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EXPLORING THE RELATIONSHIP BETWEEN GREEN VIEW INDEX AND RUNNING ACTIVITY: A CASE STUDY OF YOGYAKARTA AND SINGAPORE USING STRAVA AND GOOGLE STREET VIEW DATA

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Abstract. The Development of Geospatial Data and Volunteered Geographic Information (VGI) has been significant and can be utilized in urban and regional planning. One of the notable data sources includes Google Street View and Strava running activity data. This research investigates the potential correlation between the presence of green spaces, measured by the Green View Index (GVI) using Google Street View data, and the level of running activity recorded by Strava, a popular running application. The novelty of this study lies in the integration of GVI analysis with Google Street View and Strava data, providing a comprehensive understanding of the relationship between green environments and physical activity by leveraging Big Data. In this research, two locations are compared: Yogyakarta, identified to have a low GVI category, and Singapore, identified to have a high GVI category. The findings reveal a moderate negative correlation between GVI and the Strava running index in Yogyakarta, while a moderate positive correlation is observed in Singapore. These results contribute to the growing research on urban vitality and emphasize the importance of integrating green spaces into urban planning and development using big data. This study serves as a foundation for further research on the relationship between green environments and various forms of physical activity, contributing to the development of healthier and more sustainable cities in the future.

Keyword: Green View Index; Volunteered Geographic Information; Strava Running Index; Urban Vitality

[Judul: Mengeksplorasi Hubungan Antara *Green View Index* dan *Running Activity*: Studi Kasus Yogyakarta dan Singapura dengan Menggunakan Data Strava dan *Google Street View*]. *Perkembangan geospasial data dan juga Volunteered Geographic Information (VGI) sangat masif dan dapat digunakan dalam perencanaan wilayah dan kota. Salah satunya adalah data Google Street View dan data running activity Strava. Penelitian ini menyelidiki keterkaitan potensial antara keberadaan ruang hijau, yang diukur dengan GVI (Green View Index) menggunakan data Google Street View, dengan tingkat aktivitas lari yang tercatat oleh Strava, sebuah aplikasi populer yang digunakan dalam aktivitas berlari. Kebaruan dari penelitian ini terletak pada integrasi analisis GVI dengan data Google Street View dan Strava, yang memberikan pemahaman komprehensif mengenai hubungan antara lingkungan hijau dan aktivitas fisik dengan memanfaatkan Big Data. Dalam penelitian ini diperbandingkan dua lokasi yaitu Kota Yogyakarta yang teridentifikasi mempunyai GVI dengan kategori rendah dan Singapore dengan kategori GVI tinggi. Temuan penelitian ini adalah hasil di Kota Yogyakarta GVI dan strava running index berkorelasi moderat dan negatif sedangkan hasil di Singapore berkorelasi moderat dan positif. Hasil ini berkontribusi pada penelitian tentang vitalitas perkotaan yang semakin berkembang dan menekankan pentingnya mengintegrasikan ruang hijau dalam perencanaan dan pengembangan perkotaan menggunakan big data. Penelitian ini menjadi dasar untuk penelitian lebih lanjut mengenai hubungan antara lingkungan hijau dan berbagai bentuk aktivitas fisik, yang berkontribusi pada pembangunan kota yang lebih sehat dan berkelanjutan di masa depan.*

Kata Kunci: *Green View Index; Volunteered Geographic Information; Strava Running Index; Urban Vitality*

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1. INTRODUCTION

The development of geospatial data and Volunteered Geographic Information (VGI) is currently significant and has a broad impact worldwide (Goodchild & Li, 2012; Huang, Tian, & Yuan, 2023; Norman, Pickering, & Castley, 2019). Firstly, advancements in technology such as satellite sensors, drones, and mobile devices have resulted in a large and more accessible geospatial data. This enables researchers, governments, and the general public to gather and analyze geographical information more effectively for various purposes, including regional planning, disaster mitigation, natural resource management, and environmental monitoring. Secondly, VGI, which refers to the voluntary contributions of individuals in collecting, sharing, and analyzing geographic data, has also experienced rapid development. Platforms like OpenStreetMap and user-based applications such as Strava and Waze have encouraged active participation from the community in gathering geospatial data. The data collected through VGI can provide valuable information for detailed mapping and better understanding of specific areas. Additionally, VGI plays a crucial role in decision-making and public participation in issues related to space and the environment. Thirdly, advancements in geospatial data analysis and processing have opened up new opportunities for understanding and utilizing available information. Techniques such as image processing, spatial analysis, and machine learning have allowed for more accurate pattern identification, prediction, and modeling. This expands the ability to gain new insights from geospatial data and provides a more solid foundation for decision-making across various contexts.

