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Estimating Urban Green Open Space Requirements Using Landsat 8 NDVI and Oxygen-Demand Assessment in Pekanbaru, Indonesia

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ABSTRACT

Urban green open spaces provide important ecological functions in densely populated cities. However, conventional assessments of green space availability may not adequately reflect vegetation distribution and estimated oxygen demand. This study assessed existing green open space and estimated oxygen-related green space requirements in Marpoyan Damai District, Pekanbaru, Indonesia, using satellite-derived vegetation density and population and motor vehicle data. The study employed a quantitative approach based on Landsat 8 imagery acquired in 2020, the Normalized Difference Vegetation Index (NDVI), field observations, population statistics, and household questionnaire data. Vegetation density was classified into four reported greenness categories, and areas with medium and high vegetation density were used to estimate existing green open space. The source calculations identified 434.77 ha of existing green open space, while the reported oxygen-demand estimate was 200,362.89 kg per hour. The thesis further reported a green space requirement of 834.85 ha and an additional requirement of 400.07 ha. However, inconsistencies in the oxygen-production coefficient, time units, and mapped area require recalculation before these estimates can be considered validated findings. The study provides a basis for integrating satellite-based vegetation mapping with oxygen-demand assessment in urban green space planning. Future work should harmonize the calculation units, verify spatial boundaries, and validate vegetation classifications using independent reference data.

Keywords:
urban vegetation mapping; landsat 8; NDVI classification; oxygen-demand assessment; green infrastructure; spatial planning.

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INTRODUCTION

Urban Green Open Space as a Challenge in Sustainable Urban Planning

Urban green open space is an important component of sustainable urban planning because it supports ecological functions, environmental quality, and human well-being(Teimouri et al., 2023, p. 14170). Urban parks, tree-lined streets, urban forests, and other vegetated areas provide ecosystem services associated with climate regulation, habitat provision, recreation, and the quality of urban environments(Richards & Belcher, 2019, p. 23; Ryczkowski, 1993, p. 6). However, these benefits depend not only on the total area of green space but also on its spatial distribution, vegetation characteristics, and relationship with the surrounding built environment. A systematic review by Haaland & Konijnendijk (2015) highlighted the importance of integrating green space into urban planning and identified the need to consider the spatial configuration and multifunctionality of urban green infrastructure. More recent evidence also shows that urban green spaces provide multiple ecosystem services, although the methods used to evaluate their contributions vary considerably across studies (Evans et al., 2022).

In Indonesia, urban green open space (ruang terbuka hijau, RTH) is also a spatial planning concern. Law No. 26 of 2007 concerning Spatial Planning established a minimum green open space proportion of 30% of the urban area, including a minimum public green open space proportion of 20% under the original statutory framework (Law No. 26 of 2007 Concerning Spatial Planning, 2007). These provisions provide an important planning benchmark. Nevertheless, compliance with an area-based target does not necessarily indicate whether vegetation is distributed equitably, whether individual green spaces contain sufficient vegetation, or whether their ecological functions are consistent with local environmental requirements. Recent research in Indonesian cities has demonstrated the value of remote sensing for mapping urban green space and examining differences in vegetation coverage. Agustiyara et al. (2025), for example,

used Sentinel-2 imagery and vegetation indices to investigate green space patterns in five major Indonesian cities. Their study illustrates how satellite observations can support the identification and monitoring of urban vegetation across different urban settings. However, mapping vegetation coverage and evaluating the functional requirements of green space represent distinct analytical tasks. A spatial inventory can identify where vegetation occurs, but additional assumptions and calculations are required to estimate whether the available green space meets a specified ecological demand(Hansen & Pauleit, 2014, p. 526; Liu & Russo, 2021, p. 102787).

This distinction is important for urban districts experiencing a combination of residential development, commercial activities, transportation infrastructure, and fragmented vegetation. Planning decisions require information about both the spatial extent of vegetation and the criteria used to determine green space requirements. An assessment based solely on total area may overlook differences in vegetation density, while an assessment based solely on vegetation greenness may not distinguish designated green space from other vegetated land. Therefore, a more informative planning assessment should combine spatial vegetation information with a clearly defined requirement indicator and explicitly document the limitations of each measure.

Remote Sensing and NDVI for Urban Vegetation Assessment

Remote sensing provides a practical approach for assessing vegetation over large areas using consistent spatial data. Satellite imagery enables researchers to characterize vegetation patterns across administrative boundaries and identify differences between vegetated and predominantly built-up areas. Shahtahmassebi et al. (2020), in their review of remote sensing applications for urban green spaces, identified the growing role of satellite-based approaches in mapping, monitoring, and characterizing urban vegetation. The review also highlighted continuing methodological challenges related to spatial resolution, vegetation characterization, and the assessment of ecological properties.

The Normalized Difference Vegetation Index (NDVI) is widely used to characterize vegetation greenness from optical satellite imagery. The index is calculated from the contrast between near-infrared and red reflectance: $NDVI = \frac{NIR-Red}{NIR+Red}$

For Landsat 8 Operational Land Imager (OLI) data, the calculation uses Band 5 for near-infrared reflectance and Band 4 for red reflectance (Boukhari et al., 2020, p. 117). The index provides a continuous measure of spectral vegetation response that can be classified into greenness categories for spatial comparison. Its mathematical simplicity and broad availability make NDVI useful for urban vegetation mapping and environmental monitoring (Shahtahmassebi et al., 2020; Tucker, 1979).

However, NDVI should not be interpreted as a direct measurement of green open space area, vegetation biomass, or oxygen production. It measures spectral properties associated with vegetation rather than the legal status, accessibility, or complete ecological function of a particular land parcel. Consequently, a pixel with a relatively high NDVI value may represent a public park, private garden, roadside tree cover, or another vegetated surface. The interpretation of NDVI therefore depends on the classification thresholds, spatial resolution, land cover characteristics, and analytical scale.

Recent empirical research has further demonstrated these limitations. Martinez & Labib (2022) found that the relationships between NDVI and different vegetation types were nonlinear and sensitive to the spatial scale of analysis. Their findings indicate that changes in mean NDVI cannot be translated directly into equivalent changes in every vegetation category. Similarly, Ju et al. (2024) found that NDVI predicted urban green space coverage more reliably than several structural characteristics, including average tree height. They also identified mixed-pixel, spatial-scale, and saturation effects that can introduce uncertainty into the interpretation of satellite-derived vegetation indices. These limitations are particularly relevant to heterogeneous urban landscapes, where a single pixel may contain vegetation, buildings, roads, and other land cover types.

Spatial resolution also affects the estimated extent and distribution of urban green space. Wu et al. (2023) compared satellite datasets with different spatial resolutions and found that coarser-resolution imagery could overestimate green space coverage and population exposure to green space. Martin et al. (2024) addressed a related issue by combining land cover information with NDVI to evaluate urban nature coverage across 96 cities. Their approach demonstrates the value of distinguishing land cover categories from continuous vegetation indices when evaluating urban green space provision.

