INVESTIGATING GREENERY IN URBAN STREET PERSPECTIVE USING STREET VIEW IMAGES

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Abstract: With the urban development, the negative impacts such as air pollution and urban heat island effect have led to poor life quality, especially for physical and mental health. Therefore, urban greenery has become an imperative issue within the policy-making process. Most related studies have used Normalized Difference Vegetation Index (NDVI) as an index of urban greenery. However, the NDVI ignores the vertical greenery occluded greenery and grass. In this study, street view imagery is used to extract urban greenery based on a deep learning method. The Green View Index (GVI) is calculated according to the percentage of green in each street view imagery. In order to analyze the correlation between GVI and NDVI, the Geographically Weighted Regression (GWR) is utilized in this study. The results revealed that spatial heterogeneity is existed between NDVI and GVI. To briefly sum up, the higher R^2 is mostly in areas with dense trees, and regression coefficients are affected by the number of trees and the visibility of trees. The lower R^2 is mostly in areas with few trees, and regression coefficients are affected by the number of trees, vertical greenery, occluded greenery and grasses.

Keywords: Urban greenery, Street View Imagery, Deep learning

1. INTRODUCTION

Urbanization has become a trend all over the world, and Taiwan is no exception. Yonghe District has the highest district-scale population density in Taiwan (37,000 people/km^2). However, it causes severe air pollution and the heat island effect due to the increased population density accompanied by high-density buildings and the lack of green space. The positive effects of greenery in urban areas include reducing environmental stress (e.g., air pollution, noise, etc.), reducing physical and mental burdens, and promoting social cohesion and development (Markevych et al., 2017). Therefore, urban greenery is not only beneficial to the urban environment but also improves our life quality.

According to the Urban Planning Law in Taiwan, "Parks, sports venues, green spaces, plazas, and children's playgrounds shall be systematically arranged in accordance with the planned population density and natural environment, and shall occupy no less than 10% of the total planned area, except under special circumstances”. However, the percentage of the area of parks, green areas, and plazas in Yonghe District (Figure 1) are about 8.5% calculated based on the land use data, which is derived from the National Land Surveying and Mapping Center, Ministry of the Interior. Most areas with greenery are mainly located outside the embankment, while only a few parks are in the urban area.

To assess the distribution of greenery, the Normalized Difference Vegetation Index (NDVI), which is often derived from aerial or satellite images, is commonly used as an indicator. However, the perspectives of aerial or satellite images are diverse from different people's view (Li et al., 2015). To understand the relationship between urban greenery and health and well-being, panoramic images are more effective than aerial and satellite images for the representation. (Jiang et al., 2017). Therefore, Yang et al. (2009) calculated Green View Index (GVI) using street images as an evaluation metric for urban greenery. Also, researchers can virtually conduct a field survey of the street environment using GSV (Rundle et al., 2011).

In recent years, Convolutional neural networks (CNN) have had pioneering results in image processing in recent decades (Albawi et al., 2017). In particular, with the improvement of CNN, Fully convolutional neural networks (FCN), we can further classify pixels and perform semantic segmentation of images effectively (Long et al., 2015). Based on the street images with geographic coordinates and the deep learning model, urban spatial features are accessible and quantifiable, which brings the following three research objectives in this study:

(1) Calculate the GVI of street view images using a deep learning model.
(2) Explore the GVI of street perspective using the Geographic Information System tool.
(3) Comparing the analysis results of NDVI and GVI.

2. LITERATURE REVIEW

2.1 Urban Greenery Indicator

The common indicator of urban greenery is the Normalized Difference Vegetation Index (NDVI) calculated from satellite images.

(1)

Where NIR and RED are near-infrared and red band respectively, and the NDVI value range from -1 to 1. The positive values indicate vegetated areas and the negative values might indicate such as water, barren, and clouds (Yuan & Bauer, 2007). Overall, the higher NDVI values, the higher the vegetation density.

