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# The effect of urban sprawl on forest carbon stocks in La Mesa Watershed Reservation, Metro Manila, Philippines

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**ABSTRACT.** The La Mesa Watershed Reservation (LMWR) has experienced deforestation due to rapid urbanization. However, urban expansion at the expense of forest has resulted in changes in carbon storage in the watershed, which have not been fully quantified, hence this study. QGIS and TerrSet Land Change Modeler (LCM) were used to detect and map the emerging urbanization in LMWR using the supervised land cover classification generated from 2010 and 2020 Landsat satellite images. For the analysis of urbanization impacts on forest carbon stock, the transition from open forest to built-up areas was measured, and the carbon stock lost from the conversion was quantified using the 2020 forest resource inventory collected from the Metropolitan Waterworks and Sewerage System (MWSS). The results revealed that the forest cover loss between 2010 and 2020 was directly associated with urban sprawling. About 28 ha of forests were converted into built-up areas, resulting in a carbon stock loss of 3,525.17 tons in tree biomass, equivalent to 12,925.62 tons of $CO_2$ emissions. Furthermore, the total forest carbon stock in 2020 would increase by 1.42% if the forest were not converted into built-up areas and would have had 252,019.42 tons of carbon or sequestered 924,071.19 tons of $CO_2$. Thus, urban sprawl negatively influences the total forest carbon stock of the watershed. Urban sprawl, driven by socio-economic factors and whose human activities—such as waste disposal, livelihood, and illegal activities—seriously threaten any conservation, reforestation, and protection efforts in the area. However, urbanization provides critical space for housing, industry, and economic development, which may improve livelihoods and support societal progress. The trade-offs are evident as urban sprawl can significantly hinder reforestation, conservation, and protection efforts, exacerbating environmental degradation. Human activities associated with urban growth—such as waste disposal, livelihood pressures, and illegal practices—further contribute to the loss of valuable ecosystem services, necessitating careful planning and management to balance these competing land-use demands. The capacity of the watershed to effectively store carbon and provide other essential ecosystem services is contingent upon alterations in governmental spatial policy planning and management interventions that regulate urban land use development and guarantee the preservation of the existing forested areas.

**Keywords:** carbon stock assessment, forest resource inventory, QGIS, TerrSet land change modeler

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## INTRODUCTION

Watersheds are crucial in providing diverse ecosystem services, encompassing regulating, supporting, provisioning, and cultural functions (MEA, 2005; Kumar, 2010). Watersheds, however, are plagued by issues brought on by natural and man-made forces that change the landscape's composition (*e.g.*, loss or decrease of forest cover), which can then impact their structures and functions (*e.g.*, the decreasing capacity of carbon sinks). According to Wang *et al*. (2022), urbanization has been identified as a significant factor in deforestation, resulting in adverse reduction of emissions and enhancement of forest sinks. Likewise, a study by Lyu *et al*. (2023) quantified the impact of land use change on land carbon flux in the world's 100 largest cities by using annual land cover data based on LandSat 8 images and land carbon stock parameters provided by the Intergovernmental Panel on Climate Change (IPCC). It was found that significant urban expansion could be observed in 83 cities, while 29 cities showed a deforestation trend, and croplands in 42 cities have shrunk. The land cover change reduced carbon stock by more than 112 M tons in the 100 selected cities from 2013 to 2022. Thirty-nine cities showed significant negative trends in land carbon stock mainly caused by urban sprawl and shrinkage in forest or cropland, among which Kolkata, Chongqing, Seoul, Guangzhou, and Hefei showed the greatest decline. Because forest and cropland growths, or reduction in barren land and grassland, 28 cities showed clear positive trends in land carbon stock.

Another study by Legessea *et al*. (2023) examined carbon stocks' spatial and temporal dynamics in the Upper Awash Basin over three decades due to land use and land cover changes. They used remote sensing, ArcGIS, and the InVEST model to map land use, land cover, and carbon storage changes. The study showed that between 1993 and 2023, forests, shrublands, and wetlands decreased by 27.7%, 41.7%, and 60.7%, respectively, while cropland and built-up areas increased by 9.7% and 154.7%, respectively. Thus, the overall carbon stock decreased by 15%, from 17.3 to 14.8 M tons. It identified agriculture expansion, overexploitation of forests for wood and charcoal production, settlement, population growth, and urban development as the primary drivers of carbon loss.

Li & Kong (2024) examined the driving factors of land cover changes in typical cities. It simulated their carbon stocks in multiple scenarios to promote the development of sustainable use of land resources and to achieve the goal of "dual-carbon." The study revealed that the rate of surface cover change in Shijiazhuang City is relatively fast, but the rate of surface cover changes gradually slowed down in 20 years. Land cover change mainly manifests in the mutual transfer of cropland, woodland, and grassland. Simulations projected that as cropland, water bodies, and bare land decreases, the business-as-usual development scenario will have the most drastic increase in construction land. On the other hand, changes in woodland and grassland are seen to weaken, with a corresponding increase in economic benefits. In the Ecological Priority Development scenario, woodland, and grassland are expected to expand significantly while construction land growth stagnates, and ecological functions will be restored. In the Ecologically and Economically Balanced Development scenario, ecological land will increase, and the growth of built-up land will slow down, resulting in economic and environmental benefits.

