Sustainability strategies for carbon sequestration in South Tangerang City using InVEST model to support sustainable urban planning

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Abstract. Rapid urbanisation in South Tangerang City has triggered substantial conversion of green spaces, critically impacting the carbon-sequestration capacity of urban ecosystems. This study integrates remote sensing technology, Cellular Automata-Markov predictive modelling, and the InVEST Carbon Storage model to examine the spatiotemporal dynamics of land cover and estimate carbon stocks over the 2016–2025 period. Random Forest classification achieved an accuracy of 93.61% with a kappa coefficient of 0.874, demonstrating robust temporal consistency across all observation periods. The analysis revealed a decline in carbon stocks of 90,028 tC (9.6%), from 939,287 tC to 849,259 tC, with carbon density decreasing from 64.93 to 58.04 tC/ha. Forest ecosystems accounted for 67.1% of total carbon stocks, despite absolute losses of 106,336 tC. Landscape metrics demonstrated structural improvements, with mean patch size increasing by 50.4% and connectivity enhancing by 14.7%, indicating successful habitat consolidation. Key predictors of carbon sequestration sustainability include mean patch size as the strongest predictor of carbon density ($r = 0.82$), urban development pressure ($r = 0.847$), and NDVI-carbon correlation ($r = 0.85$). A strong positive correlation ($r^2 = 0.87$) between forest area and carbon stocks confirms that vegetation conservation policies are essential for maintaining urban carbon sequestration capacity in rapidly urbanising regions.

1 Introduction

The IPCC Sixth Assessment Report indicates that human activities have elevated the global mean temperature by 1.1 °C above pre-industrial levels, with atmospheric CO_2 concentrations reaching 421 ppm in 2023 [1]. Urban areas currently house 56% of Indonesia's population, with projections reaching 66.6% by 2035, generating 70% of global carbon emissions while serving as centers for sustainable solutions.

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South Tangerang City, which is part of the Jabodetabek metropolitan area, exemplifies the challenges of urban sustainability. The city experienced rapid transformation, with an annual population growth of 3.4% and economic expansion of 6.2%. Approximately 2,847 hectares of vegetation cover were converted to residential and infrastructure developments between 2010 and 2020 [2], resulting in urban heat island effects with a mean temperature increase of 1.8 °C and air quality deterioration.

Urban vegetation-based carbon sequestration offers cost-effective climate mitigation with co-benefits for multiple SDG targets. Indonesian urban forests demonstrate carbon sequestration potential of 150-200 tC/ha [3], yet realizing this potential requires monitoring and management frameworks. Urban carbon dynamics are increasingly recognized as critical components of climate change mitigation, with cities serving as significant carbon sinks when managed properly [4]. Research across tropical cities has documented substantial carbon losses during rapid urbanization, with the conversion of forests and agricultural lands accounting for the majority of carbon depletion. Landscape fragmentation, vegetation characteristics, and urbanization pressure interact to determine the carbon sequestration capacity.

Recent advances in geospatial technology have enabled real-time land cover monitoring and supported data-driven decision-making [5]. Despite technological capabilities, assessments integrating multi-temporal land cover analysis with carbon stock estimation remain limited in Indonesian cities. This study had two objectives: (1) to evaluate carbon stock dynamics in relation to green open space changes over 2016-2025; and (2) to identify key factors affecting carbon sequestration, including landscape structure, development pressure, and vegetation characteristics. The methodological approach integrated Random Forest classification, CA-Markov projection modeling, and the InVEST Carbon Storage model.

2 Methodology

2.1 Study area and period

The investigation was conducted in South Tangerang City, Banten Province (6°13′10″-6°22′10″ S and 106°38′-106°47′ E), encompassing an area of 147.19 km^2. The primary data comprised Sentinel-2 Level-2A satellite imagery with a 10-meter spatial resolution for 2016, 2019, 2022, and 2025, acquired from the Copernicus Open Access Hub. Secondary data included Indonesian Topographic Maps (1:25,000 scale), administrative boundaries, SRTM Digital Elevation Model, road network from OpenStreetMap, and demographic statistics. Image preprocessing involved radiometric calibration, atmospheric correction utilizing the Sen2Cor algorithm, and geometric correction with an RMSE below 0.5 pixels.

