TREE PLANTING PRIORITIZATION IN NATIONAL CAPITAL REGION, PHILIPPINES USING REMOTE SENSING, ANALYTIC HIERARCHY PROCESS AND GIS

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ABSTRACT:

The need for trees in cities is rapidly increasing because of global warming, rapid population growth, and urbanization. To maximize the benefits of trees, areas of greatest need should be identified and prioritized. In this study, a geospatial framework for tree planting prioritization is developed for NCR using remotely sensed datasets, AHP, and GIS. A Planting Priority Index (PPI) for NCR is derived based on five criteria with corresponding weights calculated based on ratings from 18 experts – air quality (25.2%), tree cover (23.8%), land cover (17.8%), population (17.4%), and land surface temperature (15.8%). The AHP resulted in a consistency ratio (CR) value of 1.7% and a consensus value of 53.2%. PPI values were calculated and statistically significant prioritization clusters and outliers were identified using Anselin Local Moran's I statistics. The resulting PPI and cluster maps showed that the high-priority areas for tree planting clustered near the region's center and northwest portion covering the cities of Malabon, South Caloocan, Navotas, Quezon City, Marikina, San Juan, and Mandaluyong, while the low priority areas were found mostly along the region's outskirts at cities of Pasay, Las Piñas, Muntinlupa, Taguig, Valenzuela, and North Caloocan. The generated maps showing PPI values across the region may aid local government agencies and environmental organizations in evaluating and recalibrating their local greening programs. The workflow presented in this study can also be adopted in other regions with localized variables and site-specific goals relevant to tree planting and greening programs.

1. INTRODUCTION

1.1 Background of the Study

Urban green spaces (UGS) refer to vegetated land areas in cities such as parks, gardens, and urban forests (De Haas et al., 2021). In the National Capital Region (NCR), Philippines, the amount of UGS is limited to five square meters per Filipino which falls behind the recommended nine square meters per capita by the World Health Organization (Economist Intelligence Unit, 2011). Decreased green spaces almost always mean a decline in vegetation cover and contribute to many worsening environmental conditions. It results in a drastic rise in land surface temperature causing urban heat island (UHI) effects due to surface albedo and limited shade provision. The lack of natural filters also significantly reduces air quality. On a larger scale, it leads to climate change and global warming due to precipitation extremes and greenhouse gases.

Planting trees is one effective way of addressing environmental issues. Trees help reduce environmental degradation caused by rapid urbanization, mitigate climate change, and enhance urban sustainability and biodiversity. It ameliorates air quality, reduces the effects of UHI, and plays a significant role in carbon sequestration. Current activities of the NCR Local Government Units include identifying open areas for their greening program (Department of Environment and Natural Resources, 2014). However, aside from locating open areas, the placement of trees and their beneficiaries needs thoughtful consideration and planning. Strategic planning maximizes the benefits of tree planting, optimizes resource allocation, and reduces the cost of logistics.

1.2 Research Objectives

This study aims to create a geospatial framework for tree planting prioritization that can be used in NCR. Specifically, it aims to (1) quantify the perceived relative importance of different factors affecting tree planting prioritization in NCR; (2) calculate and map a PPI for NCR using GIS and remote sensing; and (3) identify spatial patterns present in the PPI map.

1.3 Significance of the Study

The United Nations Sustainable Development Goals (UN SDGs) are a collection of 17 interconnected goals that all UN member states have agreed to work towards and achieve by 2030. These goals aim to end poverty and injustice, create sustainable cities, and protect the environment to ensure peace and prosperity now and in the future. By promoting reduced inequality and an increase in urban forests and green spaces, this study will contribute to three UN SDGs. These are SDG number 3 (Good Health and Well-being), SDG number 11 (Sustainable Cities and Communities), and SDG number 13 (Climate Action).

This study will also contribute to the scarce literature on tree planting prioritization in the Philippines, specifically in NCR. The findings of this study will provide a baseline for future tree-planting prioritization studies and the spatial methods or location-based approaches used in this study may be utilized for similar tree-planting research in other areas within the country. The tree planting prioritization maps that will be produced in this research will help the Local Government Units (LGUs) and environmental agencies and organizations in NCR recalibrate their existing tree planting and greening projects to provide better action plans on where to plant trees efficiently to solve the issues

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of environmental degradation. Doing so will help sustain a sufficient amount of urban green spaces in the region benefiting human health and improving the environmental conditions of NCR.

