Shu Xingxing

LARP 750 Final Project Proposal

Professor Dana Tomlin

How Green are Neighborhoods in Philly?

1.Background

Urban thermal comfort would influence human outdoor activities and the utilization of urban space. With the rise in global warming, many cities are expected to experience more severe heat waves. Carbon pollution is already changing weather patterns in Philadelphia, in 2014, more than 53,138 sensitive Philadelphians lived in hotter than average neighborhoods. But we can make sure that these shifts are as limited as possible by reducing our contributions to climate change. The city's canopy can reduce the temperature of the city by blocking short-wave radiation and increasing the evaporation of water, while also creating a more comfortable microclimate and reducing air pollution caused by daily urban activities. Their absorptive root systems also help to avoid heavy rains and floods during storms. So, in general, trees are important for both cities and communities.

Accurate assessment of the tree canopy in our communities is the very first step to improve living conditions of residents. Calculating NDVI by remote sensing to get a picture of tree canopy cover has been widely used to evaluate the amount of street trees, but this method has several limitations. First, traditional remote-sensing techniques for NDVI are based on moderate-resolution imagery (e.g., 30 m of LANDSAT 8 open source data) which has limited utility at the scale of cities for it cannot fully reflect the shading condition of street trees like details of green density and vertical information. More recent works are using high-resolution satellite images like LiDAR to do a better job, but however the request of data is of high costs and need very specialized software which is not kind to most researchers.

We used Google Street View images to represent a perspective view of a city's streets and is able to cover the entire city communities, so we developed and tested a new method to quickly quantify and characterize urban vegetation, especially trees. Our goal is to prove that we can perceive the existence of urban street trees and quantify the coverage of trees from the perspective of pedestrians by: i) sampling a series of continuous streetscape image scenes; ii) quantifying the amount of tree coverage present therein; and iii) Model the relationship between the tree coverage of these sample points and the characteristics of community they are in. To evaluate the accuracy of this method, we compared our results with traditional remote sensing techniques (i.e., 30-m LANDSAT 8 data) used to estimate urban canopy coverage.

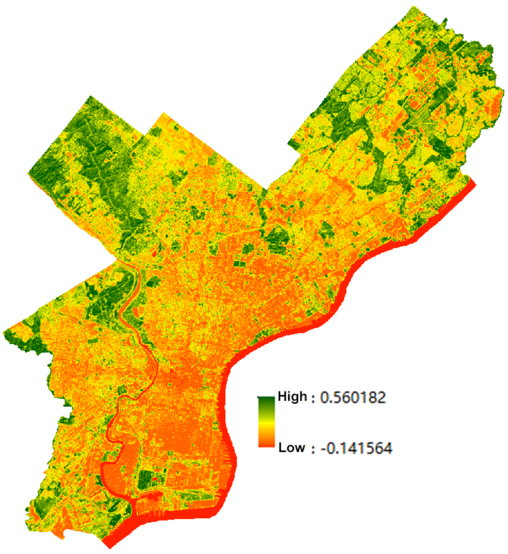
2.Abstract

In view of the city's complex spatial structure, traditional remote sensing methods cannot allow ordinary researchers to map and study the distribution of urban green

space due to high costs or poor spatial resolution. Moreover, these tools cannot see the urban landscape from the perspective of the residents. We tested a new type of computer vision application to quantify urban tree coverage on the street level in Philadelphia. We do this by leveraging the existing rich open source image data of city street views (Google Street View). We show a multi-step computer vision algorithm that can subdivide and quantify the tree coverage in streetscape images to achieve high accuracy. Then, by modeling the characteristic relationships of the communities where the sampling points are located, we can more accurately assess the perceptible tree cover in the urban street landscape. Although this method cannot replace high-resolution remote sensing technology (for example, LiDAR), this method provides a new urban tree cover metric that can quantify the existence and distribution of trees from the same perspective as citizens experience and observe trees, giving cities Planners, policy makers, and community residents understand the city in a new light.

3.Dataset

Our study area is the City of Philadelphia, PA and the datasets used in this study include building boundary data, land use data, LANDSAT 8 data, tree canopy data, and the Google street maps of Philadelphia. The LANDSAT 8 data was downloaded from USGS (https://earthexplorer.usgs.gov/). The building footprints map (https://www.opendataphilly.org/dataset/buildings) and land use map (https://www.opendataphilly.org/dataset/land-use) in the study area were collected from OpenDataPhilly. The original land use map includes 31 land use types in the study area. In order to facilitate further analysis, we aggregated similar land use types in the original land use map into several major land use types: commercial land, industrial land, recreational land, and residential land. The tree canopy data was also from OpenDataPhilly (https://www.opendataphilly.org/dataset/pa-high-resolution-tree-canopy) which is at 1m resolution and was developed from publicly available LiDAR data. The Google street data was collected by Google API and to get a more accurate result, we choose street views between June and September for more leaves are on the trees.



