops Forest Wetland Shrubland Other area	LULC data Sentinel-2 (10 m)
	Elevation	National DEM data of Indonesia (8 m)
	Precipitation	CHIRPS (Climate Hazards Group Infrared Precipitation with Stations) (annual)
	LST (Land surface temperature)	MODIS/061/MOD11A2 8-Day (1 km)
	NDVI (Normalized difference vegetation index)	MODIS/061/MOD13A1 16-Day (500 m)
	NDBSI (Normalized difference bare soil index) WET (Wetness index)	MODIS/061/MOD09A1 8-Day (500m)

The datasets used in this study originated from multiple sources and spatial resolutions. To ensure analytical consistency, all raster datasets were projected into a common coordinate system and processed within a unified spatial framework. Subsequently, variables were aggregated to administrative units using zonal statistics, whereby the mean value, total value, or proportional area was calculated according to the characteristics of each variable. This approach enabled the integration of different resolution datasets while maintaining consistency across the sub-district and urban village analytical units.

2.3 Methods

2.3.1 Carbon Sink Assessment

Carbon sink assessment was conducted using net primary production (NPP) from MOD17A3HGF v061 with 500-m resolution. The original MOD17A3HGF product reports NPP in units of kg C m^{-2}, representing the amount of carbon absorbed by vegetation per unit area. To facilitate the interpretation, the NPP values were converted into CO_2 equivalents using a conversion factor of 3.67. This conversion is based on the molecular weight ratio between CO_2 (44) and elemental C (12), as mentioned in the World Bank Metadata Glossary, where carbon quantities expressed as elemental carbon are converted to carbon dioxide by multiplying by 3.67. The carbon sink profile was analyzed from the city/municipality level to the local scales. Carbon sink calculation in each administrative boundary was conducted by adding up all the grid values contained within the boundaries of the administrative area being analyzed. The analysis was conducted using ArcMap 10.8.

2.3.2 Spatial Analysis

Spatial patterns of carbon sinks and their spatial differentiations of the interaction between carbon sinks and key factors were analyzed using multiple spatial analysis methods:

1. Global Moran's I (detect spatial clustering)

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

Equation 1. Global Moran's I

note: n is total spatial units, x_i and x_j are values of the variable of interest, x¯is variable's mean value, and w_ij is location's spatial weight between i and j.

2. Hot-spot and cold-spot identification using Getis-Ord Gi*

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{x} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

Equation 2. Getis-Ord Gi*

note: x_j is j value, w_ij is spatial weight between attribute i and j, and n is the number of features.

3. Local Moran's I (identify local clusters-outliers)

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq 1}^{n} w_{i,j}(x_j - \bar{x})$$

Equation 3. Local Moran's I

note: x_i is the value for attribute i, x¯is mean value of the attribute, and w_ij is spatial weight between attribute i and j.

4. Ordinary Least Square/OLS

OLS was employed to identify the global relationships between carbon sinks and their determinants and to establish a baseline regression model. Prior to model interpretation, multicollinearity among involved variables was checked based on Variance Inflation Factor (VIF). After the OLS regression was performed, Global Moran's I of the residuals was calculated to evaluate whether residual spatial autocorrelation remained. The OLS results served as the basis for determining the need for subsequent spatial regression analyses. The analysis was conducted using SPSS 23 and ArcMap 10.8.

5. Spatial Lag Model/SLM (address the spatial dependence)

This study adopted a progressive spatial modelling framework. Following the OLS analysis, the residuals were examined using Global Moran's I to assess spatial dependence. When significant residual spatial autocorrelation was detected, indicating that observations were not spatially independent, a Spatial Lag Model (SLM) was employed to examine the spatial interactions among neighboring units.

The SLM incorporates a spatially lagged dependent variable representing the weighted average of neighboring observations and is particularly suitable when the dependent variable in a location is influenced by the values of surrounding locations. For the SLM analysis, a first-order Queen contiguity spatial weights matrix was adopted to define spatial relationships among neighboring administrative units. This approach assumes that spatial interactions may occur between units sharing either boundaries or vertices. The SLM analysis was performed using GeoDa software.

$$y = \rho W y + X\beta + \varepsilon$$

Equation 4. Spatial Lag Model

note: y is the dependent variable, ρ is the strength of spatial dependence, Wy is the spatially lagged dependent variable, X is a matrix of independent variables, β is the coefficient vector for the independent variables, and ε is the error term.

6. Geographically Weighted Regression/GWR (account spatial differentiation of relationship between carbon sinks and key factors)

Although the SLM accounts for spatial dependence, it assumes that the relationships between carbon sinks and the determinants remain spatially stationary across the area. To further investigate local variations in these relationships, Geographically Weighted Regression (GWR) was employed.