1.4 Related Literature

Despite the many benefits of urban forests and trees, the scientific studies that were written on the systematic approach of tree planting and its prioritization planning are still limited (Nyelele & Kroll, 2021). Among the limited pool of literature written on the matter, one strong commonality lies in considering geospatially referenced information to produce prioritization plans identifying the areas that are regarded as the best tree-planting sites based on set criteria.

PPI is significantly helpful in combining multiple well-chosen sub-indicators for tree planting prioritization. It is characterized by a specific range of values where higher index values usually denote higher prioritization for planting (Nowak et al., 2016). Proper indicators and appropriate weights are crucial to creating a PPI that is reliable and useful. Indicators may be selected and weights may be assigned through participatory methods or through statistical methods (Morani et al., 2011). The choices may also be based on published literature, existing studies, and practices (Sousa-Silva et al., 2021). In choosing specific indicator combinations and associated weights, it is also important to consider the study objectives, site characteristics, and data availability.

In many related studies, after selecting the indicators and assigning weights, the values of each indicator are standardized because the indicator values are often on different scales and cannot be directly combined (Lin, 2020). After the standardization, a multi-criteria overlay analysis is performed using the weighted sum of the factors to generate the PPI. Multiple Criteria Decision Analysis (MCDA) describes the techniques that rate or rank multiple alternatives based on a structured evaluation of multiple criteria (Wotlolan et al., 2021). One common MCDA method is the AHP proposed by Saaty (1980). AHP is a popular, flexible, and structured approach for criteria weighting in GIS environments suitable for problems where the decision criteria or factors can be arranged hierarchically by performing pairwise comparisons reducing the complexity of many decision problems (Zolfaghary et al., 2021). Combining the GIS functionalities with MCDA-AHP can result in a drastically improved solution to the tree planting problem which involves multiple geospatial factors.

The application of spatial statistics allows the exploration and analysis of existing spatial patterns in a given dataset. Implementing it to the resulting PPI helps detect optimum areas for tree planting to better allocate resources. Specifically, cluster and outlier analysis using Anselin Local Moran's I Statistic can determine the correlation between weighted features, produce clusters of similar values, and identify anomalies that are crucial in the prioritization.

2. METHODOLOGY

Figure 1 outlines the general workflow undertaken to conduct the study. The data were processed in GIS software and were used to generate the PPI. Lastly, the results were analyzed and visually presented through maps.

2.1 Identification of Factors

In this study, the factors that affect tree-planting prioritization were chosen based on published literature and research (Sousa-Silva et al., 2021; Morani et al., 2011; Locke et al., 2010), and in consultation with experts from the DENR-NCR and Department of Science and Technology - National Capital Region (DOST-NCR), and representatives of relevant departments of various LGUs in NCR.They are: (1) population, (2) LST, (3) air quality, (4) tree cover, and (5) land cover. These five were determined to be the factors that best meet the study area's highest priorities, which in this case is to combat the effects of climate change (i.e., global warming) and air pollution and bring trees closer to people. Tree cover was also deemed an important factor in decreasing greening inequality and improving the spatial distribution of trees within NCR. In contrast, the land cover serves as the determining factor for the suitability of tree planting.

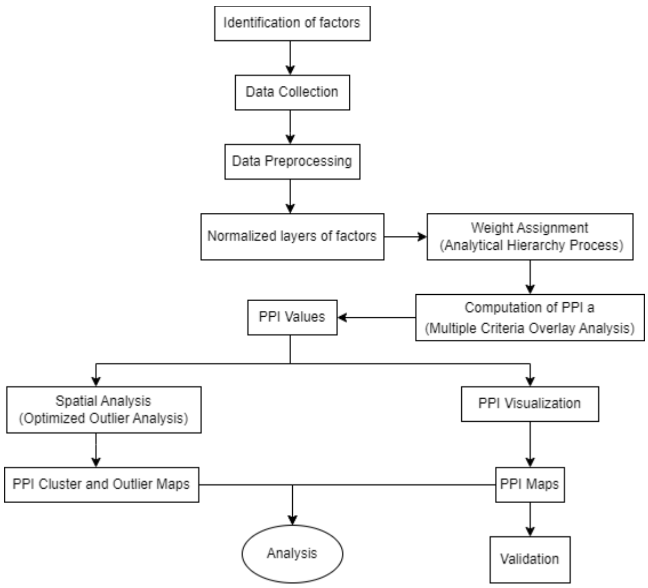

Figure 1. General workflow of methodology.

