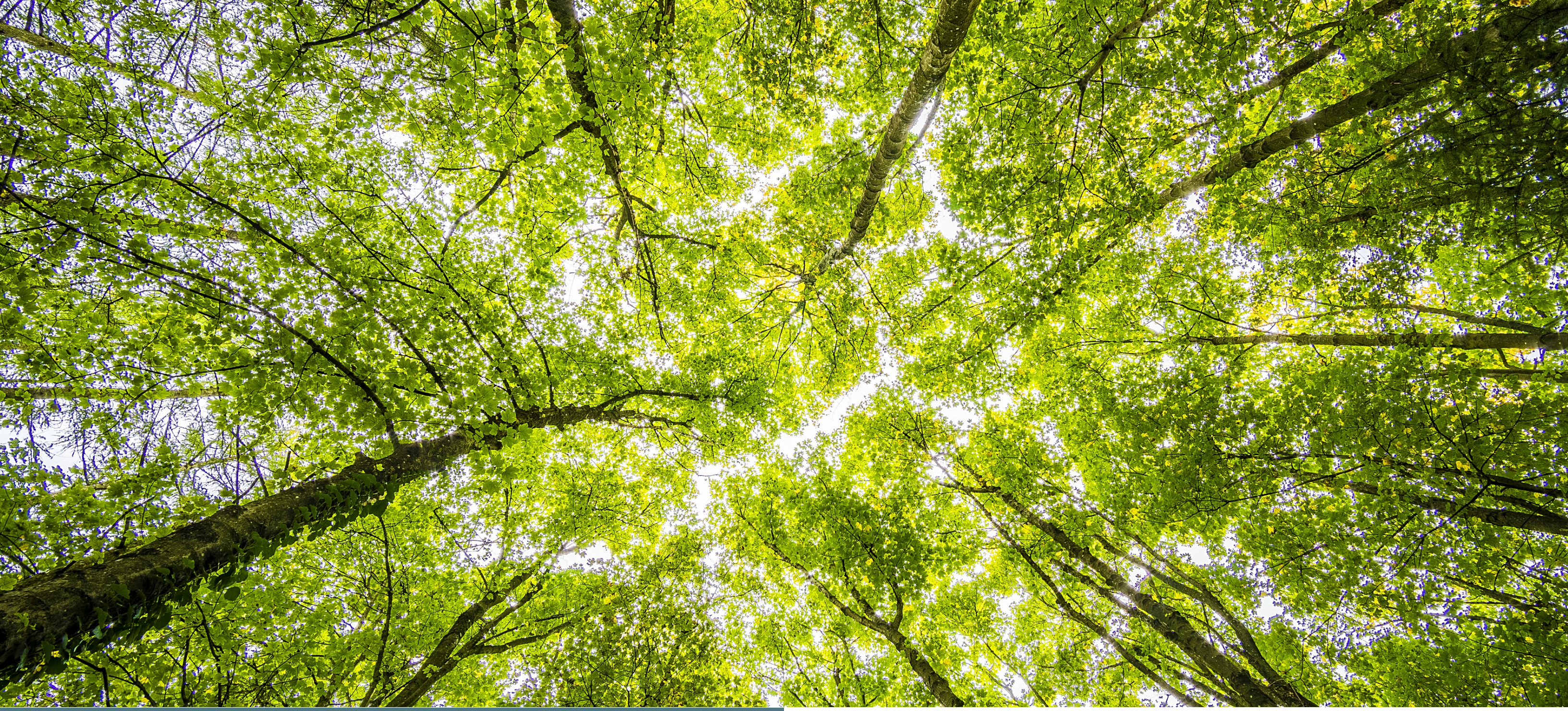


MAPPING THE SKY

in the urban environment setting.

Strategy to reduce the level of heat stress and sunlight exposure for the pedestrians in the urban areas using Machine Learning on Google Street View Images.

Authors:

Prof. Liam Peyton (University of Ottawa)
Simardeep Singh (Master's Student at University of Ottawa)

The University of Ottawa is mapping the sky along city streets in the National Capital region as part of ongoing initiatives related to climate change adaptation. By developing analytic tools which quantify shade corridor characteristics, this research will help reduce heat stress and sunlight exposure for citizens who want to stay active and healthy even as climate change drives a large increase in extreme heat events.