GWR allows regression coefficients to vary geographically, enabling the identification of location-specific relationships between carbon sinks and explanatory variables. An adaptive kernel function was adopted to accommodate the uneven spatial distribution and varying sizes of administrative units across the study area. The optimal bandwidth was determined using the corrected AICc (Akaike

Information Criterion), which balances model fit and model complexity. The analysis was performed in ArcMap 10.8.

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)X_{ik} + \varepsilon_i$$

Equation 5. Geographically Weighted Regression

note: Y_i is the DV for location i, β_0 (u_i,v_i) is the intercept term for i, β_k (u_i,v_i) is the coefficient for the k-th IV at location i, X_ik is the value of the k-th IV at location i, ε_i is the error terms, and (u_i,v_i) are the coordinates of location i. (DV = dependent variable; IV = independent variable)

2.4 Study Framework

Figure 3 presents the overall framework of this study. Under the broad methodological framework, the study consists of four main stages: (1) scale and sample selection at the sub-district and urban village levels; (2) carbon sink assessment and spatial pattern analysis using NPP-based estimation, Global Moran's I, Getis-Ord Gi*, and Local Moran's I; (3) examination of the relationships between carbon sinks and their determinants and comparison of model performance across spatial scales using OLS regression; and (4) advanced spatial regression analysis, including the application of SLM to account for spatial dependence and GWR to examine the spatial differentiation of relationships between carbon sinks and their influencing factors.

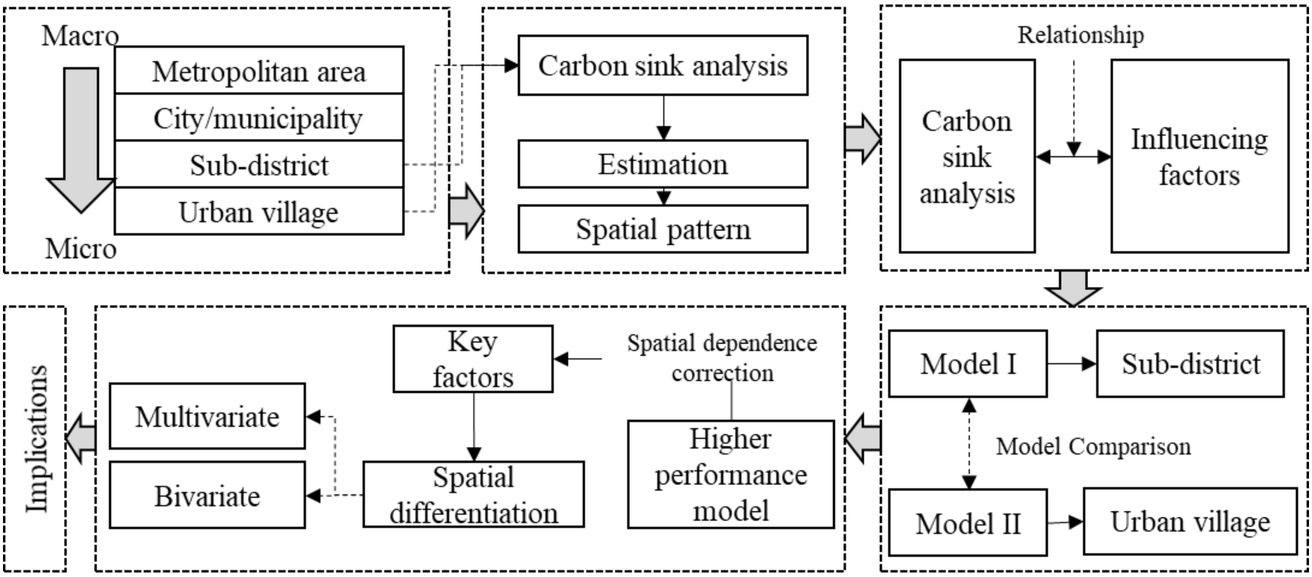


Figure 3. Study Framework.

3. Results

3.1 Carbon Sink Profile and Spatial Patterns

At the city/municipality level, the carbon sinks profile shows the contribution of each city/municipality to the SMA's overall carbon sinks. The highest contributor is Kutai Kartanegara with 66%, followed by North Penajam Paser (17%) and East Kutai (6%). These notable contributions are largely due to the extensive vegetation coverage, less urbanized area, and natural features. Three cities (Samarinda (5%), Balikpapan (4%), and Bontang (2%)) were the lowest contributors to SMA's total carbon sinks. These conditions are primarily due to the larger built-up area, limited vegetation cover, and emissions sources, which contribute to higher carbon emissions and lower carbon sink capacity compared to other regions. Figure 4 shows the city/municipality level carbon sink profile.

