DISTRIBUTION OF CARBON STORAGE AND POTENTIAL STRATEGIES TO ENHANCE CARBON SEQUESTRATION CAPACITY IN SINGAPORE

A study based on machine learning simulation and geospatial analysis

JIONGYE LI[1] and RUDI STOUFFS[2]
[1,2]Department of Architecture, National University of Singapore.
[1]lijiongye@u.nus.edu, 0009-0000-5496-0486
[2] stouffs@nus.edu.sg, 0000-0002-4200-5833

Abstract. The expansion of urbanization leads to significant changes in land use, consequently affecting carbon storage. This research aims to investigate the carbon loss due to land use alterations and proposes strategies for mitigation. Utilizing existing land use data from 2017 and 2022, along with simulated data for 2025 generated by an ANN model and Cellular Automata, we identified changes in land use. These changes were then correlated with variations in carbon storage, both gains and losses. Our findings reveal a significant loss of 36,859 metric tons of carbon storage from 2017 to 2022. The projection for 2025 estimates a further reduction, reaching a total loss of 83,409 metric tons. By employing the LISA method, we identified that low-carbon storage zones are concentrated in the southeast region of the research site. By overlaying these zones with areas of carbon storage loss, we pinpointed regions severely affected by carbon depletion. Consequently, we propose that mitigation strategies should be imperatively implemented in these identified areas to counteract the trend of carbon storage loss. This approach offers urban planners a solution to identify areas experiencing carbon storage decline. Moreover, our research methodology provides a novel framework for scholars studying similar carbon issues.

Keywords. Land use and land cover (LULC) Changes, Simulated LULC, Machine Learning Model, Carbon Storage Changes, GIS

1. Introduction

Singapore's population growth and urbanization have led to economic benefits but also changed the land use and land cover (LULC), posing urban challenges like carbon storage loss. Land use changes can decrease carbon storage and increase carbon emissions, worsening greenhouse gas emissions (Zhang et al., 2022). Research has explored the relationship between land use, carbon emissions, and storage. For instance, studies comparing land use changes over time estimate carbon loss (Zhang et al., 2022; An, 2022). Other research focuses on carbon storage and sequestration linked to

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 2, 89-98.

specific land uses, such as green roofs, forests, and wetlands (Shafique et al., 2020; Hung et al., 2021).

In addition to comparing past land use changes, researchers also employ simulated land use maps to project potential future carbon changes. Simulation models, including Future Land Use Simulation (FLUS), Cellular Automata - Artificial Neural Network (CA-ANN), Markov-Flus, and Conversion of Land Use and its Effects at Small regional extent (CLUE-S), are utilized to predict future land use (Tong and Feng, 2019; He et al., 2022). The CA-ANN model, in particular, is widely used for its ability to integrate the strengths of both Cellular Automata (CA) and Artificial Neural Network (ANN). ANN interprets the nonlinear relationship between input and output data, while CA, as a spatially explicit model, effectively regenerates the dynamics of land use and land cover changes (Tong and Feng, 2019; Wu, 2002). Algorithms and models for projecting future LULC can be embedded into software plugins to facilitate the process. For instance, the Modules for Land-Use Change Simulation (MOLUSCE) plugin in QGIS employs multiple models and algorithms, including CA, ANN, Weights of Evidence (WoE), and Logistic Regression (LR), to simulate future land use based on necessary input variables such as previous land use maps, distance to transport systems, and slope (Muhammad et al., 2022).

The Carbon Storage Index, linked to various Land Use and Land Cover (LULC) types, is essential for estimating carbon storage globally. Common LULC types, which vary by region, include cropland, forest, shrubland, grassland, and built-up areas (Zhu et al., 2021; Wang et al., 2022). Total carbon storage for each land use type is calculated by summing the carbon densities in four categories: aboveground, belowground, soil organic, and dead organic matter (Zhu et al., 2021; Wang et al., 2022; He et al., 2022). The carbon density index differs among LULC types and can vary for the same land use type in different regions or environmental settings (Zhu et al., 2021; Wang et al., 2022; He et al., 2022). These indices are used in simulation models like the InVEST Carbon Storage and Sequestration model, developed by Stanford University's Natural Capital Project, to predict carbon storage based on land use and carbon density indices. This model is widely utilized by researchers to estimate carbon sequestration across various land uses (Chen et al., 2017; Maanan et al., 2019; Zhu et al., 2021; Wang et al., 2022; He et al., 2022).