These findings establish an important methodological principle for the present study. Landsat 8 NDVI can provide a spatially consistent basis for classifying vegetation greenness in Marpoyan Damai District. Nevertheless, the resulting classes should be interpreted as vegetation indicators rather than a definitive inventory of designated green open space. The relationship between the classified area and actual RTH provision must therefore be stated explicitly, and the resulting spatial estimates require verification against the administrative boundary and available field observations.

Oxygen-Demand Assessment as an Indicator for Green Open Space Planning

The assessment of urban green open space can be extended beyond area-based standards by considering the ecological functions that vegetation is expected to provide. One approach used in Indonesian urban planning research estimates the area of green open space required to meet the oxygen demand of human populations and motor vehicles. This approach links an estimated environmental demand to an assumed oxygen-production capacity per unit area of vegetation. Mbele & Setiawan (2015) examined public green open space provision based on oxygen demand in Malang, Indonesia. Their study calculated oxygen-related green space requirements and identified planning criteria for the provision of public green open space. The research demonstrates how oxygen demand can serve as a supplementary planning indicator alongside conventional area-based standards. However, the resulting area estimate depends on the oxygen-consumption coefficients, the categories of oxygen consumers included, and the assumed oxygen-production capacity of green space. A general formulation of this approach can be expressed as: $A_RTH = \frac{D_{O_2}}{Q_{O_2}}$

where A_{RTH} is the estimated green open space area required, D_{O_2} is the total estimated oxygen demand per unit time, and Q_{O_2} is the assumed oxygen-production capacity per unit area per unit time. This formulation represents a simplified planning model. Its validity depends on whether the demand and production terms use consistent units and whether the selected coefficients are appropriate for the study context.

The distinction between estimated oxygen demand and measured oxygen consumption is particularly important when motor vehicles are included in the calculation. A vehicle inventory does not directly indicate the number of vehicles operating simultaneously, the distance travelled, or the quantity of fuel consumed during a specified period(Stead & Marshall, 2001, p. 17; Zavala et al., 2009, p. 6306). Consequently, an estimate based on vehicle counts and fixed coefficients should be interpreted as a model-based approximation rather than a direct measurement of actual oxygen consumption.

The same caution applies to vegetation production. NDVI provides information about spectral greenness, but it does not directly quantify the rate of oxygen production(Huang et al., 2020, p. 5; Tucker & Sellers, 1986, p. 1415). Vegetation characteristics, environmental conditions, and the distinction between gross photosynthesis and net oxygen exchange affect how vegetation contributes to the oxygen balance(Lepage et al., 2023, p. 3630; Walther et al., 2015, p. 2994). Assigning one fixed oxygen-production coefficient to all vegetated land therefore introduces a simplifying assumption that should be justified and evaluated.

These considerations do not eliminate the potential value of oxygen-demand assessment. Instead, they establish the conditions under which the method can be interpreted appropriately. A defensible assessment should clearly define the population and vehicle categories included, specify the time basis of each coefficient, document the assumed vegetation-production rate, and distinguish estimated requirements from independently measured ecological outcomes.

Integrating oxygen-demand calculations with satellite-derived vegetation mapping can provide a more spatially explicit basis for planning. The satellite analysis identifies where vegetation occurs and how its greenness varies, while the oxygen-demand model estimates a theoretical area requirement under specified assumptions(Luo et al., 2017, p. 156; Terrado et al., 2015, p. 68). The two components provide complementary information, but their integration requires consistent spatial boundaries, transparent calculations, and careful interpretation of the resulting estimates.

Research Gap, Objectives, and Scientific Contribution

Previous research has established the usefulness of remote sensing for mapping urban green space and has demonstrated the potential of oxygen-demand calculations as an additional planning indicator. However, these approaches address different dimensions of urban environmental assessment. NDVI describes spectral vegetation conditions, whereas an oxygen-demand model estimates a theoretical requirement based on population, vehicle data, and assumed vegetation-production capacity. Their integration does not automatically produce a reliable estimate of green open space requirements.

Three methodological issues are particularly relevant to the present case. First, the use of NDVI thresholds to estimate existing green open space requires a clear distinction between spectral vegetation classes and designated green open space. Without this distinction, the mapped area may include vegetated surfaces that do not correspond directly to the RTH category being assessed. Second, the spatial area calculated from satellite imagery must be consistent with the administrative boundary of the study area. Third, oxygen-demand calculations must use compatible time units and a clearly specified oxygen-production coefficient. These requirements are consistent with recent research highlighting the sensitivity of urban green space estimates to spatial resolution, land cover composition, and analytical assumptions (Ju et al., 2024; Wu et al., 2023).

The literature also indicates that spatial mapping and ecological evaluation require different forms of validation. Shahtahmassebi et al. (2020) identified continuing methodological challenges in remote sensing applications for urban green space research. More recent studies have emphasized the need to combine vegetation indices with land cover information and to evaluate the limitations of spatial estimates before translating them into planning recommendations (Agustiyara et al., 2025; Martin et al., 2024). These findings support the need for a transparent assessment framework in which the spatial vegetation estimate, the assumed ecological function, and the calculation of green space requirements are evaluated separately before they are combined.

For Marpoyan Damai District, the original study combined Landsat 8 imagery, NDVI classification, population statistics, and motor vehicle estimates to assess green open space requirements. The present article develops this analysis into a more explicit scientific assessment by examining the reported vegetation distribution, reproducing the stated oxygen-demand calculations, and identifying internal inconsistencies that affect the interpretation of the final area estimate. The objective is not to assume that the original estimates are correct, but to distinguish the results supported by the reported data from those requiring further verification. Accordingly, this study addresses the following research questions: 1) How is vegetation greenness distributed across Marpoyan Damai District based on the reported Landsat 8 NDVI classification?; 2) How do the reported population and motor vehicle data contribute to the estimated oxygen demand under the coefficients adopted in the original study?; 3) How does the reported existing green open space area compare with the oxygen-based area requirement?; 4) To what extent are the reported spatial and oxygen-demand estimates internally consistent with the administrative area, stated calculation units, and oxygen-production coefficient?

The study has four objectives: 1) To describe the spatial distribution of vegetation greenness using the reported Landsat 8 NDVI classification; 2) To estimate the area represented by the medium and high greenness classes under the original classification procedure; 3) To examine the reported oxygen-demand calculations for human populations and motor vehicles; 4) To evaluate the internal consistency of the reported green open space requirement and identify the methodological conditions that must be satisfied before the estimate can be used for planning.

The principal contribution of this article is a transparent assessment of the integration of satellite-derived vegetation information and oxygen-demand calculations in an Indonesian urban district. The study connects spatial vegetation mapping with a demand-based planning indicator while distinguishing mapped vegetation area, theoretical green space requirements, and independently validated ecological outcomes. This distinction is important because planning recommendations should reflect not only the numerical outputs of a model but also the assumptions and uncertainties that determine those outputs.

The article therefore provides a case-based contribution to urban green space assessment by documenting how remote sensing and oxygen-demand estimates can be examined within a common spatial framework. Its findings are intended to support more reproducible green space planning and to identify the additional spatial verification, coefficient validation, and ecological measurements needed to strengthen future assessments.