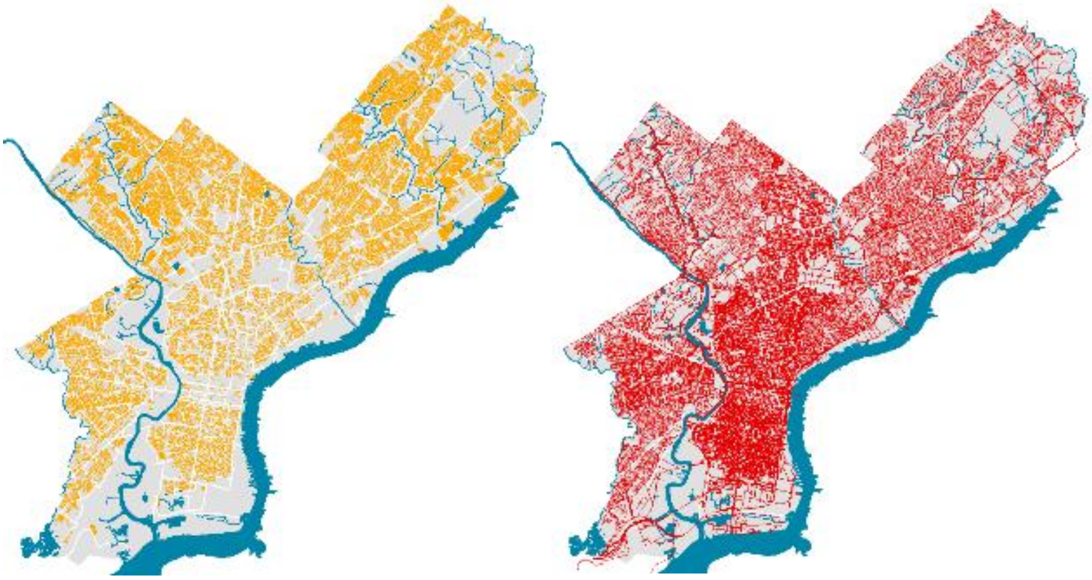


Fig.1. NDVI & Tree Canopy Map & Residential Land Map & Road Map of Philadelphia

4.Methods

4.1 Google Street View Image Analysis.

4.1.1 Choose appropriate neighborhoods for research.

I choose two residential neighborhoods with distinct Greenery Density calculated based on canopy data (Fig.4) and details shows in Table.1, which intends to answer the two questions: 1) How do sentiments and emotions differ in green dominated community compared to community with very few greenery? 2) How does the proximity of green spaces affect these sentiments and emotions?

Table.1:

	Canopy Density (%)	PCT of Residential Land (%)	Road Density (km/km²)
CT 81.02	6.1	58.7	36.85
CT 231	72.7	68.9	22.7

4.1.2 Create sample points of streets of selected neighborhoods.

With the street network and boundary shapefile of Philadelphia as input, a shapefile containing points every 50m was created to be fed into the Google API to retrieve Google Street View Images (Fig.4).