The current development of geospatial data and VGI offers extensive opportunities for understanding, analyzing, and utilizing geographical information (Goodchild & Li, 2012; Norman et al., 2019). The use of advanced technology and active community participation in data collection present significant potential for the development of effective regional planning, decision-making, and natural resource management. However, challenges such as privacy, data accuracy, and complex data management remain major concerns that need to be addressed to ensure appropriate and beneficial utilization of geospatial data and VGI in the future.

One of the geospatial data and VGI sources is Google Street View and Strava data. Google Street View and Strava data are two sources of data that can provide valuable contributions to urban and regional planning, particularly in identifying urban vitality and urban greenness (Ki & Lee, 2021; X. Li et al., 2015; Lu, 2019; Yin & Wang, 2016). Google Street View is a platform that provides visual access to the physical environment through 360-degree images of streets in various locations. Data from Google Street View can be utilized to gain a better understanding of the physical conditions of an area, including the presence and quality of green spaces, building structures, road conditions, and other environmental elements (Abdulkareem, Alsaidi, Yazid, Borhan, & Mahdi, 2020; Alexandros, 2022; Ki & Lee, 2021; X. Li et al., 2015; Yin & Wang, 2016). In urban and regional planning, this data can be used for detailed mapping, identifying areas in need of infrastructure improvements, evaluating the urban environment, and visual modeling to aid decision-making. Strava data, on the other hand, is collected through a user-based application for activities such as running, cycling, and other sports. This data includes information such as routes, distances, speeds, and elevations. In the context of urban and regional planning, Strava data can provide insights into the level of physical activity in the community, movement patterns, and preferences for the use of public spaces (Franken, Bekhuis, & Tolsma, 2023; Lin & Fan, 2020; Musakwa & Selala, 2016; Venter, Gundersen, Scott, & Barton, 2023). This information is important for planning and optimizing open spaces, bike lanes, parks, and sports facilities that support healthy lifestyles and sustainable mobility.

Although the potential of Google Street View and Strava data in urban and regional planning is

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significant, their utilization in Indonesia is still relatively rare (Afrianto & Hariyanto, 2022; Yudono, Afrianto, & Hariyanto, 2023). Some factors that may influence this include limited access to comprehensive data, lack of awareness of its benefits, and challenges in integrating the data into existing planning systems (Ciepłuch, Jacob, Mooney, & Winstanley, 2010; Venter et al., 2023). However, awareness of the importance of utilizing this data in sustainable urban planning and development is increasing. With efforts in education, collaboration between the government, researchers, and civil society, as well as the development of more inclusive geographic information systems, the potential of Google Street View and Strava data can be utilized more widely and effectively in the future.

This paper aims to explore VGI data and investigate the correlation between green view index and running activity. This study focuses on Yogyakarta City and Singapore, utilizing Strava data and Google Street View to provide valuable insights in urban vitality research. By analyzing the Green View Index (GVI) using Google Street View data and combining it with running activity data from Strava, this paper aims to explore the relationship between the presence of green spaces and physical activity. The findings of this research contribute to the understanding of how urban greenness influences the engagement of individuals in running activities. Moreover, the paper highlights the significance of integrating VGI data, such as Strava and Google Street View, into urban planning and development. The utilization of these datasets provides a comprehensive approach to measuring urban vitality, which is crucial for creating healthier and more sustainable cities in the future. This paper also offers valuable insights into the potential benefits of green spaces for promoting physical activity and urban well-being. This research serves as a foundation for further studies on the relationship between green environments and various forms of physical activity, contributing to the development of healthier and more sustainable cities in the future.

2. METHODS

2.1 Research Data

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: May 13, 2023, 10:10 am
Google Street View	Raster	Downloaded via QGIS Plugin Green View Index and Google Maps API	Access Time: May 13, 2023, 7:10 am
Strava Running Data	Raster	Downloaded via QGIS XYZ Tiles from https://proxy.nakarte.me/https/heatmap-external-a.strava.com/tiles-auth/run/bluered/{z}/{x}/{y}.png	Access Time: May 13, 2023, 7:10 am
World Green View Index	Tabular	http://senseable.mit.edu/treepedia	Access Time: May 13, 2023, 8:30 am

The research data used consists of three main sources and is classified as secondary data. All data was collected in 2023, and the types of data can be seen in Table 1. Firstly, the boundaries of Yogyakarta City and Singapore were obtained from GADM.org (Global Administrative Areas Database), which is a reliable source for administrative information worldwide. This data provides information about the administrative boundaries of Yogyakarta City and Singapore, including planning and relevant areas for the research analysis. The second data source is Google Street View data obtained using the Google Maps API. This data was obtained through the use of the QGIS Green View Index plugin, which enables visual access to 360-degree images captured by Google Street View. In the context of this research, Google Street View data is used to obtain visual information about the physical environment, including the presence of green spaces and other relevant characteristics for urban and regional planning. The third data source is raster data from Strava obtained from the Global Heatmap StravaLabs. This data was collected using XYZ tiles in QGIS, allowing access to raster data on running activities from the Strava application. The Strava raster data provides information on movement patterns and levels of physical activity in various locations within Yogyakarta City and Singapore. This information can be used to analyze the level of community engagement in running activities and understand preferences for the use of public spaces related to sports.