Urban land expansion, or urbanization, is the primary driver of several environmental and socio-economic problems on various scales (Gao & O'Neill, 2020). New urban lands' locations and processes are influenced by socio-demographic, economic, and political factors (Rosni & Noor, 2016). According to the trends, as the world's population increases, so does the need for urbanization as it promotes industrialization and economic growth. Globalization has prompted Southeast Asian governments to prioritize economic development in their respective metropolitan areas to enhance their cities' economic competitiveness (Zhao, 2011; Rosni & Noor, 2016). People will move from rural areas into cities for employment and to improve their living standards. Circumstances resulted in significant disparities between urban and rural areas in numerous Southeast Asian cities and urban sprawl (Abdullah, 2012). This phenomenon is attributed to the escalating migration rate, leading to unregulated land use/cover alterations in urban fringes. As a result, several adverse consequences arise, including overcrowding, water scarcity, air pollution, the depletion of productive agricultural lands, and the reduction of forest cover over extended periods (Seto *et al*., 2010; Sridhar *et al*., 2020). A similar study by Romero *et al*. (2018) also revealed that the increase in urban growth of 37% between 1962 and 2011 is directly associated with the clearing of 50% of the Atlantic Forest in intermediate/advanced stages and 40% in early stages in the Metropolitan Region of São Paulo, Southeastern Brazil. The finding of this study is also in line with the previous study of Encisa-Garcia *et al*. (2020), who reported that the forest fragmentation in the Baroro River Watershed, La Union, Philippines, is due to the expansion in agricultural and built-up areas.

The La Mesa Watershed Reservation in the Philippines is among the numerous watersheds that showed significant deforestation between the 1960s and 1999 (Estoque *et al*., 2018). This deforestation was mostly attributed to slash-and-burn techniques, illegal tree harvesting, and the expansion of urban areas (Tiburan *et al*., 2013). LMWR currently has a significant amount of forest cover, the last of its magnitude in the National Capital Region (NCR). As such, it acts as a crucial carbon sink and the "lungs" of the densely populated city. Forest restoration efforts have increased the amount of forest cover in the watershed. However, the increased number of informal settlers and built-up areas due to population growth has been a significant driver of forest cover changes near the LMWR (MWSS, 2014; Estoque *et al*., 2018).

Rapid industrialization and economic growth in major cities cause migration of the population from rural to urban centers for employment and to improve their standard of living. As more people now live in urban areas, the cities are expanding spatially to accommodate the migrated and increasing population, leading to sprawling urbanization (Sudhira & Ramachandra, 2007; Bhatta *et al*., 2010). Urban sprawl is a form of rapid, unpremeditated urbanization process that converts land use land cover (LULC), such as the forest, to built-up, affecting the biophysical characteristics present in the area (Sudhira & Ramachandra, 2007; Bhatta, 2010; Sonde *et al*., 2020). It can significantly alter forest spatial distribution, which may have long-term consequences on the forest's ability to store carbon and sequester carbon dioxide from the atmosphere (Josefsson *et al*., 2009; Churkina *et al*., 2010; Estoque & Murayama, 2011).

The LMWR is a crucial carbon sink that requires prompt and continuous conservation and rehabilitation efforts to fulfill its ecological functions (Presidential Proclamation No. 1336, 2007). However, the urban expansion in the area is incongruous with this objective. Conversely, sustainable urban development also depends on a thorough comprehension of urban ecosystem services, which necessitates baseline information on the structure and functions of forests (Luederitz *et al*., 2015). To assess how well urban vegetation supports the resilience of human-environment systems, biological quantities of vegetation, such as tree biomass, carbon stock, area coverage, and factors affecting distribution (*e.g.*, urbanization), have to be considered as indicators (Mitraka *et al*., 2014; Chrysoulakis *et al*., 2013). While several studies are conducted elsewhere on the topic, little is known about how urban sprawl affects the ecological integrity of La Mesa Watershed. Thus, an understanding of the relationship between the increase in built-up areas (urban sprawl) and the reduction of forest carbon stock is crucial to affirm the sustainable use of the La Mesa Watershed Reservation as a source of water for Metro Manila and as a vital carbon sink, as well as to ensure sustainable urban planning in response to climate change and environmental deterioration. In this regard, the study has sought to analyze the effects rapid urban sprawl has on forest carbon stock in the area based on changes in land cover types and estimates on the current and projected total stored carbon in aboveground and belowground biomass in the watershed.

## METHODOLOGY

### Study area

LMWR comprises the La Mesa dam, reservoir, and treatment facilities. The watershed has 2,659 ha, of which 367.17 ha are a reserve or lake (MWSS, 2014). It spans from 14.71° to 14.78° north latitude and 121.06° to 121.14° east longitude. It traverses Quezon City, Caloocan City, San Jose Del Monte City, located in the province of Bulacan, and the Municipality of Rodriguez in Rizal (**Figure 1**). The climate of the LMWR is categorized as Type 1, characterized by two different seasons: a dry season from November to April and a wet season in the remaining months of the year, according to the Corona Climate Classification System. Within the LMWR, the mean annual precipitation is approximately 2,000 mm, while the mean annual temperature is around 27°C (MWSS, 2014).

The study site is in the northern part of Metro Manila, which has been significantly impacted by urban sprawl driven by population growth and migration patterns. Metro Manila has experienced substantial population increases over the past decades. According to data from the Philippine Statistics Authority (PSA), the region's population grew from approximately 13.5 M in 2018 to about 14.4 M in 2022. This rapid growth has intensified housing and infrastructure demands, expanding urban areas into previously forested regions, including parts of LMWR.

Further, the 2018 National Migration Survey by the PSA and the University of the Philippines Population Institute revealed that Metro Manila is a primary destination for internal migrants, attracting individuals seeking better employment and educational opportunities. This influx has contributed to the region's urban sprawl, as new residents require additional residential and commercial spaces. Expanding urban areas into the LMWR has converted forested lands into built-up environments. Such conversions result in significant carbon stock losses and increased $CO_2$ emissions, undermining conservation and reforestation efforts in the watershed.

