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Mapping Nature's Canopy: Analyzing Google Street View's Big Data for Green View Index Identification

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Abstract: The lack of green open spaces in urban areas has become a global issue that is difficult to solve. This is due to the decreasing availability of land in urban areas and the increasing population density and activities. This research aims to provide discourse on identifying the level of urban greenness based on scenery and visual orientation. Big data from Google Street View images based on visual orientation in the field is utilized for the data analysis. In the case study conducted in the city of Malang, Indonesia that the application of this method resulted in a Green View Index of 0.137, or 13.7%. This value indicates a moderate correlation with the Normalized Difference Vegetation Index (NDVI), which serves as the basis for validation. The research findings suggest that this approach could be an alternative method for assessing green open spaces in urban areas. By utilizing big data from Google Street View images and focusing on visual orientation, this research provides a novel perspective for evaluating urban greenness. The Green View Index derived from this method offers valuable insights into the extent of green open spaces in urban environments. The hope is that this approach can contribute to addressing the challenges associated with urban green space assessment.

Keywords: Green View Index; Google Street View; NDVI

1. Introduction

Globally, there are many different factors that have an impact on the condition of urban green open spaces (GOS). As cities grow and give priority to housing, economic activity, and infrastructure development, there is less land available for GOS [1–5]. The lack of available land makes it difficult to provide enough green space in urban areas. Pollution, climate change, and human activities all contribute to the degradation and fragmentation of urban GOS [6–10]. The GOS is degrading due to elements like soil erosion, soil and water pollution, and the loss of natural habitats. The fragmentation of green spaces, where they are divided into smaller, disconnected patches, is another effect of urban development. This fragmentation compromises the GOS's ecological integrity and practical advantages [1,6]. Urban GOS also includes spatial inequity [11]. There is frequently a disparity in access to green spaces, with some urban areas having better access than others. Limited access to GOS is common in densely populated areas and economically underprivileged communities, which results in an uneven distribution of environmental benefits and fewer opportunities for leisure and well-being [12,13].

Despite the challenges, urban GOS offer significant environmental and health benefits. They contribute to improved air quality, help mitigate the urban heat island effect, support biodiversity, and provide recreational spaces for physical and mental well-being. Recognizing these benefits, many countries have implemented policies and initiatives to enhance urban GOS. These efforts include the creation of city parks, green infrastructure projects, urban greening programs, and the integration of GOS into urban planning strategies. In conclusion, land scarcity, degradation, fragmentation, spatial inequity, and varying degrees of policy implementation are characteristics of the state of urban GOS globally. For cities to be sustainable, livable, and resilient, efforts must be made to address these issues and encourage the growth and preservation of green spaces in urban areas. Urban GOS are essential components of sustainable and livable cities. They provide numerous benefits, including improved air and water quality, biodiversity conservation, climate change mitigation, and recreational opportunities for residents. However, the state of urban GOS globally is characterized by land scarcity, degradation, fragmentation, spatial inequity, and varying degrees of policy implementation [14–16]. To address these issues and encourage the growth and preservation of green spaces in urban areas, cities must prioritize the creation of city parks, green infrastructure projects, urban greening programs, and the integration of GOS into urban planning strategies. By doing so, cities can become more sustainable, livable, and resilient for their residents.

An approach or indicator used to gauge how green an urban area is the Green View Index (GVI). GVI stands for a visual analysis that uses Google Street View images to assess how much vegetation is present in urban areas [17–22]. In order to analyze and determine the percentage of green areas (vegetation) within an image, GVI's application uses algorithms[23–25]. Based on visual traits like color and texture that are connected to the presence of vegetation, this analysis. The result, which represents the level of greenness in the area as a percentage or decimal number, is expressed. The Green View Index can offer details regarding the general degree of greenness in an urban area, both on a city scale and within scopes like streets, parks, or building blocks. This index provides a more objective and quantifiable viewpoint on the sustainability and quality of the urban environment. The Green View Index can be applied in a variety of situations, such as studies on the quality of the urban environment, sustainable urban planning, policy evaluation, and tracking long-term urban change [17,21]. GVI offers an effective and quantifiable way to assess urban greenness and support well-informed choices for sustainable urban development by utilizing Google Street View image data. Furthermore, the Green View Index has the potential to enhance public awareness and engagement in urban sustainability issues. It can serve as a tool for citizen science initiatives, allowing individuals to contribute to data collection and analysis. Additionally, GVI can facilitate community-based planning and decision-making processes by providing a common language and metric for evaluating urban greenness. This can help promote equitable access to green spaces and ensure that sustainability efforts are inclusive of diverse communities. Overall, the Green View Index represents a promising approach for advancing urban sustainability goals and improving the quality of life in cities around the world.

