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Utilization of Google Street View to Estimate Green View Index: a case study from Bandung, Indonesia

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Abstract

The use of street view has many benefits with its popular source being Google Street View (GSV). One of the processing methods uses semantic segmentation which can classify each pixel according to the category of the pre-trained pyramid scene parsing network (PSPNet) model used. The Green View Index (GVI) is one of the semantic segmentation research trends in viewing Green Open Space (GOS) based on human perception of an area. Green Open Space (GOS) provides many benefits and more attractiveness to the community to be able to live in the vicinity. The GVI obtained gives an average value of 22.5% capturing the presence of GOS which is higher than the green open space data collected by Housing and Settlement Area, Land and Parking Offices Bandung City.

Keywords : Street imagery, Google Street View, Green View Index, Green open space.

Major Classification Code: Ecological Economics (Q57)

1. Introduction

The development of Big Data is increasing until now, which has attracted a lot of attention from the research world, especially geospatial Big Data. Geospatial big data has grown rapidly from 2009 by growth rate of 20% a year year (Dasgupta, 2013) that can be retrieved for spatial data analysis sources by extracting useful data from satellite imagery, street view imagery, etc. Geospatial Big Data is obtained by utilizing digital images, one of which is street imagery. Street view imagery has proven useful in conjunction with other data sources especially for geospatial data e.g. mapping trees (Seiferling et al., 2017). Various sources of street imagery can be obtained from various crowdsourcing sources that can be accessed by the public, one of which is the service provided by Google, namely, Google Street View (GSV). GSV provides a source of high-resolution street imagery and has become a trending research in the field of geospatial research with rapid development in recent years (Biljecki & Ito, 2021) GSV has popularity in street imagery research which is integrated with Google Maps so that it can be accessed via an openly

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provided location Application Programming Interface (API). GSV provides a source of high-resolution street imagery and has become trending research in the field of geospatial research with rapid development in recent years. The use of street imagery for urban greenery studies is mostly done with a contribution of 15.77% of all street imagery research (He & Li, 2021). Urban greening can be evaluate the visibility of urban forests with the Green View Index (GVI) (Dong et al., 2018; Yang et al., 2009).

Research that uses street imagery in Indonesia is still very minimal, especially in urban greenery which has not yet been studied based on data from the Communication and Information Office. In research, the use of street imagery for urban greenery studies is mostly done with a contribution of 15.77% of all street imagery research (He & Li, 2021). Urban greenery is included in one of the components of the direction of urban development policies in Indonesia in the National Medium-Term Development Plan For 2015-2019, including developing and implementing green open spaces and developing city activities that are environmentally sound (green economy) (van den Berg et al., 2007) Green Open Space (GOS) measures the level of greenness of all components including city parks, green lines, gardens, and others. GOS can provide many benefits for the people who live around it such as having a positive impact on physical and mental health (De Vries et al., 2013; van den Berg et al., 2007), traffic comfort, good urban structure, and others (Barbosa et al., 2007; Kabisch et al., 2016; Schüle et al., 2017).

GOS has a role in socio-economic functions in the surrounding area, including increasing tourist attraction, providing a comfortable atmosphere for living and working places, and others. This creates an area with high green open space, making people interested in even though the price is higher. In addition, office activities that have lots of trees will have an impact on high productivity (Isma et al., 2019). The green open space study obtained using an approach using satellite imagery with Leaf Area Index (LAI) (Jensen et al., 2004) and street imagery with Green View Index (GVI) has a positive relationship with income levels and has a negative relationship with poverty levels (Li et al., 2015; Meng et al., 2020).

GSV is a source of big data that can assist in providing demographic captures in the form of panoramic street imagery from locations that have been visited by agents from Google. On the other hand, satellite imagery approaches have also been widely used to view greenery levels, one of the popular approaches is using satellite imagery with the Normalized Difference Vegetation Index (NDVI) (Almanza et al., 2012; Zhang et al., 2021). However, it can still produce results that the public can reject because it provides satellite capture, which can be different from what humans see. The street imagery approach as counterpart of the results of satellite imagery, can be used to provide a panoramic street imagery that is the same as the human perspective. Street imagery can provide a more point of view by paying attention to the depth of the greenery component.

Green View Index is an indicator to measure the level of urban greenery (Li et al., 2015) and can be used to estimate the value of green space collected by direct observation in the field which consumes more energy, costs, and time in its implementation. GVI is obtained by processing using a semantic segmentation method that uses the basis of deep learning. Convolutional Neural Network (CNN) is a method that is widely used for semantic segmentation. The CNN architecture that has been developed and is popularly used in the use of semantic segmentation to calculate GVI is PSPNet (Pyramid Scene Parsing Network). PSPNet is an optimized CNN architecture by studying the global representation of each of the various map feature scales (Zhao et al., 2017).