Addressing the need for accurate estimation of carbon storage to counteract losses due to land use changes, this research introduces a novel methodology for analysing and simulating carbon storage trends in Singapore utilizing machine learning and geospatial tools. The results enable the identification of critical carbon storage mitigation areas, characterized by low current carbon storage and projected future declines. Implementing targeted mitigation strategies in these areas is essential to enhance carbon sequestration.

2. Methodology

2.1. STUDY SITE

Singapore, a densely populated city-state of 5.92 million people, as of June 2023, covers 734.3 km². It's projected to reach a population of 6.9 million by 2030 (Singapore Department of Statistics, 2023). Urbanization has been significant, with the entire population living in urban areas, compared to 70% in the 1950s. The land use has transformed drastically: agricultural land has reduced to less than 1% and forested areas to about 23% (Fraser, 1952; Corlett, 1992; United Nations, 2018;).

2.2. DATA

This research utilizes multiple datasets as illustrated in Table 1.

Data Types	Data Sources	Data Specifications
LULC Data	Sentinel-2 10m Land Use/Land Cover	Time Stamp: 2017-2022 Resolution: 10 meters
Carbon Density Index	Cities in Nature from National University of Singapore	Carbon index of various land uses Unit: metric tons/hectare Format: Float number
Road System Data	OpenStreetMap	Format: Polyline
Digital Elevation Model (DEM)	National Aeronautics and Space Administration (NASA)	Resolution: 30 meters
Carbon Storge Index of Plants	TreeSG under National Parks Board	Carbon index of individual plants Unit: Kilogram /tree Format: Float number

Table 1. Data types, sources, and specifications.

2.3. METHOD

2.3.1. Method Diagram

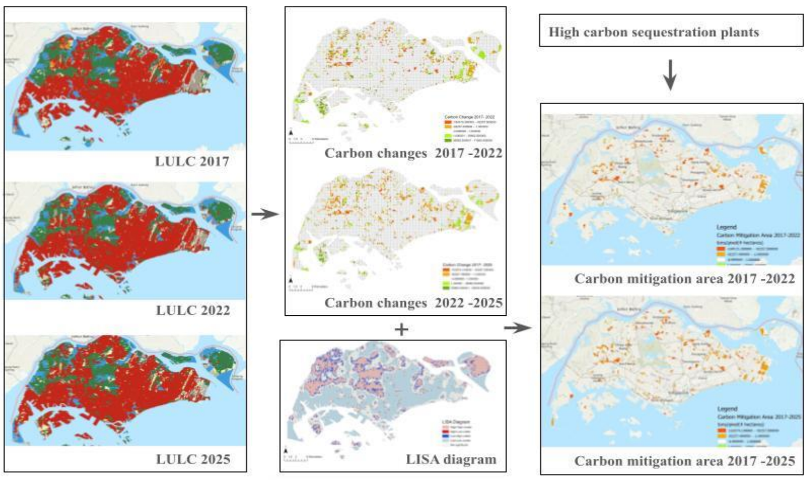

Figure1. Summarized method diagram

As illustrated in Figure 1, this study utilizes the LULC data from 2017 and 2022, along with simulated LULC for 2025, to estimate carbon storage based on the carbon density index. By analysing the estimated carbon storage maps for these years, the study identifies changes in carbon storage. Areas experiencing a reduction in carbon storage are pinpointed. Additionally, the Local Indicators of Spatial Association (LISA) method is employed to detect areas with low carbon storage. Overlaying the identified carbon loss areas with low carbon storage regions highlights zones where carbon mitigation strategies are needed. Regarding such strategies, this research suggests the utilization of high carbon sequestration plants in areas pinpointed by the LISA analysis and those showing carbon loss. Further details on these methodologies and strategies will be elaborated in subsequent sections.