The GVI will be used in this study as an alternative method for evaluating green open spaces. The use of GVI and the big data, widely accessible data used in this study, which involves big data, contribute to its novelty. The findings of this study, according to the researchers, will significantly advance regional and urban planning. The research presents a novel method for assessing the amount of vegetation in urban areas by using GVI as a tool for assessing green open spaces. Google Street View images are one example of big data that can be used to create a comprehensive and sizable dataset for analysis. This makes it possible to evaluate urban spaces' greenness more thoroughly and gain a better understanding of the quantity and quality of green open spaces. The results of this study could have a significant impact on regional and urban planning. Planners and policymakers can allocate green spaces more effectively, preserve existing vegetation, and incorporate green infrastructure into urban environments by identifying and quantifying the level of greenness using GVI. By placing an emphasis on the planning and development of green open spaces, this research ultimately aims to contribute to the creation of more sustainable and livable cities. The use of GVI can enhance public health and wellbeing, in addition to its advantages for regional and urban planning.

2. Literature Review

Depending on the viewpoints and contexts employed by experts and literature, the definition of a green open space has various point of views. Green open space is defined as areas with significant vegetation, including parks, urban parks, city forests, green infrastructure, grasslands, as well as gardens and playgrounds, in the Guidelines for Landscape and Visual Impact Assessment [1,11].

Green open space is defined by the National Recreation and Park Association (NRPA) as undeveloped or developed areas with vegetation, such as parks, forests, or other open spaces intended for recreation, conservation, and environmental quality [6,26]. According to the United Nations Environment Programme (UNEP), green open space is land that includes open spaces covered in vegetation, such as parks, urban parks, national parks, green infrastructure, conservation areas, and nature reserves. Green open space is defined as areas with both natural and artificial plants and vegetation that serve as recreational areas, habitats for biodiversity, and coolers of the urban environment in the 2014 book "Urban Green Spaces: A Study of City Parks" by Anna Jorgensen and Richard H. W. Bradshaw. Green open space generally refers to vegetated areas that are used for recreation, environmental protection, natural preservation, and enhancing urban quality of life [2]. This definition includes a variety of green spaces that benefit urban communities on an ecological, social, and aesthetic level, including parks, urban parks, city forests, and conservation areas.

The GVI can be created with the help of Volunteered Geographic Information (VGI), which can contribute to the process by providing the data required to evaluate the degree to which urban areas contain vegetation [17–19]. Within the framework of GVI, VGI contributes to the collection of street-level imagery that is used to assess the amount of vegetation present in urban environments [20]. This contribution is particularly noticeable when the imagery comes from platforms such as Google Street View. Users can take their own pictures and upload them to Google Street View from a variety of different locations, including those with significant amounts of vegetation[21]. These pictures, which were contributed by users, can be analyzed to determine the degree of greenery present in particular locations, and their results can be factored into the GVI calculation. Researchers and analysts can estimate the percentage of an urban area that is covered in greenery by combining user-generated content from Google Street View with data from other sources, such as satellite imagery or ground surveys. In order to determine the degree of greenness, this analysis makes use of algorithms that evaluate visual characteristics associated with vegetation, such as color and texture. The incorporation of VGI, which includes images contributed by users and retrieved from Google Street View, increases the amount of data that is both available and covered by the GVI calculations. It makes it possible to conduct a more in-depth analysis of the degree to which urban areas are green by considering a greater variety of viewpoints and points of view. In addition, VGI provides a valuable source of data for temporal analysis. User-contributed images can track changes in green spaces over time, making VGI a valuable source of data. Understanding the dynamics of urban vegetation and monitoring the efficacy of green space management and conservation efforts both require a consideration of time, which is why the temporal dimension is essential. In conclusion, VGI, which includes user-contributed images from platforms such as Google Street View, plays an important part in the generation of the GVI. This is because it provides valuable data for evaluating and quantifying the degree to which urban areas are covered in greenery. The incorporation of VGI improves the thoroughness and accuracy of GVI calculations, which in turn contributes to a better understanding of the distribution and quality of green spaces in urban areas.

