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Utilizing Semantic Segmentation to Analyse Google Street View Imagery for Health-Oriented Urban Planning

A Case Study of the Green View Index in Copenhagen Municipality

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Abstract

After the onset of the Coronavirus Disease 2019 (COVID-19) pandemic, the public health benefits of urban green space (UGS) have attracted increased attention. In exposure science, visibility has been considered a fundamental category for assessing green space exposure, yet evaluations in Denmark rarely address it. This study uses Copenhagen Municipality as a case study to explore the Green View Index (GVI) by analyzing Google Street View (GSV) images using semantic segmentation. The main findings include: (1) a GVI mean of 15.05% within Copenhagen Municipality, ranking below the average of six other European cities, and (2) a map showing the spatial distribution of GVI in the study area. Additionally, this paper considers the potential and possibilities of using street view imagery in future urban health studies.

Keywords: green space exposure, Green View Index (GVI), urban health, semantic segmentation, Google Street View (GSV)

1. Introduction

1.1 Background

In 2023, about 56% of the world's population lived in urban areas, with Denmark reporting urban residency between 88.1% to 88.8% (The World Bank, 2023; United Nations, 2018). In urban settings, UGS significantly contributes to human health by mitigating environmental harm and enhancing human capabilities (Markevych et al., 2017). After the COVID-19 pandemic, citizens, governments, and public welfare organizations around the world are increasingly aware of the importance of urban green space (Uchiyama & Kohsaka, 2020).

From 2017 to 2020, review papers show that health-related studies predominantly evaluate urban green space from three main categories: availability, accessibility, and visibility (Dadvand & Nieuwenhuijsen, 2019; Ekkel & de Vries, 2017; Labib et al., 2020). As the European Green Capital in 2014, Copenhagen focused on enhancing the availability and accessibility of green spaces over the past decade. However, assessments of the visibility have been lacking. This paper, adapted from the same author's master's thesis titled *Utilizing Geospatial Big Data and Open Data to Reveal Copenhagen's Green Space Exposure: Introducing A Novel Composite Index of*

Availability, Accessibility, and Visibility, focuses on revealing the visibility of green spaces in Copenhagen. There are no unified measures to evaluate “visibility” at present (Yu et al., 2023), but the GVI is widely used in practice and has been proven to correlate with health benefits (Villeneuve et al., 2018). The GVI spans a scale from 0% to 100%, serving as an indicator of the proportion of vegetation visible from a street-level perspective (Villeneuve et al., 2018).

There are two primary methods for evaluating the GVI: one involves viewshed analysis based on the digital surface model (DSM), and the other utilizes semantic segmentation models to analyze street view images. Compared to the former, the semantic segmentation method is closer to the green that people actually perceive (Liu et al., 2019; Wang et al., 2019; Wang et al., 2021), and more convenient and affordable, making it particularly effective for providing an overview of a large-scale area. Accordingly, this study adopted this method.

1.2 The study area and research questions

Besides Copenhagen Municipality, the study area also includes Frederiksberg Municipality due to their strong continuity in street space. The research aims to address two questions: (1) What is the current condition of the GVI in Copenhagen Municipality? (2) What can we learn from the results?

2. Method

2.1 Sampling and requesting GSV images

First, the coordinates of the required GSV images are predetermined. After merging the roads of Copenhagen and Frederiksberg Municipality, some minor road types, including internal park roads, were excluded. Then, Generate Points Along Lines tool was performed in ArcGIS to create points along the road network every 50m. After 13,374 points and their corresponding coordinates were generated, a Python program was executed to download GSV images (Google, 2023) and associated metadata via the GSV API. At each sampled point, four 640x640 pixel images were requested, each with a 0° pitch (horizontal view) and directions of 0°, 90°, 180°, and 270°.