Daily physical activity is important to a healthy lifestyle which contributes to better health outcomes. A recent study named 'Walk Score and the prevalence of utilitarian walking and obesity among Ontario adults' found people living in low-walkability areas with few opportunities to be active have a higher prevalence of obesity. However, global temperatures around the world have been steadily increasing. These high temperatures during the summer combined with prolonged direct sunlight exposure can cause severe heat stress, especially when exercising.

Reducing excessive sunlight exposure along city streets and pathways is an increasingly important consideration for urban planners. Access to automated tools which can quantify the degree of shade provided by trees and buildings will become increasingly necessary both for future-oriented urban planning, as well as allowing for predictive route-selection mapping tools to assist residents to select higher-shade corridors when walking, running or cycling.

With these factors in mind, students under the direction of Professor Yongyi Mao in the School of Electrical Engineering and Computer Science have embarked on a study to map the sky using data from Google Street View. The research project definition along with access to City GIS data was facilitated by Zlatko Krstulic, while he was Innovation Lead, Service Transformation at the City of Ottawa. The project is also supported by the Future Ready program of WSP Canada. As cities around the world want to implement green canopy strategies, the idea is to develop a metric using engineering design and machine learning models to evaluate and compare canopy cover. By carefully combining physical and computer generated results, one can create a suitable representation of the cityscapes, making them the perfect image collection techniques for cities and industries all around the world.

Google Street View Data Collection

Streets act as a focal point of human activity and play an essential role in the exchange of transportation and information. Thus, city streets and urban landscape planning can reflect people's lifestyle, physical, mental, and emotional state. Several methods are used to thoroughly quantify and understand the features and dynamics of the streets. Some of the methods, such as high spatial resolution remote sensing are used to study greenery in the streets, building heights, and so on. These methods offer a solid platform to not only investigate the urban environment but its social interactions and effects on human beings. However, high spatial remotely sensed data is not always available and can be different from what people experience and see from the ground. These differences can be resolved with manual data collection and inventory management, however, doing so is laborious and time-consuming.

Google Street View imaging, launched by Google, is different from the old mapping system. It is an online service from Google provides panoramic views of the city streets throughout much of the world. It captures the ground- level holistic view of the areas, capturing trees, building, cars, electric poles, sky and so on. By using Google Static Image API, one can request a street view image with the specified location coordinates. Furthermore, these images can be requested in different horizontal and vertical angles by providing requisite parameters such as heading and pitch. In addition, GSV panoramas can be downloaded from the server with the uniques Panorama ID. A complete cylindrical panorama includes 26 * 13 tiles.

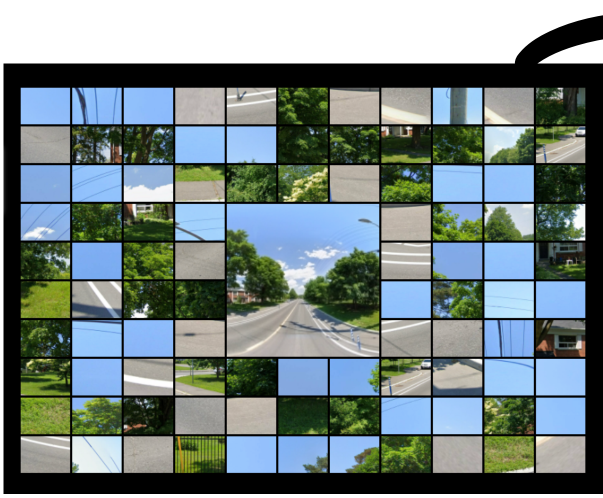


Image 1. Collection of 26*13 tiles of GSV Panorama ID **e6_KaNj7o7kXXVUHzaFhw** with **Lat :45.449662, Lon: -75.654597**