Based on BPS Statistics Indonesia in 2020, the area of Bandung's green open space is around 2,048.97 hectares, which is 12.25% of the total area of Bandung. However, the green open space data does not represent green open space which is updated from year to year due to the difficulty of collecting it and policy changes from local governments that only focus on several components of green open space, one of which is in all city parks so that it can be concluded that all green open spaces are expected. Therefore, researchers are interested in looking at urban greenery using GVI as a green open space data collection approach. The objectives of this research to estimate Green View Index (GVI) using image processing results from Google Street View in Bandung City, Indonesia

2. Materials and Methods

2.1. Sampling Points

The data collected first is spatial data in the form of shapefiles containing geometric features of regional administration based on village including the street network obtained from sources that can be accessed from www.lapakgis.com and then loaded into ArcGIS for sampling point sampling. Sampling points from the available street network, several sample points are taken to obtain latitude and longitude coordinates that can represent each street in the area. The sample points obtained were obtained using tools in ArcGIS in Generate Point Along Lines catalogue option by randomly taking the initiation point and then setting the next point with a distance between the sample points of 300 meters. Sampling points obtained as many as 1200 from all streets in the city of Bandung.

From all these sampling points, it will be traced related to availability in the collection of street imagery results from the Google Street View API.

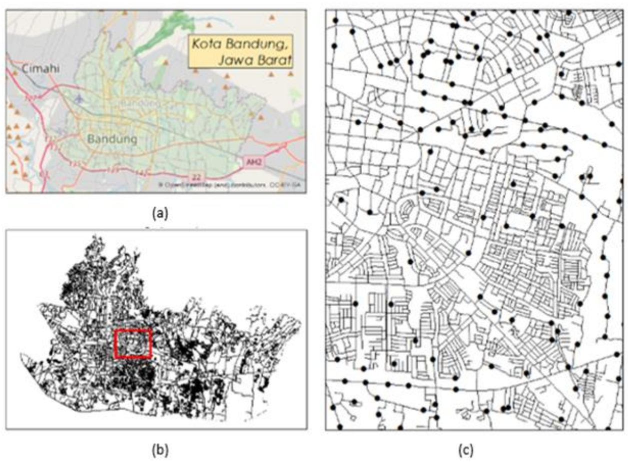

Figure 1: Selected Sampling Points on ArcGIS (a) Geographical view of Bandung City (b) City of Bandung street network that has been sampling point (c) Display of sampling point on the street network that is closer to the area in the red box

To take street imagery from the GSV API, metadata information is needed to be able to see if the image from the GPS coordinates is available and will be filtered so that when taking panoramic street imagery, it will obtain a valid image. Image collection with pitch: 0; headings: 0,90,180,270; pixels: 300x300 obtained in Python 3 on Google Collaboratory. GSV images are taken from 4 directions horizontally (see Figure 2) from the related GPS location points, so that it can be used as a complete panorama to view all sightings at the related location.

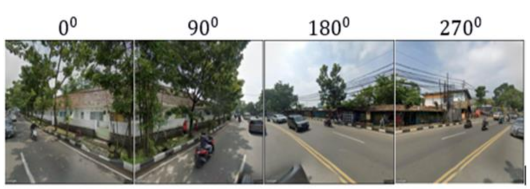

Figure 2: Google Street View (GSV) panorama

Parameters obtained for taking pictures from the Google Street View API used, including:

- copyright: from google/agents who contributed to adding GSV panoramas at related locations
- date: shooting time
- location: contains the latitude and longitude of the corresponding location
- pano_id: encoding of the associated panorama points
- status: description of whether the image is available or not.

2.2. AI Methodology and Model Selection

In this study, we employed the Pyramid Scene Parsing Network (PSPNet) for semantic segmentation of street imagery. PSPNet is a deep learning model designed for high-level pixel-wise understanding of images. The strength of this model lies in its ability to capture both local and global contexts within a scene by using a multi-scale pyramid pooling layer. This feature enables PSPNet to outperform other segmentation models like FCN or UNet in tasks that require detailed scene understanding, such as green vegetation identification in urban environments.