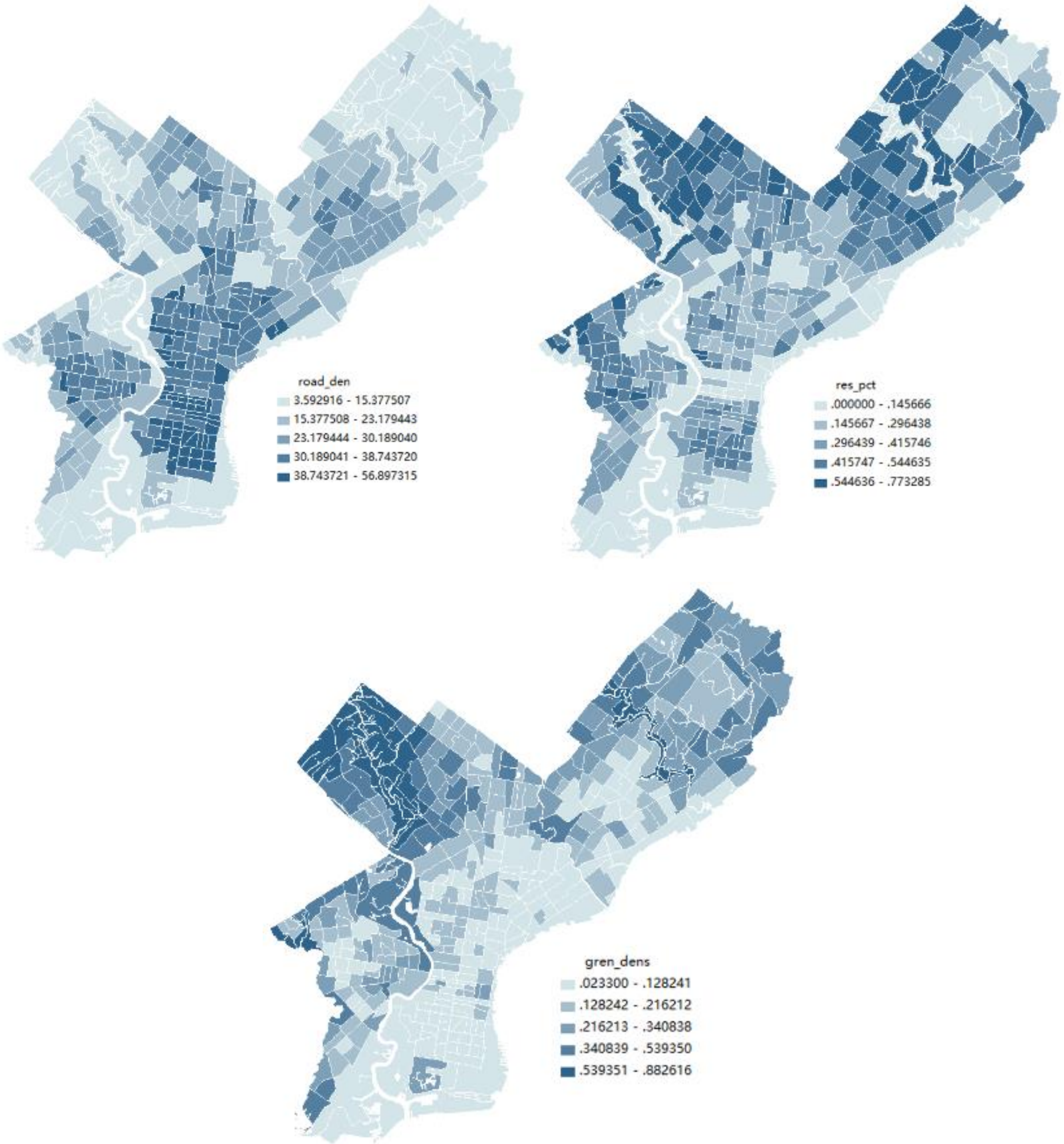


Fig.2. Road Density & Residential Building Density & Green Density Map of Philly

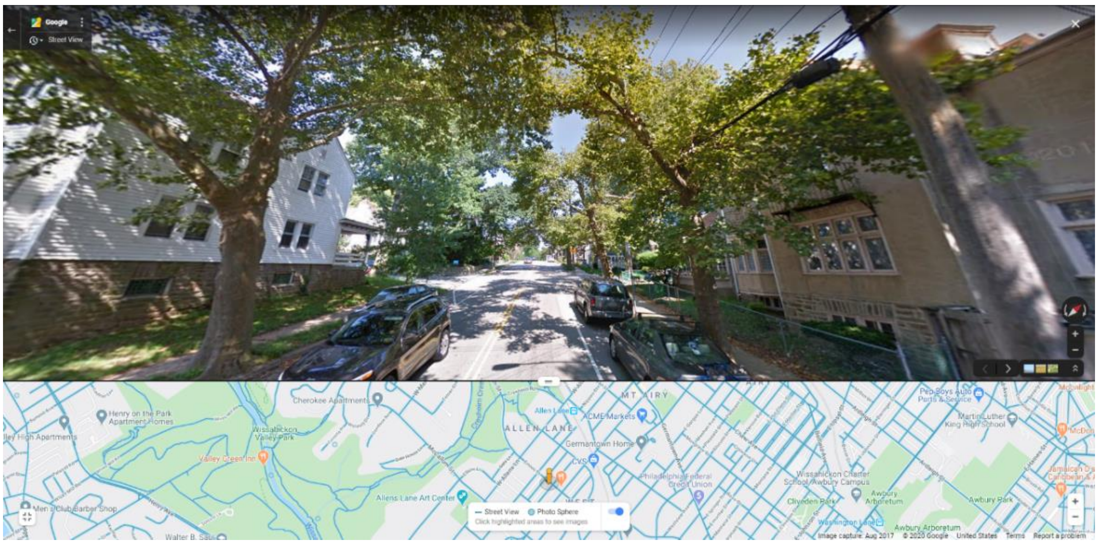


Fig.3. GSV of a sample point in the study area.

