ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-5/W4-2025
Philippine Geomatics Symposium (PhilGEOS) 2025 "Enhancing Human Quality of Life through Geospatial Technologies", 24–25 November 2025, Quezon City, Philippines

Multitemporal Analysis of Green Spaces in Manila, Philippines through a Green Index

Fredrik Angelo F. Francisco [1], Daniel Dresden O. Gonzales [1], Alexi Mae Y. Narca [1], Jommer M. Medina [1]

[1] Department of Geodetic Engineering, University of the Philippines, Diliman, Quezon City, Philippines – (fffrancisco, dogonzales1, aynarca, jmmedina)@up.edu.ph

Keywords: Change Detection, 3D Modeling, Urban Sustainability, Land Cover Change, Remote Sensing

Abstract

In a highly urbanizing settlement, such as the City of Manila, the presence of green spaces is crucial in achieving environmental quality objectives and nurturing sustainable local development. This study aimed to identify vegetation and built-up areas within Manila City across multiple remotely sensed images from 2018 to 2024. Sentinel-2 Level-2A products were processed for land cover classification, while canopy and building height datasets were used for three-dimensional analysis. Additionally, the researchers developed a Green Index, based on 3D modeling insights that considered citizen perspectives, area allocations, feature heights, and building density, which would serve as a valuable tool for decision makers in providing insights into the current state of green spaces within the city. Multitemporal analysis was conducted through ENVI's Thematic Change Detection Tool, classifying land cover changes between built-up and vegetation areas. Thematic change detection showed that at least 90% of Manila's land cover remained unchanged from 2018 to 2024, and less than 2% of the area transitioned between built-up and vegetation classes, suggesting minimal efforts in either developing new green spaces or protecting existing ones. Further analysis using the Green Index revealed that a substantial portion of Manila is dominated by built-up areas with limited nearby vegetation, resulting in predominantly negative values on the green index maps. This finding highlights the urgent need for enhanced urban greening efforts to improve liveability and environmental resilience in Manila.

1. Introduction

In 2020, the Philippine Statistics Authority reported that urbanization in the Philippines reached 54.0%, a 2.8-percentage point increase from 2015, reflecting an increase of 7.20 million in urban residents. The report further highlighted that the Philippines has 33 highly urbanized cities (HUCs), four of which recorded more than a million population namely, Quezon City (2.96 million), Manila City (1.85 million), Davao City (1.78 million), and Caloocan City (1.66 million) (PSA, 2021).

As urban areas rapidly expand, maintaining green spaces becomes critical to ensuring environmental quality and nurturing sustainable local development. According to the World Health Organization (2017), the efforts to enhance or expand urban green spaces have the potential to improve health, social, and environmental outcomes across various population groups, with a more pronounced impact on those in lower socioeconomic brackets. The continuous expansion of urban areas and sprawling development on Metro Manila leads to diminishing available space, leaving the city with fewer open green areas (Faizan, 2021).

Urban green spaces (UGS) constitute a vital aspect of urban environments, and their quantity and quality are central concerns for planners and city administrators. The objective measurement of greenness, such as the Green Index (GI), through remote sensing images is crucial in this context despite its insensitivity to spatial arrangement within the areal units (Gupta et al., 2012). The GI, as discussed in this paper, is recognized as a significant component of this set of indicators. The authors present an approach that utilizes remote sensing datasets and GIS layers to provide spatially aggregated information about green spaces. The methodology combines image processing, remote sensing, GIS, and spatial analysis tools to assess urban structures in terms of greenness.

Aligned with United Nation's Sustainable Development Goals (SDGs), particularly Goal 11 or Sustainable Cities and Communities, the study addresses Target 11.7, aiming to provide universal access to safe, inclusive and accessible, green and public spaces. This research seeks to contribute to the development of sustainable and resilient cities by highlighting the importance of preserving and enhancing our understanding of urban green spaces in Manila City.

This study aims to identify vegetation and built-up areas within Manila City across multiple remotely sensed images. Subsequently, it seeks to quantify and analyze dynamic changes in vegetation and built-up spaces over time through the application of Thematic Change Detection methods. In addition, the researchers intend to provide a three-dimensional perspective of the City of Manila by incorporating building and canopy heights. This approach will enhance the contextualization of green spaces, allowing for a more detailed understanding of the city's evolution over time. To consolidate the findings and present a comprehensive overview of the state of green spaces in Manila, the final objective is to develop a Green Index that considers citizen perspectives, area allocations, feature heights, and building density. This holistic index will serve as a valuable tool for policymakers, urban planners, and environmentalists, providing insights into the current state of green spaces within the city. Furthermore, the visual representation of this index aims to effectively communicate the findings to diverse stakeholders, encouraging a more informed and collaborative approach towards sustainable urban development in Manila.

2. Methodology

2.1 Study Area

The study area of the project is Manila City, Philippines (Figure 1). With a land area of approximately 24.98 square kilometers, Manila is recognized as one of the most densely populated cities in the world. According to the 2020 Census of Population and Housing, Manila has a population of 1,846,513, resulting in a population density of approximately 73,920 persons per square kilometer (Philippine Statistics Authority, 2021).