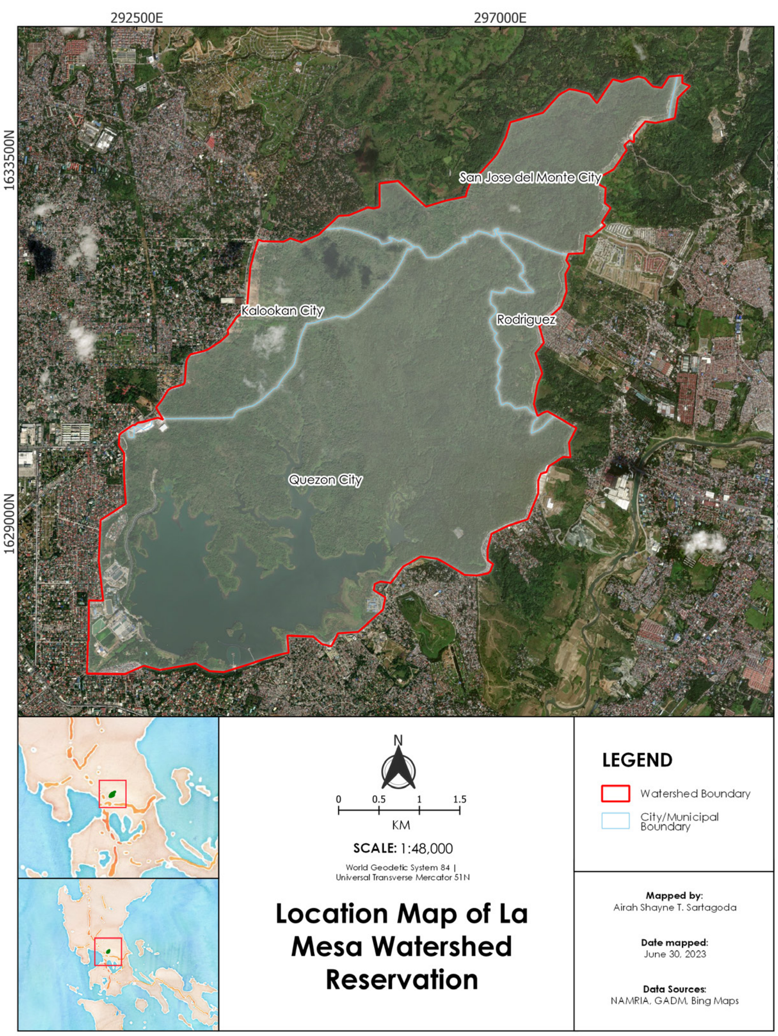


**Figure 1**. Study site map within the Northern part of Metro Manila.

**Methodological framework**

Landsat images from Google Earth Engine (GEE) for 2010 and 2020 were acquired to generate land cover maps (**Figure 2**). The utilization of remote sensing techniques and GIS tools enabled the delineation of the watershed boundary. A supervised classification method performs land use and land cover classifications. An accuracy assessment was performed to validate the accuracy of the land cover classification. TerrSet LCM was utilized from the classified images to investigate and quantify the dynamic changes in land cover classes over the study period. Emphasis was placed on analyzing the trend, pattern, and extent of urban sprawl in the forest.

The transition map in LCM is a useful tool for identifying regions experiencing significant urbanization or alterations in land use patterns. After the transition from forest to built-up areas between 2010 and 2020 was quantified, estimating the forest carbon stock lost from the conversion was assessed using standard accounting methods. This involved integrating

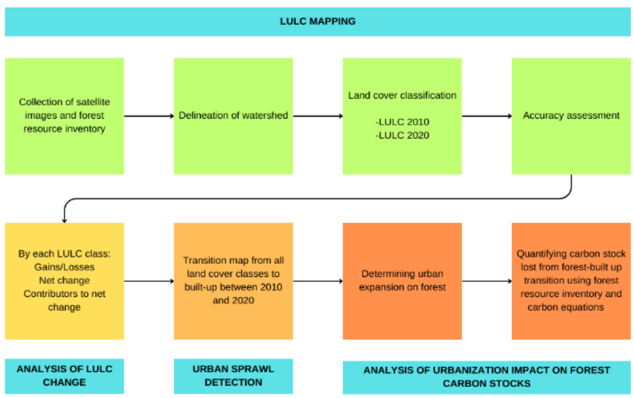


**Figure 2.** Methodological framework of the study.

secondary data, satellite-derived information, and established carbon stock equations. However, one of the study limitations was that the results do not show the linearity of the land use changes in the area. Likewise, more reliable satellite images were not considered due to time and logistical constraints. The quantification of forest carbon stock serves not only as a crucial indicator of the ecological health of the watershed but also as a baseline for assessing the impact of land use changes, particularly urban sprawl, on forest carbon sequestration.

### Satellite data acquisition and pre-processing

The LMWR's land cover was categorized differently from 2010 to 2020 using satellite pictures from the Landsat-5 Thematic Mapper (TM) and Landsat-8 operational land imager (OLI) with 30 meters spatial resolution. The GEE was used to download Landsat images. The acquired satellite images were processed using a semi-automatic categorization plugin (SCP) and QGIS version 3.16.