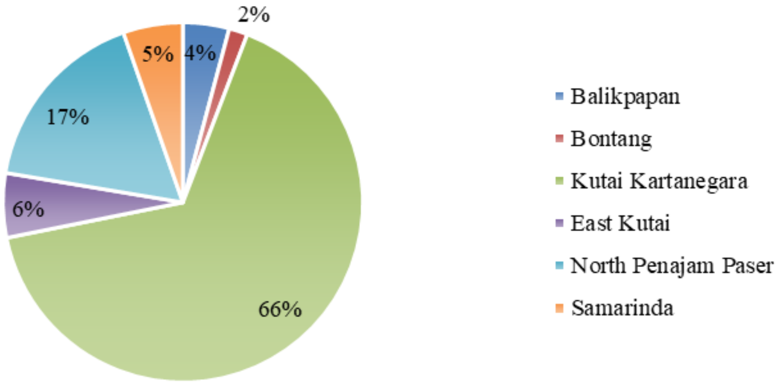
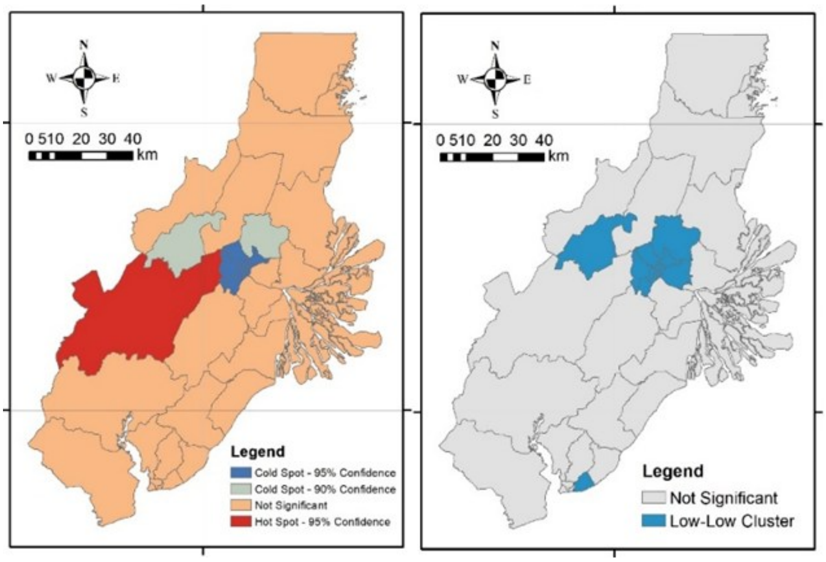


Figure 4. Carbon sink profile (city/municipality level).

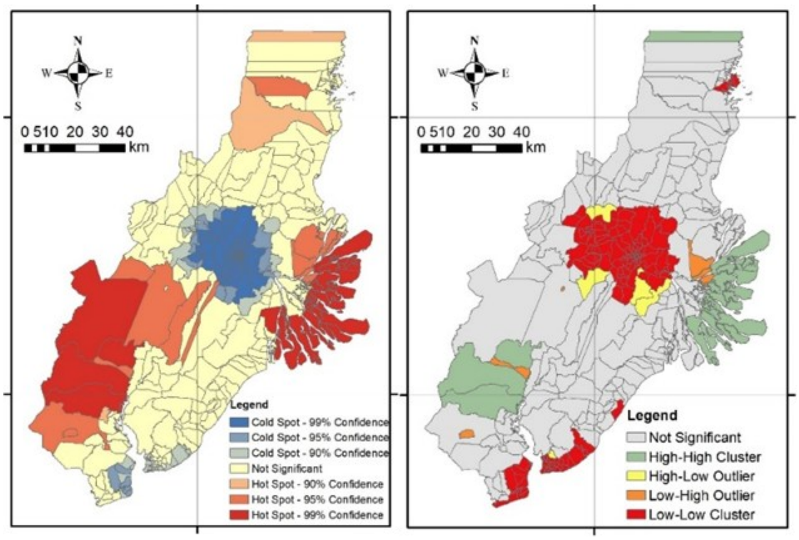
Figure 5 presents the spatial patterns of carbon sinks at sub-district level. At sub-district level, Global Moran's I value is 0.277, z-score = 2.991, and p-value = 0.003, indicates carbon sinks at this level are relatively clustered. The hot spot at 99% confidence appears in the western part of Kutai Kartanegara and borders North Penajam Paser (Figure 5: left, red areas). The values of the z-score and p-value for the hot spot are 2.35 and 0.02, respectively. Cold spots of carbon sinks are identified in the sub-district in Samarinda city, especially the western parts, where lower carbon sink levels are concentrated. The L-L (low-low) clusters are located in Samarinda city, southern Balikpapan city, and the Tenggarong sub-district (Figure 5: middle, blue areas). The values range of Local Moran's I is 0.000027-0.000907.



	Sub-district
Moran's Index	0.277
Variance	0.011
z-score	2.991
p-value	0.003

Figure 5. Carbon sink spatial pattern (Sub-district level).