2.2 Calculation of GVI

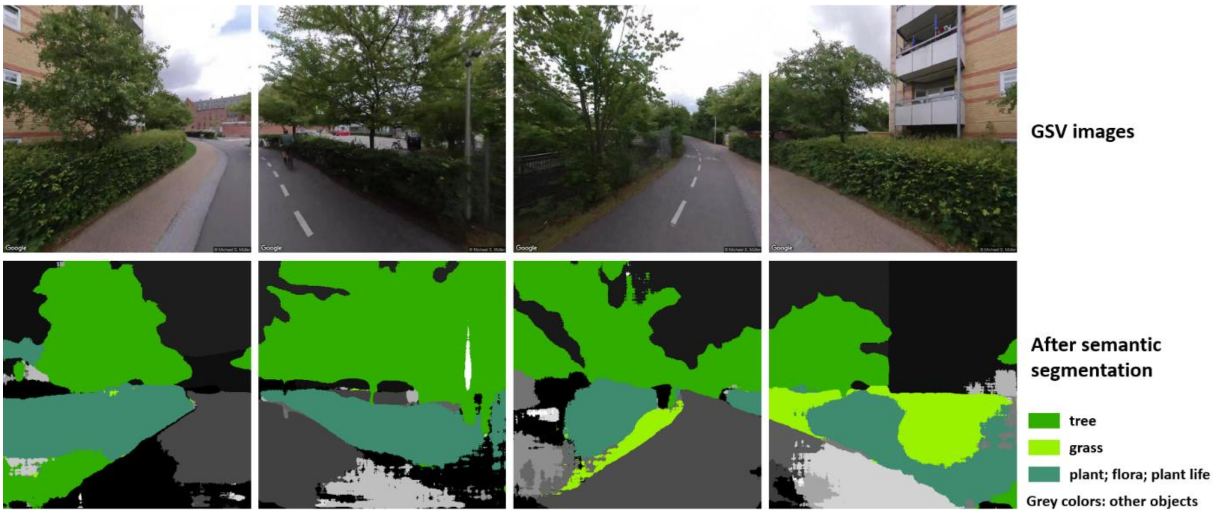

Figure 1: The GSV images in the study area and after the semantic segmentation

In this study, the Semantic Segmentation software (version 1.0) (Yao et al., 2019) was adopted because of its high accuracy and convenience among similar models. The training process of this model combines deep learning and iterative feedback (a human-machine adversarial scoring framework), making the model achieve an accuracy of 81.44% on the training dataset and 66.83% on the test dataset of the ADE-20K dataset (a commonly used cityscape dataset) (Yao et al., 2019). This software identified and quantified objects in each image, expressing them as percentages of the total picture area, measured in pixels. The objects associated with greenery – "tree", "grass", and "plant; flora; plant life" – were identified and their percentages were aggregated to compute the GVI. After that, the GVI results were correlated with metadata, including the location, captured month, and year, based on the image ID. Since the results are sensitive to the time of year, only images captured between April and October (the growing season) from 2019 to 2023 were considered in this analysis. Out of the original 53,496 images, 32,377 were retained.

2.3 Validation (Visual interpretation) of GVI

To evaluate the performance of the model applied to GSV images in the study area, a visual interpretation approach was adopted. The evaluation process consists of the following steps: (1) determining the number of samples to check, based on the total number of images and the desired confidence level; (2) randomly selecting images for sampling; (3) manually marking greenery in the sampled images with a colored layer in Photoshop; (4) calculating the percentage of greenery (the actual GVI) by using the pixel data from the Histogram Panel in Photoshop.

In step (1), given the Z-score of 1.96, an estimated proportion of 0.5, an accepted margin of error of 0.05, and a total number of images at 32,377, the proper sample size was calculated to be approximately 379.67 using the Sample Size Formula for estimating a proportion and the Finite Population Correction Formula. Accordingly, 388 images were randomly selected for visual interpretation. Once all the steps were completed, the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), the residual, and the percentage error were calculated.

3. Data

In this study, Open Street Map data and GSV data are the primarily used data. The data utilized in this study are (1) the Road Network, consisting of two entries detailing road centerlines in Copenhagen (Københavns Kommune, 2018) and the road network in Denmark (Geofabrik GmbH, OpenStreetMap Contributors, 2023), including various types of roads; (2) GSV images from Copenhagen and Frederiksberg (Google, 2023); (3) the boundaries and codes of municipalities in Denmark (Styrelsen for Dataforsyning og Effectivisering, 2018); (4) the boundaries and names of districts in Copenhagen Municipality (Københavns Kommune, 2018).