The Green View Index (GVI) measures the amount of green vegetation visible in urban areas. It is calculated by analyzing satellite imagery or street-level photos to determine the percentage of visible greenery within a given area or route [17,19,23,24,29,30)]. The GVI assigns a numerical value to the level of greenness in each location. The benefits of studying GVI are numerous. For starters, GVI provides a standardized and objective metric for assessing the presence and distribution of green spaces in urban environments. It provides a quantitative indicator that can be compared across cities or areas, allowing for green coverage benchmarking and comparisons. Second, GVI assists in determining the quality of urban green spaces. It provides insights into the accessibility and visual aesthetics of green areas by analyzing the extent of green vegetation visible from street-level perspectives. This data can help urban planners, landscape architects, and policymakers make informed decisions about green open space preservation and development. Third, GVI contributes to a better understanding of the relationship between green spaces and environmental factors. It allows researchers to investigate the relationship between the presence of greenery and a variety of urban indicators such as air quality, temperature, and human well-being. This knowledge can be used to develop strategies for increasing urban livability and sustainability. Furthermore, GVI facilitates the monitoring and tracking of changes in urban greenery over time. It is possible to identify trends, measure the effectiveness of urban greening initiatives, and track the impact of development on green spaces by conducting periodic assessments. Overall, the GVI offers standardized comparisons, insights into green space quality, an understanding of environmental relationships, and the ability to track changes over time. Because of its benefits, it is a valuable tool for urban planning, environmental management, and promoting sustainable and livable cities.

3. Method

3.1 Research Data

Any study relies heavily on research data. In this section, we will go over the data that was gathered and used in this study. The research data provides a solid foundation for the findings, analysis, and conclusions presented in this study. This part will go over the data sources, data collection methods, and data processing and analysis procedures. Furthermore, we will discuss the data's validity and dependability, as well as the steps taken to reduce bias in data collection and analysis.

The data used in this research consists of secondary data, specifically geospatial data, and tabular data. Geospatial data is data that contains geographic information related to Earth's locations. This data encompasses various elements such as geographic coordinates, administrative boundaries, topography, satellite imagery, maps, and other attributes associated with the geographical aspects of a region or location.

This research utilizes three different types of data to achieve its objectives. Firstly, to determine the administrative boundary limits, the researchers used data provided by Global Administrative Areas (GADM). GADM is a reliable data source commonly used in geospatial research. Secondly, to analyze the vegetation conditions in the study area, the researchers employed Google Street View data processed using the Green View Index plugin within the QGIS 3.22 software. The Green View Index plugin enables researchers to measure and visualize vegetation density using images from Google Street View. This provides valuable information about the environmental conditions and vegetation quality in the area. Lastly, to obtain more comprehensive vegetation density data, the researchers acquired images from https://app.climateengine.org/climateEngine . Within the application, the vegetation images have been harmonized, meaning they have been consistently adjusted for a specific time period. The researchers utilized these images, covering the period from April 23, 2023, to June 23, 2023, for a more detailed analysis of vegetation density. By utilizing these three types of data, this research aims to provide a comprehensive understanding of the administrative boundary limits, vegetation conditions, and vegetation density in the study area.

The data collection methods employed in this research are based on the research objectives and questions posed. The data retrieved consists of open data accessed during the research process. Once the data has been gathered, we will explain the data processing and analysis procedures conducted. We utilize statistical techniques and specialized Geographic Information System (GIS) software to analyze the data with the aim of addressing the research questions. Additionally, we also interpret the relevant data within the framework of the conceptual framework developed beforehand. The data utilized in this study can be observed in Table 1.

Table 1. Research Data

Data	Data Type	Data Source	Access Time
City Administrative Boundary	Polygon	GADM.org, https://gadm.org/download_country_v3.html	Access Time: June 23, 2023, 10:10 am
Google Street View	Raster	Downloaded via QGIS Plugin Green View Index and Google Maps API	Access Time: June 23, 2023, 7:10 am
Landsat NDVI	Raster	https://app.climateengine.org/climateEngine Time period 23-04-2023 until 23-06-2023 harmonized	Access Time: June 23, 2023, 7:10 am

3.2 Descriptive Statistics

Descriptive statistics is a branch of statistics that focuses on the collection, presentation, and interpretation of data in a concise and descriptive manner [30)]. The main purpose of descriptive statistics is to present data in a structured way, provide an overview of data characteristics, and describe patterns or relationships within the data. Descriptive statistics involves several techniques and methods for analyzing data. Some key concepts in descriptive statistics include:

a) Measures of Central Tendency: Measures of central tendency are used to determine the middle or representative values of data. Some commonly used measures of central tendency are the mean, median, and mode.
b) Measures of Variability: Measures of variability are used to measure the spread of data. Some commonly used measures of variability are the range (the difference between the maximum and minimum values), standard deviation, and variance.
c) Data Distribution: Data distribution describes how data is spread around its central values. Distribution can be depicted using histograms, bar charts, or distribution curves like the normal curve.
d) Graphs and Charts: Descriptive statistics utilizes graphs and charts to visually represent data more clearly. Graphs such as bar charts, line graphs, or pie charts are used to present data visually.
e) Frequency Tables: Frequency tables are used to organize data into groups or intervals and show the frequency count in each group. Frequency tables help in better understanding the distribution of data.