2.2 Generation of Layers for PPI Calculation

The datasets used in this research were a mix of open data and those requested from relevant government-funded research projects. They were preprocessed accordingly to transform the data and derive the needed information for 2020 layers. The raw layers were first reprojected into WGS84 UTM Zone 51N (EPSG:32651), the set coordinates reference system for all the data and were clipped to the study area's boundary delineated using a high-resolution Philippine PSGC administrative boundaries shapefiles acquired from this online repository: https://github.com/altcoder/philippines-psgc-shapefiles. All layers, except the air quality layer, were also resampled into a uniform spatial resolution of 30 meters. Other layers required extra processing steps based on the nature of the data. All geospatial processing methods in this study were done in QGIS.

2.2.1 Deriving 2020 Population Layer: The High-Resolution Settlement Layer (HRSL) of the Philippines for the year 2015 was acquired from the Center for International Earth Science Information Network (CIESIN) for the population data. It is a GeoTIFF file that estimates human population distribution in the country using recent census data and high-resolution (0.5m) satellite imagery from DigitalGlobe (CIESIN, 2016).

To localize the 2015 NCR HRSL data for data reliability, NCR's total population per city/municipality was calculated from the 2015 NCR HRSL layer using the Zonal Statistics algorithm and compared with the 2015 PSA Census to produce the corresponding scale factor (SF) for each city/municipality using Equation (1).

$$SF = \frac{2015\ Census_{City/Municipality}}{2015\ HRSL_{City/Municipality}} \tag{1}$$

The 2015 NCR HRSL raster data was then clipped repeatedly using the administrative boundary of each city/municipality to produce a 2015 NCR HRSL data at the regional level. The resulting 2015 city and municipal HRSL layers were then multiplied by their corresponding scale factor resulting in a localized 2015 HRSL layer for each city/municipality. Next, to derive a 2020 NCR HRSL layer, the growth rate (GR) for each city/municipality from 2015 to 2020 was calculated using the 2015 PSA Census and 2020 PSA Census and Equation (2).

$$GR = 1 + \left(\frac{2020\ Census_{City} - 2015\ Census_{City}}{2015\ Census_{City}}\right) \tag{2}$$

The localized 2015 HRSL layer for each city/municipality was then multiplied by their corresponding growth rates to produce a 2020 HRSL layer for each city/municipality. Finally, these layers were merged using GDAL's Merge algorithm to produce the 2020 NCR HRSL raster layer population data.

2.2.2 Generating LST Layer: LST data was derived from a Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imagery taken in 2020 using the GUHeat toolbox. The said toolbox is a QGIS plugin developed by UP TCAGP's Geospatial Assessment and Modelling of Urban Heat Islands in Philippines Cities (Project GUHeat) that automates the generation of LST layers from Landsat images. The process involves retrieving the top-of-atmospheric (TOA) spectral radiance from the digital numbers (DN) of Band 10, converting them into at-sensor brightness temperature (BT), applying emissivity correction from NDVI and Proportion of Vegetation (PV) values, and calculating land surface emissivity (LSE) to estimate LST.

2.2.3 Generating Air Quality Layer: Carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) are the parameters used to measure air quality in this study as they are among the air pollutants being monitored by the Environment Management Bureau (EMB) for the National Air Quality Status report. To generate the layer, the 2020 annual mean of CO, SO_2, and NO_2 vertical column densities were exported from Sentinel-5 Precursor TROPOspheric Monitoring Instrument (TROPOMI) collection through Google Earth Engine. Since there is only one corresponding weight for the air quality factor, the three parameters were expressed as a single indicator by normalizing each parameter first. This was done to transform all their values to a range of 0 to 1 where 1 is the highest and 0 is the lowest. To remove the complexity of sub-weighting, the approach was to get the average of three parameters assuming that they all contribute equally to air pollution, using Equation 3. This approach was done to avoid over-weighting and dominance of a single parameter (Lin, 2020; Locke et al., 2010). The resulting layer was the 2020 air quality layer of NCR with a resolution of approximately 1113 meters. This air quality layer was not resampled any further as it will only result in a larger file size without improving the quality of the data.

$$Air\ Quality = \frac{Normalized_{CO} + Normalized_{NO_2} + Normalized_{SO_2}}{3} \tag{3}$$

2.2.4 Generating Tree Cover Layer: Tree cover data was obtained from the UP-TCAGP's Development of Integrated Mapping, Monitoring, and Analytical Network System for Manila Bay and Linked Environments (Project MapABLE). It was derived from satellite images and LiDAR data processed using machine learning methods. The data acquired represents the percent tree canopy cover of Metro Manila in 2020 and therefore, was readily used as a layer for PPI calculation.