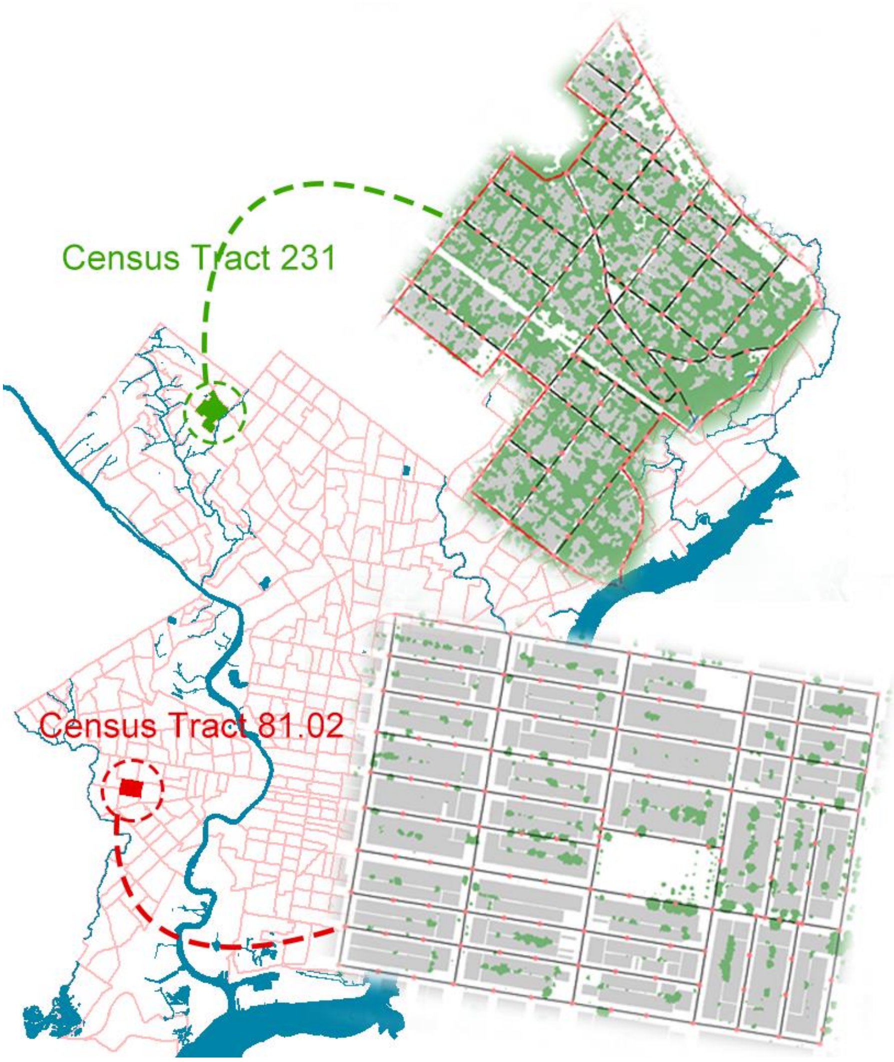


Fig.4. The location, road map, and random points of the study area.

4.1.3 Create Metadata containing GSV panoID.

Fig. 3 shows GSV of a site in census tract 81 in West Philly. The street view is the same as a user sees a GSV panorama, which is presented interactively over the Web. GSV panorama is a 360◦ surrounding image generated from the 6 original images captured by the 6 horizontal cameras by stitching together in sequences . The GSV panoramic images or panoramas have 360◦ horizontal coverage and 180◦ vertical coverage.

Each available GSV image can be requested in a HTTP URL form using the GSV Image API along with the position of the GSV car and its moving direction. By defining URL parameters sent through a standard HTTP request using the GSV Image API, users can get a static GSV image in any direction and at any angle for any point where GSV is available. An example of requesting a GSV static image is shown below.

With the shapefile as input, metadata containing the panoID, panoDate, latitude, longitude and tilt specifications for the image will be stored in text files to be later used to calculate the Green View Index.

```
samplesFeatureClass = '../sample-spatialdata/Philly50m.shp'
num = 100
ouputTextFolder = '../metadata'

metalib.GSVpanoMetadataCollector_fiona(samplesFeatureClass,100,ouputTextFolder)
```

```
The coordinate (-75.180822,39.934928), panoId is: cMPXRurXtp-eRSwaSFluOw, panoDate is: 2018-09
The coordinate (-75.180630,39.935826), panoId is: r3hfVsfMxCb7kd25f1UcXA, panoDate is: 2018-09
The coordinate (-75.181214,39.935901), panoId is: 9tgFyBlAMucneJgAGn5DYA, panoDate is: 2018-09
The coordinate (-75.181791,39.935975), panoId is: 7NgFkVM4AmmEKmwkWdOQqw, panoDate is: 2018-09
The coordinate (-75.182284,39.936039), panoId is: NRO-H-AKdYnadaU5pZ1yuA, panoDate is: 2018-09
The coordinate (-75.180847,39.935036), panoId is: _dYhBOKiIF3hvunw6wwOmA, panoDate is: 2018-09
The coordinate (-75.181381,39.935109), panoId is: iedP08c08BOn_ztxGSOJQA, panoDate is: 2018-09
The coordinate (-75.181943,39.935185), panoId is: bLMsIItTyKqG7HZM3fuDEg, panoDate is: 2018-09
The coordinate (-75.182418,39.935250), panoId is: v9DoxdFbxk_buH3IcFuvMQ, panoDate is: 2018-09
The coordinate (-75.180754,39.935233), panoId is: gO3juisC4asH1eDCEOcr1w, panoDate is: 2018-09
The coordinate (-75.180675,39.935598), panoId is: ujE_GOjSGKVzOeM4p12gzQ, panoDate is: 2018-09
The coordinate (-75.180774,39.935410), panoId is: rvGG6-5EZdiaMORcYqx1cg, panoDate is: 2018-09
The coordinate (-75.181260,39.935471), panoId is: FfSSgUT6c-nO8dt7poiCQQ, panoDate is: 2018-09
The coordinate (-75.181838,39.935544), panoId is: qbFRUh_RSj3L_-3u8LLUkQ, panoDate is: 2018-09
The coordinate (-75.182325,39.935606), panoId is: d84-CZZX3lqacEPckU1cWg, panoDate is: 2018-09
The coordinate (-75.182385,39.935568), panoId is: hEIpI6zfWs_GPR5epMWQuA, panoDate is: 2018-09
The coordinate (-75.182315,39.935897), panoId is: ROjZOENxU5oAlVm-wRoy3A, panoDate is: 2018-09
The coordinate (-75.180894,39.934608), panoId is: ERvFB7dRhdaKWsG-OOnggw, panoDate is: 2018-09
The coordinate (-75.181394,39.934673), panoId is: lYTXOtIGmtinF8M1sbLsYg, panoDate is: 2018-09
The coordinate (-75.181957,39.934746), panoId is: gdT7YfHbAeHtgxAKBCEcFw, panoDate is: 2018-09
```

Fig.5. Metadata for GSV calculation.