### Supervised land cover classification

The land cover classification utilized in this study was derived from the National Mapping and Research Information Authority (NAMRIA), encompassing distinct land cover classes such as water, forest, built-up areas, agricultural, and grassland or shrubland based on the DENR Memorandum Circular 2005–005:

a) agriculture consists of areas used for cultivating crops such as rice, corn, and coconut, often interspersed with patches of other vegetation. It is characterized by seasonal changes in vegetation cover, reflecting planting and harvesting cycles;
b) built-up areas refer to regions dominated by human-made structures, including residential, commercial, and industrial buildings and infrastructure like roads. Impervious surfaces and limited vegetation mark these areas;
c) brush or shrubland covers areas dominated by low-growing woody plants and scattered grasses, often found in degraded forests or abandoned agricultural lands. It provides habitat for certain wildlife and can serve as a transitional vegetation type in land recovery;
d) inland water includes lakes, rivers, reservoirs, and other bodies of freshwater within the country's landmass. These areas play a crucial role in water supply, biodiversity, and local climate regulation; and
e) open forests are woodlands with a sparse canopy cover, typically between 10% and 40%, allowing sunlight to reach the ground; and they are often found in upland areas and provide ecological services such as erosion control and wildlife habitat.

Using the natural image colors produced by Landsat-5 and Landsat-8, training points were allocated. The Maximum Likelihood classification algorithm, including the mean and the variance of the signature, was used to approximate the probability of classifying the pixel to its appropriate class. This algorithm was selected since other algorithms can improperly classify the outlying urban areas (Sarker, 2021).

### Accuracy assessment

The SCP plugin's post-processing capabilities in QGIS were used to process the accuracy map with a minimum accuracy of 80%. The plugin enhances the quality and usability of satellite image classifications and allows users to generate a confusion matrix by comparing the classified map with reference data to assess accuracy. It provides overall accuracy, user's accuracy, producer's accuracy, and kappa coefficient to evaluate how well the classification performed.

This study compares a reference classification or a validation point using the confusion matrix. Cross-tabulating the variables used in the reference data and the map was also necessary for the confusion matrix.

### Land change modeling

LCM is a feature of the Clark Labs TerrSet Geospatial Monitoring and Modeling System that allows users to easily depict land change dynamics (Hasan *et al*., 2020). Specifically, LCM involves analysis of land cover changes between two time periods by comparing satellite images or maps. It highlights areas of change, calculates change rates, and visualizes the transitions between different land cover types. It then uses machine learning algorithms (such as neural networks or logistic regression) to assess the factors influencing land cover transitions. These factors can include elevation, proximity to roads, or population density and help create a model of how and why changes occur. It simulates future land cover scenarios based on historical trends and transition potentials. Users can define time horizons for the predictions and create "what-if" scenarios to evaluate the impact of policy or environmental interventions. In short, LCM helps analyze the impact of land use changes on biodiversity, carbon sequestration, or habitat loss. Shapefiles must be converted to IDRISI files to access change analysis in LCM.

Supervised land cover classification images of 2010 and 2020 were used to calculate the change using LCM. From the classified images, LCM session parameters were set into the gains/losses, net change, and contributors to net change experienced by each land cover class. The transition from all land cover classes was mapped to built-up areas to analyze urban growth patterns.

### Carbon stock estimation

Secondary data were collected to assess the total amount of forest carbon stored in the LMWR in 2020. For the 2020 forest cover, forest inventory data of the LMWR from 2020 was obtained from the MWSS (**Appendix Table 1**). With 915 inventoried trees and allowing a +/– 5% margin of error, a sample size of 278 individual trees was obtained using Yamane's formula (1967). The inventory only includes trees with a diameter at breast height (DBH) ≤ 10 cm.

### Biomass calculation

Litter/necromass and soil organic carbon have not been considered as the study used forest inventory data described above, which covered a portion of the watershed using cluster sampling, particularly the DBH of sampled tree species. Having the DBH, two carbon pools were measured (**Table 1**), including the aboveground biomass (AGB) and belowground biomass (BGB) using allometric equations for tropical trees developed by Brown (1997), Brown *et al*. (1989), and Pearson *et al*. (2005), respectively. The results were used as inputs to the LCM model to estimate the total share of tree AGB and BGB.

**Table 1**. Biomass regression equations for estimating tree biomass of tropical moist trees (Brown, 1997; Brown *et al*., 1989) and root biomass computation based on tree biomass of individual trees (Pearson *et al*., 2005).

| DBH (cm) | Equation | Adjusted $r^2$ | Author |
|---|---|---|---|
| < 60 | $Y = exp\{-2.134 + 2.530 \times ln (DBH)\}$ | 0.97 | Brown (1997) |
| 60–148 | $Y = 42.69 - 12.800 \times DBH + 1.242 \times (DBH)^2$ | 0.84 | Brown *et al.* (1989) |
| 10–148 | $Y = exp\{-1.0587 + 0.8836 \times ln (AGB)\}$ | 0.84 | Pearson *et al.* (2005) |

*Where: Y = tree biomass (kg); DBH = diameter at breast height (cm); Biomass per tree was converted to ton.*

### Carbon density

The conversion of plant biomass to carbon was achieved by multiplying the carbon content percentage of each pool. This study used Lasco *et al*. (2004) average carbon content of 45.4% for ABG and Racelis *et al*. (2000) 46.9% carbon stored in roots for BGB. The total carbon density of the forest was computed by adding the carbon densities of the two carbon pools (Xiang *et al*., 2018).

### Carbon dioxide ($CO_2$) content

To determine the weight of carbon dioxide ($CO_2$) sequestered (tons $ha^{-1}$), the weight of carbon per pool was multiplied by 44/12.

### Total carbon stock

This was determined by summing up the contribution of the different C pools and then multiplied by its area (Lasco & Pulhin, 2006).