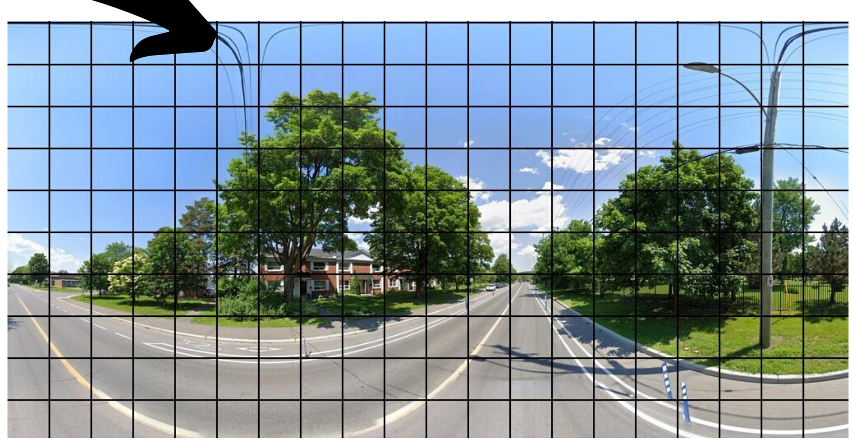


Image 2. Stitching together the GSV tiles for the unique panorama ID **e6_KaNj7o7kXXVUHzaFhw** with 338 tiles combined to form a single image.

The returned metadata from Google includes the picture acquisition date, its coordinates, and the panorama ID. The data is being collected in two steps. The first step includes getting metadata for GSV panoramas through given coordinates. The second step is to download GSV panorama tiles from Google servers(shown in Image1) and combine them to form the cylindrical panorama (shown in Image 2).

Green view calculation of GSV images using PyMeanshift and OSTU's method

In computer vision and image processing, the OSTU method, named after Nobuyuki OSTU is used to perform image thresholding through all possible threshold values ranging from 0 to 255(range of every pixel value). Image thresholding plays an important role in image segmentation and binarization within the optimal threshold value of the input image.

To embark upon, every GSV panorama image for a specific route is segmented using a mean shift algorithm written in Python. OSTU method is being used to return a single intensity threshold that separates image pixels into two classes, foreground, and background. These thresholds are required to separate green-view pixels (pixels indicating the presence of the tree, vegetation, and grass) from the non-green-view pixels (pixels indicating the sky, road, and buildings). Those pixels with higher brightness values than the optimum thresholds are green-view pixels. As shown in Image 3, the foreground pixels (green vegetation, trees, and more) are being separated from the background pixels, thus quantifying the greenery in an image.

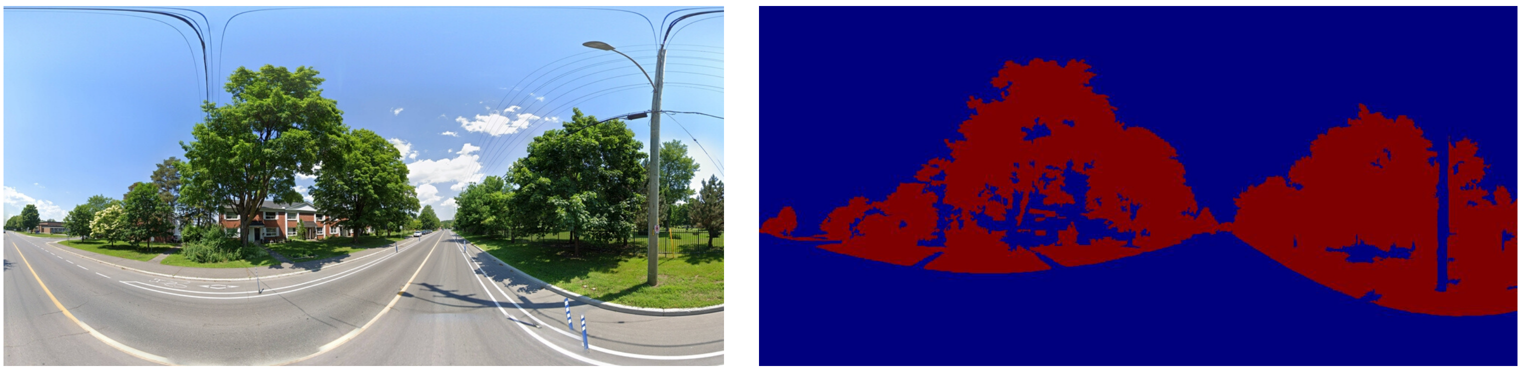


Image 3. An image from the route being segmented using OSTU algorithm. The green pixels from trees, grass and vegetation are being classified using spectral and geometrical rules and are being separated from other pixels of the image.