MATERIALS AND METHODS

Study Area, Materials, and Research Conditions

The study was conducted in Marpoyan Damai District, Pekanbaru City, Riau Province, Indonesia. The thesis reports an administrative area of 29.79 km², comprising six urban villages: Tangkerang Tengah, Tangkerang Barat, Maharatu, Sidomulyo Timur, Wonorejo, and Perhentian Marpoyan. The study used the following data sources: 1) Landsat 8 satellite imagery from 2020, obtained from the USGS; 2) Population data for 2019 reported in Kecamatan Marpoyan Damai Dalam Angka 2020; 3) Household questionnaire data used to estimate motor vehicle numbers; 4) Field observations of existing vegetation and green open space; 5) Administrative boundaries and spatial reference information used in the original mapping process.

The reported population was 132,024 residents. The vehicle inventory included 13,900 private cars and 58,500 motorcycles.

Experimental Design and Data Collection

The study used a quantitative, cross-sectional spatial assessment. Satellite-derived vegetation density was combined with population and vehicle data to estimate green space requirements. The original household survey used stratified random sampling across the six urban villages. The reported sample comprised 314 households, equivalent to approximately 1% of the recorded 31,401 households. The thesis also describes purposive field verification at 10 locations. Each reported sampling location covered 100 m × 100 m. Field observations were used to compare vegetation conditions with satellite-derived classifications. However, the original document does not report a formal classification accuracy assessment based on a confusion matrix, overall accuracy, class-specific accuracy, or an independent validation sample. The 10 field locations should therefore be treated as field verification points rather than evidence of a statistically established classification accuracy.

NDVI Calculation and Vegetation Classification

NDVI was used to classify vegetation density from the Landsat 8 imagery. The index is defined as: $NDVI = \frac{NIR-Red}{NIR+Red}$

where \(NIR\) is near-infrared reflectance and \(Red\) is red-band reflectance. For Landsat 8 OLI, these correspond to Bands 5 and 4, respectively (USGS). The original study applied the following classification thresholds.

Table 1. classification thresholds NDVI Calculation and Vegetation Classification

NDVI range	Reported classification
$-1\ to\ -0.03$	Non-vegetated land
$-0.03\ to\ 0.15$	Very low greenness
$0.15\ to\ 0.25$	Low greenness
$0.25\ to\ 0.35$	Medium greenness
$0.35\ to\ 1.00$	High greenness

The original analysis treated the medium and high greenness classes as the principal areas contributing to the estimated existing green open space. This selection produced a reported total of 434.77 ha. For reproducibility, the final analysis should confirm that the imagery was clipped to the correct administrative boundary and that all pixels were classified using the same NDVI thresholds. It should also document cloud and shadow masking, pixel-area calculations, and the handling of mixed pixels.

Oxygen-Demand and Green Space Calculations

The original study estimated oxygen demand from the population and two vehicle categories. The reported coefficients were:

Human oxygen demand: 0.035 kg per person per hour.

Private car oxygen demand: 11.634 kg per vehicle per hour.

Motorcycle oxygen demand: 0.5817 kg per vehicle per hour.

Using the reported coefficients, total oxygen demand can be represented as:

$D_{O_2} = aP + bC + mM$

where: D_{O_2} is estimated total oxygen demand; P is population; C is the number of private cars; M is the number of motorcycles; a, b, and m are the respective oxygen-demand coefficients.

The original method describes an oxygen-production coefficient of 20 kg per hectare per hour. Under that assumption, the theoretical green space area is: $A_{RTH} = \frac{D_{O_2}}{q}$

where A_{RTH} is the estimated required green space area and \(q\) is the oxygen-production coefficient per hectare per hour.

RESULTS

Spatial Distribution and Classification of Urban Vegetation

The Landsat 8 imagery acquired in 2020 was classified into four vegetation greenness categories using the Normalized Difference Vegetation Index (NDVI). The original analysis reported a total classified area of 3,081.46 ha across the study area. The largest category was very low greenness, covering 1,650.79 ha or approximately 54% of the mapped area. Low greenness covered 995.90 ha (32%), whereas medium and high greenness covered 338.10 ha (11%) and 96.67 ha (3%), respectively. Table 2 presents the reported area distribution for each vegetation class.

Table 2. Spatial distribution of vegetation greenness classes derived from Landsat 8 imagery

Vegetation greenness class	NDVI range	Area (ha)	Reported area (%)
Very low greenness	−0.03 to 0.15	1,650.79	54
Low greenness	0.15 to 0.25	995.90	32
Medium greenness	0.25 to 0.35	338.10	11
High greenness	0.35 to 1.00	96.67	3
Total		3,081.46	100

The classification indicates that areas in the very low and low greenness categories dominated the mapped landscape. Together, these categories covered 2,646.69 ha, equivalent to approximately 86% of the reported classified area. Medium and high greenness areas covered a combined 434.77 ha, or approximately 14% of the classified area. The original study treated the medium and high greenness classes as the principal components of existing green open space. Based on this classification, the estimated existing green open space was 434.77 ha. The high-greenness class accounted for 96.67 ha, while the medium-greenness class accounted for 338.10 ha. Thus, the medium-greenness class represented the larger share of the two classes used in the original green space estimate. The results provide a spatial basis for identifying areas with different levels of vegetation greenness. However, the NDVI classes represent spectral vegetation conditions rather than a direct inventory of legally designated green open space. The reported 434.77 ha should therefore be interpreted as the area estimated using the original classification rule.

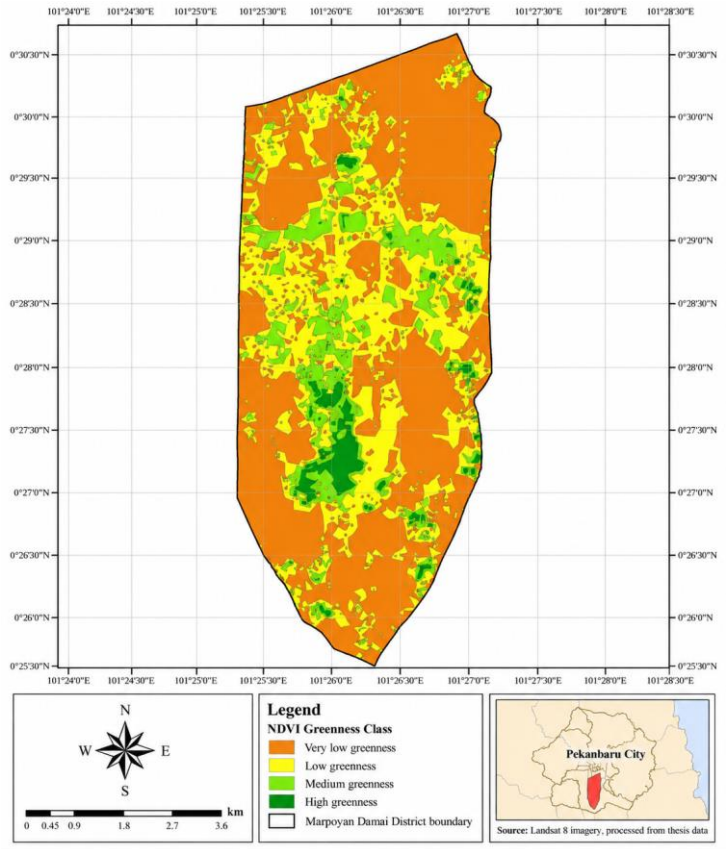


Figure 1. Spatial distribution of NDVI-derived vegetation greenness classes in Marpoyan Damai District.