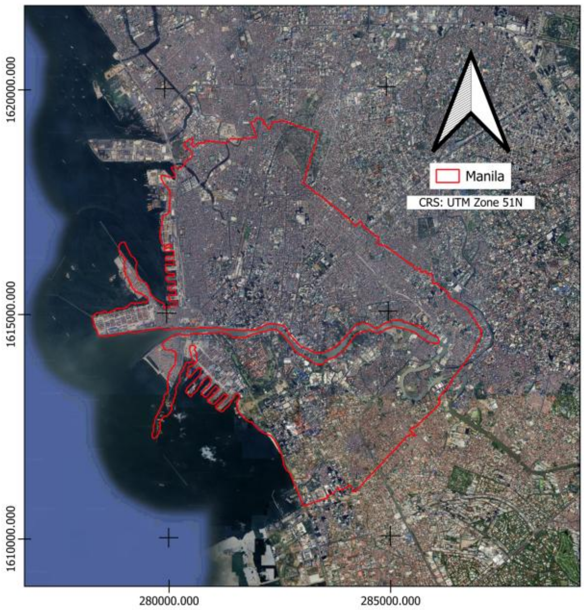

Figure 1. Manila City Administrative Boundaries

The urban landscape of the city is highly compact and dominated by built-up areas, with only limited green spaces available. Estimates indicate that Manila provides less than 1 square meter of green space per resident, which falls far below the recommendation of the World Health Organization of 9 square meters per capita (World Health Organization, 2017; Sarmiento and Porio, 2021). Notable public green spaces include:

- Arroceros Forest Park (2.2 hectares), often referred to as the "last lung of Manila" (Manila Bulletin, 2020);
- Rizal Park (Luneta) (58 hectares), serving as the largest open green space in the city; and
- Mehan Garden (2.3 hectares), one of the oldest botanical gardens in Asia.

Despite the presence of these parks, the overall green space of Manila remains insufficient to meet both the environmental and recreational needs of its residents. The ongoing urbanization and infrastructure development have continued to pressure the remaining open spaces, raising concerns about sustainable urban planning and the quality of life in the city.

2.2 Data Used

The study utilized a variety of remotely sensed raster and vector datasets to analyze the land cover and green spaces of Manila City from 2018 to 2024. The primary dataset comprised Sentinel-2 MSI Level-2A products, accessed via the Copernicus Browser and Sentinel Hub EO Browser (Copernicus Open Access Hub, n.d.). Sentinel-2 provides multispectral imagery with a band-dependent spatial resolution: 10 meters for bands B2 (blue), B3 (green), B4 (red), and B8 (near-infrared), and 20 meters for bands B5, B6, B7, B8A, B9, B11, and B12. A spectral subset was applied, removing Band 1, and the images were resampled to a uniform 10-meter resolution using nearest neighbor interpolation. The products are in surface reflectance values (0–1). Sentinel-2 Level-2A was chosen for its high spatial and spectral resolution, frequent revisit cycle, and suitability for urban land cover and vegetation analysis. These datasets and their processed versions are colored blue in the subsequent process flowcharts detailing the data processing, classification, and visualization steps.

For elevation data, Digital Surface Model (DSM) and Digital Terrain Model (DTM) rasters of Manila were sourced from the National Mapping and Resource Information Authority (NAMRIA, 2011), derived from LiDAR surveys conducted in 2011, with a 1-meter resolution. These datasets provided precise elevation information critical for generating 3D models of urban structures and canopy heights. These datasets and their processed versions are colored gray in the process flowcharts.

Building footprints were obtained from Google Open Buildings (2022), specifically Version 2, acquired in August 2022. This vector dataset includes delineations of very small buildings with a minimum confidence score of 0.65, clipped to the administrative boundaries of Manila City. This dataset and its processed versions are color-coded light blue in the pre-processing and visualization flowcharts discussed in later sections.

The Manila City administrative boundaries were sourced from the Global Administrative Areas Database (GADM, 2018), Version 4.1, which provided barangay-level delineations for precise spatial referencing. This dataset is color-coded orange in the visualization flowchart presented in a later section.

To assess canopy structure, a Canopy Height Model raster with 10-meter spatial resolution from Lang, et al. (2021) was utilized. This dataset, acquired in 2020 and available through Zenodo, provided vegetation height information essential for the 3D characterization of green spaces. This dataset and its processed versions are color-coded green in the corresponding flowcharts presented in subsequent sections.

2.3 Pre-Processing

All remotely sensed imagery underwent some preprocessing steps to ensure temporal and spatial consistency and improve classification. All bands of the Sentinel-2 MSI L2A product were upsampled to 10 m spatial resolution using Nearest neighbor. This resampling technique was used since it best preserves the original surface reflectance values of each band. It is also recommended that nearest neighbors be used for categorical purposes like land use classification, which is the intended process for this study (Esri, n.d.). After upsampling, the reflectance bands were stacked in order to reconstruct each satellite image. After layer stacking, each image was clipped using the city administrative boundary to limit the spatial coverage of subsequent processes and analyses to the study area.

To assign height attributes to the building footprints in the City of Manila, the normalized digital surface model (nDSM) was generated by subtracting the digital terrain model (DTM) from the DSM. This approach allowed for capturing the relative height of structures above ground level, essential for 3D visualization at Level of Detail 1 (LoD1). Median zonal statistics were applied to determine the representative height for each building footprint based on the nDSM values within its boundary.

The canopy height model (CHM) was also clipped to the extent of the Manila administrative boundaries to limit the dataset to the area of interest. The CHM provides information on the vertical structure of vegetation, specifically the height of trees and other green canopy layers across the city. The CHM used in this study was derived from spaceborne LiDAR and radar data, as processed and published by Lang et al. (2021), with a 10-meter spatial resolution. This dataset enabled a more detailed analysis of the spatial distribution and height of vegetation, contributing to the 3D contextualization and the subsequent calculation of the GI.