4. Results

Copenhagen Municipality's mean GVI is 15.05%, with higher values in the peripheral areas than in the city center, indicating a spatial gradient. Areas with low GVI include Indre By, eastern Vesterbro/Kongens Enghave, the Nørrebro-Bispebjerg border, and east Østerbro. Notably, the southern area of Amager Vest, despite being close to Kalvebod Fælled, also exhibits low GVI, a trend that extends to the northwestern part of Amager Øst.

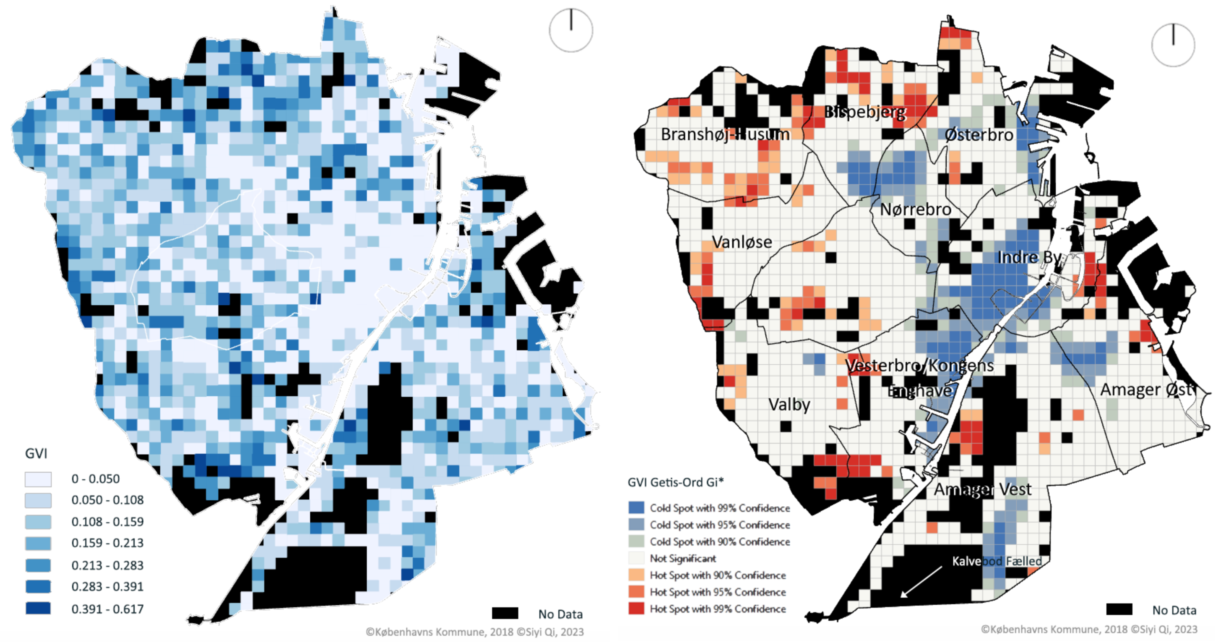

Figure 2: Left: The GVI map (Natural Breaks), in 250*250m grids; Right: The Getis-Ord Gi* of the GVI (Contiguity edges corners, False Discovery Rate correction implemented), in 250*250m grids

The validation results indicate that the overall RMSE is 0.07, and the overall MAPE is 33.92%. When considering both RMSE and MAPE, the model might overestimate or underestimate greenery more significantly in areas with a lot of vegetation, but in relative terms, these errors are smaller compared to the total amount of greenery present. Conversely, in areas with sparse vegetation, the model is more accurate in terms of absolute errors but might still incur relatively large relative errors. Furthermore, according to Figure 4, the model underestimates the GVI in almost all cases (368 out of the total 388, 94.85%). This might be attributed to the semantic segmentation model's weak capacity for identifying small-scale vegetative features within the images.