2.3.2. LULC Changes

This research aims to analyse the distribution of carbon storage and identify potential strategies to improve carbon storage in Singapore. The methodology primarily focuses on these two objectives. For analysing changes in carbon storage distribution, LULC maps from various time periods are required. Specifically, LULC maps from each year between 2017 and 2022 were collected from Sentinel-2 10m. The Modules for Land Use Change Simulations (MOLUSCE) in QGIS version 2.6.0 were used to simulate the predicted LULC map for 2025. The simulation process involves several steps using the MOLUSCE model.

In the first step, essential spatial variables identified by previous literature (Muhammad et al., 2022), such as distance to road systems, the land use map of 2017, and DEM data, are incorporated into the model. Parameters for the initial year of the LULC map are set to 2017, and the final year to 2022, along with the aforementioned spatial variables, to train the simulation model. The second step, 'Transition Potential Modelling', is the training phase of the model. Necessary parameters for training include setting the sample mode to 'random', the number of samples to '1000', method to 'Artificial Neural Network (Multi-layer Perceptron)', neighborhood to '1px', learning rate to '0.100', maximum iterations to '1000', and hidden layers to '10'. These parameters are subjected to changes to enhance the accuracy of the trained model. Using optimal parameters, the trained model produces the predicted LULC map through the Cellular Automata Simulation method. Finally, the LULC map for 2022 is predicted. The predicted LULC map and the existing LULC map of 2022 are then compared to validate the model's accuracy using the kappa value, which is calculated via formula (1):

$$K = (Po - Pe)/(1 - Pe) \qquad (1)$$

The Kappa coefficient, denoted as K, represents the probability that the predicted data and observed data match. Po is the probability of observed agreement, while Pe is the probability that agreement between the observed and predicted data occurs by chance. The value of the Kappa coefficient varies from -1 to 1, with higher values indicating better performance in predicting the Land Use and Land Cover (LULC) map. If the trained simulation model is validated as accurate, it is subsequently used to predict the LULC map for 2025.

2.3.3. Carbon Storage Changes

Once the LULC maps for 2017, 2022, and 2025 are prepared, they are integrated into the InVEST model to calculate the carbon storage for each of these years. The InVEST model requires several input datasets. Specifically, the carbon density index acquired from the Cities in Nature project at the National University of Singapore, along with the LULC maps, are fed into the InVEST model. Consequently, the carbon storage maps for each year (2017, 2022, and 2025) are generated. The carbon storage values indicated by the maps created by the InVEST model are measured in metric tons per hectare (t/ha), as documented by The National Capital Project.

By utilizing the Raster Calculator in QGIS to compare the changes in carbon storage over the three years (2017, 2022, and 2025), we have identified areas that have experienced gains and losses in carbon storage from 2017 to 2025.

2.3.4. Local Indicators of Spatial Association (LISA) and Carbon Storage Mitigation Areas

This research employs the LISA method to pinpoint areas where improving carbon storage is most needed. LISA categorizes the study site into four types: 'high-high', 'low-low', 'high-low', and 'low-high', based on their carbon storage index. 'High-high' areas are those with high carbon storage surrounded by similar areas, while 'low-low' areas have low carbon storage and are surrounded by areas with similarly low storage, signalling a need for targeted improvement. 'High-low' areas are high carbon storage zones surrounded by low storage areas, and 'low-high' are the opposite. The classification is based on the LISA values (Anselin, 1995), with significant positive values indicating 'high-high' or 'low-low' clusters, and significantly negative values indicating 'high-low' or 'low-high' scenarios.

To accurately identify areas needing carbon storage mitigation, the research overlaps 2022 and 2025 carbon loss areas with 'low-low' areas identified by LISA in ArcGIS. These overlaid maps reveal areas that have experienced or are projected to experience carbon storage loss and are in 'low-low' LISA categories, meaning these areas and their surroundings have low carbon storage.

3. Results

3.1. LULC CHANGES

Figure 2 (top left and right) displays the LULC maps of 2017 and 2022, derived from Sentinel-2 10m Land Use/Land Cover data. Figure 2 (bottom left) presents the LULC map predicted by MOLUSCE in QGIS of year 2025. The accuracy of this predicted LULC map is validated by a high Kappa value in the MOLUSCE model, indicating 85% correctness when comparing the predicted LULC map of 2022 with the existing LULC map of 2022 from Sentinel-2 10m data. By calculating the differences between LULC maps, this research identifies areas that have experienced LULC changes in two time periods: from 2017 to 2022 and from 2017 to the predicted 2025.