## RESULTS AND DISCUSSION

### Land cover classification of La Mesa Watershed Reservation

The classified land cover maps of LMWR for 2010 and 2020 (**Figures 3 and 4**) illustrate a substantial change in the landscape of the study area. The results of the Land Cover distribution for 2010 and 2020 revealed that among all the land cover classes, forest accounted for most of the area, standing at 1,906.39 ha (71.70%) and 1,966.87 ha (73.97%), respectively (**Table 2**). For 2010, forest was followed by inland water, comprising 16.82% of the watershed, while the grassland or shrubland has an area of 212.44 ha. Built-up obtained the least land cover area with an area of 93.02 ha. For 2020, the forest was also followed by inland water, making up 373.09 ha. Grassland/shrubland and built-up areas obtained an area of 187.73 ha (7.06%) and an area of 113.88 ha (4.28%), respectively. Agriculture had the least area of 17.44 ha. When analyzing the changes in land cover between 2010 and 2020, it was found that the open forest experienced the highest increase in area, growing by 60.48 ha or 2.27% concerning the total watershed area. As forest cover increased, built-up areas and agricultural lands increased by 0.78% and 0.66%, respectively. Conversely, inland water decreased in area by 2.79% and grassland/shrubland by 0.93%.

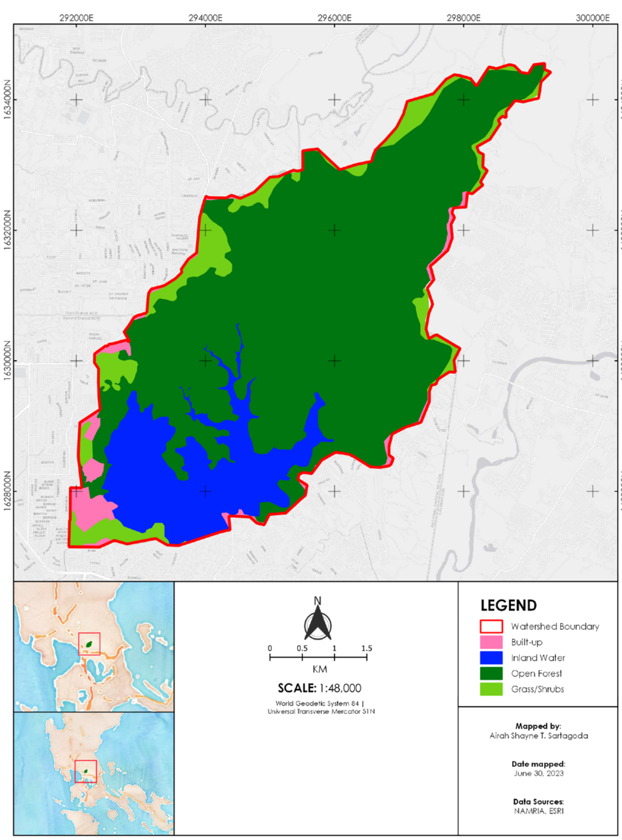


**Figure 3**. 2010 Supervised land cover classification of LMWR.

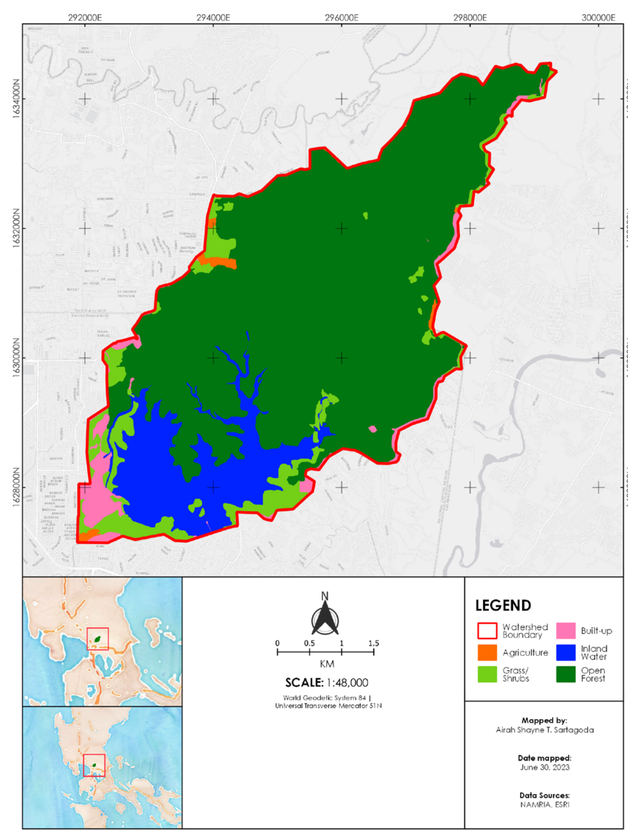


**Figure 4.** 2020 Supervised land cover classification of LMWR.

**Table 2**. Summary of land cover change data between 2010 and 2020 in LMWR.

| Land cover type | Land cover 2010 | | Land cover 2020 | | Difference (2010–2020) | |
|---|---|---|---|---|---|---|
| | Area (ha) | Area (%) | Area (ha) | Area (%) | Δ area (ha) | % change |
| Agriculture | 0 | 0 | 17.44 | 0.66 | 17.44 | 0.66 |
| built-up | 93.02 | 3.50 | 113.88 | 4.28 | 20.86 | 0.78 |
| Grass/ Shrub | 212.44 | 7.99 | 187.73 | 7.06 | –24.71 | –0.93 |
| Inland water | 447.15 | 16.82 | 373.09 | 14.03 | –74.06 | –2.79 |
| Open forest | 1,906.39 | 71.70 | 1,966.87 | 73.97 | 60.48 | 2.27 |
| Total | 2,659 | 100 | 2,659 | 100 | | |

*Negative value indicates a decrease in the area covered.*

## Accuracy assessment

A Kappa hat classification of 0.8113 and 87.59% accuracy was obtained for the 2010 land cover, while the land cover classification for 2020 has a Kappa hat classification of 0.8373 and an accuracy of 89.03%. A good classification or agreement is one with a kappa coefficient of 0.8–1. With this, the 2010 and 2020 classifications are considered good.