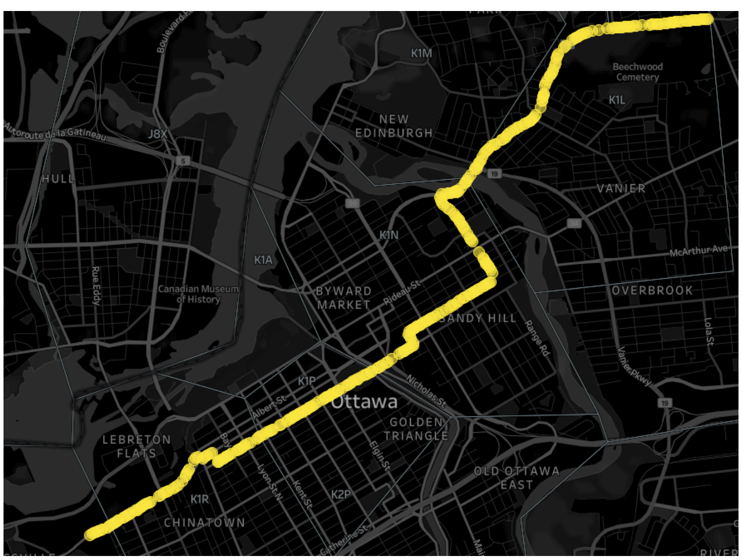


Image 4. - A specific route in Ottawa is chosen with each point defining specific latitude and longitude for every 10 m distance. For each latitude and longitude, a GSV panorama is downloaded to do further segmentation using OSTU and mean shift algorithm in Python.

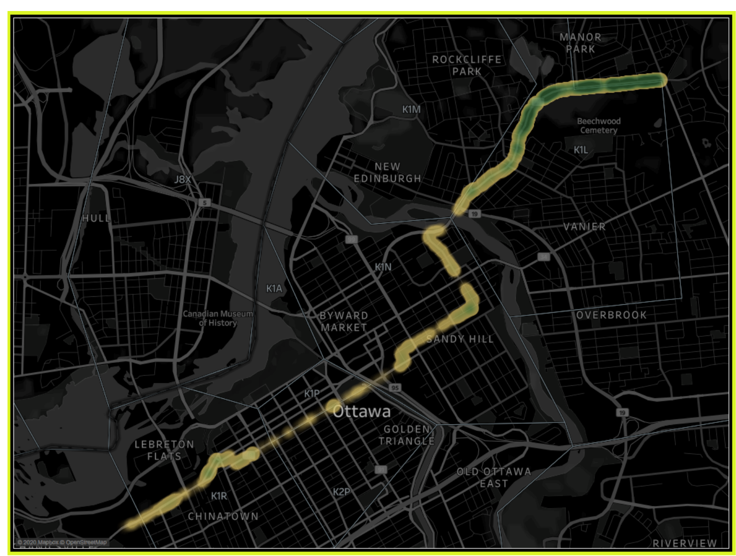


Image 5. After segmenting each image using OSTU and mean-shift algorithm, one can easily visualize the results of the same route. The areas highlighted in green colors are the ones with high density of vegetation, tree and plant growth as compared to the other areas which are highlighted in color yellow.