Yang et al. (2009) proposed the Green View Index (GVI) to evaluate urban greenery, which takes images from four directions and calculates the proportion of greenery area:

(2)

Where is the greenery pixels in images taken among the four directions, and is the total pixels in images taken among the four directions.

2.2 Urban Greenery and Urban Environment (Urban Heat Island Effect)

Rapid population growth and urban sprawl have caused the negative impact on the urban environment. For example, the increase in the impervious area has exacerbated the urban heat island (Chun & Guldmann, 2018), especially the extreme temperature phenomenon and the worsening of air pollution, which have the negative effect on health and well-being of people (Xiao et al., 2018). As a result, Greenery plays an important role in mitigating the urban heat effect (Yu & Hien, 2006).

Some Studies reveals that greenery has a positive effect on mitigating urban heat islands. For example, Rani et al. (2018) calculated the NDVI and LST from satellite images, to investigate the changes in greenery and urban heat island over time. It was found that the overall NDVI decreased gradually over time due to urban sprawl, which also led to an increase in the overall LST, confirming the aggravation of urban heat island. Shih & Mabon (2018) got NDVI from satellite images and land cover to investigate the extent to which different land covers in the Taipei basin affect the cool island effect and heat island effect. In terms of spatial scale, since there are more cold islands in Taipei City, such as Daan Forest Park and linear patterned street trees, the overall surface temperature is lower compared to New Taipei City, which has more dense buildings and lack of greenery.

Because of the top-down approach of aerial and remote sensing technologies, the temperature at the top of the greenery is obtained, the effect on the surface cannot be investigated from the whole greenery structure, and the relationship between small-scale greenery and surface temperature cannot be effectively obtained due to the image resolution. Therefore, some studies investigated the association between street greenery and surface temperature using street view images. For example, Li et al. (2022) used street view images to classify the captured greenery into trees, shrubs, and grasses, then used Geographic Weighted Regression (GWR) to investigate the relationship between different greenery types and land surface temperature. The results showed that the three types of greenery can reduce the surface temperature, among which trees are the most effective. However, in addition to the type of greenery, the distribution and scale of greenery are also very important to the mitigation of heat island effect.

2.3 Urban Greenery and Urban Environment (Physical and Mental)

In recent years, urban sprawl has brought negative externalities such as noise and air pollution, so many studies have focused on the relationship between urban greenery and the physical and mental of people. For example, Reid et al. (2018) used satellite data and land cover at different resolutions to investigate the relationship between self-assessment of people's health and greenery in different areas. It was found that, due to the characteristics of different data resolutions, there is a Modifiable Areal Unit Problem (MAUP) in addition to the data, so it is necessary to consider the data characteristics and spatial scale, and also provide a distance that is optimal for the positive effect of greenery on health, in order to clarify the theory that "proximity to greenery is beneficial to health". Chern et al. (2018) used MODIS satellite images to investigate the association between NDVI and bipolar affective disorder and found a negative correlation between the two. In other words, when there is more greenery, the incidence of bipolar disorder can be reduced.

In addition to the distribution of greenery in a single location, the relevance of greenery to daily life can be more precisely explored if the greenery status of the surrounding environment is considered together. For example, Meng et al. (2020) used street view images to obtain the proportion of buildings, roads, street widths, and greenery in Macau to assess the potential health effects of these indicators on elderly people. It was concluded that when there are more open streets or more greenery, there is a positive impact on the health of elderly people, while when there are too many buildings, there is a negative impact on the health of elderly people. Helbich et al. (2019) also included the proportion of greenery in street images to examine the association of greenery with depression in older adults in Beijing, and found a significant negative association.

3. MATERIAL AND METHODS

The greenery obtained using street view images and deep learning method, the spatial distribution characteristics of the difference between street view and aerial and remote sensing perspectives are also important in the study. After examining the spatial distribution correlation between NDVI and GVI, we can not only gain a deeper understanding of the characteristics of urban green distribution but also provide suggestions for subsequent planning. The research process consists of street view images acquisition and processing, data analysis, and discussion of the results.