Figure 6 depicts the spatial pattern of carbon sinks at the urban village level. At the urban village level, the Global Moran's I value is 0.099, z-score = 6.054, and p-value = 0.000, meaning carbon sinks at this level are significantly clustered. Higher carbon sinks tend to cluster, and the same phenomenon also appears for lower carbon sinks. The urban village spatial pattern can represent the distribution of carbon sinks better than at the sub-district level. At the urban village level, the hot spots with 90–99% confidence appear in two key areas: the eastern coast and the western part of Kutai Kartanegara, extending to the western part of North Penajam Paser (Figure 6: left, red areas). This status is related to the characteristics of the areas, which are coastal areas and areas with higher elevation. Cold spots of carbon sinks are identified in the urban villages in Samarinda city and the surrounding areas. The H-H (high-high) clusters are situated on the border of Kutai Kartanegara and North Penajam Paser, the eastern coast of Kutai Kartanegara, and the northern area of East Kutai (Figure 6: middle, green areas). The values of Local Moran's I for H-H clusters is 0.00047-0.003449, where these clusters show higher carbon sink capacity. In contrast, L-L (low-low) clusters are found in three cities in the SMA and affect their surroundings (Figure 6: middle, red areas). The values range of Local Moran's I for L-L clusters is 0.000114-0.002848.



	Urban village
Moran's Index	0.099
Variance	0.0003
z-score	6.054
p-value	0.000

Figure 6. Carbon sink spatial pattern (Urban village level).

3.2 Relationships Between Carbon Sink and Its Determinants

The correlation between independent variables with carbon sink was assessed using Pearson's correlation analysis. Table 2 is the result of the analysis at sub-district and urban village scales. The results of correlation analysis are useful for understanding the association between dependent variable with changes that occur in the independent variables. Therefore, this finding can provide insight for further analysis.

Table 2: Correlation Analysis at Both Levels.

Indicators	Correlation Coefficient	
	Sub-district	Urban village
Population	-0.118	0.043
Built-up area	0.013	-0.076
Water	0.711**	0.666**
Crops	0.528**	0.367**
Forest	0.828**	0.789**
Wetland	0.641**	0.634**
Shrubland	0.710**	0.585**
Other area	0.281	0.194**
Elevation	0.542**	0.432**
Precipitation	-0.048	-0.051
LST	-0.587**	-0.292**
NDVI	0.443**	0.231**
NDBSI	-0.599**	0.021
WET	0.395*	0.236**

Note: *significant at 0.05 level (2-tailed), **significant at the 0.01 level (2-tailed).

Multiple variables were chosen for further investigation at each level, determined by correlation analysis. Variables are selected based on indicators with significance levels ≤ 0.05 (inclusive of 0.05 and 0.01), suggesting that the interaction between both variables is unlikely to be due to random chance. Variables significantly associated with carbon sinks were used in regression analysis to understand the relationship of carbon sinks with their factors. The analysis also included a multicollinearity (VIF) test.

Multicollinearity test is used to evaluate the intercorrelation between independent variables. After performing the multicollinearity test, the indicators with VIF values higher than 10 will be excluded to adjust the model. At the sub-district scale, the excluded variables were water (VIF = 106.038), forest (VIF = 15.666), wetland (VIF = 99.397), LST (VIF = 11.323), and NDBSI (VIF = 18.181). At the urban village scale, water (VIF = 19.441) and wetland (VIF = 18.859) were excluded. It should be noted that several excluded variables are theoretically relevant to carbon sink dynamics. However, these variables exhibited strong multicollinearity with other explanatory variables and were therefore removed to avoid redundancy and unstable parameter estimates. Additionally, the greater number of variables exhibiting multicollinearity at the sub-district scale may also reflect the aggregation of characteristics within larger administrative units, which tends to increase correlations among variables. After VIF exclusion, the regression was then re-performed. Influencing factors at the sub-district scale with VIF value less than 10, including crops, shrubland, elevation, and NDVI. Influencing factors at the urban village scale with VIF value less than 10, namely: crops, forest, shrubland, other areas, elevation, LST, NDVI, and WET. Regression analysis was carried out in ArcMap 10.8 using OLS (Spatial Statistics). Following the OLS regression, Global Moran's I of the residuals was also performed. Table 3 is the outcome of regression analysis, and Table 4 is the outcome of Global Moran's I of residuals.

Table 3: Relationship between carbon sink and its determinants.

Indicators	Sub-district		Indicators	Urban village	
Crops	0.083	(0.469)	Crops	0.002	(0.040)
Shrubland	0.559	(2.420)	Forest	1.045	(11.858)
Elevation	0.155	(0.793)	Shrubland	-0.084	(-1.222)
NDVI	0.296	(0.536)	Other area	0.0003	(0.006)
			Elevation	-0.076	(-1.479)
			LST	-0.015	(-0.421)
			NDVI	-0.124	(-1.734)
			WET	0.242	(4.508)
n	34			289	
R^2	0.526			0.669	
Adjusted R^2	0.461			0.659	
AICc	-10.380			-756.727	

Note: t-value in parentheses.