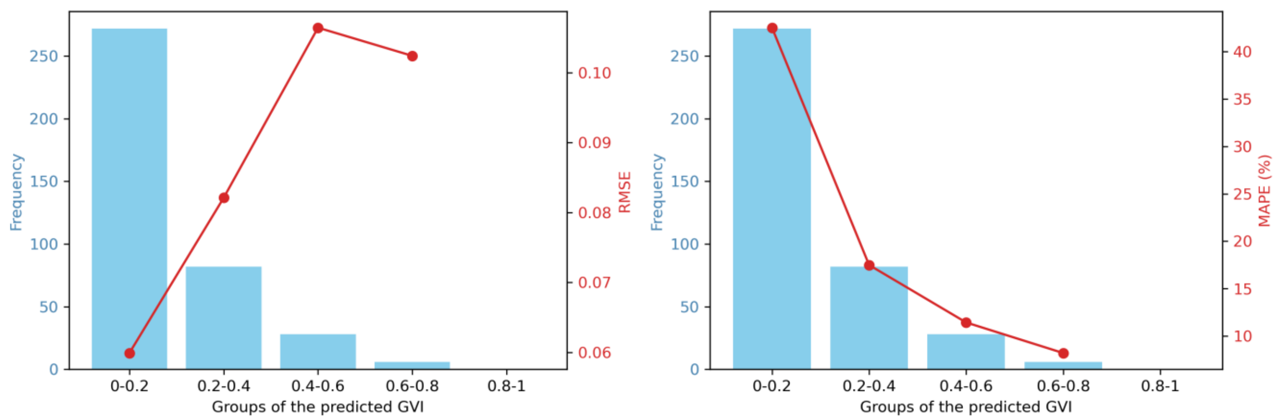

Figure 3: Left: The RMSE of the predicted GVI; Right: The MAPE of the predicted GVI

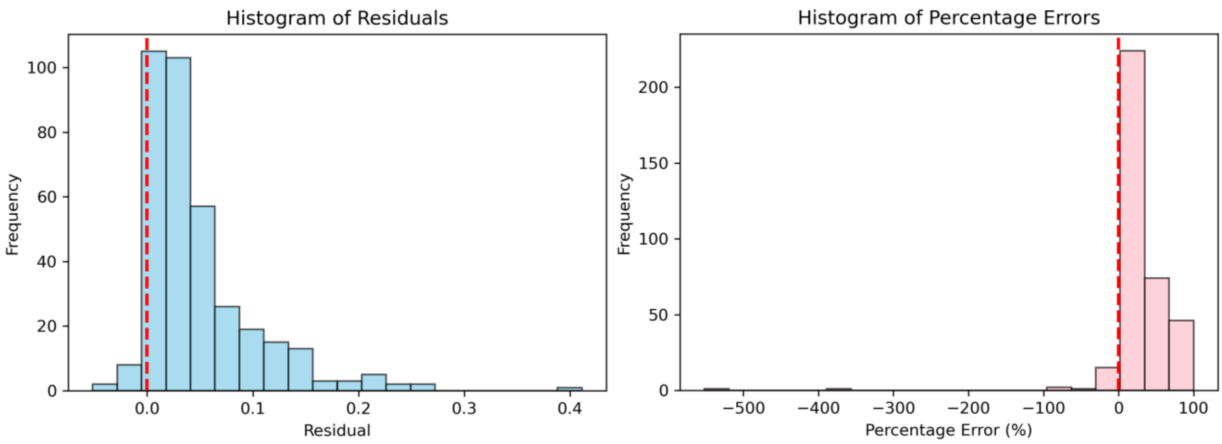

Figure 4: Left: The Residuals of the predicted GVI; Right: The Percentage Errors of the predicted GVI

5. Discussion

Compared to other European cities listed in Table 1, Copenhagen's mean GVI is below average, highlighting opportunities for enhanced street greening. The GVI levels in these cities might correlate with their land development intensity and population density. However, differences in data collection methods and semantic segmentation models limit the effectiveness of such comparisons.