Figure 2 Overall research workflow

3.1 Street View Images

This study obtains static street view images through HTTP URL requests from Google Street View Static API. The request URL format is:

https://maps.googleapis.com/maps/api/streetview?parameters

The parameters contain image size (size), location (location), azimuth (heading), field of view (FOV) and pitch (pitch) (Table 1).

Table 1 The parameters of Google Street View Static API

parameters	definition	example
image size（size）	The pixel size of image length and width	Size=500x500
location (location)	The coordinates of the street view images	Location=25.02,121.51
azimuth (heading)	The azimuth of the camera (0 to 360 degrees)	Heading=60
field of view (FOV)	The angle of the horizontal field of view of the street view images (up	FOV=120

	to 120 degrees)	
pitch (pitch)	The vertical angle of the camera (-90 degrees to 90 degrees)	Pitch=0

3.2 NDVI Data

The NDVI images are obtained from Sentinel-2 satellite in January, March, September, and December 2021 using Google Earth Engine platform, and then the NDVI images are averaged and cropped to the study area.

3.3 Road network

The road network layers are extracted from the road network of the Open Street Map (OSM) and captured to the study area as the basis for subsequent sampling points.

3.4 Pre-processing

The road network layers are simplified and then sampled every 30 meters in the GIS software. Then, the Google Street View Static API is used to automatically download the street view images based on the coordinates. The parameters of this study are shown in Table 2. Finally, the pre-trained Deeplab v3+ deep learning model (Chen et al., 2018) is used to obtain the GVI for each sampling point based on the method of Yang et al. (2009). The example of GVI calculation is shown in Figure 3

Table 2 The parameters of Google Street View Static API in this study

Parameters	Parameters in this study
image size（size）	512x512 pixels
location (location)	The coordinates of every street view images
azimuth (heading)	0、90、180、270
field of view (FOV)	90
pitch (pitch)	0

3.5 Data Interpolation

First, the descriptive statistics and the GVI of sampling points are performed to understand the distribution of GVI. Then, calculate the GVI of basic statistical area in the study area using the IDW interpolation method. Since the spatial distribution of GVI and NDVI is spatially dependent on each other. Therefore, the hot spot analysis will be used to investigate the local hot and cold area distribution.

3.6 Regression Analysis

The NDVI and GVI values of each basic statistical area are analyzed by regression analysis of the independent variables and dependent variables, respectively, and the equations are as follows:

(3)

Where = 44.06， 4.96， Adjust-R^2 = 0.3569

However, Ordinary Least Squares (OLS) regression is a global regression, which can only obtain the overall correlation, and spatial heterogeneity, which is a function or coefficient of spatial analysis, can change or drift between variables with different spatial locations due to many factors, which can lead to spatial instability (Jhang et al., 2017). Therefore, after OLS regression and spatial autocorrelation of residuals, it is found that the spatial autocorrelation of residuals is not consistent with the normal distribution. Therefore, Geographic weighted Regression (GWR) will be conducted later to investigate the local GVI and NDVI correlations with the following equation:

(4)

Where is the spatial coordinate of the *i*th sample, is the regression coefficient of the continuous function at point *i* andis the residual of point *i*.

Finally, due to the different perspectives of the two metrics, the relationship between local R^2 and regression is presented in the bivariate method.

4. RESULTS

4.1 Distribution of Points Layers

The descriptive statistics of GVI is shown in Figure 4. The street perspective greenery, with an average of 11.35% and a median of 8.28%, and most of the streets are less than 10% green, indicating that the degree of street greenery in Yonghe District is relatively low. The GVI of sampling points is shown in Figure 5, some locations have higher proportion of greenery, such as the green belt along the embankment of the road, the campus and large parks, but the GVI is mostly less than 7.5%.

4.2 Distribution of Polygon Layers

The IDW interpolation method is used to obtain the GVI, which is assigned to the basic statistical areas, as shown in Figure 6. The GVI values along the street of parks and schools are higher than other areas, and hot spot density areas and the cold spot density areas are located at west-north and east areas respectively. The result of NDVI (Sentinel 2) shown in Figure 7 is similar to the GVI.