Table 4: Global Moran's I of Residuals.

	Sub-district	Urban village
Moran's I	-0.010	0.0477
Variance	0.009	0.0002
z-score	0.215	3.540
p-value	0.830	0.0004

Comparing the sub-district and urban village models, the urban village model demonstrates better performance, with a lower AICc value (-756.727) and a higher R^2 value than the sub-district model, indicating a better model fit. This is likely attributable to several factors. First, the finer spatial resolution of urban villages allows greater representation of local environmental heterogeneity and reduces the masking effects that may occur when diverse land-cover characteristics are aggregated within larger administrative units. Second, urban villages are more sensitive to localized spatial processes and environmental variations, enabling the model to capture relationships that may be obscured at the sub-district scale. Although the larger sample size at the urban village level (n = 289) may also contribute to improved statistical performance, the results suggest that the enhanced

representation of spatial heterogeneity and reduced aggregation effects play an essential role in explaining model performance. Therefore, urban village model was selected for further analysis.
Global Moran's I analysis of urban village model residuals indicated significant spatial autocorrelation, with a z-value of 3.540. This outcome indicates that spatial dependence remained in the model residuals and that the assumption of spatial independence was not fully satisfied. To address this issue, SLM was subsequently employed to examine spatial interactions among neighboring urban villages.
Considering the spatial dependencies, a spatial lag model can help to comprehend the interaction between carbon sinks and their factors more deeply. The spatial lag coefficient indicates the effect of the dependent variable's values in neighboring areas. In the urban village model context, the spatial lag coefficient value is 0.198, which suggests that carbon sink has a positive influence on the neighboring areas and tends to cluster together spatially (Table 5). Also, the value of AICc is -722.664, which indicates a better model fit, with R^2 = 0.688, which is higher than the previous regression analysis.

Table 5: Spatial Lag Model Result

Variable	Coefficient	Std. Error	z-value	p-value
Crops	0.004	0.042	0.108	0.91
Forest	1.020	0.085	12.051	0.00
Shrubland	-0.082	0.066	-1.258	0.20
Other area	0.002	0.053	0.045	0.96
Elevation	-0.112	0.050	-2.275	0.02
LST	0.003	0.036	0.073	0.94
NDVI	-0.131	0.068	-1.918	0.05
WET	0.225	0.052	4.365	0.00
R^2		0.688		
Spatial lag coeff. (Rho)		0.198		
AICc		-722.664		

Based on the SLM, variables with a p-value ≤ 0.05 were considered statistically significant. The key variables identified by the SLM were forest (coefficient = 1.020), elevation (coefficient = -0.112), NDVI (coefficient = -0.131), and WET (coefficient = 0.225). These variables contribute meaningfully to explaining the spatial variation in carbon sink potential at the urban village scale. The spatial differentiation of the relationships between these significant variables and carbon sinks was subsequently analyzed using GWR.

3.3 Spatial Differentiation of Interactions Between Carbon Sink and Its Key Factors

The significant factors influencing carbon sinks at the urban village scale were further examined to understand their spatial differentiation in more detail using two approaches: multivariate (carbon sinks versus all significant variables) and bivariate (carbon sinks versus each significant variable). Table 6 presents the multivariate and bivariate GWR results.
The multivariate GWR results presented reveal a strong relationship between carbon sinks and the significant variables identified in the SLM, namely forest, elevation, NDVI, and WET. The AICc value of -839.769 indicates a well-fitting model, as lower AICc values suggest better model performance. The R^2 value of 0.757 and the adjusted R^2 value of 0.745, presents that the model shows significant percentage of variability in carbon sink capacity at the urban village scale, with nearly 75% of the variance being explained by the model.

Table 6: Multivariate and bivariate GWR result.

GWR Parameter	Multivariate result	Bivariate result			
		Csink & Forest	Csink & Elevation	Csink & NDVI	Csink & WET
AICc	-839.769	-972.458	-703.461	-540.810	-607.478
R^2	0.757	0.949	0.800	0.318	0.480
Adj. R^2	0.745	0.904	0.694	0.280	0.437

In the bivariate GWR analysis, individual relationships between carbon sinks and each significant variable were explored. The relationship between carbon sinks and forests has the highest R^2 (0.949) and an adjusted R^2 = 0.904, suggesting an excellent fit for the model. This implies that forest is the most influential variable in explaining spatial differentiation in carbon sinks at the urban village scale. The AICc value of -972.458 for this relationship further supports the robustness of the model. In contrast, the interaction between carbon sink and NDVI has a significantly lower R^2 value of 0.318, indicating a weaker fit. The adjusted R^2 value of 0.280 further confirms the limited explanatory power of NDVI in this context. The AICc value of -540.810 for this relationship is the lowest compared to other variables. The relationships between carbon sinks and elevation and between carbon sinks and wetness index show moderate explanatory capacity, with R^2 values of 0.800 and 0.480, respectively. These results indicate that while elevation and wetness index do influence carbon sinks, their impact is weaker than that of forests.