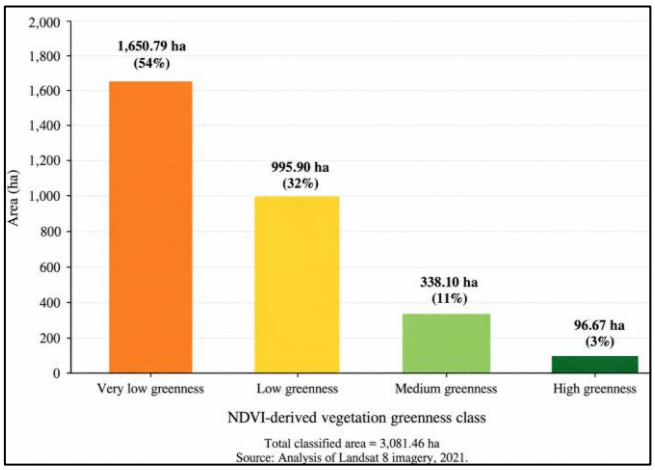


Figure 2. Area distribution of NDVI-derived vegetation greenness classes.

Field Observations and Interpretation of Vegetation Classes

Field observations were used in the original study to examine the physical characteristics associated with the satellite-derived vegetation classes. The observations described different vegetation conditions across roads, residential areas, vegetated land, roadside planting, and locations with relatively dense tree cover. Very low greenness areas included roads and residential areas containing limited or scattered vegetation. Low greenness areas were described as vegetated land. Medium greenness areas included shrubs and taller vegetation along roads, whereas high greenness areas were associated with urban forest patches and groups of trees with relatively dense canopies.

Table 3. Field interpretation of NDVI-derived vegetation classes

NDVI class	Reported field characteristics	Examples or locations described in the thesis
Very low greenness	Roads and residential areas with limited or scattered vegetation	Residential areas and Lapangan Bola Belimbing
Low greenness	Vegetated land with relatively limited canopy density	Vegetated parcels and TPU Kuini
Medium greenness	Shrubs and taller vegetation along roads	Taman Wisata Mini Arifin Ahmad
High greenness	Urban forest patches and groups of trees with dense canopies	Dense roadside green corridors

The field observations provide contextual support for interpreting the NDVI classes. They indicate that vegetation greenness varied according to the type and density of vegetation present at the observed locations. However, the available results do not establish the statistical accuracy of the classification.

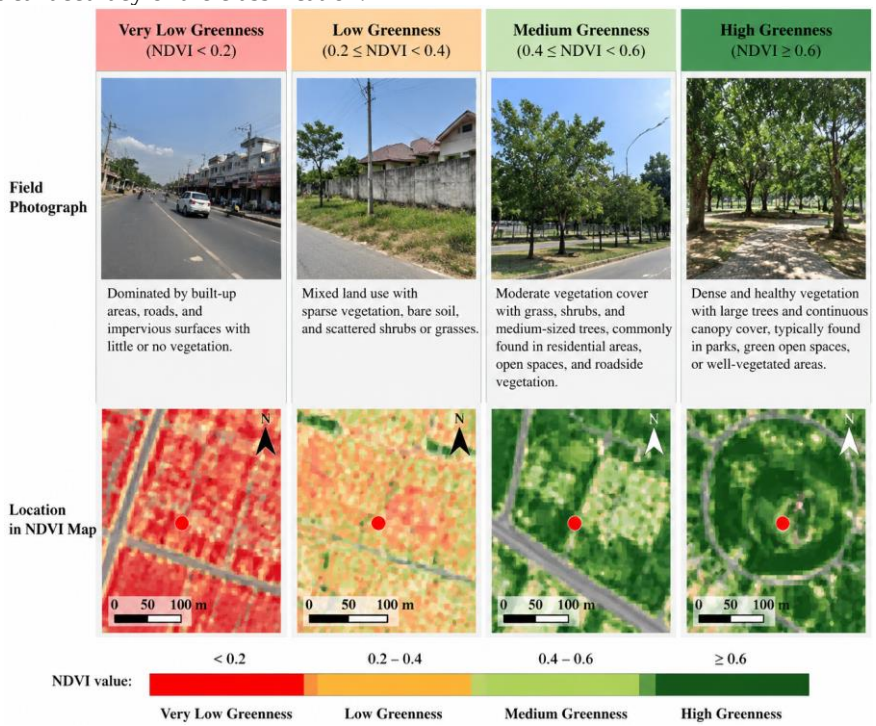


Figure 3. Representative field observations of vegetation conditions associated with the NDVI classes.

Population Distribution and Estimated Human Oxygen Demand

The population data used in the original study covered six urban villages. The total population was reported as 132,024 residents. Tangkerang Tengah had the largest population, with 34,420 residents, followed by Sidomulyo Timur with 26,917 residents. Maharatu had the smallest reported population, with 11,549 residents.

Table 4. Population distribution and oxygen-demand values reported in the original thesis

Urban village	Population (persons)	Oxygen-demand value printed in the thesis table
Tangkerang Tengah	34,420	29,738.88
Tangkerang Barat	18,756	16,205.18
Maharatu	11,549	9,978.34
Sidomulyo Timur	26,917	23,256.29
Wonorejo	20,243	17,489.95
Perhentian Marpoyan	20,139	17,400.10
Sum of the six village values	132,024	114,068.74
District total reported separately in the thesis	132,024	4,620.84 kg/h

Table 4 the original table labels the village-level values as kg/h, but their numerical values correspond to 0.864 kg per person per day. The district total of 4,620.84 kg/h corresponds to the separately stated coefficient of 0.035 kg per person per hour. Tangkerang Tengah had the largest reported village-level oxygen-demand value, whereas Maharatu had the smallest. This pattern follows the population distribution when a common per-person coefficient is applied. The village-level values and the district total, however, do not share a consistent time basis. The six village values sum to 114,068.74, while the district total is reported as 4,620.84 kg/h. These figures must not be combined without resolving the difference between daily and hourly oxygen demand. For consistency, the human oxygen demand calculated using the hourly coefficient stated in the original methodology is:

$$D_{human} = 132{,}024 \times 0.035 \text{ and } D_{human} = 4{,}620.84 \frac{kg}{h}$$

Motor Vehicle Inventory and Estimated Oxygen Demand

The original study included two vehicle categories: private cars and motorcycles. The reported inventory comprised 13,900 private cars and 58,500 motorcycles,

giving a total of 72,400 vehicles. Table 4 presents the reported distribution across the six urban villages.