Descriptive statistics is crucial in data analysis as it provides a clear overview of observed data characteristics. The information generated from descriptive statistics aids in initial understanding, comparison, and concise presentation of data that is easily comprehensible.

3.3 Green View Index Analysis

The Green View Index (GVI) has garnered considerable interest in the past few years as a quantifiable measure for evaluating urban green spaces specifically at the street level. Unlike the satellite-derived Normalized Difference Vegetation Index (NDVI), which offers a vegetation assessment from an aerial standpoint, GVI relies on street-level imagery to gauge the existence of vegetation from a human's visual perspective. In recent literature, the GVI has emerged as a valuable tool for comprehending the extent of greenery in urban areas. By utilizing street-level imagery, it provides a more fine-grained analysis of vegetation presence and distribution, capturing the experience of individuals navigating through the streets. This stands in contrast to the NDVI, which lacks the street-level perspective and may not capture the nuances of greenery that are vital for urban planning and design.

While the concept of GVI was initially introduced in 2009 [18,29,32–36)], its broader recognition came about in 2015 following the development of an automated technique for extracting vegetation pixels from Google Street View panoramas [17,35)]. Since then, GVI has gained widespread popularity in research, serving as a valuable tool for investigating its correlations with various factors such as health [35,37,38)] and socioeconomic variables [36)]. A notable project known as Treepedia, led by MIT's Senseable City Lab, has undertaken the calculation of GVI scores for over 25 cities worldwide, providing rankings based on average values (http://senseable.mit.edu/treepedia). This initiative has not only produced valuable GVI data but has also made two versions of their code available, enabling further exploration and analysis of GVI in diverse urban contexts.

The GVI is a valuable tool for assessing the presence and extent of urban greenery at the street level. This street-level approach enables a more human-eye viewpoint, considering the green elements that are visible and accessible to people at ground level. The practicality and applicability of the GVI gained further momentum in 2015 with the development of an automated method for extracting vegetation pixels from Google Street View panoramas, as highlighted by Li et al. (2015). This advancement allowed for a more efficient and scalable calculation of the GVI, expanding its potential for widespread use in research and urban planning. It was calculated according to the following formula: [23,35].

$$Green\ View = \frac{\sum_{i=1}^{6}\sum_{j=1}^{3} Area_{g\_ij}}{\sum_{i=1}^{6}\sum_{j=1}^{3} Area_{t\_ij}} \times 100\% \quad (1)$$

Where Area g_i corresponds to the total amount of green pixels in the picture taken in the i_{th} direction (among the north, east, south, and west) for one intersection, and Area t_i corresponds to the total amount of pixels of the picture taken in the i_{th} direction.

3.3. Correlation Analysis

Correlation analysis is a statistical technique for determining the link or association between two variables [39–41]. Correlation analysis is used to examine how closely the variables move together or change over time. Correlation analysis is employed as a validation method for GVI and NDVI in this scenario. The correlation coefficient expresses the magnitude and direction of the association between the variables. The correlation coefficient is between -1 and 1. A value of one represents a perfect positive relationship, while a value of one represents a perfect negative relationship. A 0 value shows that there is no linear relationship between the variables. We require data that includes the values of both variables being examined in order to conduct a correlation analysis. The correlation coefficient can then be calculated and interpreted using statistical tools or spreadsheets. The meaning of the correlation coefficient is dependent on the obtained result, with values closer to 1 or -1 indicating a stronger association and values closer to 0 indicating a weaker or no relationship. The following equation describes the correlation coefficient:

$$r = \frac{n\Sigma XY - \Sigma X \Sigma Y}{\sqrt{(n\Sigma X^2 - (\Sigma X)^2)(n\Sigma Y^2 - (\Sigma Y)^2)}} \quad (2)$$

r: Correlation coefficient
Y: variable (NDVI)
X: variable (GVI)