CNN Backbone: We used the ResNet-50 architecture as the backbone for PSPNet. ResNet-50, a convolutional neural network (CNN), is widely known for its ability to address the vanishing gradient problem, thus facilitating deeper networks. The model has been trained which is used with transfer learning with a training dataset that already has image annotations classified into various categories of objects in it which are collected in the ADE20K dataset (Zhou et al., 2017, 2019). This architecture enhances the model's capacity to extract more accurate features from the images, making it particularly effective for differentiating green areas from other urban elements.

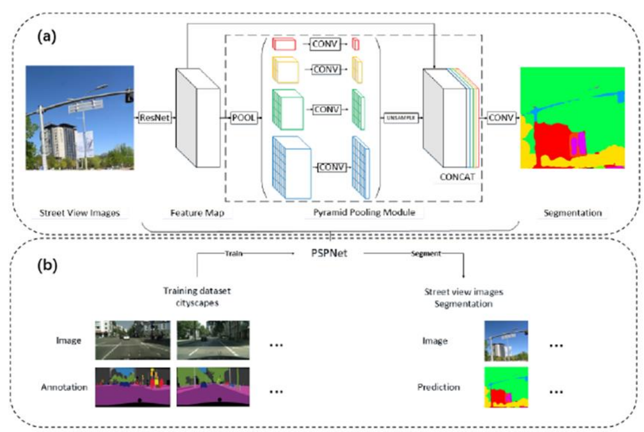

Figure 3: (a) Architectural view and segmentation workflow of the PSPNet architecture. (b) Dataset used as training data and GSV as prediction data (Zhao et al., 2017)

2.3. Green View Index (GVI) Analysis and Evaluation

All street imagery from the location of the sample points used is segmented with the model of PSPNet. The results of the semantic segmentation of each waypoint are used in the GVI calculation by taking the total pixels that fall into the green category and compared with the total pixels of each street panoramic image (Ki & Lee, 2021; Li et al., 2015; Li et al., 2015; Meng et al., 2020; Wu et al., 2020). The GVI calculation is formulated as follows:

$$GVI = \frac{\sum_{i=1}^{4} Area_{g\_i}}{\sum_{i=1}^{4} Area_{t\_i}} \times 100\% \quad (1)$$

where $Area_{g\_i}$ is the area or number of green pixels and $Area_{t\_i}$ is the total area or number of pixels of the entire image.

Green View Index (GVI) which is the result of the calculation of the total pixels included in the object of semantic segmentation as green vegetation. From the results of the processing, it is necessary to carry out an evaluation that can describe how the GVI value obtained is in accordance with the results of manual segmentation on the panoramic image of the road used (ground truth). Ground truth was carried out using Adobe Photoshop software (Li et al., 2015; Li et al., 2015) which can perform image processing with visual graphics techniques carried out by users according to the features available in the application.

Ground truth development was carried out by 3 different subjects including researchers to avoid subjective manual segmentation processing results. The GVI that has been generated from each sample point is then mapped into a Geographic Information System (GIS) with the QGIS application. From the collection of sample points that already contain the GVI value is then taken to take the median value from each point that is incorporated into the same administrative boundary at the village/kelurahan level (Li, Zhang, Li, Kuzovkina, et al., 2015). After the grouping is done at each village level, each village can be used in the next model to see its effect on the poverty level.

3. Research Methods and Materials

3.1. Street View Collection Results

After collecting street imagery data from each sam ple point, obtained with the available street imagery as many as 1026 panorama id only with status = "OK", therefore the dataframe is reduced according to the a vailable metadata. Based on the distribution graph in Figure 4, the street imagery obtained are spread over t he range from 2013 to 2021. The most valid and mos t collected street views are in 2021 as many as 547 p anoramas or 53.3% of the total GSV images obtained. It happens that the API from Google will retrieve the most updated street imagery from each location point used in the study.

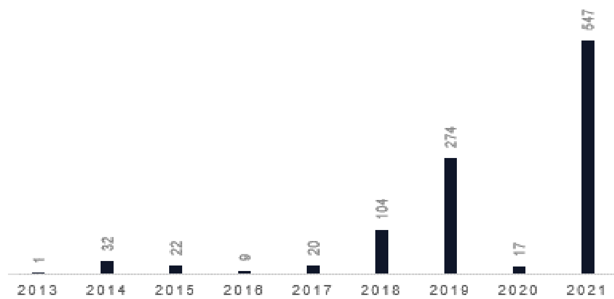

Figure 4: GSV Street View Distribution by year

3.2. Street View Processing Results

Semantic segmentation is carried out using a pre-trained model from the "image-keras-segmentation" package with the CNN model used, namely ResNet50, and the PSPNet model with training data available ADE20K on Google Collaboratory. The results of the segmentation generated from the model with the two training datasets above on the GSV panoramic image segmentation used are depicted in the following display.