## Land cover change analysis

To aid in interpreting the changes occurring in the watershed, gross gains and losses for each land cover class from 2010 to 2020 were evaluated using the TerrSet LCM (**Figure 5**). Unfortunately, conversion of the vector data to raster is needed to use the LCM, which somewhat degrades the data (HSU, 2018). Thus, classification error pertinent to the actual cover is inevitable. A positive value denotes a gain state, whereas a negative value signifies loss. Among all the land cover types, open forest had the highest gain, accumulating an increase of 2.54%, while grassland/shrubland had the highest loss of 2.25%. Major changes in other land cover types include loss of inland water (92 ha or 1.65%) and gain of built-up (41 ha or 0.74%). Open forest, built-up, and agriculture classes had net expansions to balance gains and losses, whereas inland water and grassland/shrubland contributed to the net reduction. In net expansions, open forest got the highest positive change of 59.94 ha with 1.07%, while in net reduction, inland water got the highest negative change of 74.79 ha with 1.34%. The greatest contributor to the net change experienced by open forest, inland water, and agriculture was grass/shrub, while for built-up and grass/shrub, open forest had the highest contribution to their net change.

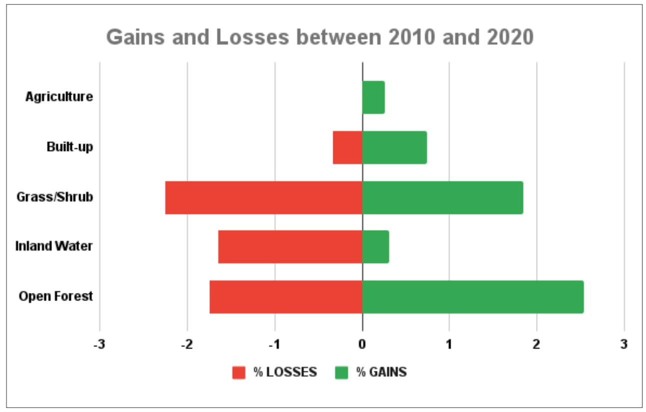


**Figure 5**. Land cover classification gains and losses.

## Urban sprawl

This occurs when there is a rapid increase in urbanization (Viana *et al*., 2019). **Figure 6** shows the rapid increase of urban areas within the boundary of the study site between 2010 and 2020, which was already explained earlier. Aside from the 0.74% total gain in built-up, it also has a persistence of 72.66 ha (**Table 3**). The increase in built-up areas resulted in changes in open forest, grassland/shrubland, and inland water. **Table 4** shows that the forest has the highest value of change to urban growth as it contributes 67.69% or 27.90 ha to the total gain of the urban area. This was followed by the conversion of grassland/shrubland, which has 11.88 ha of land area or 9.49% of the total loss of the respective land class. Inland water, on the other hand, also contributed to the urban growth in LMWR, as there are 1.56% changes in the loss of inland water. Thus, the loss of area in forest cover had the greatest contribution to the growth of built-up areas in the watershed (**Figure 7**). There was also noticeable high urban growth in Quezon City, while there are patches of new urban areas in San Jose del Monte City, Bulacan; Rodriquez, Rizal; and Caloocan City.