The overall pre-processing workflow is summarized in Figure 2, which outlines the steps for preparing Sentinel-2 images, generating building height attributes, and extracting canopy heights for the City of Manila.

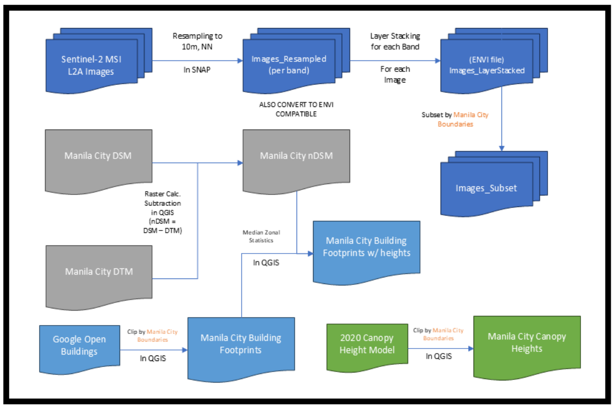

Figure 2. Pre-processing flowchart steps for resampling, layer stacking, subsetting, and generating building and canopy height attributes

2.4 Land Cover Classification

Land cover classification was executed in ENVI with the following technical details and summarized in Figure 3. Using ISODATA classification algorithm, a minimum of four and maximum of eight classes were set, along with the number of maximum iterations of 12. The rest of the parameters in the algorithm were left on default settings. A minimum of four classes was chosen as the focus of the study narrowed down to only built-up and vegetation areas later on. Majority analysis with a 5x5 kernel was applied. This was chosen rather than a 3x3 kernel since a generalized land cover classification of Manila was the goal of this key process. Cloud masks were not applied due to the decision to further generalize classes after classification for change detection, which is discussed further in this section.

Built-up areas, vegetation, water, and clouds were the general land cover classes generated after post-classification of the ISODATA classes. In replication, other land cover such as barren land or wetlands should be taken into consideration. However, Manila is a high-density urban area with patches of vegetation (e.g., green spaces and parks) and waterbodies (e.g., rivers). Barren land, like the sand along the shores of Manila Bay, or bare soil areas are too small and few in number and would most likely be generalized as other classes such as water due to proximity to the bay or built-up due to similarity in spectral properties. For further analyses, these possible outputs were noted, but should not significantly impact the analysis because of the general land cover and land use characteristics of the city.

Accuracy assessment was implemented using validation data created and cross-referenced with Google Earth Features, such as national parks for vegetation or malls for built-up areas, and the actual satellite image. After satisfying the accuracy requirement of traditional 85% for user's, producer's, and overall accuracies (Foody, 2008), each classified image was further generalized into just three classes for change detection, namely, built-up, vegetation, and neither which consisted of water and clouds. This additional generalization will simplify the analysis to be done in change detection.

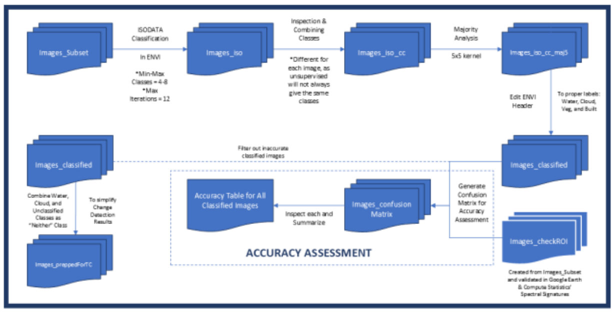

Figure 3. Land cover classification flowchart

2.5 Change Detection

Land cover images were paired with one another to examine how they changed between two time periods. For this, the Thematic Change Workflow tool in ENVI was used. The output of this process was a thematic image showing a change in land cover from one class to another. These changes were also quantified. An example of this can be seen in Figure 4.

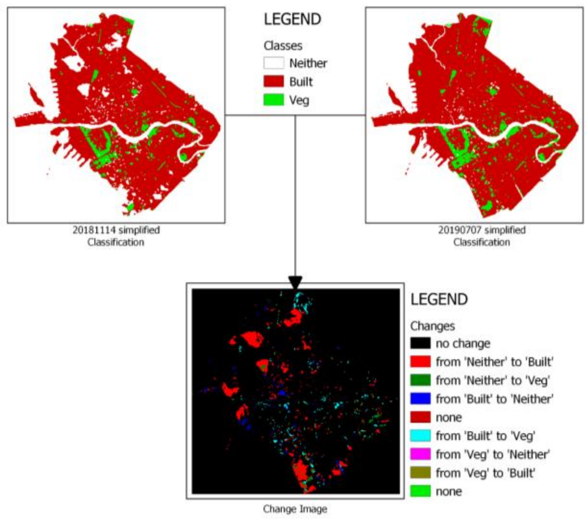

Figure 4. Change Detection Example

Smoothing and aggregation were also applied with default settings in the Thematic Change Workflow tool. A Green Development matrix that showcases a positive or negative change in green spaces or vegetation areas in Manila was created by subtracting the Veg to Built percent area from the Built to Veg percent area for each pair of images. a positive value indicated an increase in vegetation between two successive periods, while a negative value indicated a decrease in vegetation. Additionally, the Thematic Change Workflow tool also provides the value for the percent area with no changes between images (i.e. Veg Area in 2020 was still Veg Area in 2024). These values were compiled into the "No Change" Matrix. Interpreting the Green Development matrix and the No Change matrix provided insights on the overall state of Manila's green spaces and general land cover.