Estimating and mapping the Sky, Tree and Building View Factor

Sky view, tree view, and building view factor represent the proportion of the hemisphere accounted for the sky, tree, and buildings when viewing from the ground up. SVF, TVF and BVF are three important visual indices of the urban outdoor environment and are also used to determine the amount of solar radiation lost due to sky obstruction. However, from the pedestrians' perspective, SVF relates to the accessibility of light and thermal heat. A case study showing the relationship between SVF and thermal comfort in arid climate gives evidence that the compact urban areas tend to be warmer than the dispersed form. Google street view images act as a great source for SVF information and provide a close look up at several aspects of the urban space including buildings, roads, pedestrians, traffic, and greenery. Among all these factors, the visible green space and enclosure for the street can be measure by TVF and SVF.

For parsing the Google Street View images to extract SVF,TVF, and BVF a scene parsing method from deep-learning framework is used to extract features such as sky, trees and buildings. This model, famously known as Pyramid Scene Parsing network (PSPNet), is a deep convolutional neural network that allows multiple processing layers to understand representations of the natural data with different levels of abstractions including sky, trees and buildings. With the growth of deep-learning mechanisms, a number of CNN based models have a good understanding of the street features and pay more attention to feature ensembling and structure prediction. PSPnet model used in this study provides a pixel-based prediction framework, and is capable of processing difficult context features. PSPnet easily achieve a high accuracy of 80% in predicting 150 object classes of cityscapes.