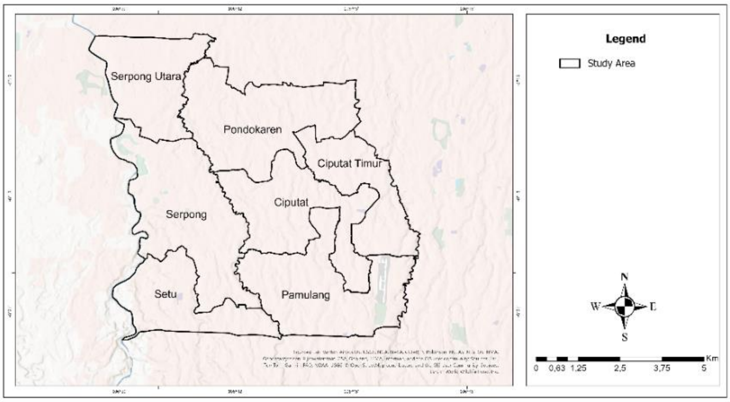

Fig. 1. Research location

2.2 Land cover classification and validation

Land cover classification employed the Random Forest algorithm on Google Earth Engine. The classification scheme adapted from SNI 7645:2010 established six classes: Forest (natural forest and dense vegetation >75% cover), Shrubland (secondary vegetation 25-75% cover), Agriculture (cultivated areas), Built-up Land (urban and infrastructure), Bare Land (exposed soil and sparse vegetation <25% cover), and Water Bodies. The predictor variables included Sentinel-2 bands (B2, B3, B4, B8, B11, and B12), vegetation indices (NDVI, EVI, SAVI, and NDWI), urban indices (NDBI and UI), texture features, and topographic variables. The training data comprised 1,256 samples per period, with 377 for validation. The annual change rates were calculated using the following exponential formula [6]:

$$R = [1/(t_2 - t_1)] \times \ln(A_2/A_1) \times 100\% \qquad (1)$$

where R represents the annual change rate (%/year), A_1 and A_2 denote the land cover area at the initial and final times (ha), and t_2 - t_1 indicates the time interval (years).

2.3 Carbon stock estimation

Carbon stock estimation was performed using the InVEST Carbon Storage module v3.12.0 [7]. The carbon pools included aboveground biomass (AGB), belowground biomass (BGB), Soil Organic Carbon (SOC, 0-30 cm), and Dead Organic Matter. Calculation:

$$C\_total = C\_AGB + C\_BGB + C\_SOC + C\_Litter \qquad (2)$$

The coefficients were derived from the IPCC Guidelines [8], established allometric equations, and local measurements. Forest carbon density (209.0 tC/ha) was calibrated using weighted calculations combining IPCC defaults (150-200 tC/ha) with local adjustments. Species-specific rates were validated using regional inventory data. Uncertainty analysis via Monte Carlo simulation (1,000 iterations) yielded ranges of ± 8.4-12.3 %.

2.4 Spatial and statistical analysis

Spatial analysis utilised the Normalized Difference Vegetation Index:

$$NDVI = (NIR - Red)/(NIR + Red) \qquad (3)$$

Spatial analysis utilized NDVI with classification thresholds [9]: >0.60 (dense), 0.40-0.60 (moderate), 0.20-0.40 (sparse), and <0.20 (non-vegetation). Landscape metrics included patch density, mean patch size, edge density, Shannon diversity, contagion, and aggregation indices [10]. Statistical analyses employed Pearson correlation, linear regression, ANOVA, and Mann-Kendall trend test (R v4.2.0, $\alpha = 0.05$).