2.6 3D Visualization

To move onward with 3D Visualization, Vegetation areas, and built-up areas from each land cover image were extracted to be used in 3D visualization. Canopy cover was generated using contour polygons from the Manila City canopy height model, which was clipped to only the vegetation areas obtained from the land cover and change detection maps. This produced the Manila vegetation features with heights for extrusion. With the building footprints, vegetation features, and DTM all available, 3D visualization was rendered using qgis2threejs. Observations from the 3D model were used as the basis for the formulation of the Green Index for Manila City, following the foundations and principles presented by Schöpfer's proposed Green Index (2005). Other technical details regarding the visualization can be found in Figure 5.

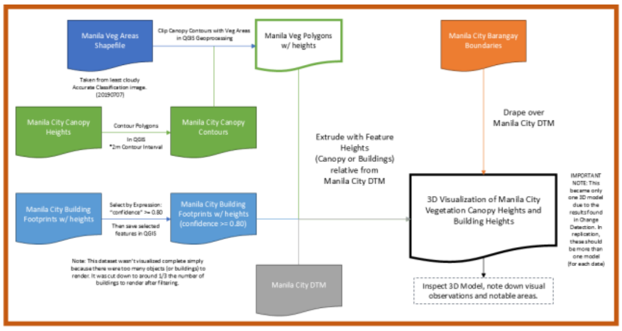

Figure 5. 3D Visualization Flowchart

2.7 Green Index Calculations

Since the variables necessary for the methodology of Schöpfer (2005) were not all present and equivalent, other means were used to achieve similar results to the Green Index. In this study, the Green Index was composed of the addition of four variables (Table 1):

$$GI = CPF + AAF + HCF + BDF \tag{1}$$

where GI is the green index
CPF is the citizen's perspective factor
AAF is the area allocation factor
HCF is the height comparison factor
BDF is building density factor

In adding all these factors, a GI range of -4 to 4 can be obtained, where -4 is completely built-up and 4 implies high greenness quality. Although Schöpfer (2005) did provide weights for each factor from their paper, the new factor introduced, AAF, is not easily commutative with their existing formulation. Thus, equal weights were given to each factor as a compromise. Each factor is elaborated further in the following paragraphs.

The CPF was mainly inspired by Schöpfer's (2005) methodology of incorporating what a citizen would see or what their perspective would be in seeing the constellation of buildings and vegetation in an area. Generally, if buildings are higher than the canopy, the area would feel less green, while if the buildings are lower than the canopy, the area would feel more green. Additionally, the context of the area nearby should be known by most citizens, thus they would know if the surrounding area has either more built-up or more vegetation, with the greenness being more appropriate to the latter than the former. This factor scales the initial greenness of a select area or location in indexing.
The AAF was a new factor introduced by the researchers in order to further modify the green index. It takes into account how much of a select area allocates vegetation and built-up area in its total area. It was included due to the necessity of dedicated green spaces in compact urban areas regarding environmental sustainability (Jim, 2004). According to Picard & Tran, Some studies even indicate that urban green spaces directly affect the well-being of its inhabitants (2021). Hence, the existing green spaces are taken into consideration through this factor.

Factor	Equation/Conditions	Range
CPF	IF Veg A > Built A AND Bldg Ht > Canopy Ht THEN -0.8; ELIF Veg A > Built A AND Bldg Ht < Canopy Ht THEN 0.8; ELIF Veg A < Built A AND Bldg Ht > Canopy Ht THEN -1; ELIF Veg A < Built A AND Bldg Ht < Canopy Ht THEN -1;	-1 to 1
AAF	IF Veg A + Built A == 0 THEN NULL; ELSE $\frac{Veg\ A - Built\ A}{Total\ A}$	-1 to 1
HCF	IF Median(Bldg Hts) > Median(Canopy Hts) THEN $-1 \cdot \frac{Median(Bldg\ Hts) - Median(Canopy\ Hts)}{Median(Bldg\ Hts)}$ ELSE 1 (where height difference is negligible)	-1 to 1
BDF	Obtained from negating the Rescaled Kernel Density of Building Footprint Centroids; IF 0, convert to 1	-1 to 1

Table 1. Green Index Factors

The HCF was another factor inspired by Schöpfer's (2005) methodology of classifying building and vegetation heights. This only becomes significant if the buildings are higher than the canopy as the buildings that are lower than the canopy or vegetation should feel more green. This allows the GI to be more refined and accurate to the principles set out by Schöpfer (2005), where the higher the buildings are than the canopy means the less green an area actually feels.

The BDF focuses on the clustering and nearness of buildings from one another, leading to a feeling of less greenness the closer multiple buildings are in an area (Schöpfer, 2005). In this study, it was using the Kernel Density Estimation tool, then joined for the GI through zonal statistics of the fishnet grid or barangay boundaries.

In the actual application of the GI, the necessary variables were generated using two spatial units: the Barangay Administrative Boundaries of Manila and a fishnet grid with a spatial resolution of 300 meters. The barangay boundaries were used to align the analysis with officially recognized administrative units, enabling direct relevance to local governance and planning. Additionally, a fishnet grid was applied to allow a finer and more uniform spatial analysis across the city, independent of barangay size and shape. Although the Sentinel-2 imagery had a spatial resolution of 10 meters, using such a fine grid for city-wide analysis would have resulted in excessive data volume and redundant detail. The 300-meter grid was chosen as a practical compromise, capturing meaningful variations in urban green spaces while maintaining computational efficiency.