Table 5. Reported motor vehicle inventory by urban village

Urban village	Private cars	Motorcycles	Total vehicles
Tangkerang Tengah	3,800	16,000	19,800
Tangkerang Barat	2,400	9,800	12,200
Maharatu	2,900	3,800	6,700
Sidomulyo Timur	1,000	9,000	10,000
Wonorejo	1,800	8,400	10,200
Perhentian Marpoyan	2,000	11,500	13,500
Total	13,900	58,500	72,400

Tangkerang Tengah had the largest reported vehicle inventory, with 19,800 vehicles. Maharatu had the smallest, with 6,700 vehicles. Motorcycles accounted for the larger share of the reported vehicle inventory in every urban village. The original study applied oxygen-demand coefficients of 11.634 kg/h per private car and 0.5817 kg/h per motorcycle. The corresponding demand estimates are presented in Table 6.

Table 5. Oxygen-demand estimates for motor vehicles by urban village

Urban village	Private car demand (kg/h)	Motorcycle demand (kg/h)	Total vehicle demand (kg/h)
Tangkerang Tengah	44,209.20	9,307.20	53,516.40
Tangkerang Barat	27,921.60	5,700.66	33,622.26
Maharatu	33,738.60	2,210.46	35,949.06
Sidomulyo Timur	11,634.00	5,235.30	16,869.30
Wonorejo	20,941.20	4,886.28	25,827.48
Perhentian Marpoyan	23,268.00	6,689.55	29,957.55
Total	161,712.60	34,029.45	195,742.05

The reported calculations indicate that private cars contributed 161,712.60 kg/h to the estimated demand, compared with 34,029.45 kg/h for motorcycles. Private cars therefore accounted for approximately 82.6% of the estimated vehicle-related demand, while motorcycles accounted for approximately 17.4%. Tangkerang Tengah had the largest combined vehicle-related oxygen-demand estimate, at 53,516.40 kg/h. Sidomulyo Timur had the smallest, at 16,869.30 kg/h. These differences reflect the reported vehicle counts and the coefficients applied in the original calculation. The results represent coefficient-based estimates rather than direct measurements of oxygen consumption. The available data do not establish how many vehicles operated simultaneously or how their activity varied by time of day.

Comparison of Estimated Oxygen Demand and Existing Green Open Space

The original study combined the reported human and motor vehicle oxygen-demand estimates to calculate total oxygen demand. The reported district-level values were 4,620.84 kg/h for humans and 195,742.05 kg/h for motor vehicles, giving a combined estimate of 200,362.89 kg/h. Motor vehicles accounted for approximately 97.7% of this total, while the human component accounted for approximately 2.3%. Table 6 summarizes the oxygen-demand and green space figures reported in the thesis.

Table 6. Summary of reported oxygen demand and green open space estimates

Indicator	Reported value
Human oxygen demand	4,620.84 kg/h
Motor vehicle oxygen demand	195,742.05 kg/h
Total oxygen demand	200,362.89 kg/h
Existing green open space estimated from medium and high NDVI classes	434.77 ha
Reported existing oxygen production	104,345.21 kg/h
Reported green open space requirement	834.85 ha
Reported additional green open space requirement	400.07 ha

The reported green space requirement of 834.85 ha exceeded the estimated existing green open space of 434.77 ha by 400.08 ha when calculated directly from the two displayed values. The thesis reports a difference of 400.07 ha, which may reflect rounding or the use of more precise intermediate values. Using the reported area estimates, existing green open space represented approximately 52.1% of the stated requirement.

Data Consistency and Verification of Reported Results

The numerical results require internal consistency checks before the estimated green space requirement can be interpreted as a validated outcome. Three issues are evident in the source data: the discrepancy between the administrative area and the mapped area, the inconsistent time units used for human oxygen demand, and the difference between the stated and implied oxygen-production coefficients. Table 7 summarizes these issues using the values reported in the original thesis and direct arithmetic checks.

Table 7. Internal consistency checks for the reported spatial and oxygen-demand results

Parameter	Value reported in the thesis	Consistency check	Implication
Administrative area	29.79 km²	Equivalent to 2,979 ha	Reference area for spatial verification
Total area from NDVI classes	3,081.46 ha	Exceeds the administrative area by 102.46 ha, or approximately 3.44%	Image boundary, area calculation, and coordinate reference system require verification
Existing green open space	434.77 ha	Sum of medium and high greenness classes is approximately 434.77 ha	Arithmetically consistent with the reported class areas
Human oxygen demand	4,620.84 kg/h	\(132{,}024 \times 0.035 = 4{,}620.84\) kg/h	Consistent with the hourly coefficient stated in the methodology
Sum of village-level human demand values	114,068.74	Values correspond to approximately 0.864 kg/person/day, not kg/person/hour	Time units in the original table require clarification
Oxygen-production coefficient	20 kg/h/ha in the methodology	Reported production implies approximately 240 kg/h/ha	Coefficient used in the final calculations must be verified
Green space requirement	834.85 ha	\(200{,}362.89 / 240 \approx 834.85\) ha	Consistent with the implied coefficient, not the coefficient stated in the methodology
Requirement using the stated coefficient of 20 kg/h/ha	Not reported as a final result	\(200{,}362.89 / 20 = 10{,}018.14\) ha	Illustrates the magnitude of the coefficient inconsistency; not a validated planning estimate
Reported additional green space	400.07 ha	\(834.85 - 434.77 = 400.08\) ha using displayed values	Small difference may reflect rounding or unreported precision

DISCUSSION

Interpretation of NDVI-Derived Vegetation Distribution

The Landsat 8 analysis identified substantial differences in vegetation greenness across Marpoyan Damai District. The original study reported 1,650.79 ha of very low greenness, 995.90 ha of low greenness, 338.10 ha of medium greenness, and 96.67 ha of high greenness. The medium and high greenness classes together accounted for 434.77 ha, which the original study used as an estimate of existing green open space. This distribution suggests that areas classified as medium and high greenness occupied a relatively limited share of the mapped landscape. Because the NDVI thresholds used to define these classes were applied to a single Landsat 8 scene, the proportion of greenness in this district should be read as a snapshot of vegetation condition at the acquisition date rather than as a stable measure of green open space.

The results illustrate the value of satellite imagery for identifying spatial variation in urban vegetation. Remote sensing provides consistent spatial coverage and allows vegetation conditions to be compared across administrative areas. Shahtahmassebi et al. (2020) identified remote sensing as an important tool for mapping and characterizing urban green spaces, while also highlighting continuing challenges in vegetation classification, spatial resolution, and the characterization of ecological properties. Their review supports the use of satellite imagery as a foundation for urban green space assessment, but it does not imply that a single vegetation index can fully represent the ecological condition of an urban landscape.

The interpretation of the present NDVI classes must therefore distinguish spectral greenness from the actual extent of designated green open space. A pixel with a medium or high NDVI value may contain a public park, private garden, roadside vegetation, or another vegetated surface(Spotswood et al., 2021, p. 1096; Texier et al., 2018, p. 6). Conversely, a designated green space containing sparse vegetation or extensive paved facilities may produce relatively low NDVI values. The classification rule used in the original study consequently represents a simplified proxy for existing green open space rather than a comprehensive inventory of public and private RTH.