3 Results and discussion

3.1 Carbon sequestration dynamics and green space changes

3.1.1 Spatiotemporal land cover transformation

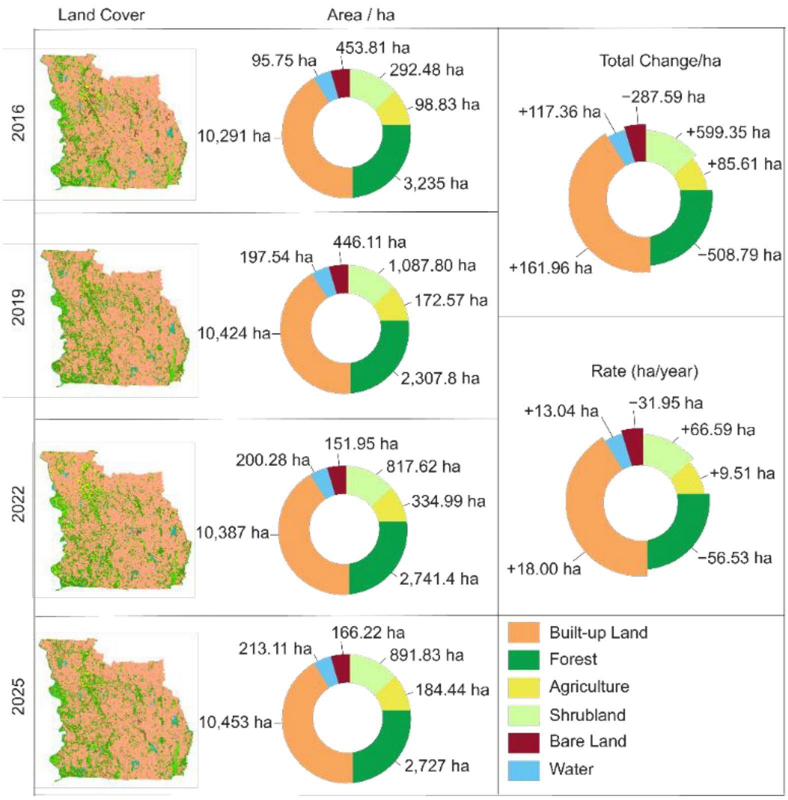

Fig. 2. Land cover map and total land cover area changes from 2016-2025

For land cover classification accuracy, Random Forest achieved a mean accuracy of 93.61% (K = 0.874) during 2016-2025, with a slight decline from 94.96% to 92.99%, reflecting increasing urban complexity. Strong temporal consistency ($r = 0.886$, $p < 0.001$) exceeded the operational accuracy thresholds, whereas the McNemar test ($p > 0.05$) indicated no systematic bias, supporting valid temporal comparisons.

The analysis revealed landscape transformation with shrubland expansion (+204.9%, from 292.48 to 891.83 ha) and water body increases (+122.6%, from 95.75 to 213.11 ha), reflecting restoration implementation. Forests experienced a net decline of 15.7% (508.79 ha) with the following temporal pattern: decrease 2016-2019 (-28.7%), recovery 2019-2022 (+18.8%), slight decline 2022-2025 (-0.5%). This U-shaped pattern aligns with the forest transition theory [11]. Built-up Land expanded by 161.96 ha (+1.6%) to 10,453 ha (71.4% of the area).

3.1.2 Carbon stock evolution

Carbon stocks exhibited a biphasic pattern: a decline phase (2016-2019) with a 17.1% reduction (from 939,287 to 778,343 tC, rate -3.91 tC/ha/year) corresponding to 28.7% forest loss; a recovery phase (2019-2022) with a positive rate of +1.74 tC/ha/year, exceeding typical tropical rates of 0.8-1.5 tC/ha/year [12]; and a stabilization phase (2022-2025) with a modest 0.6% decline. Net loss: 90,028 tC (-9.6%), density decreased from 64.93 to 58.04 tC/ha, respectively. The carbon pool distribution remained stable, with aboveground biomass at 47.7%, soil organic carbon at 33.2%, belowground biomass at 14.9%, and litter at 4.3%. Soil carbon exceeded the typical urban ranges (25-30%), reflecting enhanced management.