City	GVI(%), Year
Oslo	28.8%, n.d.
Frankfurt	21.5%, n.d.
Amsterdam	20.6%, n.d.
Copenhagen	15.05%, 2019-2023
London	12.7%, n.d.
Paris	8.8%, n.d.

Table 1: GVI values in other European cities [The GVI values, except for Copenhagen, were obtained from Treepedia (MIT Sensable City Lab, World Economic Forum, Global Shapers Community, n.d.)].

By examining GSV images and urban development areas in *Copenhagen Municipal Plan 2019*, the GVI cold spot in the southern part of Amager Vest is primarily due to ongoing, large-scale construction. Meanwhile, in the northwestern part of Amager Øst, it is solely attributed to the lack of street greening. Since GVI reflects the greening of smaller-scale street spaces, it is sensitive to distance, meaning values can change significantly even in short distances. The results can provide guidance for urban planning and public health, especially in promoting equitable visibility of green spaces. Beyond identifying large cold spots, the greater potential and advantage of GVI maps lie in assisting detailed street greening governance. Additionally, current GVI conditions can guide the locations of sanatoriums, hospitals, or kindergartens and influence property prices.

5.1 Limitations

The GSV images used to calculate the GVI exhibit inconsistencies in sampling years and seasons across different regions within the study area. Additionally, other inherent disadvantages of the data, such as different environmental light conditions and lens distortion, lead to inaccuracies.

The accuracy of the Semantic Segmentation software also requires further consideration. The model achieved 66.83% accuracy on the test dataset, while the results of visual interpretation were similar, approximately 66.08%, calculated as ”1 - mean MAPE”. In addition to its relatively low accuracy, the model demonstrates a significant inclination to underestimate GVI, with a probability of 94.85%. The improvement of street view photography and a better semantic segmentation model in the future could potentially improve the accuracy of the GVI calculation.

5.2 Expectations

The rapid development of computer vision technology has expanded the potentiality of using street view imagery in urban health studies. In 2023, META AI released the Segment Anything Model (SAM), dubbed ”the ChatGPT of Computer Vision”, showing strong generalization capabilities. This model, along with object detection models like Grounding DINO and YOLOv8, facilitates the completion of almost any semantic segmentation task. Although SAM generally performs worse than supervised models, it can provide training datasets for other models or be improved by re-training, prompt learning, or fine-tuning. For example, combining SAM with object detection models (or datasets with existing point/box/mask labels, or through human-computer interaction) can quickly augment semantic segmentation datasets, filling the gap in datasets that lack manual annotations (Wang et al., 2024). Current SAM application research has explored the identification of pedestrain obstacles through synthetic street view imagery, enhancing mobility for vulnerable groups in urban environments (Xia et al., 2023).

On the other hand, the use of GSV imagery is limited in Denmark, as data mining currently poses potential legal risks. Unlike in the United States, the civil law system in Denmark is based on codification and does not follow the principle of ”stare decisis” (the doctrine of precedent) (Marco Helbich, 2024). According to the current amendments to the Danish Copyright Act, anyone with legal access to a work can copy excerpts for text and data mining unless explicitly reserved by the rights holder (Forslag til Lov om ændring af lov om ophavsret, § 11 b., 2023). However, in the Google Maps Platform Terms of Service, it is prohibited to ”construct an index of tree locations within a city from Street View imagery” (Google, 2020). The new amendment to the Danish Copyright Act in 2024 might broaden permissible uses in the future (Foged, 2023).

6. Conclusion

This paper uses a semantic segmentation model to analyze GSV images in Copenhagen Municipality, and finds that the mean GVI is 15.05%, which is below the average compared to six other European cities. This method offers a human-centric perspective, supporting health-oriented urban planning. Its scalable nature allows for application across different cities without substantial adjustments, enabling global collaborations and benchmarking. Furthermore, the paper highlights the potential and feasibility of using street view imagery in future urban health studies, suggesting its significant role in enhancing urban environments for better public health outcomes.

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