Following the processing workflows outlined in the flowcharts, all required variables, including vegetation area, built-up area, total area, median canopy height, median building height, and building density, were calculated for each barangay and each fishnet cell. These variables were then used to compute the GI scores separately for both spatial units, enabling cross-comparison and validation of results across different spatial scales.

To obtain the vegetation area allocation per barangay, the classified vegetation areas from the land cover map were spatially intersected with the barangay boundaries. The area of vegetation within each barangay was recalculated based on the intersected features, providing a localized measure of green space distribution. Similarly, the built-up area allocation per barangay was derived by intersecting the built-up land cover classes with the barangay boundaries. The resulting built-up areas were recalculated for each barangay, allowing for a quantitative assessment of urbanization levels at the barangay scale. The total area of each barangay was computed directly from the barangay boundary dataset using the field calculator function in GIS software. This provided a baseline reference for normalizing the vegetation and built-up area metrics.

For the median canopy height per barangay, zonal statistics were applied using the vegetation areas intersected with the canopy height model. This process aggregated the canopy height values within each barangay, resulting in a median value that represents the typical vegetation height per unit area.

The median building height per barangay was determined by first simplifying building footprints into centroid points. Each building centroid was spatially joined to its corresponding barangay boundary, and building height statistics were computed by aggregating the heights of buildings within each barangay. This step provided a measure of the general building height distribution across barangays.

Lastly, the mean building density per barangay was calculated using Kernel Density Estimation on the building centroid dataset. The density values were summarized through zonal statistics for each barangay, providing insights into the spatial clustering of built-up structures. This density metric was negated and integrated into the Green Index calculation to reflect the impact of densely built environments on perceived greenness.

For each barangay and fishnet cell, the four factors of the Green Index were computed using the variables from the previous paragraphs. After calculating these factors, the Green Index for each spatial unit was generated and visualized through a map. To assess the applicability of the Green Index, the resulting scores were cross-compared with the 3D visualization model, allowing for visual inspection and verification of the greenness distribution across different areas of the city. The resulting green index maps are subject to further field validation and survey.

3. Results and Discussion

3.1 Land Cover Characteristics of Manila City

All land cover maps shown in Figure 6 achieved at least 85% accuracy across all land cover classes and accuracy metrics (i.e. Producer, User, Overall). Generally, across all maps, within the GADM boundaries of Manila, which is roughly 3667 hectares based on QGIS' field calculator, 86.25% of the land cover was classified as built-up area, 8.45% was classified as Vegetation Area, while 5.30% was classified as water.

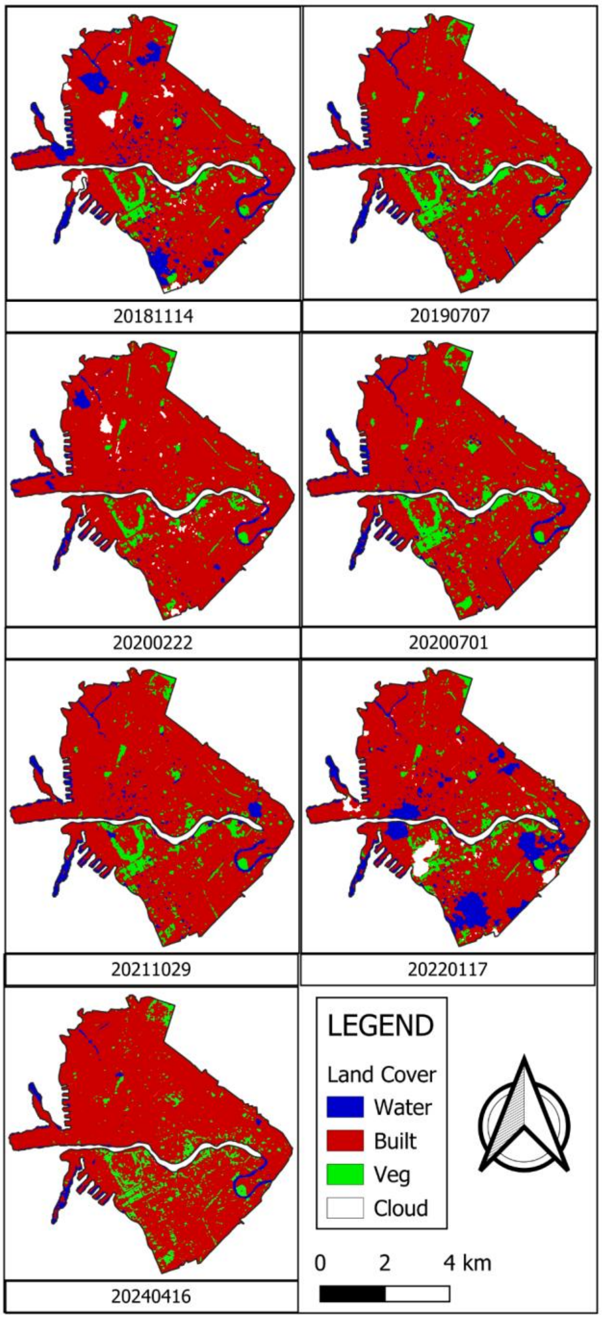

Figure 6. General land cover classification maps generated from Sentinel-2 MSI L2A images.