From 2017 to 2022, most LULC changes are concentrated in the east and west parts of the country. In the eastern areas, these changes are predominantly from bare ground to built-up areas, denoted by blue colour, and from bare ground to grass, shown in green. In the western areas, the major LULC changes include the transition from trees to built-up areas, represented by pink colour, and from trees to bare ground, indicated in blue. From 2017 to the predicted 2025, as depicted in Figure 3, the trend of LULC changes appears similar to those observed between 2017 and 2022.

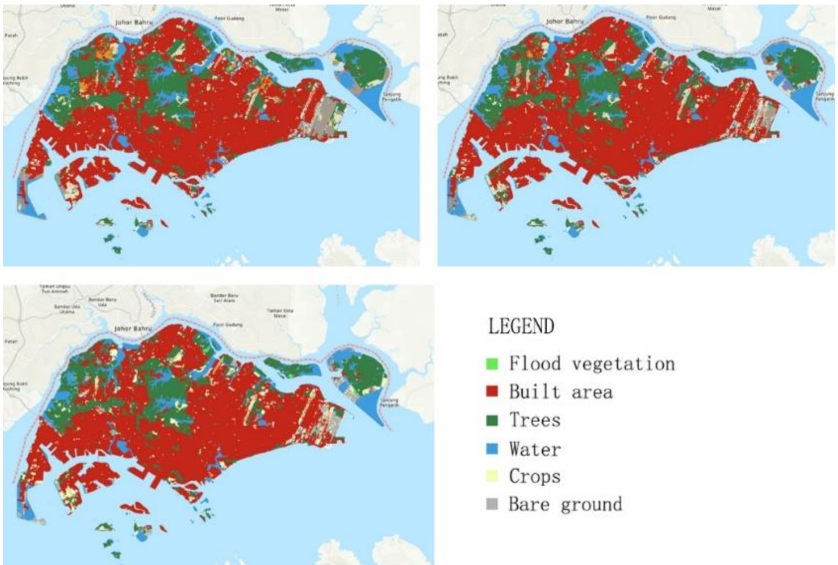

Figure 2. LULC map of 2017 (top left), LULC of 2022 (top right) and simulated LULC of 2025 (bottom left)

3.2. CARBON STORAGE CHANGES

The InVEST model generated carbon storage maps for the years 2017 and 2022 (Figure 4) and predicted the carbon storage map for 2025. According to the 2022 carbon storage map, the carbon storage values range from 0 to 231.3 mg/ha. Low carbon storage areas are predominantly found in built-up regions, while high carbon storage is concentrated in central and western tree-covered or forested lands.

By calculating the differences between these carbon storage maps in ArcGIS, this research has identified areas that experienced carbon storage gains and losses between two time periods: from 2017 to 2022 and from 2017 to 2025 (Figure 5). From 2017 to 2022, the study site has experienced a loss of 36,859 metric tons of carbon storage. Looking forward, from 2017 to the predicted year 2025, the site is projected to lose an additional 83,409 metric tons of carbon storage.

3.3. LISA DIAGRAM AND CARBON STORAGE MITIGATION AREAS

The LISA diagram regarding year 2022, as shown in Figure 6, reveals that high-high value areas are primarily found in the central and western regions, while low-low areas are concentrated in built-up areas.