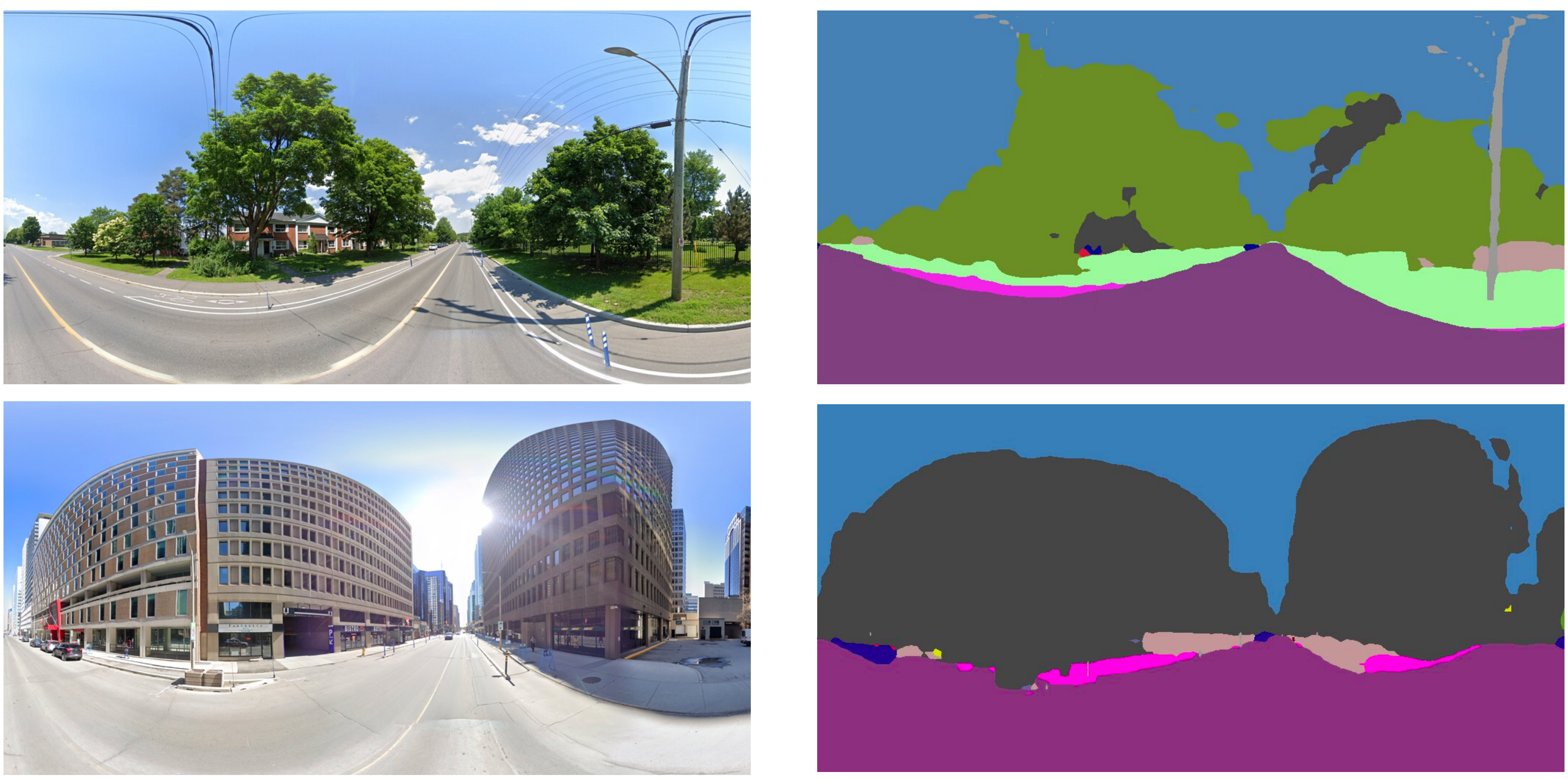


Image 6. Figures shows the workflow of the scene parsing using PSPNet. Here wo pictures, one with abundant vegetation and the other one with city buildings are being classified using deep learning neural network. Extraction of the sky (in blue), trees (in green), buildings (in grey) and road (in pink) shows the different layers and complexity of the city architecture. This extraction lays the foundation for projecting the panorama images to hemispherical fisheye images which is used to calculate and quantify SVF, TVF and GVF from the images.

Projection into fisheye images

To project a panorama image onto a hemispherical image, a photographic method is being used which projects hemispherical environment or cylindrical projection onto a circular plane and create a resulting fish eye image. This projection is defined by relationship between the pixels on fisheye image (X(f), Y(f)) and panorama image pixels (X(p), Y(p)).

$$x_p = \begin{cases} (\pi/2 + \tan^{-1}[(y_f - C_y)/(x_f - C_x)]) \times W_p/2\pi, & x_f < C_x \\ (3\pi/2 + \tan^{-1}[(y_f - C_y)/(x_f - C_x)]) \times W_p/2\pi, & x_f > C_x \end{cases}$$

$$y_p = \left(\sqrt{(x_f - C_x)^2 + (y_f - C_y)^2} / r_0 \right) \times H_p$$

Here W(p) and H(p) are width and height of panorama image, r(0) is the radius of the fisheye image , and (C(x), C(y)) are the coordinates of the center pixel on the fisheye image.