2.2 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 (Aikoh, Homma, & Abe, 2023; Helbich et al., 2019; Ki & Lee, 2021; Kumakoshi, Chan, Koizumi, Li, & Yoshimura, 2020; T. Li et al., 2021; Wang, Liu, & Gou, 2022; Zhu, Nan, Yang, & Bao, 2023), its broader recognition came about in 2015 following the development of an automated technique for extracting vegetation pixels from Google Street View panoramas (Abdulkareem et al., 2020; T. Li et al., 2021; X. Li et al., 2015). Since then, GVI has gained widespread popularity in research, serving as a valuable tool for investigating its correlations with various factors such as health (J. Wang et al., 2022; R. Wang et al., 2019; Yin & Wang, 2016) and socioeconomic variables (T. Li et al., 2021). 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 Green View Index (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 X. 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 calculate according to following formula (Alexandros, 2022; T. Li et al., 2021).

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

Where Area g_i corresponds to the total amount of green pixels in the picture taken in the i_{th} direction (among 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.

2.3 Strava Running Data Analysis

The Strava data, which is in the form of a raster obtained from the global heatmap provided by StravaLabs, undergoes a color mapping process that ranges from blue to red, representing varying levels of intensity (Lin & Fan, 2020; Musakwa & Selala, 2016). The color spectrum assigned to the Strava data ranges from 50 (blue) to 255 (red), indicating the progression from lower to higher activity levels. To enhance its interpretability, the data is further categorized using a natural breaks classification method into five distinct classes, representing very low to very high intensity levels. Once the classification is applied, the categorized Strava data is integrated into the corresponding Google Street view points. This integration allows each street View point to be enriched with valuable information regarding the running activity patterns derived from the Strava dataset. By combining the geospatial information from Google Street View with the activity data from Strava, researchers gain a comprehensive understanding of the running behaviors and preferences in different areas.

The results of the global heat map from Strava were then normalized using QGIS, resulting in a data range of 0 to 1, representing low to high intensity. This integration of Strava data into Google Street View points provides a powerful tool for analyzing and visualizing the relationship between urban environments and running activity (Franken et al., 2023; Lin & Fan, 2020; Musakwa & Selala, 2016; Venter et al., 2023). It offers valuable insights into how different locations within a city attract runners and promote an active lifestyle. Furthermore, the availability of this enhanced dataset opens up opportunities for urban planners, researchers, and policymakers to make informed decisions regarding the development of running-friendly infrastructure, the promotion of physical activity, and the enhancement of urban livability.

2.4 Correlation Analysis

Correlation analysis is a statistical method used to measure the relationship or association between two variables. The purpose of correlation analysis is to determine the extent to which the variables move together or change over time. In correlation analysis, we measure the relationship between two variables using a correlation coefficient. The correlation coefficient describes the strength and direction of the relationship between the variables. The correlation coefficient ranges from -1 to 1. A value of 1 indicates a perfect positive relationship, while -1 indicates a perfect negative relationship. A value of 0 indicates no linear relationship between the variables. To conduct correlation analysis, we need data that includes the values of both variables being tested. Then, we can use statistical software or spreadsheets to calculate the correlation coefficient and interpret the results. The interpretation of the correlation coefficient depends on the obtained value, where values closer to 1 or -1 indicate a stronger relationship, while values closer to 0 indicate a weaker relationship or no relationship. The correlation coefficient is described in the following equation.

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

r: Correlation coefficient
Y: independent variable (GVI)
X: dependent variable (Strava Index)

3. RESULT AND DISCUSSION

3.1 Green View Index Calculation

The computation of the Green View Index involves several sequential steps. It begins by delineating the administrative boundaries of Yogyakarta City and Singapore to establish the area of interest. Additionally, road data from OpenStreetMap (OSM) is acquired to provide a comprehensive representation of the city's street network. Once the administrative boundaries and road data are obtained, they are processed using the QGIS Green View Index plugin.

This powerful tool enables the extraction and analysis of relevant information related to greenery and vegetation within the designated area. It facilitates the quantification of the presence of vegetation and the calculation of the Green View Index for each specific location. To ensure a statistically representative sample, a random sampling technique is employed. In this case, 300 sampling points are generated within the defined area of interest. Moreover, a minimum distance criterion of 200 meters between each sampling point is set to ensure spatial diversity and avoid spatial autocorrelation. With the random sampling points established, the next step involves accessing and retrieving the corresponding Google Street View imagery. By accessing the imagery, valuable visual data on the surroundings of each sampling point can be obtained. This data allows for further analysis and extraction of relevant information, such as the green color index.