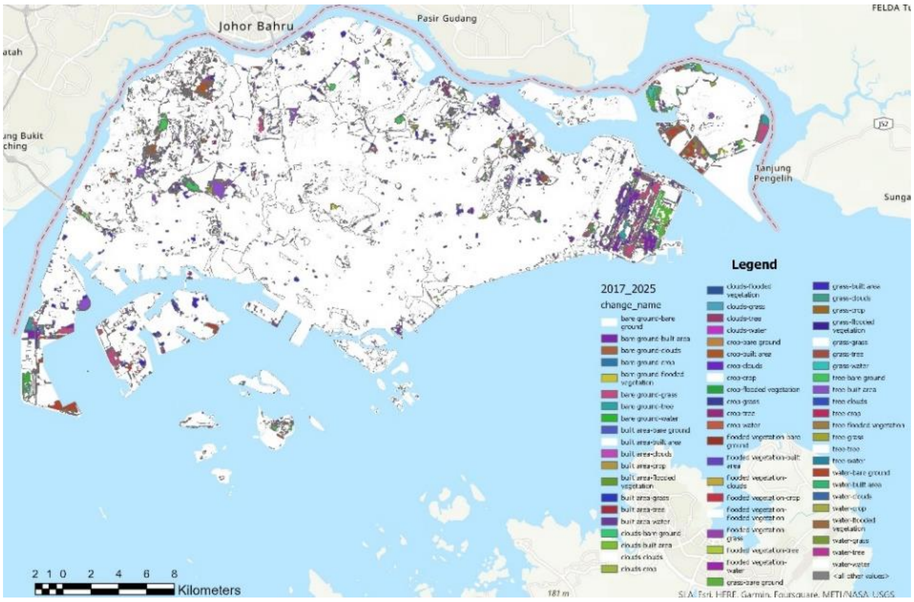

Figure 3. LULC changes from 2017 - 2025

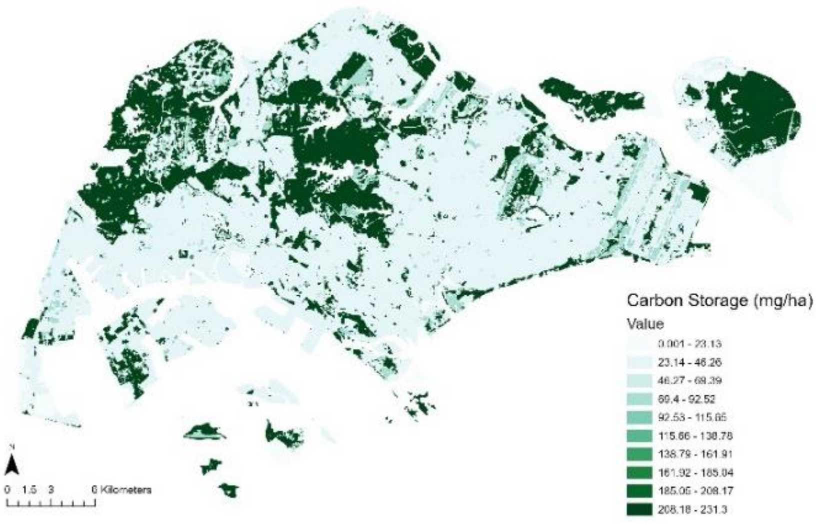

Figure 4. Estimated carbon storage of 2022 of Singapore

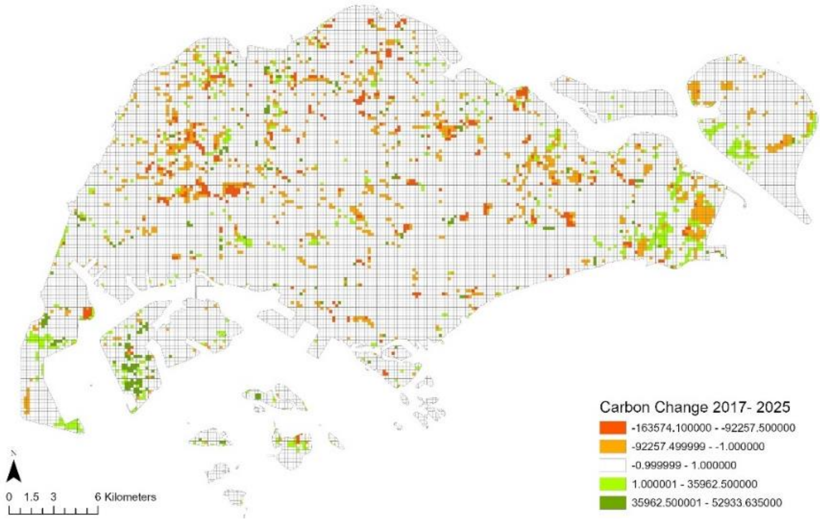

Figure 5. Carbon storage changes from 2017-2025 in tons/pixel (pixel unit: 4 hectares)