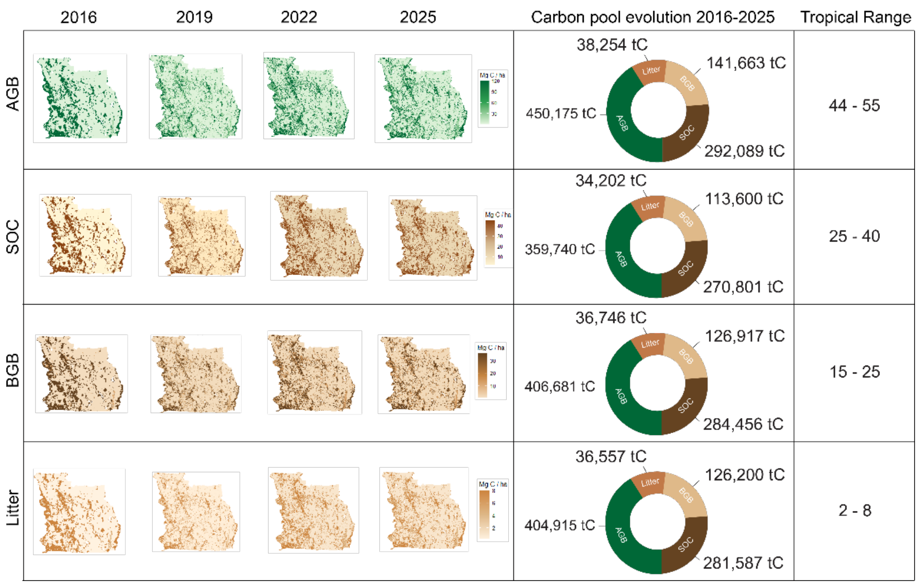

Fig. 3. Carbon stock evolution 2016-2025.

3.1.3 Land cover carbon relationships

Forests maintained a 67.1% contribution despite a 106,336 tC loss (Table 1). The average forest density of 209.0 tC/ha substantially exceeds typical tropical urban values (150-200 tC/ha) through intensive management. Forest area changes explained 87% of the carbon variance ($r^2 = 0.87$, $p < 0.001$), confirming conservation as the primary strategy. Shrubland contributed 61,537 tC (+185.0%, 7.2% of the total) with a density of 69.0 tC/ha. Built-up Land (71.4% of the territory) exhibited a low density (19.5 tC/ha), containing only 24.0% of the stocks. Spatial concentration (78% of stocks in 32% of the area) creates vulnerability.

The temporal carbon stock distribution demonstrates that while forests experienced an absolute decline from 676,298 tC (2016) to 569,962 tC (2025), they maintained dominance through consistently high carbon density. The contribution of shrubland increased substantially from 21,607 tC (2016) to 61,537 tC (2025), partially compensating for forest losses. This temporal pattern validates the critical role of forest conservation in maintaining the urban carbon sequestration capacity.

Table 1. Carbon stock distribution by land cover class 2025

Land Cover Type	Carbon Stock (tC)	Contribution (%)	Carbon Density (tC/ha)
Forest	569,962	67.1	209.0
Built-up Land	203,851	24.0	19.5
Shrubland	61,537	7.2	69.0
Agriculture	11,251	1.3	61.0
Bare Land	2,660	0.3	16.0
Water Bodies	0	0.0	0.0
TOTAL	849,261	100.0	58.03