2.2.5 Generating Land Cover Layer: Land cover satellite-derived data for Metro Manila in 2020 was obtained from UP-TCAGP's Project MapABLE. It had 12 classifications initially before they were reclassified into 0 to 5 based on their suitability and effectiveness for tree planting. Based on related literature (Nyelele & Kroll, 2021) and inputs of stakeholders and experts, grassland was given a score of 5, shrubland, annual crop, permanent crop, and short vegetation with a score of 4, barren land with a score of 3, forest with 2, and dense urban/continuous urban fabric and sparse urban/discontinuous urban fabric with a score of 1. On the contrary, water, aquaculture, mangrove, and paddy rice were scored 0 because of their incapacity to accommodate trees.

2.2.6 Normalization and Handling of Null Values: The data values of the factors have different scales (i.e., the maximum value of one factor is not necessarily equal to the maximum value of another factor). To prevent one variable from being overly influential in the computation of PPI and to allow the values of each factor to be aggregated, normalization of factor values was done to rescale the values to a range of 0 to 1. For population, air quality, land surface temperature, and land cover in which higher values correspond to higher prioritization, the values were normalized using:

$$I = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{4}$$

where I is the normalized factor value, X is the original factor value, X_{min} is the minimum factor value, and X_{max} is the maximum factor value (Lin, 2020). In contrast, for tree cover in which lower values correspond to higher prioritization, the values were normalized using:

$$I = \frac{X_{max} - X}{X_{max} - X_{min}} \tag{5}$$

In both cases, the resulting range of normalized values was from 0 to 1 where 0 indicates lower prioritization and 1 indicates higher prioritization for planting. The normalized layer of each factor was applied with GRASS GIS r.null function to replace the null, which occurs after clipping by mask layer (vector mask: municipal-level administrative boundary of NCR), with 0. This ensured that the resulting weighted overlay layer had no evident holes within the study area.

2.3. Implementation of AHP

AHP was utilized to determine the respective weights of the factors. A questionnaire with 10 paired comparison questions (given the five factors) was prepared for the key participants to determine which among the two factors in the pairwise comparison is more important and by how much using Saaty's nine-point scale (Saaty, 1990; a score of 1-9 where 1 signifies equal importance). Local stakeholders and experts were identified as key participants in this study. Specifically, local politicians and other appointed LGU officials/employees who represent their respective cities were considered stakeholders. Meanwhile, experts included those identified as having extensive knowledge of urban greening programs and related fields (e.g., engineers, researchers, etc.). It also included those who are knowledgeable of their city's planning and urban development program as related to tree planting such as professionals working in their respective city planning and development offices (CPDOs) and city environment and natural resources offices (CENROs).

2.4. Weight Computation of PPI Factors

The inputs of the participants are transformed into a positive reciprocal pair-wise comparison Matrix A where the entries a_{ij} (*i* corresponds to the row of the element and *j* corresponds to the column of the element) are governed by the following rules (Sallahuddin, 2013):

a. for the upper diagonal, $a_{ij} > 0$;
b. $a_{ij} = 1$ where $i = j$
c. for the lower diagonal, $a_{ji} = 1/a_{ij}$

The respective weights of each criterion for each input were then obtained through the row geometric mean method (RGMM) given by Equation (6) and normalized using Equation (7):

$$r_i = exp\left[\frac{1}{N}\sum_{j=1}^{N} ln(a_{ij})\right] = \left(\prod_{i=1}^{N} a_i\right)^{\frac{1}{N}} \quad (6)$$

$$p_i = \frac{r_i}{\sum_{i=1}^{N} r_i} \quad (7)$$

with pairwise NxN comparison matrix $A = a_{ij}$ and *ln* representing individual responses (Goepel, 2013b). Meanwhile, the consistency ratio (CR) was computed using the linear fit proposed by Alonso and Lamata (2006) given in Equation (8) where max λ_{max} is the calculated principal eigenvalue and N corresponds to the matrix dimension:

$$CR = \frac{\lambda_{max} - N}{2.7699N - 4.3513 - N} \quad (8)$$

The participants' assessments were aggregated using the Eigenvector method (EVM) to get the final corresponding weights of each criterion. All mentioned processes were computed using the Business Performance Management Singapore (BPMSG) AHP Excel Template with multiple Inputs (Goepel, 2013b).