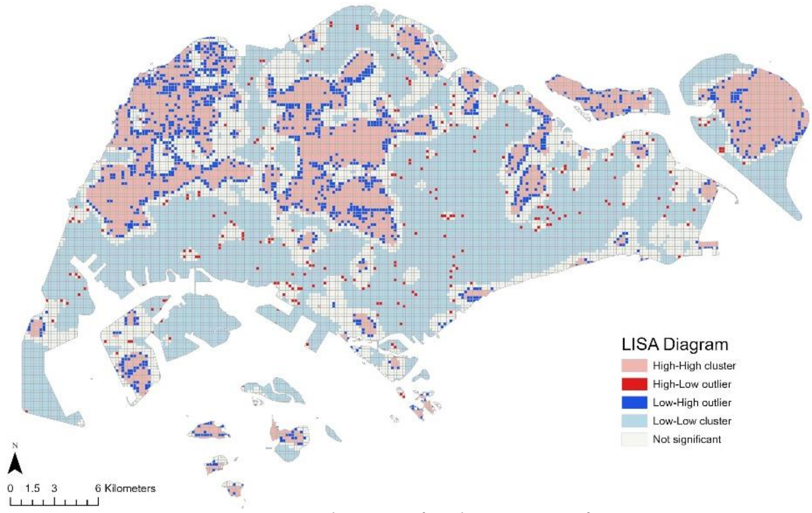

Figure 6. LISA diagram of carbon storage of 2022

To identify carbon storage mitigation areas, where carbon storage levels need to be improved, this research overlapped the carbon changes map with the LISA maps. Two overlap maps were created to showcase carbon storage mitigation areas for the two time periods, 2017 to 2022, and 2017 to 2025 (Figure 7). Each pixelated area, measuring 200 meters by 200 meters, belongs to the low-low areas as identified by the LISA maps, and all have experienced or are predicted to experience carbon storage loss. These areas of carbon storage loss are represented by two different colours on the maps, indicating two levels of carbon storage loss. This differentiation helps in prioritizing areas for intervention based on the severity of carbon storage loss.

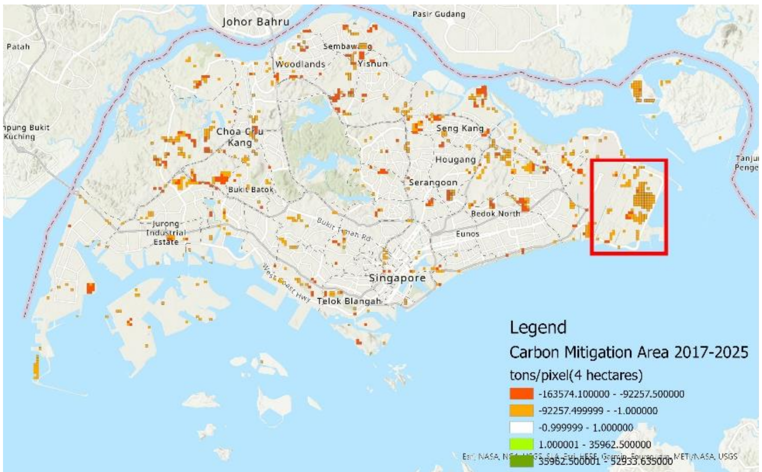

Figure 7. Carbon storage mitigation map from 2017-2025

4. Discussions and Potential Strategies

This study uses LULC maps from 2017 and 2022 and a simulated map for 2025 to estimate carbon storage changes in Singapore using the InVEST model and data from the National University of Singapore. It finds a projected carbon loss of 36,859 metric tons from 2017 to 2022 and 83,409 metric tons from 2017 to 2025. The LISA diagram indicates that areas with low carbon storage are primarily located in the southeast region. By overlaying the carbon loss diagram with the LISA diagram, we identify crucial carbon storage mitigation areas—zones with low carbon storage that are also experiencing carbon loss. This overlay suggests the necessity for targeted carbon loss mitigation strategies. Such strategies may include transitioning land covers with low carbon storage indices to those with higher indices where feasible or introducing plant species known for their high carbon sequestration capacities into these areas to improve carbon storage. The potential of plant species for carbon sequestration has been extensively studied in relation to their Diameter at Breast Height (DBH) and Total Height (TH), offering insights into their role in mitigating carbon loss trends (Miah et al., 2020; Chave et al., 2005).