3.2 Key factors affecting sustainability

3.2.1 Landscape structure

Peak fragmentation in 2019 showed the highest patch density (4.89 patch/100 ha) and lowest mean size (5.73 ha), coinciding with the maximum carbon loss. Subsequent improvement included a 50.4% mean patch size increase (from 8.94 to 13.45 ha), directly correlating with recovery ($r = 0.78$, $p < 0.01$). The connectivity index and aggregation increased by 14.7% and 7.9%, respectively. Mean patch size was the strongest predictor of carbon density ($r = 0.82$, $p < 0.001$). Shannon diversity declined from 1.743 to 1.612 (-7.5%), suggesting landscape simplification. The edge density decreased by 23.2% (from 167.3 to 128.4 m/ha), reflecting reduced fragmentation. Recent innovations in vegetation-based bioengineering have demonstrated integrated benefits for carbon sequestration [13].

3.2.2 Development pressure and spatial patterns

Spatial regression revealed urban pressure as the strongest loss predictor ($r = 0.847$, $p < 0.001$) in core-periphery gradients. Distance from the center explained 72% of the density variance, with an exponential decline within a 5 km radius. District depletion rates varied from -0.76% (East Ciputat, active conservation) to -1.14% (Serpong, commercial pressure) annually. Population density was a secondary factor ($r = 0.64$, $p < 0.01$), with areas >10,000 persons/km^2 experiencing accelerated loss.

3.2.3 Vegetation health and climate interactions

Forest areas showed NDVI increase of +0.036 ($p < 0.05$), rising from 0.687 to 0.723, approaching optimal ranges (0.70-0.80). The NDVI-carbon density correlation ($r = 0.85$, $p < 0.001$) confirmed vegetation vigor as a determinant. Forests >15 years sequestered 2.3× more carbon than younger forests. Areas maintaining >60% canopy cover achieved 4.2× higher densities than areas with <30% cover. A strong negative correlation ($r = -0.89$, $p < 0.001$) between NDVI and surface temperature validated the cooling role of dense vegetation (NDVI >0.60), which provided -8.5 °C benefits. Evapotranspiration rates were correlated with NDVI ($r = 0.91$, $p < 0.001$): 6.2 mm/day in dense forests versus 1.0 mm/day in non-vegetated areas. Carbon valuation methodologies applied to tropical ecosystems provide frameworks for environmental assessments [14, 15].