4.1.4 Collect Google Street View Image.

Based on the metadata we created, use Google Street View Static API to request street images of sample points. GSV panoramas can be requested by inputting coordinates through Google's Application Programming Interface (API). Fig.5 shows a requested GSV static image. In this example, parameter size specifies the output size of the image in pixels, location provides the geo-location of the GSV; heading indicates the compass heading of the camera; fov (default is 90) determines the horizontal field of view of the image; pitch (default is 0) specifies the up or down angle of the camera relative to the Street View vehicle; radius (default is 50) sets a radius, specified in meters, in which to search for a panorama, centered on the given latitude and longitude. In previous studies, the horizontal field view was chosen between 50°and 60°. For our research, we set the fov to 60°; thus, six images can cover the 360° horizontal surroundings (Fig. 6). A Python script was developed to read the coordinates of each sample site and download the GSV images at that site by parsing GSV URL automatically.

The GSV images have no capture time information and with some images captured during winter. Therefore, we manually deleted those sites where images were captured during winter by setting time limit from April to September.

Finally, 1069 street images were collected for Census Tract 231 and Census Tract 81 has 590 street images.

Fig.6. GSV image of two sample points on 6 directions.

4.1.5 Green area extraction from GSV images.

Traditionally we need near infrared band and red band to detect vegetation because vegetation shows high reflectance at near infrared band but shows high absorption at red band. However, GSV images do not have both near infrared band and red band but only red, green and blue bands. So we developed and used a simple automatically unsupervised classification method to extract green vegetation from GSV images.

First, two images Diff 1 and Diff 2 were generated by subtracting respectively red band and blue band from green band. Then the two difference images were multiplied to generate one Diff image. Considering green vegetation normally shows higher reflectance values in the green band than in the other two visible bands, the green vegetation pixels generally have positive values in the Diff image. Those pixels with smaller values in green band than in blue or red band show negative values in the Diff image. If pixel values in green band are smaller than those in both red and blue bands, the corresponding values in the Diff image are still positive. So an additional rule that pixel values in green band must be larger than those in red band was added.

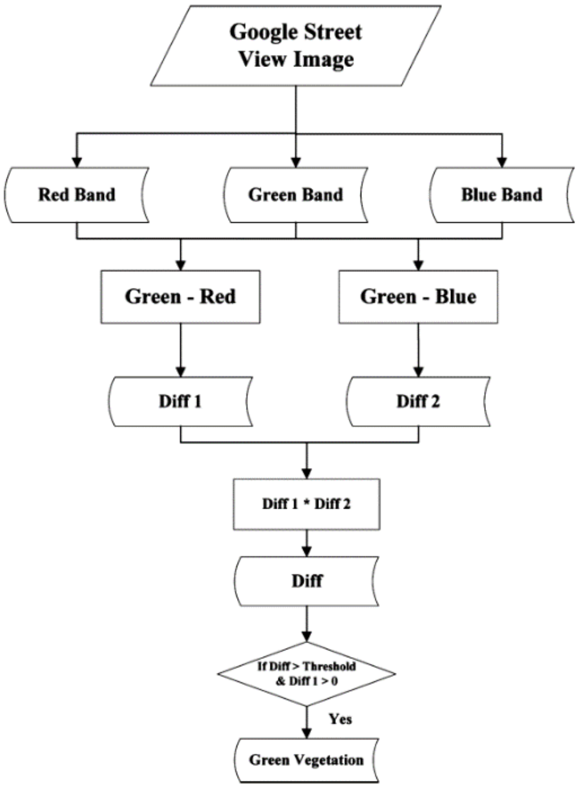


Fig.7. The workflow for green vegetation extraction from GSV images.

4.1.6 GVI Calculation.

GVI was defined as the ratio of the total green area from four pictures taken at a street intersection to the total area of the four pictures, calculated using the following equation:

$$Green\ View = \frac{\sum_{i=1}^{6} Area_{g\_i}}{\sum_{i=1}^{6} Area_{t\_i}} * 100\%$$

where $Area_{g-i}$ is the number of green pixels in one of these images captured in six directions (0°, 60°,120°,180°, 240°,300°) for each sample site, and $Area_{t-i}$ is the total pixel number in one of the 6 GSV images.