2.4. PPI Computation

The PPI values were computed using Multi-Criteria Overlay Analysis given by Equation (9):

$$PPI = (I_1 \times W_1) + (I_2 \times W_2) \cdots + (I_n \times W_n) \quad (8)$$

where *PPI* is the resulting planting priority index value, *I* is the normalized score of a specific indicator, *W* is the associated weight of a specific factor, and *1, 2, … n* are the PPI factors (Sousa-Silva et al., 2021; Lin, 2020; Morani et al., 2011). This was done using the *Raster Calculator* function of QGIS.

2.5. Generation of Planting Priority Index Maps

The computed PPI values were normalized using Equation (4) and multiplied by 100 to get a range of values from 0 to 100 for better visualization. Higher values signify higher priority for tree planting areas, while lower values indicate lower priority. The resulting raster pixels were converted into polygons and were clipped with the extent of the study area, then categorized into five classes and mapped.

2.6. Validation of PPI Results

To perform a validation of the resulting planting prioritization scheme, the priority areas in the resulting PPI map at the pixel level were compared with the potential sites targeted by DENR for greening expansion as indicated in the Metro Manila Greening Plan (DENR, 2014). The geographic coordinates of these areas were obtained using Google Earth Pro and plotted in QGIS to generate a point layer of the potential sites targeted by the DENR. This point layer was intersected with the PPI layer at the pixel level to extract the PPI value for each target area. The resulting layer was categorized based on the classes of the PPI at the pixel level to determine the prioritization of the target area.

2.7. Cluster and Outlier Analysis

To add insight for a better interpretation of PPI values, cluster and outlier analysis was conducted. The *Optimized Outlier Analysis* tool was used because it automatically determines the settings that will produce optimal cluster and outlier analysis results. Cluster and outlier analysis was done on the resulting PPI layer. The number of permutations used was the default 499, which balances the processing speed and precision. The *Optimized Outlier Analysis* uses the Anselin Local Moran I's statistic given by the following equations (Anselin, 1995):

$$I_i = \frac{x_i - \underline{X}}{S_i{}^2} \sum_{j=1, j\neq 1}^{n} w_{i,j}(x_j - \underline{X}) \quad (10)$$

where x_i and x_j are the PPI values at locations i and j respectively, $\underline{X}$ is the average PPI values within the specified neighborhood, and $w_{i,j}$ is the spatial weight between features i and j, and where n is the total number of features:

$$S_i{}^2 = \frac{\sum_{j=1, j\neq 1}^{n}(x_j - \underline{X})^2}{n-1} \quad (11)$$

The result of the Optimized Outlier Analysis was a cluster and outlier output layer for the PPI layer. It has five classifications, namely statistically significant high-high and low-low clusters, high-low, and low-high outliers, and not significant or area surrounded by diverging prioritization. The resulting layers were mapped.

3. RESULTS AND DISCUSSION

This study built the PPI from population, LST, air quality, tree cover, and land cover data using weights arising from the AHP after which the cluster and outlier analysis was performed.

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3.1 Weights calculated from AHP

We obtained 18 responses from participants affiliated with various government agencies such as DENR, DOST, NAMRIA, and LGU personnel working in their respective cities' CENROs or CPDOs. The 18 participants ranked the five factors using Saaty's nine-point scale through pairwise comparisons. The aggregated AHP results have a consistency ratio (CR) of 1.7% which is within the acceptable value. The CR is a measure of the consistency of the participant's answers across the pairwise comparisons.

Table 1 shows the result of the AHP Analysis. Among the five factors, the air quality factor was given the most importance. It was followed by tree cover, land cover, population, and land surface temperature. This implies that the participants see air pollution and the unequal spatial distribution of trees as the more pressing issues to be solved. However, these weights were obtained with a relatively low consensus value of 53.2%. A low consensus value means that there are disagreements between the responses of the participants regarding which factors should be prioritized. The participants' assessment could have been influenced by their profession and local community context considering that the participants came from different cities and have different domain expertise.