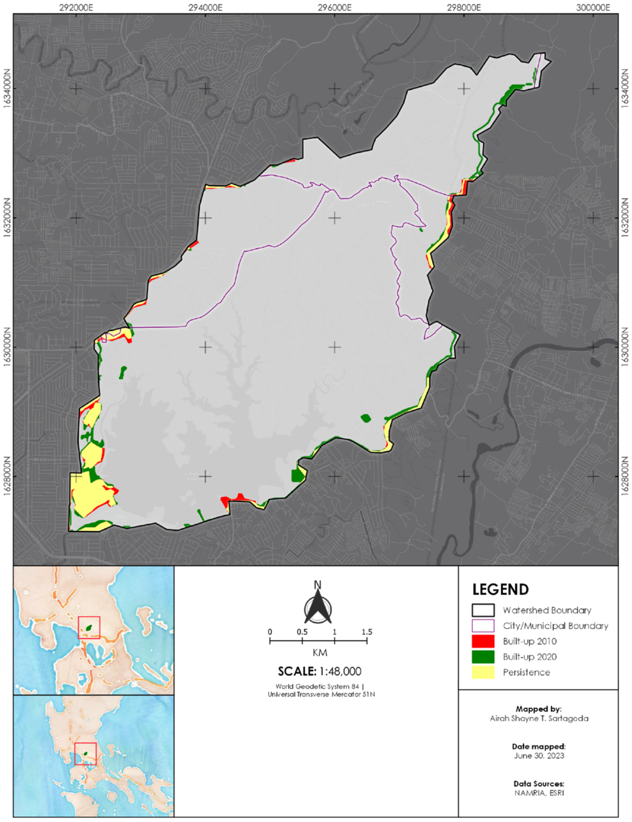


**Figure 6**. Built-up area map of LMWR between 2010 and 2020.

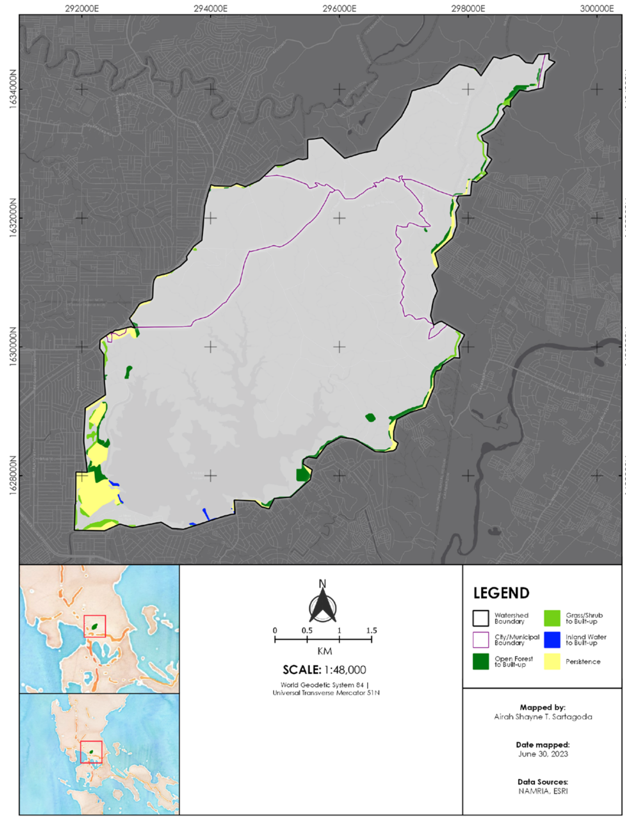


**Figure 7**. Transition from all land classes to the built-up area in LMWR.

**Table 3**. Built-up increase and persistence between 2010 and 2020.

| | Area (ha) | Area (%) |
|---|---|---|
| Built-up 2010 | 93.02 | 3.50 |
| Built-up 2020 | 113.88 | 4.28 |
| Persistence | 72.66 | 2.73 |
| Total gain | 41.22 | 0.74 |

**Table 4**. Transition from all land cover classes to built-up between 2010 and 2020.

| Built-up 2010–2020 | Area (ha) | Area (%) |
|---|---|---|
| Persistence | 72.66 | 63.80 |
| Open forest to built-up | 27.90 | 24.50 |
| Grass/Shrub to uilt-up | 11.88 | 10.43 |
| Inland water to built-up | 1.44 | 1.26 |
| Total | 113.88 | 100 |

## Forest carbon storage

Due to the increase in built-up areas in the watershed, forest cover lost 27.90 ha. It made the greatest contribution to the growth of built-up areas in the watershed, while built-up was the second land cover that had the most impact on the loss of forest cover between 2010 and 2020, as mentioned in the land cover change analysis. The occurrence of substantial decreases in forest coverage due to urbanization has the potential to result in a decrease in the amount of carbon stored in forests, as well as an increase in the release of carbon into the atmosphere (Seto *et al*., 2012; Moisa *et al*., 2023). Using the forest inventory data from 2020, the forest's total biomass and total carbon density at that period were estimated to calculate the amount of forest carbon lost and $CO_2$ -e released from the forest-built-up transition.

**Table 5** shows that the amount of carbon lost from the open forest to built-up conversion between

**Table 5**. Total forest carbon stock lost from built-up areas.

| | Area (ha) | Biomass density (tons $ha^{-1}$) | Carbon density (tons $ha^{-1}$) | Carbon stocks (tons) | $CO_2$ -e (tons) | Carbon increase per year (tons $yr^{-1}$) | $CO_2$ -e increase per year (tons $yr^{-1}$) |
|---|---|---|---|---|---|---|---|
| Open forest | 27.90 | | | | | | |
| AGB | | 241.51 | 109.65 | 3,059.24 | 11,217.21 | 305.92 | 1,121.72 |
| BGB | | 35.60 | 16.70 | 465.93 | 1,708.41 | 46.59 | 170.84 |
| Total | | 277.11 | 126.35 | 3,525.17 | 12,925.62 | 352.52 | 1,292.56 |
| | | Lost carbon sequestration potential due to urban sprawl (tons) | | | Lost carbon sequestration potential per year (tons $yr^{-1}$) | | |
| Total | | 3,525.17 | | | 352.25 | | |

2010 and 2020 is 3,525.17 tons or 126.35 tons $ha^{-1}$, which is equivalent to a total of 12,925.62 tons or 463.28 tons $ha^{-1}$ of $CO_2$ emissions. This is significantly lower than the findings of a pioneering study by Lasco *et al*. (2004), which estimated the total biomass (above and below ground) of secondary forest in the Mount Makiling Forest Reserve (MMFR) to be 250 tons $ha^{-1}$ excluding soil carbon, which comprised about 40% of the total. The difference is explained by the lower tree density of planted open forests compared to a secondary natural forest. Thus, about 3,525.17 tons of carbon would have been sequestered had this forest area not been converted to built-up. Furthermore, the area has the potential to sequester 352.52 tons of carbon $yr^{-1}$. Regarding the total carbon stock in 2020 (**Table 6**), if the forests were not converted to built-up, its total carbon sequestration would increase by 1.42%. It would have had 252,019.42 tons of carbon or sequestered 924,071.19 tons of $CO_2$.