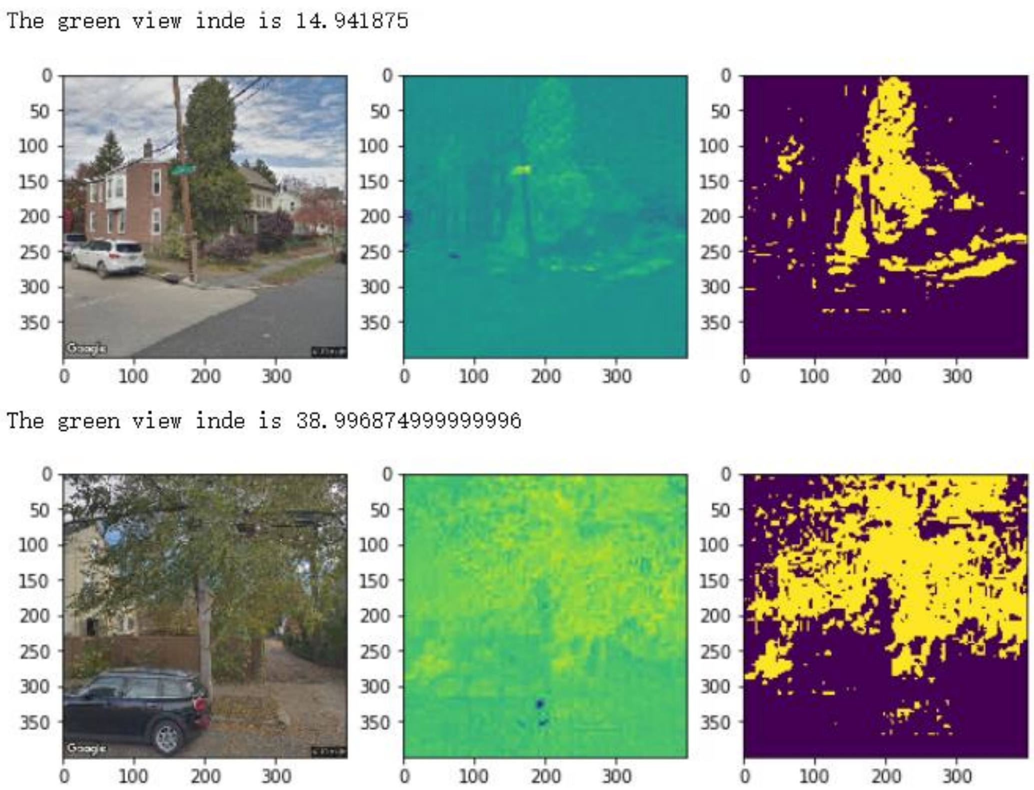


Fig.8. Results of green vegetation extraction.

4. Results

Fig. 8 shows the green vegetation extraction results of three GSV images. Compared with the original GSV images, most of the green vegetation pixels in the GSV image were correctly delineated in the pre-classified image. There, however, still exist some spark points in the pre-classified image. Those spark points are noises and should not be considered as green vegetation. Therefore, we filtered these out using Adobe Photoshop software was used to extract the green vegetation manually as references to validate the automatically unsupervised classification results.

5.1 Comparison of NDVI & GVI results.

Fig.9 shows the histograms of Green View Index and NDVI of the two Census Tracts in Philly. In greener community, Census Tract 231, NDVI is greener than GVI. In Fig.10, most of those sample sites with higher GVI values are located in the south part of the community where near Wissahickon Valley Park. This means that the of the community may look “greener” than other places in the eyes of citizens, based on the chosen sample sites. But sample points in north part has higher NDVI while with small GSV which indicates that residents on the road do not consider the view they see as ‘greener’. But in community that is less green from the view of satellite, the difference between GVI and NDVI is not that obvious. Though in several sample sites, we observe high GVI but relatively low NDVI, the overall difference is that distinct as in community that is greener in both indexes.