4. Result and Discussion

4.1 The Green Color Detection Process

The Green View Index (GVI) is an important indicator used in research to estimate the number of green pixels in street-level photography. This index provides useful information about the amount of greenery in metropolitan areas. The availability of data from Google Street View (GSV), which serves as a comprehensive collection of 360-degree street-level photos, is a significant advantage of using GVI. GSV has grown in popularity as a trustworthy data source for urban sensing, enabling researchers to quantify the presence of greenery in a more objective and uniform manner. Traditional approaches, such as semi-structured interviews and questionnaire surveys, are typically subjective and hampered by biases, resource limits, and time constraints. Researchers can overcome these limitations and gain a more precise and comprehensive understanding of greenery distribution in urban contexts by employing GSV. The application of GVI and GSV in urban studies has created new opportunities for measuring and monitoring green spaces. Researchers can examine GVI values gathered from street-level photography to find patterns, trends, and variations in greenery throughout various parts of a city. This data is critical for urban planning, landscape design, and environmental management because it allows decision-makers to assess the quality of green spaces, identify areas for improvement, and make educated resource allocation decisions. Furthermore, using GVI and GSV in research contributes to the expanding fields of urban sensing and remote sensing. Researchers can broaden their understanding of urban environments and facilitate evidence-based decision-making processes by leveraging the power of technology and geospatial data. The combination of GVI and GSV provides a dependable and efficient method of monitoring greenery in urban environments, enabling more thorough and data-driven evaluations.

The selection of Malang as the research site for the Green View Index (GVI) study is significant for several reasons. To begin with, Malang is known for its natural beauty, as it is surrounded by mountains and has a pleasant climate. Because of its abundance of green spaces and vegetation, it is an excellent candidate for assessing and evaluating the greenness of urban areas using GVI. Second, Malang's status as a renowned educational center contributes to the feasibility and potential impact of the research. With a large student population and numerous universities, there is a strong emphasis on academic research and a welcoming community that can actively participate in data collection and validation processes. Furthermore, Malang's reputation as a tourist destination adds to the city's importance for studying GVI. To attract visitors and provide a positive experience, the tourism industry emphasizes the importance of preserving and improving green open spaces. Evaluating GVI in Malang can provide useful insights for urban planning, environmental management, and the development of sustainable tourism. Furthermore, Malang's diverse population, made up of various ethnic groups and cultures, provides a unique opportunity to investigate the relationship between green spaces and community well-being. Understanding how different communities interact with and perceive urban greenery can help to develop inclusive and culturally sensitive strategies for improving city green spaces. The study's choice of Malang as the research location aims to provide specific insights into the city's greenness, inform urban planning decisions, and contribute to the development of sustainable and livable urban environments. This study's findings and recommendations could serve as a model for other cities facing similar challenges in balancing urban development and the preservation of green open spaces.

Malang is a diverse city that is home to people of various ethnic backgrounds and cultures. Malang's population is dominated by the Javanese ethnic group, with the Madurese close behind. After Gerbangkertosusila, the Malang Metropolitan Area (Malang Raya) is East Java's second-largest metropolitan area. Malang has a total area of 114.26 square kilometers. In 2021, the population of Malang is estimated to be 843,810 people, with a population density of 7,667 people per square kilometer, according to data from "*Kota Malang Dalam Angka.*" (The Malang City Statistic book of the Year 2021)

Malang is well-known for its tourism industry, earning the city the moniker "City of Tourism." It has a diverse range of tourist attractions both within the city and throughout the Malang Raya region (Malang Regency and Batu City). The city is home to a wide range of culinary experiences, heritage sites, themed villages, city parks, festivals and events, MICE (Meetings, Incentives, Conferences, and Exhibitions), and religious attractions. Its strategic location in the heart of Malang Raya makes it an ideal starting point for exploring natural attractions such as coastal areas, Mount Bromo, and the region's various theme parks. Aside from tourism, the city is also a significant educational center. Malang, with over 50 public and private universities and academies, attracts over 300,000 students from all over the country, making it one of the most important educational cities in Indonesia's east. Brawijaya University, the State University of Malang, Muhammadiyah University of Malang, Malik Ibrahim State Islamic University, the Islamic University of Malang, the National Institute of Technology (ITN), and Merdeka University are among the notable universities (Unmer). Malang was known as an industrial city in its early days as a municipality until the 1980s due to the presence of numerous industries. However, as regional structures and spatial patterns changed, the industrial sector shifted to trade and services. Over the last decade, the creative industry ecosystem has emerged as a rapidly growing sector, projected to be the driving force of the city's future economy, in line with the emerging human resource potential.

Several stages are required to determine the GVI using Google Street View images to evaluate the vegetation coverage in a specific area. The first stage is to generate reference points for the analysis by generating sample points. In this study, 100 random sample points were generated within the Area of Interest (AOI), which includes the administrative boundaries of Malang City and the OpenStreetMap (OSM) road network. These sample points were spaced 400 meters apart to ensure a representative sample of the study area.

After establishing the sample points, it is necessary to obtain the corresponding Google Street View images for each point. Using the pitch and heading parameters, the images are obtained. Pitch represents the vertical displacement of the camera, and the values chosen for this analysis were -45°, 0°, and 45°. Alternatively, heading refers to the horizontal movement of the camera and was captured at 0°, 60°, 120°, 180°, 240°, and 300° intervals. Each combination of pitch and heading offers unique perspectives of the sample sites, thereby ensuring a diverse set of images for analysis. Downloading the images at a resolution of 400x400 pixels enables a detailed examination of the vegetation within each image.