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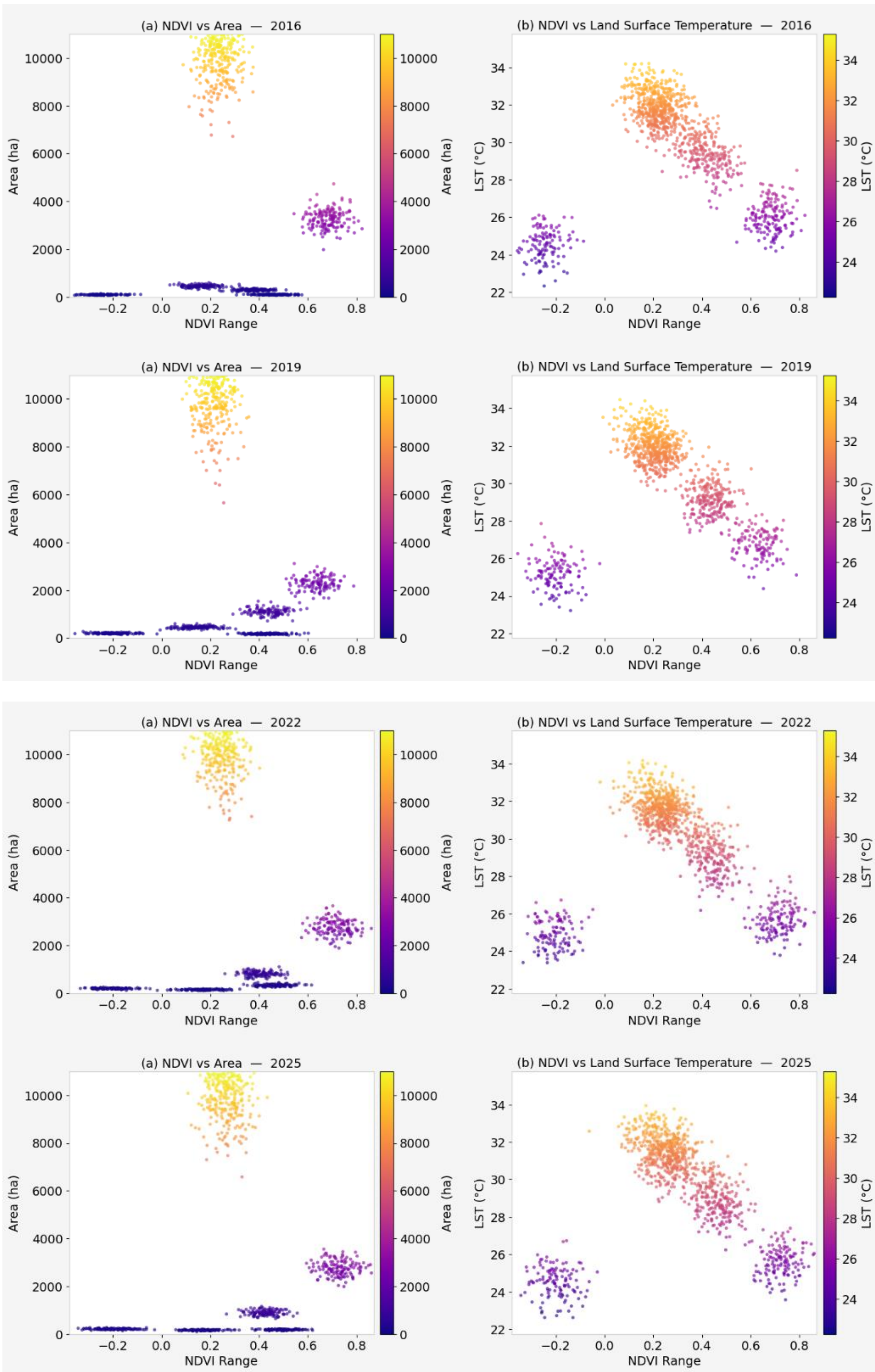

Fig. 4. Relationship between NDVI and land surface temperature (2016-2025)

4 Conclusion

This study developed an integrated framework combining Random Forest classification (93.61% accuracy, kappa 0.874), CA-Markov projection modeling, and InVEST Carbon Storage modeling for South Tangerang City during 2016-2025. Objective 1 findings revealed biphasic carbon stock dynamics: a decline phase (2016-2019: -17.1%) corresponding to forest loss (-28.7%), a recovery phase (2019-2022: +9.8%) matching restoration (+18.8%), and a stabilization phase (2022-2025: -0.6%), resulting in a net loss of 90,028 tC (-9.6%). Forests contributed 67.1% of the total carbon stock, with a density of 209.0 tC/ha, exceeding typical tropical urban values (150-200 tC/ha).

Objective 2 analysis identified key factors: landscape fragmentation with mean patch size as the strongest carbon density predictor ($r = 0.82$); urban development pressure as the strongest loss predictor ($r = 0.847$); vegetation health with NDVI-carbon correlation ($r = 0.85$); vegetation maturity with mature forests sequestering 2.3× more carbon; and climate-vegetation interactions providing -8.5 °C cooling. A strong correlation ($r^2 = 0.87$) between forest area and carbon stocks confirms that vegetation conservation is the primary strategy. Landscape metrics demonstrated improvements, including mean patch size (+50.4 %), connectivity (+14.7 %), and aggregation (+7.9 %). This study provides baseline data for South Tangerang and a replicable methodological framework for tropical urban contexts, supporting sustainable urban planning and climate change mitigation targets.

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