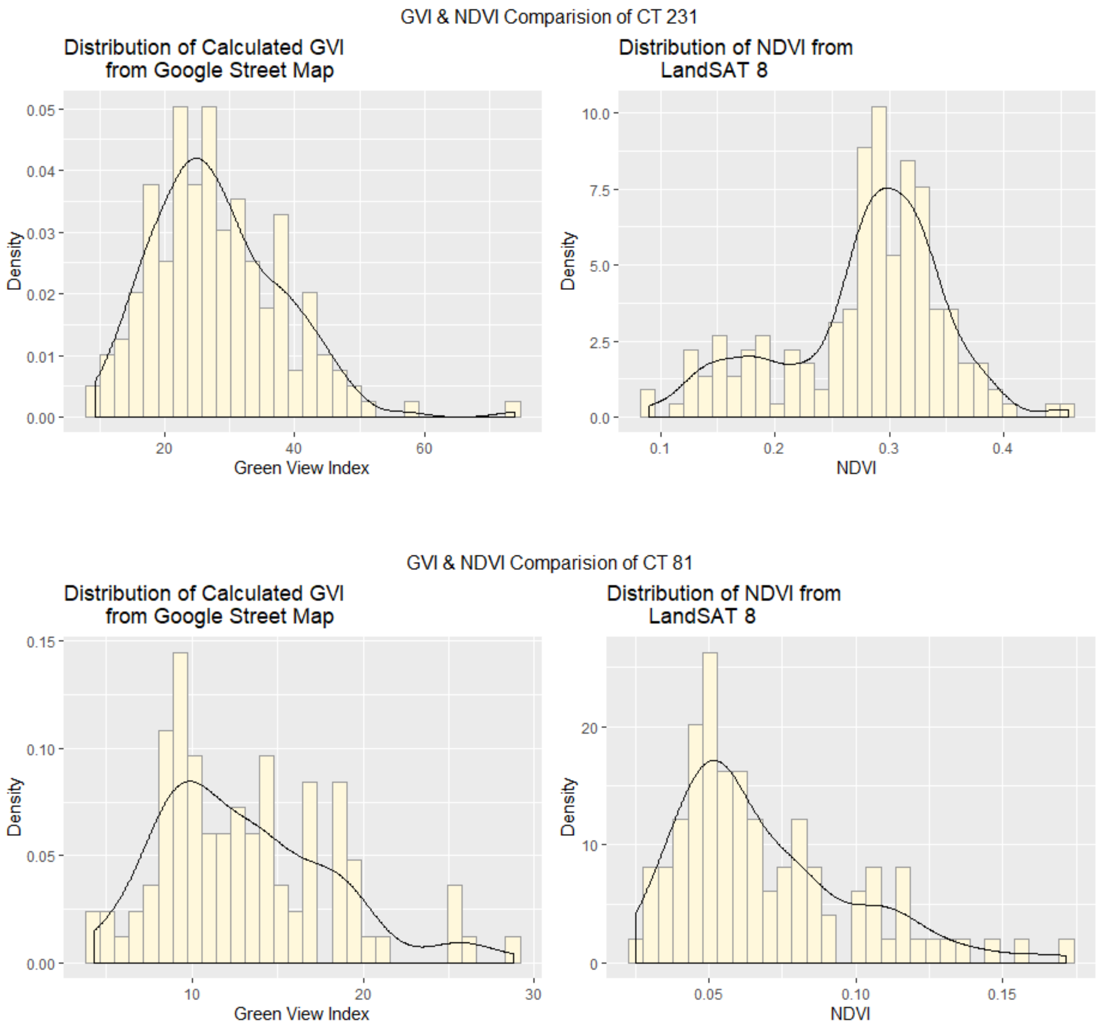
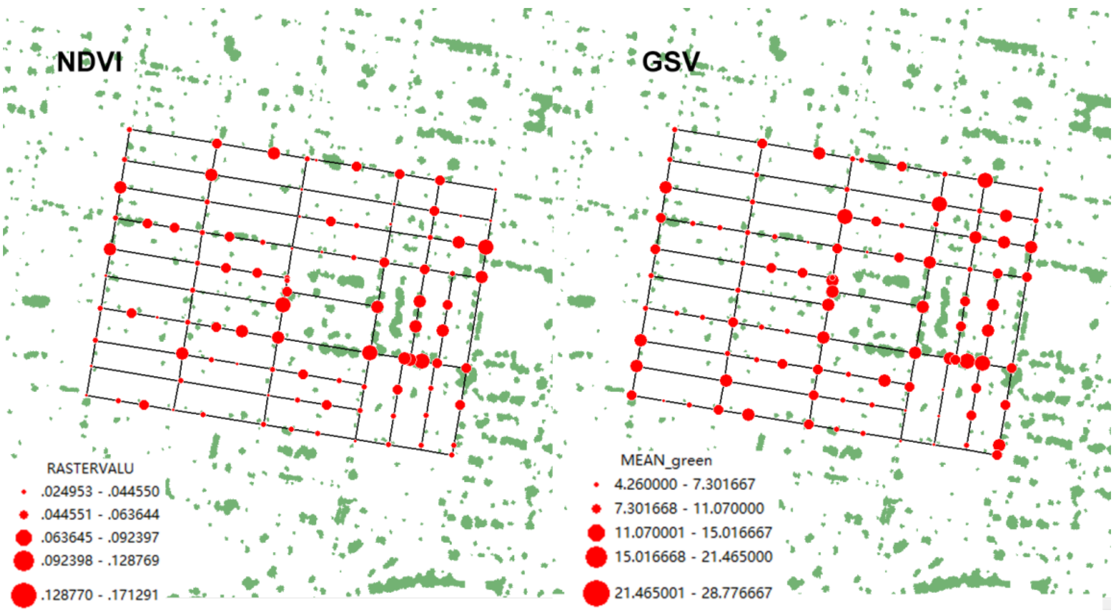


Fig.9. Histogram of the calculated green view index & NDVI.



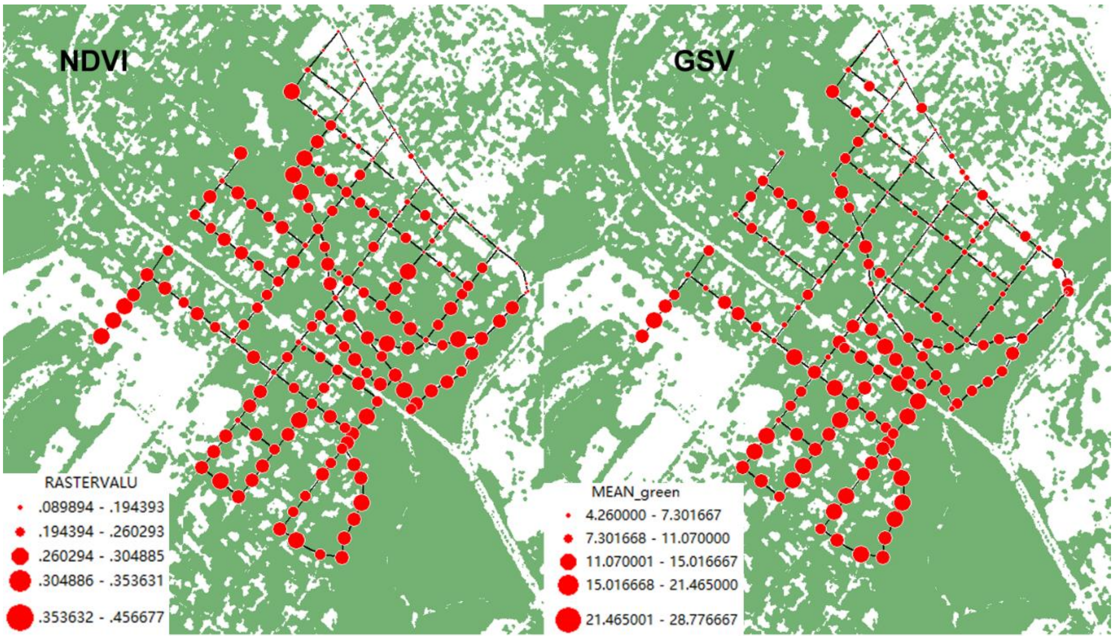


Fig.10. NDVI & GVI results of the two study census tracts (a) Census Tract 81 (b) Census Tract 231.