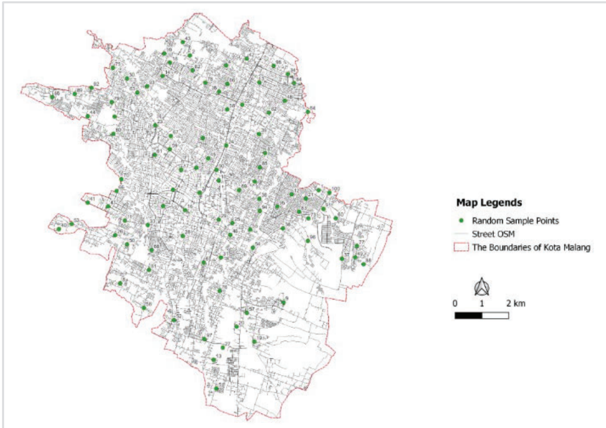


Fig. 1: Random Sample Points

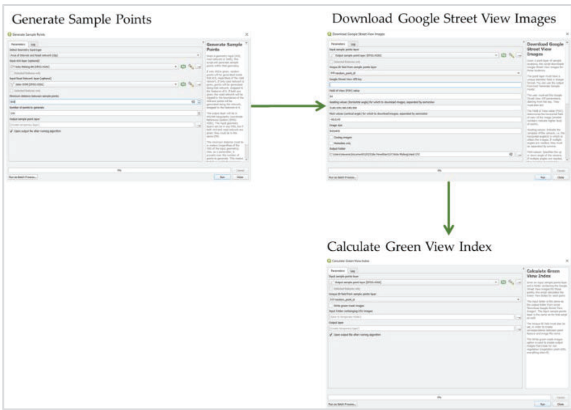


Fig. 2: The Green View Index process in QGIS 3.22

Following the collection of images, the GVI value at each sample point must be calculated. The GVI indicates the quantity of green vegetation in an image. To calculate the GVI, the green component of the street view image is extracted. This involves analyzing the image's pixel values to ascertain the intensity of the green color. The extracted green color values are then utilized in the GVI formula to calculate the GVI value for each sample point. The GVI value indicates the density or extent of vegetation in the analyzed area. In this study, the GVI discovery process entails the selection and generation of sample points, the downloading of Google Street View images based on the sample points, and the subsequent calculation of GVI values by extracting and analyzing the green color from the downloaded images. This exhaustive method permits an evaluation of the coverage and density of vegetation within the specified study area. These steps can be observed in Fig. 1.

The GVI was calculated by the researcher using a GIS. As an example, sample point number 16 was picked. The GIS system extracted green color from each pitch and heading combination from this sample point. The GVI was then determined using the supplied formula. The GVI value for sample point 16 is 0.185, according to the results. The presence of a dense tree canopy, particularly at pitches 00 and 450, is confirmed by the Google satellite image shown in Fig. 3. This corresponds to the calculated GVI value of 0.185, which indicates the presence of green vegetation in that area.