Figure 7 depicts the spatial variation of the relationship as determined by the coefficient by multivariate GWR. The disparity in local associations illustrates the geographic variations in the influence of factors like as forest, elevation, NDVI, and WET on carbon sinks at the urban village level. Regions exhibiting robust correlations between carbon sinks and various factors are indicated by coefficient values, underscoring areas where these factors significantly influence carbon sinks.

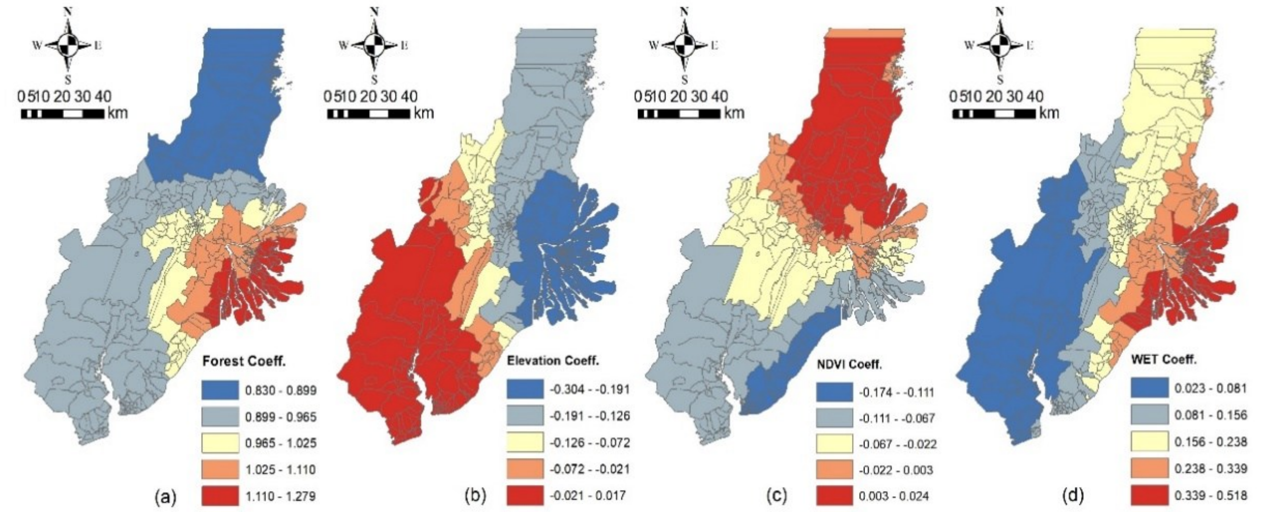


Figure 7. Spatial differentiation of coefficient based on multivariate GWR.

Figure 7a shows a positive association between forest and carbon sink, with coefficient values range: 0.830-1.279. The red areas on the east coast of the SMA demonstrate the strongest influence of forest, meaning that an increase in the forest area in these regions will increase carbon sinks by 1.110–1.279. Figure 7b presents the local variance of elevation's impact on carbon sinks, with coefficient values range: -0.304-0.017. Elevation generally shows a negative association with carbon sinks, indicating that lower elevations, typically associated with coastal areas, have a stronger potential for carbon sinks (as indicated by the blue areas). Figure 7c illustrates the distribution of NDVI's influence on carbon sinks, with coefficient values range: -0.174-0.024. In the northern part of SMA (red areas), higher NDVI is associated with slightly higher carbon sinks (0.003-0.024), but this influence gradually weakens and turns negative towards the southern part. This result shows that the interaction between vegetation greenness and carbon sinks varies spatially and may be influenced by differences in land-cover composition and vegetation characteristics across the SMA. Lastly, Figure 7d depicts the spatial differentiation of WET influence on carbon sinks, with coefficient values range: 0.023-0.518. This result indicates a positive association between wetness and carbon sinks, with the most significant impact noted in the red areas, with the coefficient values range: 0.339-0.518, showing that increased wetness is consistently associated with higher carbon sinks.