This distinction is consistent with Ju et al. (2024), who examined the relationship between NDVI and several physical characteristics of urban green space. Their findings showed that NDVI predicted green space coverage more reliably than structural characteristics such as tree height. They also identified mixed-pixel effects, scale dependence, and saturation as important sources of uncertainty. These sources of uncertainty are not unique to the Landsat 8 NDVI classification used here, and they therefore constrain how the thresholds of 1,650.79 ha, 995.90 ha, 338.10 ha, and 96.67 ha should be interpreted, particularly in heterogeneous urban fabric where vegetation is sparse or intermixed with built structures (Scheiber et al., 2025, p. 101827).

For Marpoyan Damai, the implication is that the reported 434.77 ha should be interpreted as the area assigned to the medium and high greenness classes under the original classification procedure. It should not automatically be interpreted as the definitive area of legally designated or ecologically functional green open space. Establishing the latter requires additional information on land use, land ownership or designation, vegetation structure, and the spatial boundaries of individual green spaces. Until these boundaries are defined, the NDVI-based estimate should be treated as an indicative measure of vegetation presence rather than as a verified inventory of urban green open space, since spectral greenness cannot distinguish between tree canopy, grassland, and other vegetated surfaces with different ecological functions (Martinez & Labib, 2022, p. 2).

The reported distribution nevertheless provides a useful preliminary basis for further investigation. Areas classified as low greenness may contain opportunities for vegetation improvement, while existing medium and high greenness areas may warrant protection or more detailed assessment. Such decisions should depend on field verification and land use information rather than NDVI values alone. Future assessments should therefore combine NDVI-based classification with complementary data sources, such as ground-truth surveys, high-resolution aerial imagery, or LiDAR, which can better resolve vegetation structure and reduce the misclassification of heterogeneous urban surfaces (Rodríguez-Gómez et al., 2022, p. 127790).

Implications of Spatial Resolution and Area Consistency

A major issue emerging from the spatial analysis is the discrepancy between the total classified area and the reported administrative area. The four NDVI classes sum to 3,081.46 ha, whereas the thesis reports a district area of 29.79 km², equivalent to 2,979 ha. The classified area therefore exceeds the reported administrative area by 102.46 ha, or approximately 3.44%.

This discrepancy is important because the total area of the study boundary provides the denominator for interpreting vegetation coverage. If the mapped area does not match the administrative area, the reported percentages and subsequent estimates of existing green open space may be affected. The difference could arise from a boundary mismatch, image clipping, projection settings, pixel-area calculations, or another spatial processing issue. However, the available evidence does not establish which explanation is responsible.

Spatial resolution is also relevant. Landsat 8 provides 30 m spatial resolution for the red and near-infrared bands used in NDVI calculations. In a heterogeneous urban environment, a pixel may contain several land cover types. This mixed-pixel effect can complicate the separation of vegetation from roads, buildings, and other surfaces. Ju et al. (2024) showed that the predictive performance of NDVI depends partly on the resolution of the source imagery and the scale at which green space characteristics are assessed. Their findings support the need to verify area estimates when satellite-derived vegetation classes are used to represent urban green space.

The spatial discrepancy also limits comparisons with studies that use different satellite products, classification rules, or definitions of green space. Martin et al. (2024), in their assessment of urban nature coverage across 96 C40 cities, combined categorical land cover information with satellite-derived NDVI. This approach distinguishes the identification of land cover categories from the measurement of vegetation greenness. Their study demonstrates why these two information sources can provide complementary evidence for urban green space assessment.

For the present study, the administrative boundary should be verified and the image-processing workflow repeated before the area estimates are finalized. The analysis should document the coordinate reference system, boundary source, image clipping procedure, pixel-area calculation, and handling of invalid or mixed pixels. If the verified area differs from the current result, all class areas and percentages should be recalculated consistently.

This issue is not merely a technical detail. The spatial area forms the basis for the subsequent comparison between existing vegetation and the estimated requirement. Correcting the mapped area is therefore necessary before the study can provide a reliable numerical basis for planning.

Interpretation of Population and Motor Vehicle Oxygen-Demand Estimates

The original study estimated total oxygen demand at 200,362.89 kg/h, comprising 4,620.84 kg/h for the population and 195,742.05 kg/h for motor vehicles. Under the coefficients used in the thesis, motor vehicles accounted for approximately 97.7% of the combined estimate. Private cars contributed 161,712.60 kg/h, while motorcycles contributed 34,029.45 kg/h.

These results indicate that the motor vehicle component dominates the model output. However, this dominance follows from the selected coefficients and the reported vehicle inventory. It does not independently establish that motor vehicles consume oxygen at the calculated aggregate rate throughout every hour.

The distinction is important because the original calculation uses vehicle counts as inputs without directly measuring the number of vehicles operating simultaneously, vehicle-kilometres travelled, fuel consumption, or operating duration. A count of vehicles associated with a district does not necessarily represent the number of vehicles in operation at a particular time. The calculated values should therefore be interpreted as coefficient-based estimates rather than direct measurements of hourly oxygen consumption.

The spatial distribution of the vehicle inventory also provides a preliminary indication of where transport-related demand may be concentrated under the model assumptions. Tangkerang Tengah had the largest reported vehicle inventory, comprising 3,800 private cars and 16,000 motorcycles. It also had the largest reported population, with 34,420 residents. The coincidence of high population and vehicle counts identifies this urban village as a relevant location for more detailed transport and land use assessment. Nevertheless, the current data do not establish a causal relationship between population size, traffic activity, and actual oxygen consumption(Khan et al., 2020, p. 138586; Liu et al., 2023, p. 280).

A more robust assessment would distinguish vehicle ownership or inventory from observed traffic activity. Traffic counts collected over specified periods, vehicle classifications, average operating duration, and information on fuel consumption would provide a more defensible basis for estimating vehicle-related oxygen demand(Liu et al., 2017, p. 12710; Osses et al., 2022, p. 1362). Where such information is unavailable, the model should report the adopted coefficients explicitly and examine how the resulting estimate changes under alternative assumptions.

The original human oxygen-demand calculation presents a separate consistency issue. The district total of 4,620.84 kg/h is arithmetically consistent with the stated coefficient of 0.035 kg per person per hour and a population of 132,024. However, the individual village values printed in the thesis correspond to a different time basis. The village-level values sum to 114,068.74, which cannot be reconciled directly with the stated district total without clarifying the units and coefficient used.

This inconsistency affects the interpretation of the comparison between human and motor vehicle demand. The human estimate can be reproduced from the stated hourly coefficient, but the village-level figures should not be treated as directly comparable with the motor vehicle estimates until their time basis is verified.

Oxygen Production and the Validity of the Green Space Requirement

The original thesis reported 104,345.21 kg/h as the oxygen production associated with 434.77 ha of existing green open space. It also reported an oxygen-based green space requirement of 834.85 ha and an additional requirement of 400.07 ha. These figures imply that the estimated existing area was insufficient to meet the modelled oxygen demand.