Factors	Weight	Rank
Air Quality	25.21%	1
Tree Cover	23.76%	2
Land Cover	17.81%	3
Population	17.42%	4
Land Surface Temperature	15.80%	5

Table 1. Result of AHP analysis.

3.2 Planting Priority Index in NCR

The final equation used in the tree planting prioritization index computation is given below.

$$PPI = (AQ \times 0.252) + (TC \times 0.238) + (LC \times 0.178) + (POP \times 0.174) + (LST \times 0.158) \quad (9)$$

where PPI is the computed planting priority index values, AQ is the normalized air quality factor layer, TC is the normalized tree cover layer, LC is the normalized land cover, Pop is the normalized population layer, and LST is the normalized land surface temperature layer.

The resulting index was mapped into a proposed tree planting prioritization scheme in NCR. In this analysis, we used the Jenks natural breaks algorithm to classify and, consequently, visualize the PPI values (Sousa-Silva et al., 2021). This classification method considers the inherent characteristics of the data by minimizing the variation within classes and maximizing the variation among classes resulting in the most similar data being grouped whose class boundaries are set where there are big jumps in the data values. This is particularly useful in this study where the variability of the PPI scores matters to better distinguish between different prioritization levels. We have five (5) levels of planting priority: very low priority, low priority, moderate priority, high priority, and very high priority.

3.3 Tree Planting Priority Areas

Areas in Navotas, Malabon, South Caloocan, Mandaluyong, Marikina, and Taguig were classified as very high-priority areas for tree planting as shown in Figure 2. These were areas with high average LST and air pollution, relatively low percent tree canopy cover, and mostly built-up areas. Most of these areas were classified as urban, characterized by an impervious surface that is not highly suitable for tree planting. Given that these cities have high tree planting priority but are mostly composed of built-up areas, appropriate strategies should be formulated to incorporate tree planting in physical infrastructure projects. Meanwhile, areas classified as very low priority are scarce and are situated within bodies of water and aquaculture areas unsuitable for tree planting. This implies that tree planting is needed in many areas within NCR.

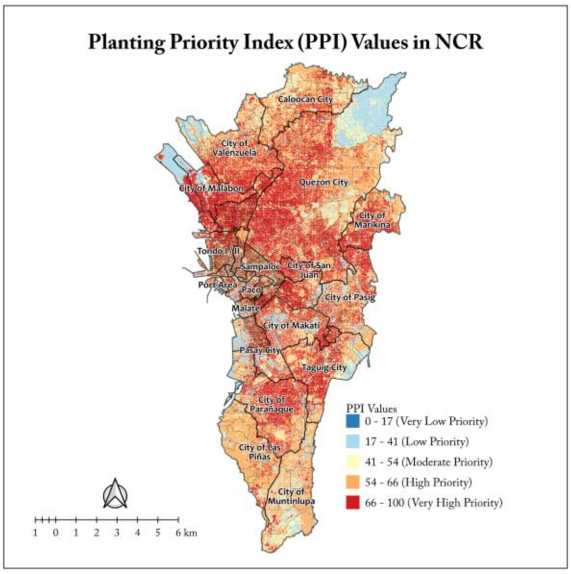

Figure 2. Planting Priority Index (PPI) map of NCR.

On the other hand, high-high clusters were found in the southern part of Navotas and Malabon, South Caloocan, the northern portion of Manila, and the west side of Quezon City as shown in Figure 3. Areas included in these high-high clusters must be prioritized as they meet one or more prioritization criteria (i.e., high population, high LST, high air pollution, and low percent canopy cover).

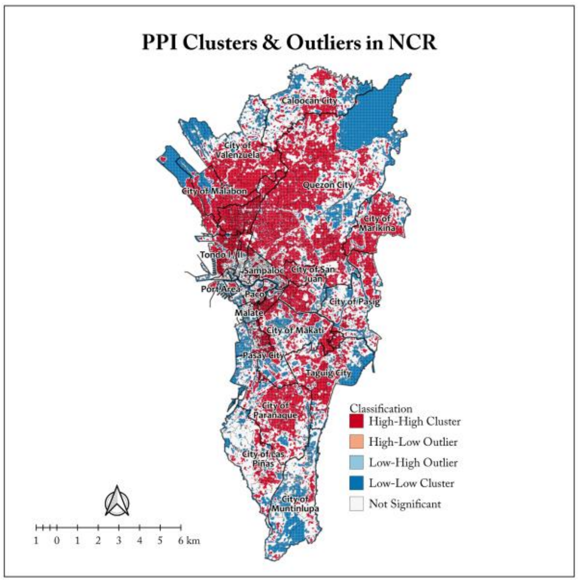

Figure 3. Cluster and outlier map of NCR.