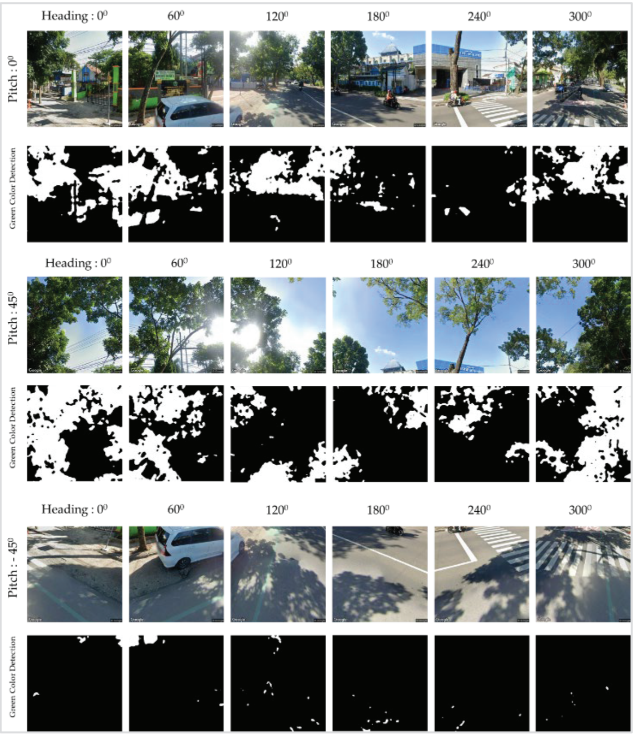


Fig. 3: Green Color Detection

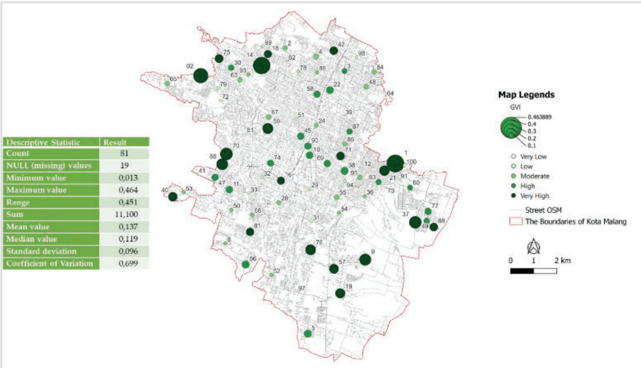
Green color extraction from different pitch and heading combinations allows for the GIS-based study of greenness levels in the studied area. Therefore, this information sheds light on the greenness and plant density of the observed area. By combining GVI analysis with GIS and green color extraction techniques, researchers can gain a more complete understanding of the vegetation in the studied area. There may be other research-related uses for this data as well. For example, it could be used to monitor changes in vegetation over time, or to identify areas that are particularly vulnerable to environmental stressors. Additionally, the information gathered through green color extraction could be used to inform land-use planning and management decisions. By understanding the distribution and density of vegetation in each area, policymakers can make more informed decisions about how best to allocate resources and protect natural habitats. Overall, the combination of GVI analysis, GIS technology, and green color extraction techniques offers a powerful tool for researchers and policymakers alike, providing valuable insights into the health and vitality of our natural world.

Fig. 4: GVI Calculation on Point Number 16

4.2 Green View Index

The Green View Index (GVI) results can be studied further using descriptive statistics to shed more light on the data's properties. The analysis is based on a total of 100 sample points; however, due to the lack of Google Street View photos for the remaining 19 spots, only 81 have valid GVI values. The lowest GVI score observed is 0.013, indicating a place with the least amount of green vegetation coverage in the study area. On the other end of the spectrum, the maximum GVI score is 0.464, indicating the highest level of observable greenness. The range is found to be 0.451 when the difference between the maximum and minimum values is calculated. This large range reflects the degree of variation in GVI values among sample points. When the data is examined for central tendency, the overall sum of the GVI values for the 81 valid points is 11.100. The mean GVI is derived by dividing the entire sum by the number of valid points to determine the average level of green vegetation coverage. The mean GVI in this situation is calculated to be 0.137. This value shows the average greenness found within the investigated area, and it serves as an overall indicator of vegetation density. The standard deviation is a useful tool for assessing the variability of GVI values. The standard deviation is calculated to be 0.096 in this analysis. This modest level of standard deviation implies that the GVI values around the mean vary moderately. The coefficient of variation, which is the standard deviation-to-mean ratio, is 0.699. This score indicates a relatively high amount of relative variability in the GVI values when compared to the mean, emphasizing the data's range and dispersion. In summary, the GVI results' descriptive statistics provide crucial insights into the distribution and characteristics of green vegetation covering the sample locations. The range, mean, standard deviation, and coefficient of variation all work together to provide a thorough knowledge of the variability, central tendency, and relative variability of the GVI data. These statistics help evaluate the general greenness and density of vegetation observed in the study area.

Further analysis reveals that the distribution of GVI in Malang City is predominantly higher in the outskirts compared to the city center. This indicates that the outskirts of Malang have a higher level of green vegetation compared to the city center. In other words, the peripheral areas of Malang have more vegetation and significant green coverage.



Descriptive Statistic	Result
Count	81
NULL (missing) values	19
Minimum value	0,013
Maximum value	0,464
Range	0,451
Sum	11,100
Mean value	0,137
Median value	0,119
Standard deviation	0,096
Coefficient of Variation	0,699

Fig. 5: GVI of Malang City

This observation suggests that there is a greater need to enhance vegetation and raise the GVI in the city center of Malang. The city center may have a higher degree of urbanization with limited green open spaces, which can affect the level of greenness in that area. It is important to note that this understanding is based on the specific analysis of GVI in Malang City and may not be generalized to other cities or different contexts. To develop a more comprehensive understanding of the relationship between GVI values, vegetation distribution, and environmental conditions in the city center, further research and in-depth analysis can be conducted. With this information, authorities and policymakers can consider efforts to enhance greenery in the city center of Malang. Steps such as tree planting, creating parks, or implementing sustainable urban design can help increase vegetation levels and improve the environmental quality in the city center, thus raising the overall GVI value.