The final step encompasses the computation of the Green View Index for each sampling point. Utilizing the extracted green color index values, the index is calculated by considering the ratio of green pixels or the amount of vegetation to the total area captured by the Google Street View imagery. This process provides a standardized measure of the level of urban greenery at each sampled location. From the initial 300 sampling points, the analysis reveals that 282 of these points correspond to road segments that have available Google Street View imagery in Yogyakarta. Meanwhile, in Singapore, 261 points were obtained with Google Street View photos to calculate the GVI values out of a total of 300 sample points. This subset of locations with imagery allows for a more in-depth examination and assessment of the Green View Index, contributing to a comprehensive understanding of the distribution of urban greenery within Yogyakarta City and Singapore. The process of calculating GVI using QGIS with the Green View Index plugin can be seen in Figure 1.

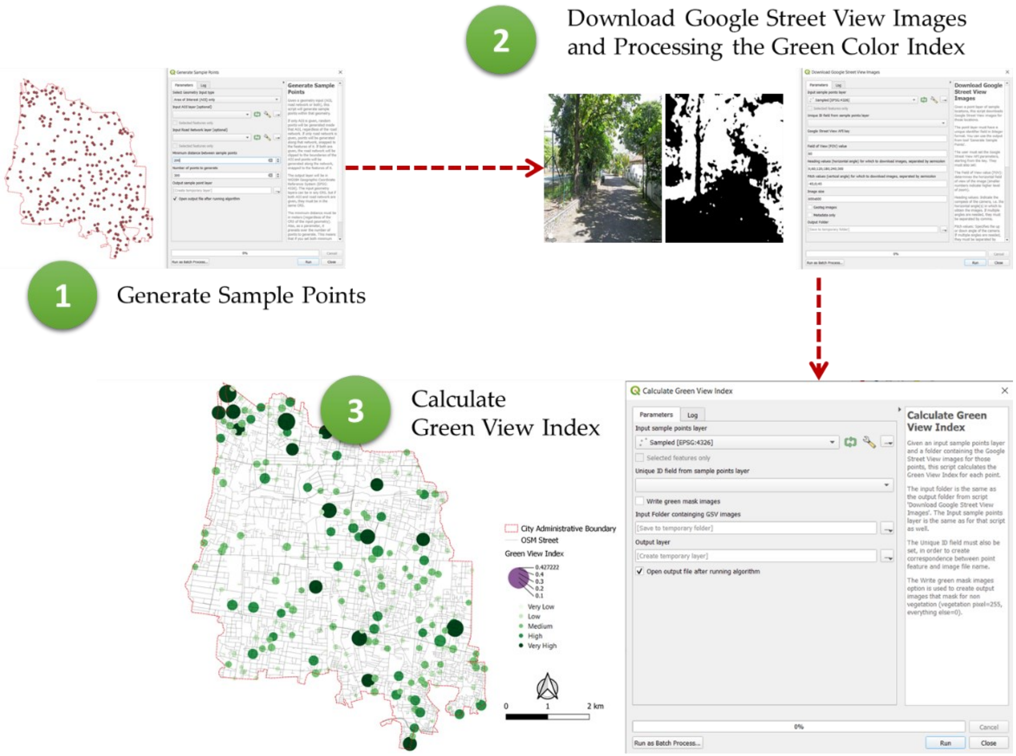

Figure 1. Green View Index Calculation Process

Table 2. Descriptive Statistics of GVI Data in the City of Yogyakarta

Descriptive Statistic	GVI
Mean	0,116
Standard Error	0,005
Median	0,099
Mode	0,048
Standard Deviation	0,081
Sample Variance	0,007
Kurtosis	1,935
Skewness	1,313
Range	0,426
Minimum	0,001
Maximum	0,427
Sum	32,626
Count	282,000

From the descriptive statistical calculations presented in Table 2, the following results were obtained for the Green View Index (GVI) in Yogyakarta City. The average GVI value is recorded at 0.116 or 11.6%. The maximum value observed is 0.427, indicating areas with a high presence of urban greenery, while the minimum value is 0.001, representing areas with minimal green coverage. The total sum of GVI values across all sampling points is 32.626. Analyzing the dispersion of the data, it can be observed that the standard deviation is relatively close to the mean, indicating a homogenous spread of the GVI values. This suggests that the data points exhibit a similar level of variation around the mean value. To visually represent the distribution of the sampled points and their corresponding GVI values, refer to Figure 2 and Figure 3. These figures provide a graphical depiction of the spatial patterns of urban greenery in Yogyakarta City, highlighting areas with higher and lower GVI values. The distribution patterns observed in these figures contribute to a better understanding of the spatial distribution and variability of urban greenery within the city.