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3.4 Validation

The following are the goals and objectives of DENR for NCR's urban greening: (1) to maintain, protect, and conserve existing green spaces, and (2) to increase green spaces in the cities (DENR, 2014). For the first objective, DENR targeted existing parks, industrial, and commercial spaces for enrichment. For the second objective, DENR searched for potential greening sites in "cities, barangays, and municipalities that are lacking trees" (DENR, 2014, p. 60). A sample of 62 potential sites for greening expansion identified by the DENR was chosen. We excluded the non-specific areas listed by DENR (e.g., spaces in every home, condominiums/high-rise buildings, etc.) because their coordinates cannot be extracted.

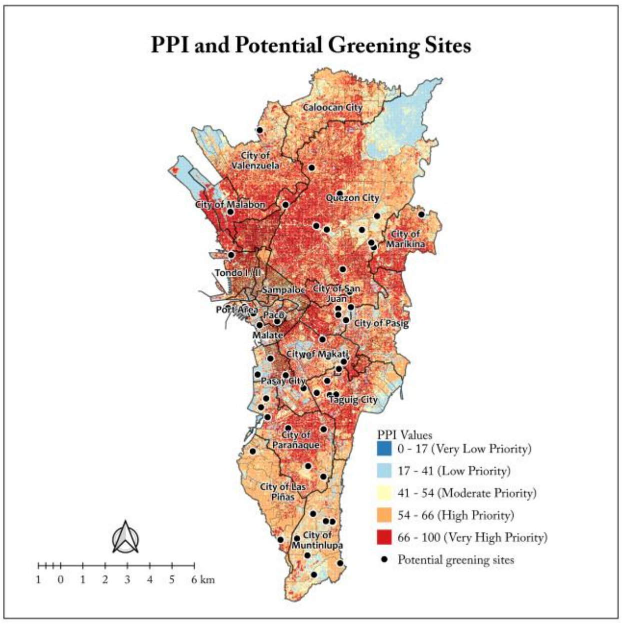

Figure 4. PPI map overlaid with the identified potential greening sites.

Figure 4 shows the pixel-level PPI map overlaid with the chosen potential sites. Among the 62 potential sites for greening expansion, 11 areas were classified as having very high PPI scores greater than 66. Meanwhile, 23 sites got high PPI scores ranging from 54-66 and the other 23 got a score of 41-54. The remaining five targeted areas received PPI scores of 17-41. None of the areas scored lower than 17. This indicates that the proposed prioritization scheme, to an extent, agrees with the target sites of DENR since approximately 54.8% of sample areas were classified as high priority (PPI score greater than 54).

It should be noted that there are some limitations to the validation approach used in this study. The validation data used were from a 2014 greening plan whereas the data used to generate the PPI map were from 2020. Lastly, the target sites were represented as points instead of polygons. This introduced limited spatial information which in turn also limited the validation approach.

CONCLUSIONS AND RECOMMENDATIONS

This work presents a systematic approach to determine a tree planting prioritization scheme in NCR where tree benefits would be maximized. PPI maps and PPI cluster maps were produced to communicate NCR's tree planting prioritization levels. These maps are powerful visual tools for planners allowing for an explicit spatial understanding of the prioritization assignment in the region. These maps can also be directly used to guide urban reforestation and green expansion efforts in the region or policymaking.

The resulting PPI maps showed that many areas clustered near NCR's center require high priority in tree planting. These areas were situated in Navotas, Malabon, South Caloocan, northern and southern portions of Manila, and the western side of Quezon City. There were also a few scattered high-priority areas in Marikina, San Juan, Taguig, Mandaluyong, Makati, Pateros, and Parañaque. Meanwhile, some low-priority areas were scattered near NCR's center but most of them are found near the region's outskirts specifically along the boundaries of Pasay, Navotas, Valenzuela, North Caloocan, Taguig, the eastern portion of Quezon City, Muntinlupa, and Las Piñas. On the other hand, high-high clusters formed in the southern part of Navotas and Malabon, South Caloocan, the northern portion of Manila, and the west side of Quezon City. Lastly, low-low clusters can be found in central Manila, west of Pasay, upper Navotas, Valenzuela, east of Taguig, east of Mandaluyong, and the western part of Pasig.