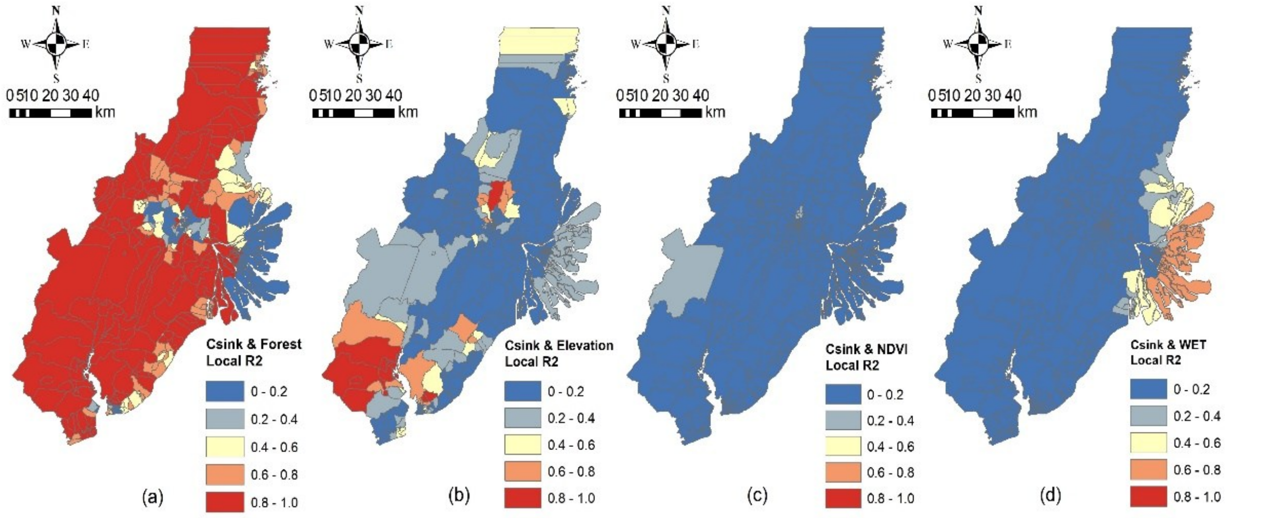


Figure 8. Spatial differentiation of local R^2 based on bivariate GWR.

Figure 8 shows the spatial differentiation of local R^2 for each factor, illustrating how their relationships with the carbon sinks vary across different parts of the urban villages. Regions with high local R^2 values indicate areas where these factors exert a strong influence on carbon sinks. The local R^2 values range from 0 to 1.0, with intervals of 0.2. This indicates the degree of fit for the local regression model, where values closer to 1.0 represent a stronger relationship between carbon sinks and the key factors, while values towards 0 indicate a weaker relationship at the urban village level.

4. Discussions

4.1 Local-scale Carbon Sinks and Their Determinants

The spatial pattern of carbon sinks exhibits clustering patterns, indicating that high carbon sinks are geographically clustered and the same as low carbon sinks. This pattern suggests that carbon sinks can influence and be influenced by the surroundings, which aligns with several studies on carbon sinks' spatial dependencies (L. Wang et al., 2024; X. Wang et al., 2023; Zhang & Deng, 2022). The study also confirms that clusters with lower carbon sinks appeared in the core cities in the region; this condition supports the earlier studies that showed how urbanized areas negatively affect carbon sinks (Han et al., 2024; Ye & Chuai, 2022; Zhuang et al., 2023).

By comparing key factors of carbon sinks at local scales, the urban village model demonstrates better performance than the sub-district model, indicating that the relationship between carbon sinks and the factors can be explained more effectively at a finer administrative level, which supports the previous study on localized carbon sinks (Khodakarami, 2024). The key factors that affect carbon sinks at the urban village scale are forest, elevation, NDVI, and WET, where these factors contribute meaningfully to the local variations of carbon sinks. Based on the SLM results, forest and WET showed positive impacts on local-scale carbon sinks, with values of 1.020 and 0.225, respectively. These results are in line with previous research on the key roles of forest and water-rich ecosystems as carbon sinks (Piao et al., 2022; Tagesson et al., 2020).

The spatial differentiation identified by the GWR analysis further suggests that the mechanisms governing carbon sink capacity are not spatially uniform across the SMA. Forest cover exerts the strongest influence in the eastern coastal area, where extensive natural vegetation and relatively limited urban development support greater carbon sequestration capacity. In contrast, urbanized areas such as

Samarinda and Balikpapan exhibit lower carbon sink potential due to land conversion, landscape fragmentation, and reduced ecological connectivity. Similarly, the positive influence of wetness highlights the importance of water-associated ecosystems, including wetlands and coastal ecosystems, which contribute to biomass productivity and carbon storage. These findings indicate that local environmental characteristics and land-use configurations play a critical role in shaping carbon sink dynamics across the coastal metropolitan landscape.

Elevation and NDVI exhibit weak negative effects, with values of -0.112 and -0.131, respectively. While higher elevation often coincides with forested landscapes, the environmental conditions or human activities at higher altitudes may cause the negative impact on carbon sinks, which is in line with the existing research (Chimdessa, 2023; Kobler et al., 2019). The negative coefficient of NDVI aligns with previous literature, which shows the contradictory impact of NDVI on urban-scale carbon sinks (Lin et al., 2023; H. Wang et al., 2019). The negative value of NDVI requires careful interpretation because NDVI primarily measures vegetation greenness rather than vegetation biomass or carbon storage capacity. In the SMA, areas with relatively high NDVI values may include agricultural land, shrubland, or secondary vegetation that exhibit high spectral greenness but store less carbon than mature forest ecosystems. This interpretation is supported by the strong positive effect of forest cover identified in the SLM results, suggesting that forest extent is a more direct indicator of carbon sink capacity than NDVI alone. Furthermore, the GWR results reveal spatial variation in NDVI coefficients, with positive relationships observed in the northern part of the SMA and negative relationships in the southern part. This spatial heterogeneity suggests that the interaction between vegetation greenness and carbon sequestration is context-dependent and influenced by differences in land-cover composition, vegetation structure, and urban development intensity across the metropolitan area.