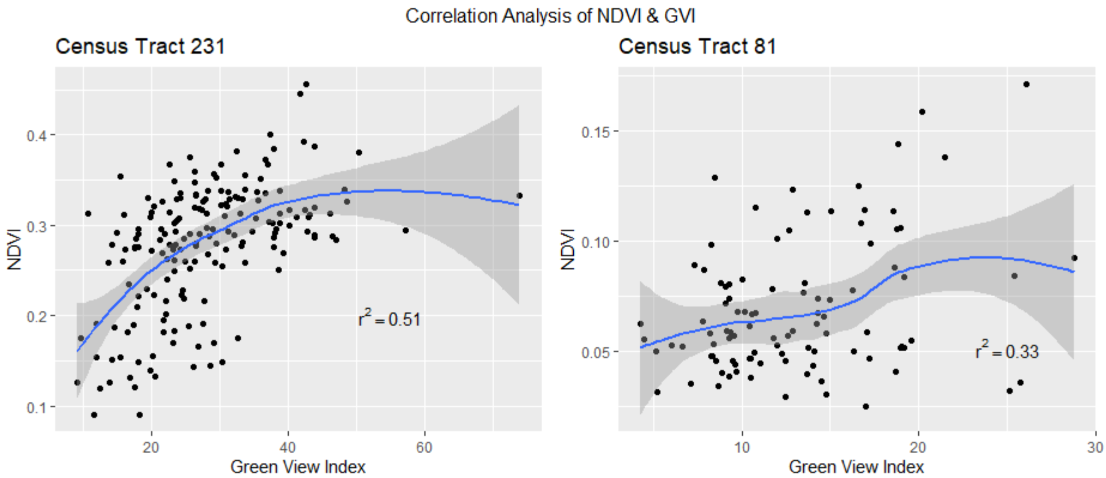


Fig.11. Correlation Analysis btw NDVI & GVI.

4.Discussion

In this study, we propose to use GSV images to evaluate street greening in urban areas. The GSV images taken by Google have a similar perspective to pedestrians on the ground and are used to assess the richness of street greening. Since GSV images can be displayed horizontally and cover the surrounding environment of 360 °, we have modified GVI to make it more reasonable. The modified GVI should be more suitable for representing green plants that pedestrians can see on the ground.

The spatial distribution of sampling points with higher GVI values does not match the spatial distribution of vegetation coverage in the land cover map of the study area. This can be explained in part by the difference between the street ground view (as represented by GVI) and the aerial top view (as represented by the land cover). The profile view is affected by the layout of buildings and vegetation, the size of urban trees, the vertical structure of trees, and the distance between trees and viewers. However, the top view provided by remote sensing images does not cover these factors. In some areas in the southwest of the study area, the greening rate in the land cover map is low, but there are some high greening points expressed by GVI. By examining the GSV images of these locations, we found that most of these locations are located in alleys beside small trees. In the top view, the trees next to these alleys are not large green coverings, but in the longitudinal section, the sites look greener. On the contrary, the GVI value of some sites with large green areas in the land cover map is lower than 10. The main reason should be related to the pedestrian's observation mirror on the street, which cannot cover the green space away from the street or blocked by buildings. Therefore, observing a larger vegetable cover from a height may not mean that a higher GVI is observed on the street. This shows that it is not enough to measure urban greening based on the greening information in the vegetation coverage map, which is usually derived from remote sensing satellite images or aerial photos. GVI can be used as other information / data to help urban planners and others to more accurately assess or quantify urban greening by considering visual greening at the street level.

However, there are still some problems in this study. Although the first Google has been constantly updating GSV images, GSV only provides static images of urban street spaces. Considering the greening of streets and the constantly changing urban environment, therefore, at different times of the year The GVI calculated under different weather conditions and the influence of other things around is also different. Although the approximate time of the picture can be simply filtered by month, accurate time information is temporarily unavailable. The second is that GSV only covers a limited amount of urban greenery. Because GSV images are mostly collected by cameras installed on the top of the car, some alleys that cannot be accessed by cars and urban spaces without roads cannot be measured. Finally, how to effectively solve the noise problem of image recognition, there are often things similar to the color of green plants on the street, such as cars, billboards, buildings, etc., which are sometimes mistaken for green plants, and some are not green Plants may not be counted as green plants. This problem has not been solved very efficiently for the time being, but is manually screened manually. This approach is obviously not realistic when dealing with street space evaluations like Philadelphia.

In addition, the study did not involve other issues that may affect the quality of the community space, such as the layout of green and buildings, the pattern of green distribution, topographic factors and environmental psychological factors.

6.Conclusion

We studied the use of GSV images to measure the amount of ground greening that people can see on different street stops in the city. We use GSV images to visualize the urban greening of two communities in Philadelphia and use GSV images to measure street-level landscapes. The results show that GSV images are suitable for evaluating street greening, and the improved GVI may more objectively measure the level of greening at the street level. The revised GVI formula is easier for ordinary people to understand, because it can measure the urban greening that is generally visible on the ground. Therefore, GVI can help city planners and others to further understand the sensory functions of urban green spaces.

7.References

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