After classification, change detection was executed, and as seen in the Green Development Matrix (Table 2), the actual overall vegetation of Manila had little to no changes, whether positive or negative. As discussed in the methodology, the table was the result of the subtraction of the changes from built to vegetation area from the changes from vegetation to built area. What the values demonstrate is that the changes in land cover were negligible throughout the whole time period. This little change could even be attributed to just slight misclassifications between images.

This finding is further supported by the No Change Matrix (Table 3). The No Change matrix shows that at least 90% of Manila's Land Cover had not changed from 2018 to 2024. This finding, in conjunction with the Green Development matrix, implies that no new green spaces were developed, and existing ones were neither expanded nor removed. Subsequently, this result makes analysis of greenness of a single period sufficient rather than doing it multi-temporally, because Manila had stayed relatively stable in terms of land cover change from 2018 to 2024. In replication with varying land cover changes, we do suggest applying the methodologies for all images rather than a single period.

Dates	11/14/2018	07/07/2019	02/22/2020	07/01/2020	10/29/2021	01/17/2022	04/16/2024
11/14/2018	0	0.55	-0.42	0.89	0.47	0.37	0.55
07/07/2019	0.55	0	-1.34	0.14	-0.17	-0.20	-0.25
02/22/2020	-0.42	-1.34	0	1.54	1.08	0.76	1.27
07/01/2020	0.89	0.14	1.54	0	-0.34	-0.47	-0.45
10/29/2021	0.47	-0.17	1.08	-0.34	0	-0.14	-0.10
01/17/2022	0.37	-0.20	0.76	-0.47	-0.14	0	0.18
04/16/2024	0.55	-0.25	1.27	-0.45	-0.10	0.18	0

Table 2. Green Development Matrix (in %)

Dates	11/14/2018	07/07/2019	02/22/2020	07/01/2020	10/29/2021	01/17/2022	04/16/2024
11/14/2018		94.98	94.70	94.64	94.81	91.43	93.31
07/07/2019	94.98		95.95	98.92	97.61	92.29	96.85
02/22/2020	94.70	95.95		96.06	96.34	92.27	95.56
07/01/2020	94.64	98.92	96.06		97.85	92.52	97.06
10/29/2021	94.81	97.61	96.34	97.85		93.23	97.13
01/17/2022	91.43	92.29	92.27	92.52	93.23		92.03
04/16/2024	93.31	96.85	95.56	97.06	97.13	92.03	

Table 3. No Change Matrix (in %)

3.2 3D Visualization of Built-up and Vegetation Areas

The significant portion of Manila being built-up areas with minimal vegetation areas was further reinforced by the rendering of each building compared to the vegetation areas and canopy heights. We can see these visualizations by looking at a top view (Figure 7) and a bird's eye view (Figure 8) of Manila City.

Another key observation from the 3D model was that many vegetation areas were small and fragmented throughout Manila. These fragments were either public or commercial parks or sparse greenery in select locations. This can be particularly observed in the views of North (Figure 9) and Southeast (Figure 10) Manila.

Lastly, the key observation that allowed the researchers to apply the Green Index to Manila was that the largest 1vegetation areas were usually surrounded by even higher buildings. This is best seen in the views West of Manila or those highlighting Rizal Park and the Intramuros Golf Course, in Figure 11. Buildings that were in the highest quantile according to height were found relatively near the largest canopy structures like Rizal Park. This finding gave quantitative credit to the idea of applying the Green Index, as now, Citizen's Perspective has proper merit by context.

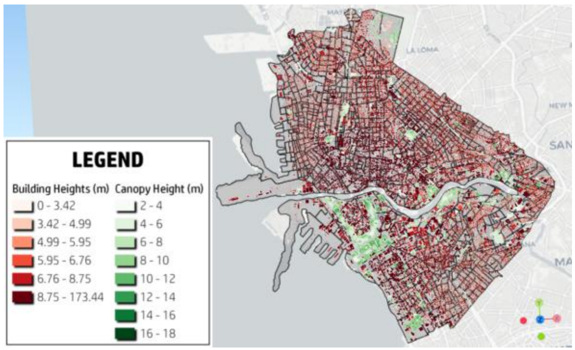

Figure 7. 3D Visualization of Manila - Full Top View

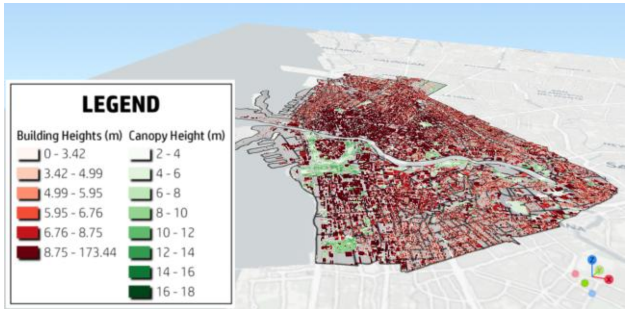

Figure 8. 3D Visualization of Manila - Bird's Eye View

Figure 9. 3D Visualization of North of Manila. Fragmented vegetation areas are encircled.

Figure 10. 3D Visualization of Southeast Manila. Fragmented vegetation areas are encircled.

Figure 11. 3D Visualization of Manila - West of Manila.