**Table 6**. Potential forest carbon sequestration in 2020.

| | 2020 Forest carbon (tons) | 27.9 Hectare carbon sequestration potential (tons) | 2020 Carbon sequestration potential (tons) | Amount increased (%) |
|---|---|---|---|---|
| C stored (tons) | 248,494.25 | 3,525.17 | 252,019.42 | 1.42 |
| $CO_2$ -e (tons) | 911,145.57 | 12,925.62 | 924,071.19 | 1.42 |

**Effect of urban sprawl on forest carbon stock**

The reduction of forest cover caused by urban sprawl led to a carbon stock loss of 3,525.17 tons in tree biomass, equating to 12,925.62 tons of $CO_2$ emissions. Thus, deforestation due to urban sprawl negatively affects the forest carbon stock of the watershed. This study's findings align with the study of Drummond & Loveland (2010), which found that the decrease in agricultural land use facilitates the restoration of forests. However, a significant land cover shift has occurred, transitioning from a pattern of regional forest-cover gain to one characterized by forest-cover loss due to urbanization. The transition above carries significant implications for the estimation of carbon fluctuation. A similar study by Shrestha *et al*. (2010) also found that converting forests to alternative land uses reduced vegetation carbon, with a maximum loss of 22.7 kg C $m^{-2}$. Conversely, converting other land use types into forests increased vegetation carbon. In the Philippines, a study conducted in the Pantabangan-Carranglan Watershed by Dida *et al*. (2021) showed the impacts of LULC changes and forest disturbances on carbon dynamics. Results show an increase in the grassland and forest areas in Pantabangan-Carranglan Watershed from 2014 to 2020 based on the LULC classification process of Landsat-8 images. Reforestation, plantation, agroforestry establishment, and other human interventions may have caused the changes. The LULC changes from 2014 to 2020 confirmed the changes in the NDMI values. The decrease in open/barren areas matched the decline in forest disturbances. The InVEST model used in the study showed that the increase in forest areas from 2014 to 2020 increased total carbon stock. Likewise, the decrease in the NDMI, an indicator of forest disturbances, matched the reduction of open/barren LULC classes from 2014 to 2020.

According to the 2008 DENR NCR study, “Profiling and Characterization of the La Mesa Watershed Reservation,” which was included in the Integrated Watershed Management Plan for the La Mesa Watershed Reservation for 25 Years, the watershed is now bordered by expansive urban development. Although LMWR is officially recognized as a titled property under the MWSS, a significant number of informal settlers reside inside some areas of the LMWR.

Relocation was done in 2014 but was not successfully executed due to the inadequacy of the Relocation Action Plan (RAP). The settlers articulated their intention to remain in the LMWR not solely to acquire residential plots but to establish a lasting space dedicated to agricultural pursuits, such as cultivating vegetables and fruit trees. Consequently, the compulsion for individuals to return to their original means of sustenance within the watershed was evident. This can be supported by Almeida (2005) and De Ridder *et al*. (2008), which highlighted the influence of socioeconomic factors on the expansion of urban areas. Owing to the comparatively reduced cost of living and convenient access to resources and basic amenities, individuals in urban areas sometimes tend to relocate from the city center and establish residences in the surrounding verdant regions. However, this unpremeditated urbanization process drives deforestation and results in the loss of terrestrial carbon stored in vegetation biomass. According to Hedblom & Soderstrom (2008), urban sprawl directly affects carbon density by changing the forest stand's type of trees, age structure, and vegetation. Tropical forests store most of their carbon in vegetation (biomass). When deforestation arises as a consequence of urban expansion, a substantial portion of the carbon that trees have stored is subsequently emitted into the atmosphere in the form of carbon dioxide, leading to higher carbon emissions and degradation of ecosystem services, in particular, carbon sequestration and storage (Shao *et al*., 2008; Behnisch *et al*., 2022).

## CONCLUSION

Watersheds are important sources of ecosystem services. Yang *et al*. (2019), as cited by Codilan *et al*. (2024), mentioned that watersheds provide essential services to the community, like food and water production, regulating services (flood control and soil conservation), supporting devices (nutrient cycling), and cultural services. However, rapid urbanization drives deforestation, result in the loss of carbon stored in tree biomass and adversely affect its carbon sequestration capacity.

The study analyzed the effect of urban sprawl on forest carbon stock in the La Mesa Watershed Reservation, Philippines, using TerrSet LCM and Carbon Stock Assessment. The analysis of the historical changes in land cover in LMWR revealed that between 2010 and 2020, grassland/shrubland and inland water decreased in the area while forest, built-up, and agriculture increased. A high increase in built-up or urban sprawl can be seen in the lower part of the watershed, within the Quezon City boundary. This rapid growth in built-up areas is at the expense of forest cover. This means that forest cover loss contributed the most significant amount to the growth of built-up areas in the watershed. About 27.90 ha of forest were converted into built-up areas, resulting in a carbon stock loss of 3,525.17 tons in tree biomass, equivalent to 12,925.62 tons of $CO_2$ emissions. Furthermore, the total forest carbon stock in 2020, if the forests were not converted into built-up areas, would increase by 1.42%. It would have had 252,019.42 tons of carbon or sequestered 924,071.19 tons of $CO_2$, absorbing 5.3% of the carbon emissions of the metropolis. Thus, urban sprawl negatively influences the total forest carbon stock of the watershed. Urban sprawl, driven by socio-economic considerations and whose human activities—such as waste disposal, livelihood, and illegal activities—seriously threaten any conservation, reforestation, and protection efforts in the area. Reversing this scenario depends on changes in government spatial policy planning and management interventions aimed at controlling urban land use development and ensuring the maintenance of the remaining forest for increased capacity of the watershed in sequestering carbon and other important ecosystem services. To further improve the quality of future urban sprawl studies, conducting field validation of random points is suggested as a basis for accuracy assessment. In addition, satellite images that cover smaller areas, such as Sentinel 2 with 10-m spatial resolution, can produce a more accurate land cover classification. Furthermore, it is recommended that the future detection tool of Idrisi TerrSet be used to model future urban sprawl and landscape changes in the forest of La Mesa Watershed Reservation. Regarding carbon stock assessment, further studies should perform primary data collection of biomass densities in different carbon pools of the watershed to improve the study's accuracy.

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