A primary limitation of this research is the applicability of the carbon mitigation area map to specific contexts. For instance, Figure 7's red box highlights regions within Changqi airport's vicinity, which, according to the carbon mitigation map, would require land alteration to enhance carbon storage. Yet, modifying an airport's land use is not typically feasible. Therefore, the carbon mitigation map should be interpreted and applied in conjunction with realistic land-use considerations.

5. Conclusion

This research presents a novel approach to tackle carbon storage loss by analysing Land Use and Land Cover (LULC) changes from 2017 to 2025 in a specific study site. It finds a significant carbon storage loss—36,859 metric tons from 2017 to 2022 and a projected loss of 83,409 metric tons by 2025. Overlapping with low carbon storage areas that identified by the LISA diagram, it finds out areas severely affected by carbon loss to designate 'carbon storage mitigation areas.' These identified regions require immediate implementation of mitigation strategies to augment carbon storage. However, a limitation of this research is that the map depicting carbon storage mitigation areas is a general representation, and greater specificity is required when employing this map as a guide for enhancing carbon storage levels.

References

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*, 27 (2), 93-115.

An, Y. (2022). Impact of Covid-19 on Associations between Land Use and Bike-Sharing Usage. In *27th Conference on Computer Aided Architectural Design Research in Asia, CAADRIA 2022* (pp. 605-614). The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA).

Chave, J., Andalo, C., Brown, S., Cairns, M. A., Chambers, J. Q., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., Lescure, J.-P., Nelson, B. W., Ogawa, H., Puig, H., Riéra, B., & Yamakura, T. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, 145, 87-99.

Chen, D., Deng, X., Jin, G., Samie, A., & Li, Z. (2017). Land-use-change induced dynamics of carbon stocks of the terrestrial ecosystem in Pakistan. *Physics and Chemistry of the Earth*, Parts A/B/C, 101, 13-20.

Corlett, R. T. (1992). The Ecological Transformation of Singapore, 1819-1990. *Journal of Biogeography*, 19, 411.

Fraser, J. M. (1952). Town Planning and Housing in Singapore. *Town Planning Review*, 23, 5.

He, Y., Xia, C., Shao, Z., & Zhao, J. (2022). The Spatiotemporal Evolution and Prediction of Carbon Storage: A Case Study of Urban Agglomeration in China's Beijing-Tianjin-Hebei Region. *Land,* 11, 858.

Hung, L. Q., Asaeda, T., & Thao, V. T. P. (2021). Carbon emissions in the field of land use, land use change, and forestry in the Vietnam mainland. *Wetlands Ecology and Management*, 29, 315-329.

Maanan, M., Maanan, M., Karim, K., Kacem, A., Ajrhough, Rueff, Snoussi, & Rhinane. (2019). Modelling the potential impacts of land use/cover change on terrestrial carbon stocks in north-west Morocco. The International Journal of Sustainable Development and World Ecology, 26, 560-570.

Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L. (2022). Spatiotemporal Change Analysis and Prediction of Future Land Use and Land Cover Changes Using QGIS MOLUSCE Plugin and Remote Sensing Big Data: A Case Study of Linyi, China. Land, 11_(3), 419.

Shafique, M., Xue, X., & Luo, X. (2020). An overview of carbon sequestration of green roofs in urban areas. Urban Forestry & Urban Greening, 47_, 126515.

Wang, J.; Zhang, J.; Xiong, N.; Liang, B.; Wang, Z.; Cressey, E.L. Spatial and Temporal Variation, Simulation and Prediction of Land Use in Ecological Conservation Area of Western Beijing. Remote Sensing. 2022, 14, 1452.

Zhang, S., Zhong, Q., Cheng, D., Xu, C., Chang, Y., Lin, Y., & Li, B. (2022). Landscape ecological risk projection based on the PLUS model under the localized shared socioeconomic pathways in the Fujian Delta region. Ecological Indicators, 136_, 108642.

Zhu, G., Qiu, D., Zhang, Z., Sang, L., Liu, Y., Wang, L., Zhao, K., Ma, H., Xu, Y., & Wan, Q. (2021). Land-use changes lead to a decrease in carbon storage in arid region, China. Ecological Indicators, 127_, 107770.