3.3 Green Index Maps

The Green Index was first applied using the barangay extents as seen in Figure 12. The barangay index result allows for a more contextual view of the Greenness of Manila. Inspecting each factor separately in tandem with the index, we noticed that while building density and built-up allocation were more intense in the northern barangays, this portion of Manila was middling in the index. Taking into account the other factors regarding heights (CPF and HCF), what this tells us is that these barangays, though very dense with buildings, do not have very tall infrastructures that could disrupt or bother a citizen's experience, as well as potentially have areas for green space development. On the other hand, the two extremes of the green index are observed more in the southern portions, where the barangays with national parks (i.e. Rizal/Luneta, Arroceros, Malacañang) and dedicated green areas (i.e. Intramuros golf course) are offset by the dense and tall built-up areas in neighboring barangays, which could in turn, also give a middling feeling for a citizen traversing through Manila in these portions due to the sudden shifts in infrastructure.

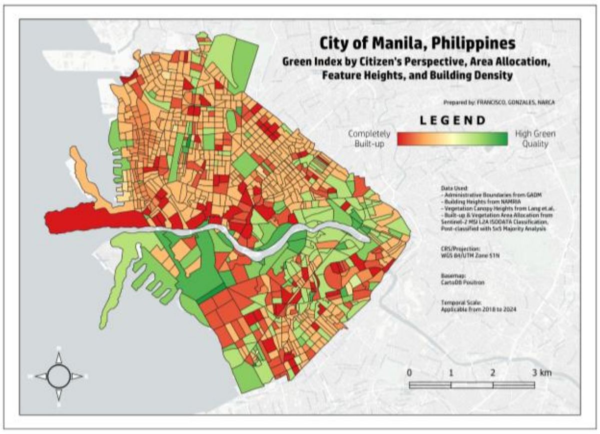

Figure 12. Green Index applied using barangay extents

The Green Index was then applied using a 300 m fishnet grid, which can be seen in Figure 13. In contrast with the areas mentioned for the barangay index, the northern areas, when gridded, depict the intensity of built-up areas further. What this could mean is that while the potential for green spaces is present as shown in the barangay index, it may not be the priority for the northern areas of Manila, since a significant number of grid cells are nearing or at the built-up extremes in the green index. Nevertheless, further context and analysis in other studies, like in urban planning, are necessary to understand the feasibility of developing green spaces within this area. In the southern portions, the same findings can be observed, similar to the barangay index, where the high green quality cells are offset by near-to-complete or completely built-up cells.

Due to being calculated for each barangay extent, understanding and appreciation may be better found in the barangay output for local citizens or even governing bodies in each barangay. Furthermore, additional attributes known by each barangay may be implemented to further refine the Green Index of Manila, provided that the appropriate scale and formulation are done as well. However, this output has some miscalculations, as the current index assumes that all spatial extents are single polygons or ROIs. Some sections of Manila are not listed under any Barangay, leading to a multi-polygon that is found in different locations but all attributed to one feature. This leads to a miscalculation of greenness in this multi-polygon.

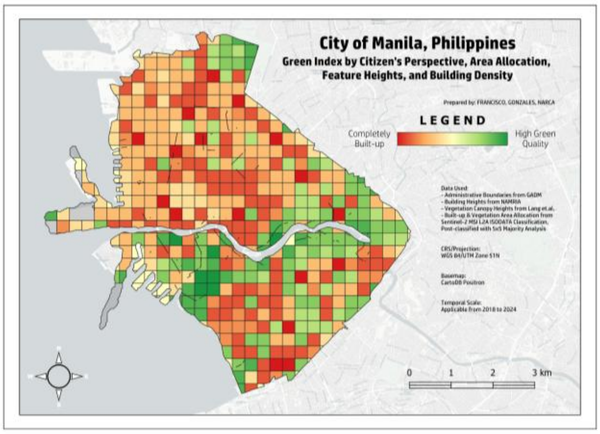

Figure 13. Green Index applied using a fishnet grid

Alternatively, the gridded GI provides a more uniform output that allows better overall visualization and understanding of Greenness throughout Manila. It can highlight specific areas of concern better while even providing an output for further spatial or image analysis in Remote Sensing. However, it does not provide enough context on other possible factors affecting greenness due to its uniformity, as these other attributes are most likely attached to other spatial extents and not the fishnet grid. Additionally, it may be difficult to properly appreciate this output as a common citizen or layman, as the uniformity loses the preconceived knowledge of well-known locations in Manila.

Overall, the Green Index provided a good overview of the greenness quality of Manila and highlighted that a significant portion of the city is completely built-up and lacks nearby vegetation. These results, in turn, could be evidence or reason as to the feeling of citizens about decreasing green spaces, likely due to a lack of changes and sudden shifts in environments, besides understanding related sociocultural phenomena. However, the Green Index is not yet fully refined, as the formulation could be better optimized and advised with more precise metrics by experts. Additionally, although visual inspection and comparison with the 3D visualizations and green index maps show clear references with one another, the resulting green index maps are subject to further field validation and survey, especially regarding citizens' perspectives on greenness and green quality.

4. Conclusions

Manila's land cover had not significantly changed from 2018 to 2024. Despite this, the feeling of decreasing green spaces did not disappear or turn over. Upon modeling the City of Manila and creating an appropriate Green Index according to the context of citizens' perspective, area allocation, feature heights, and building density, it was found that a substantial portion of Manila was mostly built-up area with little nearby vegetation or green space, leading to majority negative to middling values in the green index maps.