However, the numerical relationship between oxygen demand, oxygen production, and required area is inconsistent with the production coefficient stated in the original methodology. The methods specify a coefficient of 20 kg/h/ha, whereas the reported production values correspond approximately to 240 kg/h/ha. The reported area requirement of 834.85 ha is also consistent with dividing the total estimated demand of 200,362.89 kg/h by approximately 240 kg/h/ha rather than by 20 kg/h/ha.

This discrepancy prevents the reported area requirement from being interpreted as a validated result. If the stated coefficient of 20 kg/h/ha were applied directly to the reported total demand, the calculated requirement would be 10,018.14 ha. This alternative value is a diagnostic calculation intended to expose the inconsistency. It should not be interpreted as a corrected planning target because the validity and applicability of the coefficient itself have not been established.

The relationship between vegetation and oxygen production also requires careful interpretation. NDVI measures spectral greenness rather than photosynthetic oxygen flux. Vegetation density, tree size, biomass accumulation, species characteristics, and environmental conditions can affect the relationship between remotely sensed greenness and ecological productivity. Consequently, a fixed production rate applied uniformly to every hectare of classified vegetation represents a substantial simplifying assumption.

Research by Khodakarami et al. (2022) illustrates an alternative approach to estimating oxygen production in urban green spaces. Their study combined field measurements of tree characteristics, allometric equations, high-resolution satellite imagery, and geographically weighted regression to estimate the spatial distribution of carbon sequestration and oxygen production in Isfahan, Iran. Rather than assigning a single uniform value to all green areas, their method linked remotely sensed information with ground-based tree measurements.

The difference between these approaches is methodologically important. The original Marpoyan Damai study uses NDVI classes to identify areas considered eligible for oxygen-production calculations and then applies a fixed

coefficient. The Isfahan study estimates tree-related ecological functions using measured biophysical characteristics and a spatial model. These approaches are not directly equivalent, but the comparison illustrates the importance of matching the complexity of the ecological claim to the evidence available.

Nowak et al. (2007) also examined oxygen production by urban trees and discussed the relationship between tree growth, carbon accumulation, and net oxygen production. Their analysis emphasizes that oxygen production is one of several ecosystem services provided by urban trees and that other benefits may be more consequential for environmental quality and human health. Consequently, the estimation of oxygen production in urban green spaces should be interpreted as an indicative planning metric rather than a precise measure of atmospheric oxygen balance, particularly because greenspace metrics derived from NDVI are sensitive to the spatial scale and the type of vegetated surface being captured (Martinez & Labib, 2022, p. 115157).

For Marpoyan Damai, the immediate priority is therefore not to adopt a larger or smaller green space target without further evidence. It is to verify the intended production coefficient, reconcile the units, and recalculate the oxygen-demand and area estimates from the underlying data. If the coefficient of 20 kg/h/ha is retained, the resulting estimate must be recalculated accordingly. If another coefficient is intended, its source, scientific basis, and units must be documented. Until this verification is completed, the reported additional requirement of approximately 400 ha should be described as a provisional estimate from the original calculation, not as an established ecological deficit.

Comparison with Previous Research and the Contribution of the Study

The present study shares two methodological elements with previous urban green space research: satellite-based vegetation classification and demand-based estimation of green space requirements. Its contribution lies in examining these elements together within a specific urban district and making the consistency of the resulting calculations an explicit part of the interpretation. Mbele & Setiawan (2015) investigated public green open space requirements based on oxygen demand in Malang, Indonesia. Their study used oxygen demand as an additional criterion for green space provision rather than relying exclusively on a fixed area proportion. The Marpoyan Damai study follows a similar conceptual approach by comparing estimated demand with the area assigned to selected vegetation classes. However, both the coefficients and the spatial data must be sufficiently documented before such comparisons can support planning decisions. Such comparisons remain provisional until the coefficient, its units, and the underlying NDVI classification are independently verified, since the greenspace mapping itself carries accuracy limitations that propagate into any demand-based area estimate (Tian et al., 2024, p. 15). The remote sensing component also relates to the broader literature on urban vegetation mapping. Shahtahmassebi et al. (2020) reviewed the increasing use of remote sensing for urban green space characterization and highlighted continuing methodological challenges in the measurement of vegetation characteristics. Ju et al. (2024) further demonstrated that NDVI performance varies according to the specific green space characteristic being estimated. Martin et al. (2024) showed that combining categorical land cover data with NDVI provides a useful framework for evaluating urban nature coverage across different cities. Together, these studies support the use of satellite-derived vegetation information while emphasizing the need to distinguish greenness, land cover, and ecological function.

The current study does not demonstrate that integrating NDVI with oxygen-demand estimates is a new method in itself. Previous research has already explored oxygen-based green space planning and the use of remote sensing to estimate vegetation-related ecosystem services. Its more defensible contribution is the case-specific evaluation of how these components are combined and the identification of inconsistencies that materially affect the resulting area estimate(Rioux et al., 2019, p. 11; Veerkamp et al., 2023, p. 101501).

This contribution is relevant to urban planning research because model outputs can appear precise even when their input units or spatial boundaries are inconsistent. By separating the reported spatial findings from the calculations that require verification, the analysis makes the assumptions underlying the proposed green space requirement more transparent. It also identifies the specific evidence needed to move from a preliminary planning estimate to a reproducible and independently assessable result.

Implications for Urban Green Open Space Planning

Despite the unresolved numerical issues, the spatial assessment provides a preliminary basis for identifying areas that may warrant further investigation and vegetation management. The NDVI classification indicates that medium and high greenness areas account for a relatively small share of the reported mapped area. This pattern can help direct field surveys toward locations where vegetation protection, canopy improvement, or green space expansion may be relevant.

However, planning interventions should not be determined by NDVI thresholds alone. A low-greenness area may include a road, a residential parcel, an open field, or a designated green space with sparse vegetation. These land uses have different constraints and opportunities for intervention. Similarly, a high-greenness area may contain private vegetation that cannot be treated as publicly accessible green space.

A practical planning framework should therefore distinguish three spatial categories: existing designated green open space, other vegetated land, and land potentially suitable for future green space development. This classification would help planners determine whether a location requires protection, vegetation enhancement, or a change in land use designation. Combining land cover data with vegetation indices would improve the distinction between these categories, consistent with the approach used by (Martin et al., 2024).

The results also suggest that urban green space planning should consider the distribution of vegetation across the six urban villages rather than relying exclusively on a district-wide total. The population and vehicle inventory indicate differences among locations, while the NDVI results provide a basis for further investigation of vegetation distribution. Integrating these datasets could support a more spatially targeted assessment, provided that their geographic boundaries and time periods are aligned.

The oxygen-demand approach may remain useful as a supplementary planning indicator, but its numerical output

should not replace established land use planning standards or direct ecological assessment. A theoretical oxygen-based area requirement does not independently establish whether a green space is accessible, whether its vegetation is healthy, or whether it provides sufficient canopy coverage and other ecosystem services.