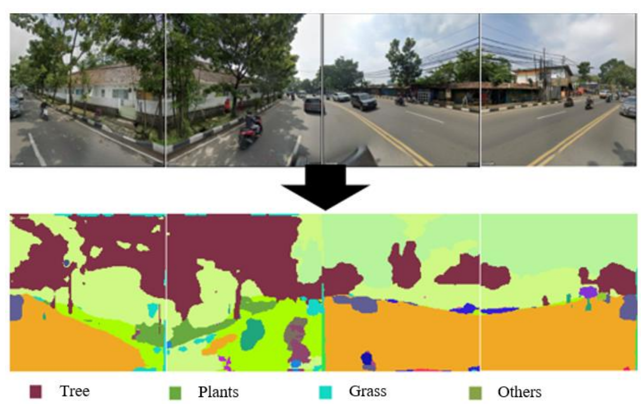

Figure 5: Street imagery from Google Street View (above) PSPNet segmented image with the ADE20K training dataset (below)

The model used provides the classification results of each object contained in the classification defined from the ADE20K 150 training data for the object category with annotation results that provide an overview of the segmentation results (see Figure 5) that are more in line with the panoramic data of GSV street imagery in the city of Bandung. Information on the green label taken from the segmentation results using the PSPNet model with the ADE20K training dataset, each category will be used in the GVI calculation by taking the number of pixels from each object that is included in the greenery category.

3.3. Green View Index (GVI) Results

Estimate green open space from the results of semantic segmentation used to produce output in the form of Green View Index (GVI) indicator values. The GVI value is described by the greenness percentage value obtained from road images. The following is the distribution of the GVI indicator values shown below (see Figure 6).

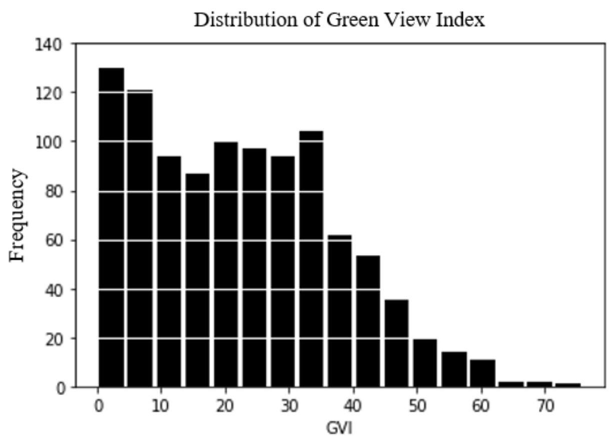

Figure 6: Distribution of Green View Index Results

The distribution of GVI values shown in Figure 14 shows that GVI in the city of Bandung has an average of 22.48% which can describe the percentage of green open space in 2021 in the City of Bandung. This value when compared with the existing green open space in the Bandung City DPKP3 service data in 2020 is 12.25% which shows a fairly large gap. This happens, because conventional green open space data collection has not been carried out thoroughly in accordance with the details of green open space data obtained from the DPKP3 service which only updates the details of green open space data on the area of green open space for city parks regularly (DPKP Kota Bandung, 2023), while other details of green open space, such as green open space for nurseries, Funeral green open space, green line green open space, and others have not been updated regularly until the end of 2021. GVI obtained from each sample location point used is mapped on the Geoographic Information System (GIS) using QGIS Desktop 3.22.6. The visualization of the size of the GVI value is described by a color scale with the division of the color range based on the quantile of all the GVI values obtained.

Figure 7: Results of mapping the distribution of GVI indicator values in QGIS.

The visualization with dots (see Figure 7) does not yet provide a more general interpretation but is based on location sample points that provide very diverse GVI values, so grouping is done based on certain characteristics to get more general interpretation results. The grouping is done based on the median value (concentration value used to avoid outliers) from each point that is incorporated into one village level. The results of this grouping are carried out on a GIS by mapping the appropriate regional administrative SHP files based on the village level (see Figure 8).