The results show that current urban planning in Manila does not prioritize green space development or protection sufficiently. The minimal change in green spaces and dominance in built-up areas suggests the need to revise land use strategies. As described in previously mentioned studies and from the results, without proper and feasible intervention through urban planning and policy change, the lack of green spaces may potentially worsen environmental quality and conditions related to health, comfort, and overall well-being.

In addition, we recommend applying more pertinent temporal data, for DSM & DTM in particular, to incorporate building development and construction for analysis within a study area. Also, we recommend modifying methodology to test different indexed approaches (possibly closer to the original Green Index Reference paper by Schöpfer) in future studies. Lastly, incorporate new factors into the Green Index such as environmental layers (e.g., air pollution), other phenomena (e.g., traffic), or spatial patterns (e.g. population density) to further contextualize the green index for citizen and societal use.

References

Bruzzone, L., n.d. 6th ESA Advanced Training Course on Land Remote Sensing: Multitemporal Analysis. rslab.disi.unitn.it. (17 January 2024)

Bruzzone, L., n.d. Multitemporal Analysis. rslab.disi.unitn.it. (17 January 2024)

Copernicus Open Access Hub., n.d. Sentinel-2 Multispectral Instrument (MSI) Level-2A products. European Space Agency. dataspace.copernicus.eu/data-collections/copernicus-sentinel-data/sentinel-2 (17 January 2024)

Faizan, J., 2021. Nature's prescription: making room for green spaces in highly dense cities to combat urban stress. Unitec Institute of Technology, Auckland, New Zealand. hdl.handle.net/10652/5065 (17 January 2024)

ESRI., n.d. FAQ: What is the difference between nearest neighbor, bilinear interpolation and cubic con. support.esri.com/en-us/knowledge-base/faq-what-is-the-difference-between-nearest-neighbor-bil-000005606 (17 January 2024)

Foody, G. M., 2008: Harshness in image classification accuracy assessment. *International Journal of Remote Sensing*, 29(11), 3137-3158. doi.org/10.1080/01431160701442120

GADM., 2018. Database of Global Administrative Areas, Version 4.1. gadm.org/ (17 January 2024)

Gonzales, L. P., & Magnaye, D. C., 2017: Measuring the urban biodiversity of green spaces in a highly urbanizing environment and its implications for human settlement resiliency planning: The case of Manila City, Philippines. *Procedia Environmental Sciences*, 37, 83–100. doi.org/10.1016/j.proenv.2017.03.024

Google Open Buildings., 2022. Open Buildings Dataset V2. sites.research.google/open-buildings (17 January 2024)

Gupta, Kshama & Kumar, Pramod & Pathan, S.K. & Sharma, Komal., 2012: Urban Neighborhood Green Index – A measure of green spaces in urban areas. *Landscape and Urban Planning*. 105. 325–335. doi.org/10.1016/j.landurbplan.2012.01.003.

Jim, C., 2004: Green-space preservation and allocation for sustainable Greening of compact cities. *Cities*, 21(4), 311-320. doi.org/10.1016/j.cities.2004.04.004

Lang, N., Schindler, K., Wegner, J.D., 2019: Country-wide high-resolution vegetation height mapping with Sentinel-2, *Remote Sensing of the Environment*, Vol. 233. doi.org/10.1016/j.rse.2019.111347

Lang, N., Weigand, M., Schramm, M., & Tiede, D., 2021: Global Canopy Height Model. Zenodo. doi.org/10.5281/zenodo.5012448

Manila Bulletin., 2020. Arroceros Forest Park to become Manila's first public city forest park. mb.com.ph/article/382982/Philippines/manila-declares-arroceros-forest-park-as-permanent-forest-park (17 January 2024)

NAMRIA., 2011. Digital Surface Model (DSM) and Digital Terrain Model (DTM) of Manila. National Mapping and Resource Information Authority.

Philippine Statistics Authority, 2021: Highlights of the Philippine Population 2020 Census of Population and Housing (2020 CPH). psa.gov.ph/content/highlights-philippine-population-2020-census-population-and-housing-2020-cph. (17 January 2024)

Picard, P., & Tran, T., 2021: Small urban green areas. *Journal of Environmental Economics and Management*, 106, 102418. doi.org/10.1016/j.jeem.2021.102418

Sarmiento, C., & Porio, E., 2021: Urban Green Spaces and Health Equity in the Philippines: A Study of Metro Manila's Green Spaces. *Journal of Urban Health*, 98(1), 23–34. doi.org/10.1007/s11524-021-00517-8

Schöpfer, E., Lang, S., and Blaschke, T., 2005: A Green index incorporating remote sensing and citizen's perception of green space. *Proc. Int. Arch. Photogramm. Remote Sens. Spatial Inf.* Sci. 37. 1-6. isprs.org/proceedings/XXXVI/8-W27/schoepfer.pdf (17 January 2024)

Sirko, W., Kashubin, S., Ritter, M., Annkah, A., Bouchareb, Y.S.E., Dauphin, Y., Keysers, D., Neumann, M., Cisse, M., Quinn, J.A., 2021: Continental-scale building detection from high resolution satellite imagery. doi.org/10.48550/arXiv.2107.12283.

World Health Organization., 2017. Urban Green Space Interventions and Health: A review of impacts and effectiveness. full report. World Health Organization. who.int/andorra/publications/m/item/urban-green-space-interventions-and-health--a-review-of-impacts-and-effectiveness.-full-report (17 January 2024)