The comparison between the GVI data from Treepedia and Yogyakarta reveals interesting insights about the level of urban greenery in these two contexts. The average GVI in Treepedia cities is recorded at 19.59%, while Yogyakarta has an average GVI of 11.6%. When compared to cities worldwide, Yogyakarta falls into the same category as Paris, Buenos Aires, New York, Tel Aviv, Guadalajara, Sao Paolo, and Turin, which have low GVI values despite their high population densities. More information about this data can be found in Table 3 and Figure 4.

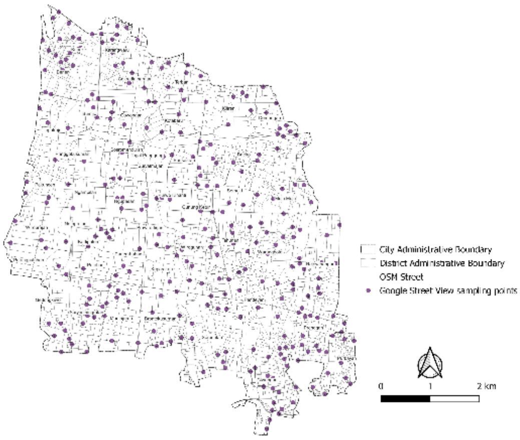

Figure 2. Distribution of Sample Points

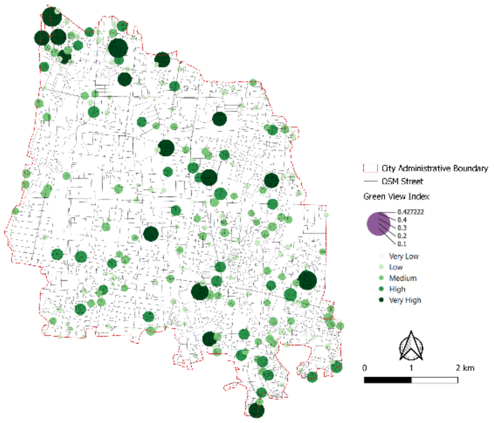

Figure 3. Visualisation of Green View Index

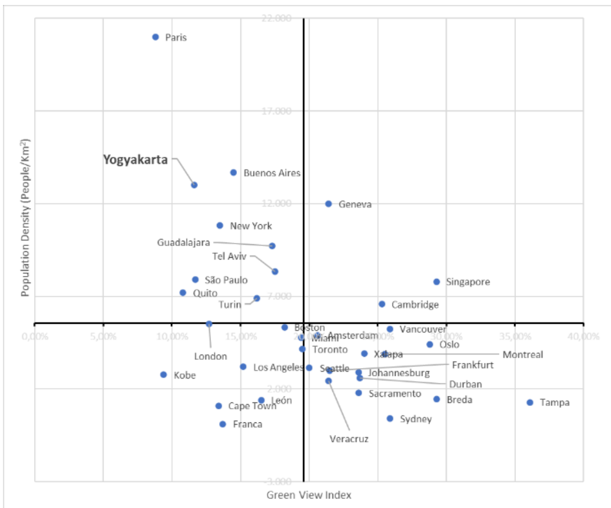

Figure 4. Global GVI Comparison Between Yogyakarta and Other Cities in Treepedia

The comparison highlights an important observation regarding the relationship between urban greenery and population density in these cities. Although Yogyakarta has a relatively lower GVI compared to the global average and Treepedia cities, it shares similarities with other urban centers in terms of the challenges faced in maintaining and expanding urban green spaces in densely populated areas.

This finding suggests the need for targeted strategies and interventions to address the green infrastructure deficit in Yogyakarta and other comparable cities. It calls for innovative approaches to create and preserve green spaces within limited land availability and high urbanization pressures.

Table 3. GVI Data from Treepedia

City	GVI	Population Density (People/Km^2)
Paris	8,80%	21.000
Kobe	9,40%	2.783
Quito	10,80%	7.200
Yogyakarta	11,60%	13.007
São Paulo	11,70%	7.913
London	12,70%	5.518
Cape Town	13,40%	1.100
New York	13,50%	10.831
Franca	13,70%	122
Buenos Aires	14,50%	13.680
Los Angeles	15,20%	3.198
Turin	16,20%	6.900
León	16,50%	1.409
Guadalajara	17,30%	9.730
Tel Aviv	17,50%	8.353
Boston	18,20%	5.344
Miami	19,40%	4.770
Toronto	19,50%	4.150
Seattle	20,00%	3.151
Amsterdam	20,60%	4.908
Geneva	21,40%	12.000
Veracruz	21,40%	2.457
Frankfurt	21,50%	3.000
Johannesburg	23,60%	2.900
Sacramento	23,60%	1.800