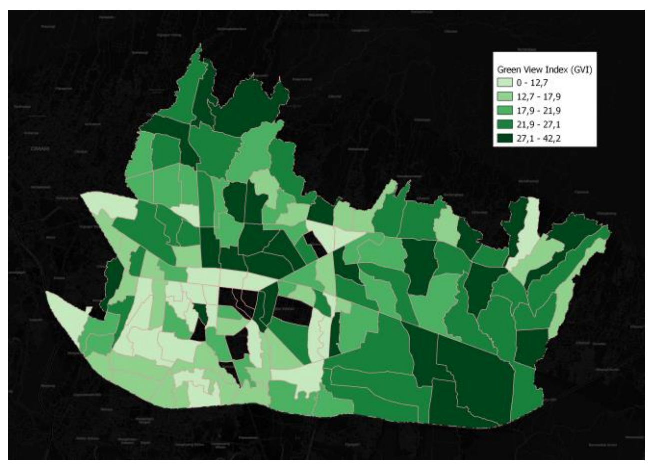

Figure 8: Spatial distribution of GVI by village

From the results of the grouping, a more general interpretation can be taken based on the village level. Of all the median GVI values obtained, there are only 140 villages that have a median GVI value, while other villages do not have street imagery obtained from the GSV. From these results, it was found that the village with the lowest GVI of 1.92% was in the Jamika Village, while the largest GVI was 43.28% in the Ciumbuleuit Village.

3.3. Green View Index (GVI) Evaluation

The results of manual segmentation on the street imagery used are calculated using a pixel calculation matrix conversion based on the RGB color corresponding to the color overlay which is determined as greeness vegetation. This calculation is used in determining the new GVI index with the results of manual processing done using Python. The results of the manual GVI were obtained by taking the average of the manual GVI obtained from the three subjects and then seeing how it correlated with the semantic segmentation GVI results (see Figure 9).

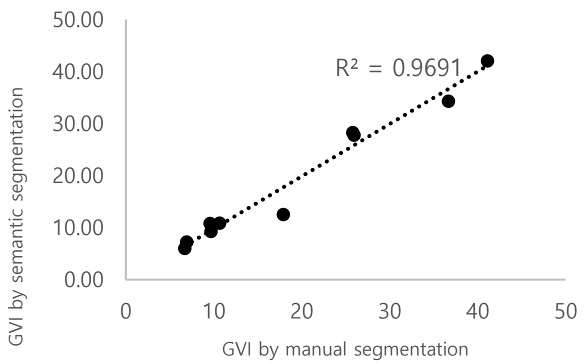

Figure 9: Correlation between GVI values based on semantic segmentation results and GVI values based on manual segmentation results for evaluation

It was found that the R^2 correlation coefficient was 0.97 which indicated that the GVI obtained from the two methods had a strong relationship and indicated the same value between the GVI results from the two methods. So that the GVI obtained by the semantic segmentation method is of high quality (Li et al., 2015) to be used at the next research stage.

4. Discussion

This research aims to provide an estimation of Green View Index (GVI) by Google Street View images for green space to evaluate an alternative data collecting of Green Open Space (GOS) in urban environments. This study also supplies references for understanding the GVI estimation from semantic segmentation by street imagery. The contents of the discussion section are organized as follows: first, we tell how the accuracy and efficiency of the PSPNet model to make street images are segmented; second, we analyze the distribution of GVI values for different villages.

The accuracy of semantic segmentation uses the development of the Convolutional Neural Network (CNN) model which is organized into an architecture known as PSPNet (Zhao et al., 2017). The model is used in the results of street imagery obtained from Google Street View which are arranged into panoramic street images. The results of semantic segmentation using this model have good accuracy with similar results to manual segmentation that has been done (Ki & Lee, 2021; Li et al., 2015; Li 2015; Meng et al., 2020) which states that the accuracy of the model is very good in performing semantic segmentation of the street imagery used.

The value of GVI spreads with various ranges of values according to the village area that corresponds to the urban structure. High GVI values tend to be in the city center and some on the outskirts of the city which indicates that greenery in urban centers is more concerned with supporting more productivity activities in these areas than some other urban areas which are more designated as factories and industrial areas that can cause pollution. the air to make all the green components around it disturbed.

5. Conclusions

Google Street View (GSV) provides the latest street imagery results, with the most years being in 2021. The Green View Index (GVI) generated in capturing Green Open Space (GOS) based on Google Street View (GSV) street imagery with the final reference year 2021 in the city of Bandung produces a GVI with an average of 22.48% which captures more gaps in the existing green open space data in 2020 which is only 12.25%. For the government, especially the Housing and Settlement Area, Land and Parking Offices (DPKP3), it is necessary to update the green open space data completely so that it can be compared in a more real way with the GVI study and the results of processing other Big Data to be Green Open Space alternative data collection.

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