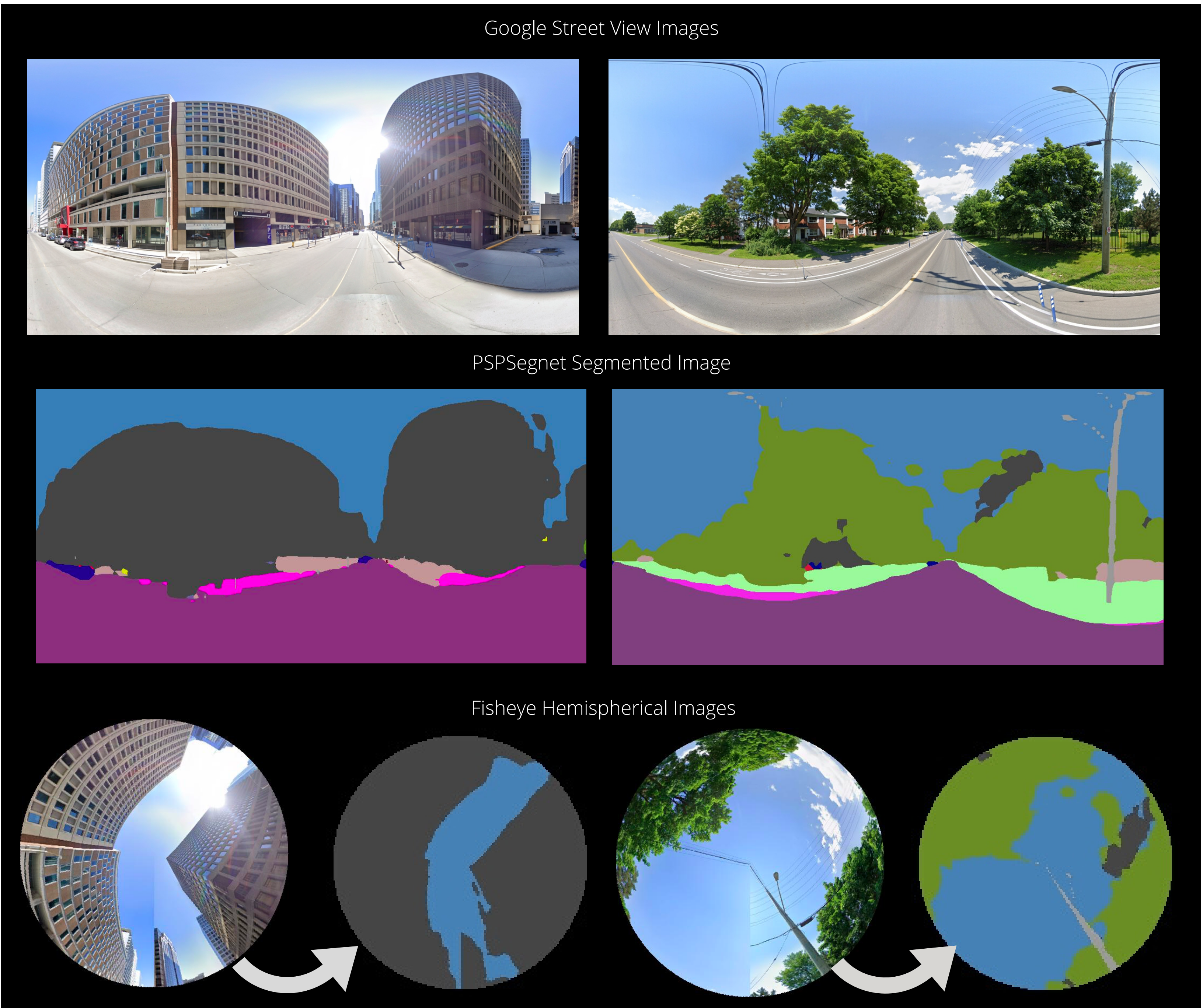


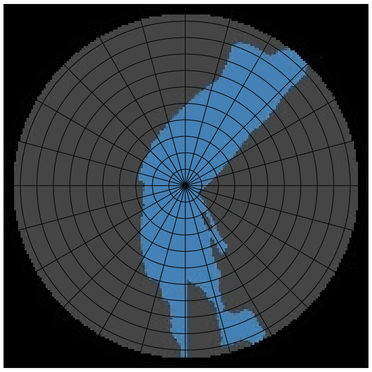
Image 7. Fisheye images are created by projecting panorama images to azimuthal projection. Based on these projections, SVF, TVF and BVF are calculated.

Calculation and Results

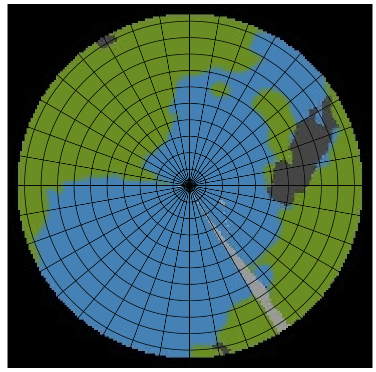
To calculate view factors, the whole fisheye image is divided into concentric circles of equal width and then are summed up all the annular sections representing sky,trees and buildings to calculate the SVF, TVF and BVF respectively, using the formula:

$$\Psi_x = \frac{1}{2\pi}\sin\frac{\pi}{2n}\sum_{i=1}^{n}\sin\left[\frac{\pi(2i-1)}{2n}\right]\alpha_{i,x}$$

x can either be sky, trees and buildings; n is the total number of rings; i is the index of the ring; a(i.x) is the angular width of pixels of feature x in the ith ring.