City	GVI	Population Density (People/Km²)
Durban	23,70%	2.600
Xalapa	24,00%	3.920
Cambridge	25,30%	6.586
Montreal	25,50%	3.889
Sydney	25,90%	400
Vancouver	25,90%	5.249
Oslo	28,80%	4.421
Breda	29,30%	1.459
Singapore	29,30%	7.797
Tampa	36,10%	1.283
Average	**19,59%**	**5.567**

As a point of comparison, Singapore will be chosen, where the Green View Index (GVI) data falls under the category of a city with a very high GVI and a moderate population. The GVI data for Singapore is recorded at 29.30%, while Yogyakarta City has a GVI of 11.60%. Singapore's GVI score of 29.30% indicates that the city has a high level of greenery and vegetation coverage in its urban areas. This suggests that Singapore places a strong emphasis on urban greening and has implemented effective measures to preserve and enhance its natural environment despite being a highly developed and densely populated city. On the other hand, Yogyakarta City, with its GVI score of 11.60%, reflects a lower level of greenery and vegetation coverage compared to Singapore. While Yogyakarta may still have green spaces and natural elements within the city, the GVI score indicates a relatively lower extent of urban greening compared to Singapore. By comparing the GVI data of Singapore and Yogyakarta, it becomes evident that Singapore has achieved a significantly higher level of greenery and vegetation integration within its urban landscape. The city's commitment to urban greening has contributed to its reputation as a garden city and serves as a benchmark for other cities aspiring to enhance their environmental sustainability and livability.

3.2 Strava Running Activity Index Calculation

As explained in the methodology section, the calculation of the Strava Index value involves interpreting the color values in the global heatmap raster from StravaLabs. The colors range from 29 (blue) to 255 (red), indicating the level of running activity intensity recorded in the Strava application. Based on the calculations at the sample points of GVI in Yogyakarta City, the average Strava Index value falls within the range of 0.209. Main roads and stadiums are identified as points with high intensity of running activity. Descriptive statistical data resulting from the attribute join of the Strava Index values at GVI sample points can be observed in Table 4. The table provides a summary of the key statistical measures that characterize the distribution and variability of the Strava Index values within the GVI sample points.

Table 4. Descriptive Statistic of Strava Index in the city of Yogyakarta

Descriptive Statistic	Strava Index
Mean	0.209
Standard Error	0.018
Median	0.018
Mode	0
Standard Deviation	0.304
Sample Variance	0.092
Kurtosis	0.158
Skewness	1.264
Range	0.996
Minimum	0
Maximum	0.996
Sum	59.593
Count	285

The Strava Index serves as a valuable metric to assess and understand the patterns of running activities within the city. It provides insights into the areas where running is most prevalent and helps identify popular routes, recreational areas, and sports facilities that attract a high volume of runners. The identification of main roads and stadiums as hotspots for running activity suggests that these locations play a significant role in promoting an active lifestyle and providing accessible opportunities for physical exercise. This data can inform decisions on the allocation of resources for the improvement and expansion of running tracks, the creation of pedestrian-friendly routes, and the enhancement of public spaces to encourage physical activity. Overall, the analysis of the Strava Index values in the sample points of GVI in Yogyakarta City provides valuable insights into the running activity patterns and highlights key areas that contribute to the overall physical vitality of the city. This information can guide future urban planning strategies and interventions aimed at creating healthier and more active environments for the residents of Yogyakarta.

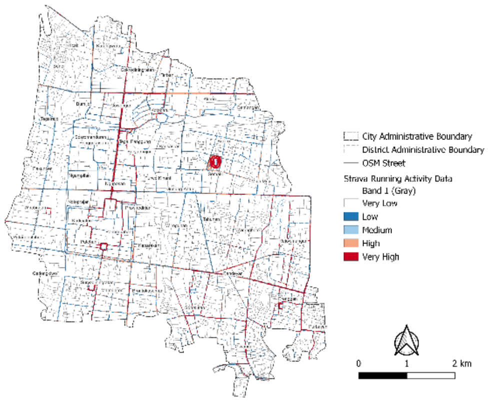

Figure 5. Strava Running Activity in the City of Yogyakarta

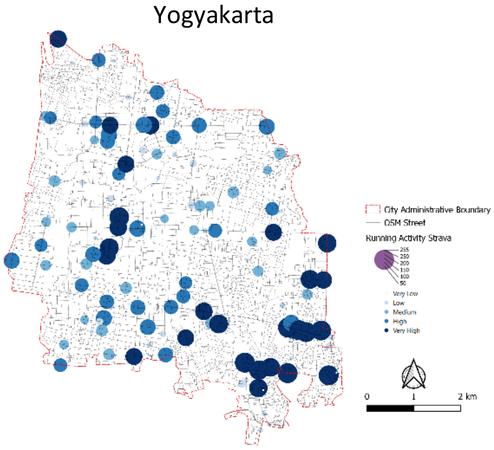

Figure 6. The Attribute Join of The Strava Index Values at GVI Sample Points in The City of Yogyakarta