Improvements to this research can be made. Because of data limitations and the complexity of the analysis, we excluded soil types and tree species as factors, and ozone and particulate matter as air quality parameters. Introducing sub-weighting to refine the aggregation of air quality parameters or individually using the air quality parameters as factors of the index may improve the reliability of the research results. Up-to-date and higher-resolution datasets are also worth looking into for more accurate analyses. In addition, other goals and objectives can be investigated such as tree protection or conservation instead of planting, water quality improvement, and flood prevention. Lastly, other weighting approaches, visualization/classification techniques, and validation methods can be explored to improve the insights drawn from the analysis.

In truth, there is no single correct approach to tree planting prioritization but there are diverse alternatives that meet locally relevant requirements. Therefore, it is crucial to first identify the study area's goals, needs, and priorities as this will significantly change the resulting PPI and cluster maps. We hope that this study will contribute to the improvement of the different greening strategies in the Philippines, spark conversations regarding the importance of urban forests, and motivate more people to replicate, adapt, and improve this research.

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REFERENCES

Alonso, J. A., Lamata, M. T., 2006. Consistency in the analytic hierarchy process: a new approach. *International journal of uncertainty, fuzziness and knowledge-based systems*, 14(04), 445-459.

Anselin, L., 1995. Local indicators of spatial association—LISA. *Geographical analysis*, 27(2), 93-115.

De Haas, W., Hassink, J., Stuiver, M., 2021. The Role of Urban Green Space in Promoting Inclusion: Experiences From the Netherlands. *Frontiers in Environmental Science*, 9. https://doi.org/10.3389/fenvs.2021.618198

Department of Environment and Natural Resources, 2014. Metro Manila Urban Greening Plan.

Economist Intelligence Unit, 2011. Asian Green City Index. Siemens AG. Munich, Germany. https://w1.siemens.com.cn/userfiles/AGCI%20Report_EN.pdf (1 June 2022).

Goepel, K. D., 2013. New AHP Excel template with multiple inputs. Business Performance Management Singapore. URL: https://bpmsg.com/new-ahp-excel-template-with-multiple-inputs/ (1 June 2022).

Lin, J., 2020. Developing a composite indicator to prioritize tree planting and protection locations. *Science of the Total Environment*, 717, 137269.

Locke, D. H., Grove, J. M., Lu, J. W., Troy, A., O'Neil-Dunne, J. P., Beck, B. D., 2010. Prioritizing preferable locations for increasing urban tree canopy in New York City. *Cities and the Environment (CATE)*, 3(1), 4.

Morani, A., Nowak, D. J., Hirabayashi, S., Calfapietra, C., 2011. How to select the best tree planting locations to enhance air pollution removal in the MillionTreesNYC initiative. *Environmental Pollution*, 159(5), 1040-1047.

Nowak, D. J., Bodine, A. R., Hoehn, R., Ellis, A., Low, S. C., Roman, L. A., Endreny, T., 2016. The urban forests of Philadelphia. Resource Bulletin NRS-106. *Newtown Square, PA: US Department of Agriculture, Forest Service, Northern Research Station*. 80 p., 106, 1-80.

Nyelele, C., & Kroll, C. N., 2021. A multi-objective decision support framework to prioritize tree planting locations in urban areas. *Landscape and Urban Planning*, 214, 104172.

Saaty, T. L., 1980. The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation: McGraw-Hill. New York.

Sallahuddin, A. N. S., 2013. Development of an Excel Based Spreadsheet of Analytical Hierarchy Process And Decision Making Grid For Maintenance Policy Decision.

Sousa-Silva, R., Cameron, E., Paquette, A., 2021. Prioritizing Street Tree Planting Locations to Increase Benefits for All Citizens: Experience From Joliette, Canada. *Frontiers in Ecology and Evolution*, 9.

Wotlolan, D. L., Lowry, J. H., Wales, N. A., Glencross, K., 2021. Land suitability evaluation for multiple crop agroforestry planning using GIS and multi-criteria decision analysis: A case study in Fiji. *Agroforestry Systems*, 95(8), 1519-1532.

Zolfaghary, P., Zakerinia, M., Kazemi, H., 2021. A model for the use of urban treated wastewater in agriculture using multiple criteria decision making (MCDM) and geographic information system (GIS). *Agricultural Water Management*, 243, 106490.