4.3 Geographically Weighted Regression (GWR)

The local R^2 and regression coefficients of the geographically weighted regressions are shown in Figure 8:

In this study, the relationship between NDVI and GVI is further discussed through the R^2 (representing the consistency of NDVI and GVI changes) and the regression coefficients (the degree of NDVI influence on GVI). Therefore, the study is divided into four quadrants by the median of R^2 and the regression coefficients to investigate the relationship between the local distribution, which is presented in Figure 9.

(1) Higher R^2 and higher regression coefficients: trees dominate and high visibility of streets.

(2) Higher R^2 and lower regression coefficients: trees dominate but the visibility of streets is low.

(3) Lower R^2 and lower regression coefficients: the mixture of trees, small greenery and vertical greenery, but small greenery and vertical greenery dominate.

(4) Lower R^2 and higher regression coefficients: the mixture of trees, small greenery and vertical greenery, but trees dominate.

The areas with Higher R^2 and higher regression coefficients (shown in dark blue color) are located around parks, government offices, schools, and streets with retreating green belts and dense existing greenery. The reason for the higher R^2 and higher regression coefficients in these areas is that if areas are more trees, the volume is larger, so there will be a significant impact on GVI.

The areas with Higher R^2 and lower regression coefficients (shown in pink color) are mostly located in larger parks, around schools, and along riverbanks where trees are more densely distributed. However, the reason for the higher R^2 and lower regression coefficients in these areas may be because the GVI is statistically interpolated from the street sampling points to the whole areas, so locations that cannot be obtained from the street sampling points (e.g., parks, school interiors, riverbanks) may be underestimated by vegetation. The NDVI obtained from the view angle of the top of the head can obtain vegetation that cannot be observed from the street, thus resulting in a high correlation between NDVI and GVI changes, but with a lower degree of influence.

The areas with Lower R^2 and lower regression coefficients (shown in light gray color) are located in areas without major roads, parks, schools, etc. The reason for the lower R^2 and lower regression coefficients in these areas may be that there is no absolute amount of trees and small or wall greenery in the streets. Since there are more small trees or wall greenery, the NDVI from the overhead view is not strongly related to the GVI and has less influence.

The areas with Lower R^2 and higher regression coefficients (shown in light blue color) are also located in areas without major roads, parks, and schools. The reason for the lower R^2 and higher regression coefficients in these areas may be that there is no absolute amount of trees and small or wall greenery in the streets. The NDVI from the overhead perspective is not strongly related to the GVI, but the influence is large.

The cases in the four quadrants of the research results are shown in Table 3, and it can be found that areas with high R^2 and regression coefficients have denser trees on both sides of the road; areas with high R^2 and low regression coefficients also have rich greenery, but the distribution is more uneven, and the GVI measurement can only get the greenery closest to the street, and cannot get a more comprehensive distribution of greenery on the principle street. This is also the limitation of using GVI to observe greenery, and the GVI calculation may be overestimated or underestimated due to the width of the streets.

Table 3 Examples of the relationship between local R^2 and regression coefficients shown in the bivariate method

The higher R^2 and higher regression coefficients	The higher R^2 and lower regression coefficients
The lower R^2 and lower regression coefficients	The lower R^2 and higher regression coefficients

5. CONCLUSION

In urban areas, a larger number of trees is clearly effective regarding visual impact, reducing direct sunlight on the ground, intercepting rainfall, and slowing down the amount of surface runoff. However, the light gray or light blue color areas analyzed in Figure 9 has shown that there are more small or vertical greenery in the streets, which also indicates that there may be less space for tree planting.

This study investigated the relationship between NDVI and GVI using GWR and found that the use of greenery indicators from different perspectives allows us to obtain urban greenery comprehensively. Especially in urban areas with high building density and narrow streets, GVI is a proper indicator for urban greenery investigation. Finally, Planting vertical greenery can be a means to increase the degree of urban greenery, which can not only reduce the visual pressure but also control the urban microclimate.

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