The average Strava Running Index from the GVI sample points in Singapore is 0.129, suggesting a relatively high level of running activity in the city. This index is derived from analyzing the data captured by the popular fitness tracking app, Strava, which provides insights into the intensity and frequency of running activities in different areas. The measure of data dispersion, indicated by a standard deviation of 0.188, implies that there is some variability in the Strava Running Index values across the sample points in Singapore. However, it's important to note that the standard deviation alone does not provide information about the specific patterns or distribution of the data.

Table 5. Descriptive Statistic of Strava Index in the city of Singapore

Descriptive Statistic	**Strava Index**
Mean	0.129
Standard Error	0.012
Median	0.040
Mode	0
Standard Deviation	0.188
Sample Variance	0.035
Kurtosis	3.318
Skewness	1.919
Range	0.903
Minimum	0
Maximum	0.903
Sum	33.619
Count	261

However, an interesting observation is that the distribution of Strava Running Index points in Singapore tends to be relatively uniform along each major road. This suggests that the pedestrian system in Singapore is well-developed and provides favorable conditions for running activities. The uniform distribution indicates that runners have ample access to safe and well-maintained pathways throughout the city.

To gain a better understanding of the running patterns and popularity in different areas, Table 5 provides detailed calculations of the Strava Running Index, while Figure 7 illustrates the global heatmap of Strava Running, which gives a visual representation of running activities worldwide. Additionally, Figure 8 specifically showcases the dispersion of Strava Running Index values at the GVI sample points, allowing for a localized analysis of running trends within the context of the GVI data.

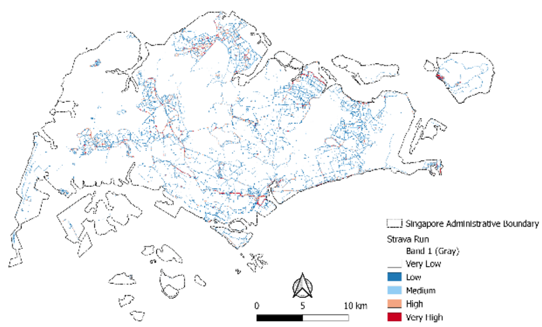

Figure 7. Strava Running Activity in the City of Singapore

These findings highlight the positive aspects of Singapore's pedestrian infrastructure, indicating that the city has invested in creating a runner-friendly environment with well-connected pathways and safe routes. This comparison also suggests that Yogyakarta might benefit from further developing its pedestrian infrastructure to enhance running and recreational activities within the city.

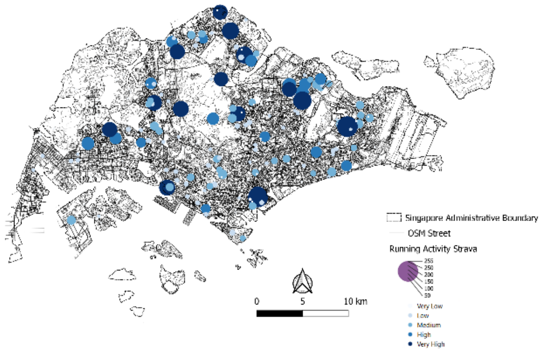

Figure 8. The attribute Join of the Strava Index values at GVI sample points in the city of Singapore

3.3 Relationship between Green View Index and Strava Running Activity Index

3.3.1 Yogyakarta

The correlation between GVI and Strava Index of -0.323 indicates a moderate and negative relationship between the two variables. A negative correlation value suggests an inverse tendency between changes in GVI and changes in the Strava Index. In this context, as the GVI value increases, the Strava Index value tends to decrease, and vice versa. However, it is important to note that the correlation of 0.323 indicates a moderate relationship between the two variables.

Table 6. Correlation between Average of GVI and Average Strava Index in the city of Yogyakarta

	Average of GVI	***Average of Strava Index***
Average of GVI	1	
Average of Strava Index	-0.323	1

This means that the variation in GVI can only explain a small portion of the variation in the Strava Index. There are other factors that influence the level of running activity that are not directly related to the presence of green spaces represented by GVI. The results of the correlation calculation between GVI and Strava Index can be seen in the Table 6 and Figure 9.