4.2 Implications

Carbon management can start at the local scale, where monitoring, implementation, and evaluation can be integrated into existing administrative structures (Boehnke et al., 2019; Guarini et al., 2022). Collaboration and coordination can also be facilitated through local-scale interventions (Brink & Wamsler, 2018; Fuhr et al., 2018; Schoon & Cox, 2018). The findings further suggest that local-scale carbon management contributes to broader urban resilience by strengthening ecosystem functions and enhancing climate mitigation capacity in rapidly urbanizing coastal regions.

The positive influence of forest and wetness highlights the importance of ecological assets in supporting carbon sequestration and maintaining environmental stability. In particular, the significance of wetness indicates the relevance of blue carbon governance in coastal metropolitan regions, where wetlands and other coastal ecosystems can complement conventional terrestrial carbon management approaches. Furthermore, the observed spatial heterogeneity suggests that metropolitan ecological planning should move from uniform conservation strategies to place-based interventions that account for local environmental conditions and carbon sink potential.

Identifying local-scale potentials can therefore support the design of targeted urban planning instruments aimed at enhancing carbon sinks and integrating ecological priorities into spatial development policies. Several priorities include forest and wetland conservation, blue carbon management, ecological restoration, and coastal ecosystem protection (Hoque et al., 2021; Sapkota & White, 2020; Were et al., 2019). These priorities can be operationalized through ecological protection zones in local spatial plans, blue carbon integration into coastal planning, and ecological corridor development to maintain ecosystem connectivity. Furthermore, spatial differentiation of carbon sinks and the relationships with key factors suggests that interventions should be localized and prioritized in areas with greater potential for carbon sink enhancement. Integrating these priorities in urban development can support sustainable development goals (Hurlimann et al., 2021). In addition, local-scale carbon management can benefit from maintaining traditional practices, protecting ecologically sensitive areas, promoting environmentally friendly lifestyles, and engaging with local communities.

Beyond its practical implications, this study contributes academically by demonstrating how multiscale spatial analysis can reveal differences in carbon sink determinants that may remain hidden at coarser administrative levels. The findings suggest that finer-scale governance units can provide additional insights for understanding carbon sink dynamics in rapidly urbanizing coastal regions. Although the results are context-specific to the SMA, the analytical framework and localized planning perspective may be transferable to other metropolitan coastal regions that face similar pressures from urban expansion, ecological change, and climate mitigation challenges.

5. Conclusions

This study examined the distribution of carbon sinks and their factors at local administrative scales in the SMA, Indonesia. The results show that carbon sinks are primarily concentrated in the Kutai Kartanegara municipality and exhibit significant clustering patterns at both the sub-district and urban village scales. Among the multiscale models, the urban village model demonstrated better performance in explaining carbon sink dynamics, suggesting that finer administrative units are more capable of capturing local environmental heterogeneity and spatial processes. Forest, elevation, NDVI, and WET were identified as the main factors influencing local-scale carbon sinks, while their spatially differentiated relationships indicate that carbon sink dynamics should be understood within specific local contexts rather than through uniform assumptions.

These findings provide implications for climate-sensitive urban governance and coastal metropolitan planning by emphasizing that carbon management strategies should be localized and spatially targeted. Rather than applying generalized approaches, planning interventions may prioritize ecological protection, wetland restoration, blue carbon integration, and ecosystem conservation in areas with greater carbon sink potential. This study also demonstrates the value of multiscale spatial analysis for supporting local-scale planning and monitoring efforts in rapidly urbanizing coastal regions and may offer methodological insights for other metropolitan coastal areas with comparable urbanization and environmental pressures.

Despite its contributions, this study presents several limitations. First, the analysis was based on a single-year dataset and therefore does not capture temporal variations in carbon sink dynamics. Second, the use of administrative boundaries may introduce aggregation effects and obscure environmental heterogeneity across space. Third, uncertainty associated with remote sensing datasets, differences in spatial resolution among variables, and residual spatial effects may influence the results. Future studies may incorporate multi-temporal datasets, alternative spatial units, and comparative analyses across metropolitan coastal regions to improve temporal robustness and further examine the transferability of localized carbon management approaches.

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No new data were created in this study; all sources are cited within the article.

Institutional Review Board Statement

Not applicable.

CRediT Author Statement

Conceptualisation; Data curation; Formal analysis; Methodology; Software; Validation; Visualisation; Writing – original draft; Writing – review & editing: A.H. Author has read and approved the final version of the manuscript.

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