4.3 Validation

In order to validate the results of the Green View Index (GVI) using Google Street View images, a comparison is made with the Normalized Difference Vegetation Index (NDVI). NDVI is a remote sensing algorithm that utilizes Landsat 9 satellite imagery within the last 60 days, starting on April 23, 2023. The correlation between the GVI and NDVI results is determined using Pearson correlation, resulting in a correlation coefficient of 0.617. The correlation coefficient of 0.617 indicates a moderately positive correlation between the GVI and NDVI values. This suggests that there is a significant association between the green vegetation coverage observed through Google Street View images (GVI) and the vegetation index derived from Landsat 9 satellite imagery (NDVI).

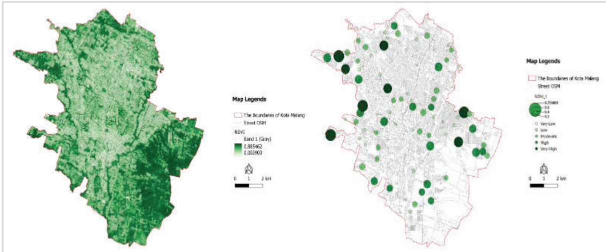
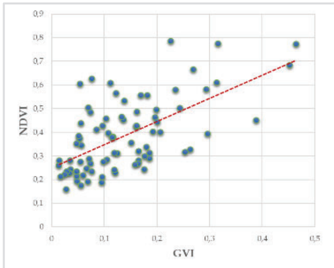


Fig. 6: NDVI of Malang City and Sample Raster NDVI Value on GVI Points



	GVI	NDVI
GVI	1	
NDVI	0,617	1

Fig. 7: Scatter Plot and Correlation Between NDVI and GVI

The positive correlation indicates that areas with higher GVI values are likely to exhibit higher NDVI values as well, indicating a greater density of green vegetation. Conversely, areas with lower GVI values would correspond to lower NDVI values, indicating lower vegetation density. This validation through the correlation between GVI and NDVI helps reinforce the reliability and accuracy of the GVI results. The remotely sensed NDVI values derived from satellite imagery support it further evidence that the GVI accurately captures and quantifies the green vegetation coverage in the studied area. It's important to note that the correlation coefficient of 0.617 signifies a moderate correlation, and further analysis may be required to gain a more comprehensive understanding of the relationship between GVI and NDVI. Additionally, the specific characteristics of the study area and the accuracy of the satellite imagery used can also influence the correlation results. Furthermore, it is crucial to consider other factors that may affect vegetation coverage, such as climate, topography, and human activities. Climate can impact the availability of water and nutrients for plants, while topography can affect the amount of sunlight received by different areas. Human activities like deforestation and agriculture can also significantly alter vegetation coverage. Therefore, it is essential to conduct a comprehensive analysis that considers all these factors to gain a better understanding of the vegetation dynamics in the studied area. This information can be useful for land management decisions and conservation efforts aimed at preserving or restoring vegetation cover. In conclusion, while NDVI values provide valuable information on vegetation coverage, they should be interpreted with caution and complemented with other data sources to obtain a more accurate picture of the situation.

5. Conclusion and Future Research

This research presents a pioneering approach to assessing green open spaces based on scenery, utilizing the Green View Index (GVI). The utilization of Google Street View data offers significant advantages in addressing the challenges of limited data availability and the high costs associated with manual identification methods. By employing this methodology, the calculation of the GVI for Malang City provides valuable insights into the extent of green vegetation coverage, with an average value of 0.137, or 13.7%. Furthermore, the validation of the GVI through its correlation with the Normalized Difference Vegetation Index (NDVI) reveals a moderately positive correlation of 0.617. The application of GVI as a measure of greenness is a groundbreaking approach to assessing urban environments. By leveraging the extensive dataset from Google Street View, researchers can capture a comprehensive picture of the green view within the study area. This methodology offers a more cost-effective and efficient solution compared to traditional manual identification methods, which are often labor-intensive and time-consuming.

However, it is important to acknowledge the limitations of this approach. One notable drawback lies in the reliance on color segmentation techniques employed by the software. The accuracy and effectiveness of the segmentation process can vary, which may introduce potential errors or biases in the GVI calculation. Therefore, future improvements and refinements in segmentation algorithms are necessary to enhance the accuracy and reliability of the results. To further strengthen the validity and generalizability of the findings, future research endeavors should consider expanding the sample size. By incorporating a larger number of sample points, researchers can obtain a more representative and robust dataset, leading to more accurate and precise GVI values.

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