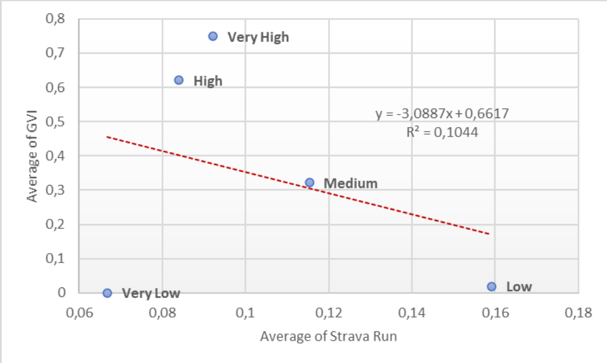

Figure 9. Scatter Plot of Average of GVI and Average of Strava Index in the City of Yogyakarta

Further research is needed to examine other variables that may affect the relationship between GVI and running activity. Additionally, contextual and social factors that can influence the level of physical activity in a specific area should also be considered.

3.3.2 Singapore

In contrast to Yogyakarta, the correlation obtained in Singapore is moderate and positive, with a value of 0.363. This indicates that locations with a high Green View Index (GVI) in Singapore are also associated with high levels of running activity. The positive correlation suggests that the availability of green spaces and well-designed pedestrian infrastructure in Singapore contributes to increased running engagement.

Table 7. Correlation between Average of GVI and Average Strava Index in the city of Singapore

	Average of GVI	***Average of Strava Index***
Average of GVI	1	
Average of Strava Index	0.363	1

This observation further emphasizes the positive relationship between the quality of pedestrian systems and the level of running activity in a city. The pedestrian infrastructure in Singapore is known for its efficiency and connectivity, providing residents with safe and convenient routes for outdoor activities such as running. This well-developed system encourages people to incorporate physical activity into their daily routines. The correlation between the GVI and running activity in Singapore can be observed in Table 7, which presents the calculated correlation values, and Figure 10, which illustrates the scatter plot depicting the relationship between the GVI and Strava Running Index. The scatter plot visually demonstrates how higher GVI values are associated with higher Strava Running Index values, indicating the positive connection between green spaces and running activity.

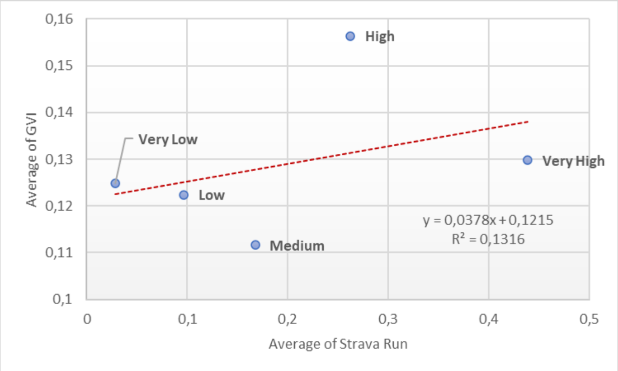

Figure 10. Scatter Plot of Average of GVI and Average of Strava Index in the City of Singapore

Comparatively, Yogyakarta may have a different pattern due to variations in its pedestrian infrastructure and green space distribution. Enhancing the pedestrian system in Yogyakarta could potentially result in a similar positive correlation between the GVI and running activity, as observed in Singapore. Overall, the findings from the correlation analysis and the scatter plot highlight the positive impact of a well-designed pedestrian system and abundant green spaces on promoting running activity. It underscores the importance of urban planning and infrastructure development in creating environments that encourage physical activity and contribute to the overall health and well-being of residents.

4. CONCLUSION

The utilization of geospatial data and Volunteered Geographic Information (VGI), specifically Google Street View and Strava running activity data, holds great potential in evaluating the Green View Index (GVI) and running activity index. By comparing and analyzing the relationship patterns between these two indices, valuable insights can be obtained regarding urban vitality and its comparison with global city databases.

Yogyakarta, with a GVI value of 11.6%, presents interesting findings when compared to the average GVI values obtained from Treepedia, placing it below the global average. When considering its relation to other cities worldwide, Yogyakarta shares similar characteristics with several cities that fall within the low GVI quadrant, accompanied by high population density. This observation highlights the need to further investigate the interplay between green spaces, urban development, and population dynamics in Yogyakarta. Additionally, the correlation analysis between GVI and the sample point data reveals a moderate negative correlation. This also indicates that locations with high GVI are not favored by runners according to Strava data. Other factors are expected to be related to and influence Yogyakarta aside from GVI. When compared to Singapore, which has a GVI value of 29.3% and falls under the high GVI classification with a moderate positive correlation between GVI and Strava running index, the situation in Yogyakarta is contrary. Factors such as pedestrian infrastructure and facilities for public activities may contribute to these differences. Further research is needed in this regard.

To enhance the accuracy of GVI-based urban vitality models, future research endeavors should incorporate additional relevant variables. By expanding the scope of analysis and considering various factors that influence urban vitality, a more comprehensive understanding can be achieved, enabling effective planning and development strategies for sustainable and attractive cities.

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