This distinction is consistent with the findings of Nowak et al. (2007), who discussed oxygen production as one of several ecosystem services associated with urban trees. Urban green space decisions should therefore consider a broader range of functions, including shade, thermal regulation, habitat provision, recreation, and the spatial distribution of vegetation. These functions should be assessed using appropriate indicators rather than inferred from oxygen calculations alone.

For Marpoyan Damai, the most defensible planning implication is to use the current spatial results to guide further verification and site assessment. Specific planting targets, land acquisition decisions, or claims of an oxygen deficit should be established only after the spatial inventory and oxygen-production calculations have been corrected.

Limitations and Directions for Future Research

Several limitations affect the interpretation and generalizability of the findings.

First, the total area classified from NDVI exceeds the reported administrative area. The difference of 102.46 ha indicates that the spatial analysis requires verification. Until the boundary and area calculation are corrected, the reported class percentages and derived green space estimate cannot be treated as fully validated spatial measurements.

Second, the NDVI classification was not accompanied by a reported confusion matrix or quantitative classification accuracy assessment. The original thesis describes 10 purposively selected field verification locations, but it does not provide sufficient information to establish the classification accuracy for each vegetation class. Future research should use a documented reference sample and report appropriate accuracy metrics. Where suitable reference data are available, the analysis should also distinguish designated green space from other vegetated land.

Third, the oxygen-demand calculation uses fixed coefficients for humans, private cars, and motorcycles. The reported vehicle inventory does not directly measure operating vehicles or traffic activity during a specified period. Future studies should incorporate observed traffic volumes, vehicle operating conditions, and a clearly defined temporal basis for the demand estimates. These improvements would reduce the dependence on unverified assumptions.

Fourth, the oxygen-production coefficient is inconsistent across the original methodology and results. The study does not provide sufficient evidence to determine which coefficient should be retained. Future analysis should verify the original source and units of the coefficient and, where possible, compare the assumed production rate with field-based or scientifically documented estimates of vegetation productivity. Research that integrates tree measurements and remote sensing, such as (Khodakarami et al., 2022), provides one possible methodological direction.

Fifth, the satellite imagery, population statistics, and field observations do not necessarily represent the same observation period. The original analysis used Landsat 8 imagery from 2020, population data for 2019, and fieldwork reported in 2021. These differences may affect the spatial and temporal comparability of the inputs. Future studies should document data dates explicitly and consider multitemporal imagery where the research objective requires the assessment of vegetation change.

Finally, the study does not report a formal sensitivity analysis. The estimated green space requirement may change substantially when the oxygen-production coefficient, vehicle demand coefficients, or mapped vegetation area changes. Future research should evaluate these parameters separately and report how alternative assumptions affect the final area estimate. Such an analysis would help distinguish robust planning conclusions from results that depend strongly on a single coefficient.

These limitations do not eliminate the value of the current spatial assessment. Instead, they define the conditions under which its results can be strengthened. The most important next step is to reconcile the spatial area and oxygen-demand calculations before drawing quantitative conclusions about the additional green open space required in Marpoyan Damai District.

Overall Discussion

The findings demonstrate the potential of combining satellite-derived vegetation mapping with an oxygen-demand framework for examining urban green open space provision. The NDVI classification provides a preliminary description of vegetation greenness, while the population and vehicle data form the basis of the original demand calculation. Together, these datasets provide a starting point for spatially explicit urban green space assessment.

However, the study also shows that the reliability of an integrated assessment depends on the consistency of its spatial data, coefficients, and units. The mapped area exceeds the stated administrative area, the human oxygen-demand table uses inconsistent time units, and the reported oxygen-production figures do not match the coefficient stated in the methodology. These discrepancies directly affect the interpretation of the estimated green space requirement.

The study's principal scientific contribution is therefore a transparent assessment of the assumptions and calculation requirements involved in linking vegetation mapping with oxygen-demand estimates. It does not yet establish a definitive additional RTH requirement for Marpoyan Damai District. A validated estimate requires correction of the spatial boundary, verification of the oxygen-production coefficient, and recalculation of the area requirement using consistent units.

Once these issues are resolved, the resulting framework could support more defensible green space planning by distinguishing actual vegetation coverage, designated green space, and theoretical ecological requirements. This distinction would help ensure that planning recommendations are based on reproducible calculations and evidence appropriate to the environmental function being evaluated.

CONCLUSION

This study assessed urban vegetation distribution and estimated oxygen-related green open space requirements in Marpoyan Damai District, Pekanbaru, Indonesia, using Landsat 8 imagery, the Normalized Difference Vegetation Index (NDVI), population statistics, and motor vehicle data. The findings provide a preliminary spatial assessment of vegetation greenness and demonstrate the potential for integrating satellite-derived vegetation information with an oxygen-demand framework for urban green space planning.

The NDVI classification reported 338.10 ha of medium-greenness vegetation and 96.67 ha of high-greenness vegetation, resulting in a combined area of 434.77 ha. The original study used this combined area as an estimate of existing green open space. However, because NDVI represents spectral vegetation characteristics rather than designated land use, this estimate should not be interpreted as a definitive inventory of public and private green open space.

The original calculations reported a total oxygen demand of 200,362.89 kg/h, comprising 4,620.84 kg/h for the human population and 195,742.05 kg/h for motor vehicles. The study also reported an oxygen-based green open space requirement of 834.85 ha and an additional requirement of approximately 400.07 ha. These area estimates remain provisional because the stated oxygen-production coefficient is inconsistent with the coefficient implied by the reported results. In addition, the total area obtained from the NDVI classification exceeds the stated administrative area by 102.46 ha. These discrepancies prevent the reported additional green space requirement from being accepted as a validated planning target.

The principal contribution of this study is its integration of satellite-based vegetation classification and oxygen-demand estimation within a district-level urban planning assessment, together with the identification of methodological conditions that affect the reliability of the resulting estimates. The findings highlight the importance of distinguishing mapped vegetation greenness, designated green open space, and theoretical ecological requirements when evaluating urban green space provision.

Future research should verify the administrative boundary and spatial area calculations, reconcile the oxygen-demand and oxygen-production units, and establish a scientifically justified production coefficient. Independent validation of the NDVI classification, improved information on actual motor vehicle activity, and sensitivity analysis should also be incorporated to assess the robustness of the estimates. Further studies could integrate land cover data, field-based vegetation measurements, and tree canopy characteristics to improve the spatial representation of green open space and its ecological functions.

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CRediT Author Contributions

Demonisis Ademika: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Visualization, and Writing of the original draft.

Faizan Dalilla: Supervision, Methodology, Validation, and Writing, review and editing.

Data Availability Statement

The Landsat 8 satellite imagery used in this study is available from the United States Geological Survey (USGS). Population statistics were obtained from *Kecamatan Marpoyan Damai Dalam Angka 2020*, published by Statistics Indonesia (BPS) of Pekanbaru City

Code and Software Availability

No custom code was developed specifically for this study. The software used for satellite image processing, NDVI classification, and spatial analysis should be identified by its name and version after verification against the original project files.

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