- **Sky View Factor - 0.2318**
- **Tree View Factor - 0.0092**
- **Building View Factor - 0.5618**
- **Panorama ID:- 064JNmfKOk_-CS3IHe4vfg**

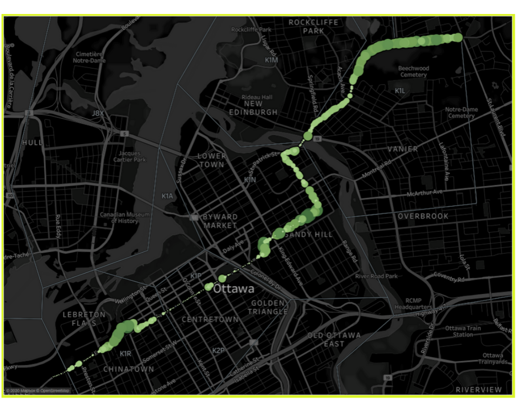


- **Sky View Factor - 0.5084**
- **Tree View Factor - 0.2694**
- **Building View Factor - 0.0190**
- **Panorama ID :- _e6_KaNj7o7kXXVUHzaFhw**

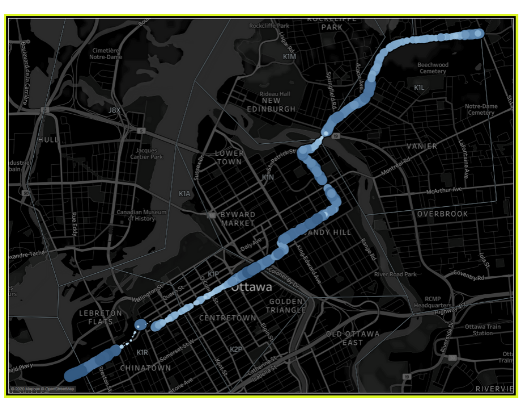
Visualizing the SVF, TVF and BVF onto the selected route

GSV provides a close-up look at many aspects of the urban space including buildings, roads, pedestrians, traffic, greenery, and socio-economic activities. This information combined with SVF, BVF, and TVF can help cities to analyze visible green space and visual enclosure of the street which can have an impact on street walkability. In the given images, these images can assist in research aimed at comprehending the relationship between urban geometry and temperature, which varies not only in space but also with time and seasonality. With an extensive SVF sample within a city, one can easily understand the effects of urban geometry on urban environmental indicators such as outdoor thermal comfort, solar radiation, daylight availability, traffic noise, and so on. Images shown below capture the spatial distributions of GSV-based SVF, TVF, and BVF estimates on a single high-density urban route in Ottawa.

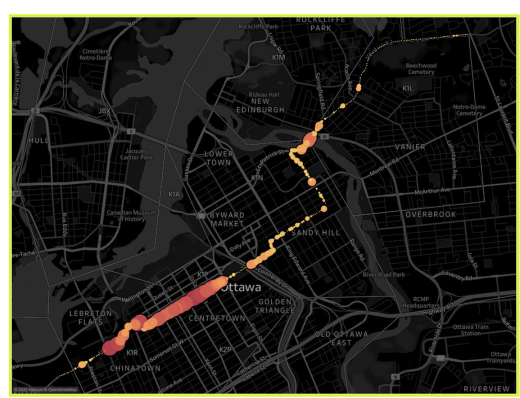
The SVF value ranges from near 0, indicating little sky openness, to 1.0, indicating total sky openness. Areas with higher density have lower SVF, lower TVF and higher BVF, and vice versa. The TVF in the high building density area is dominated by values less than 0.1 and the mean value is 0.143. The low TVF is mainly limited by the high building density and narrow streets. SVF, on the other hand, is close to an even distribution between 0.2 and 0.9, with a peak between 0.4 and 0.5, while BVF has a decreasing frequency when its value increases.



Green View Factor



Sky View Factor



Building View Factor

Conclusion and future study

Increasing walkability along streets and neighborhoods helps to promote an active lifestyle, has long been recognized as beneficial to human health. Through this research, street-level greenery is used to indicate the natural environment and built environment at the neighborhood level. Through machine learning techniques and Google Street View images, Green View Index is calculated to measure the greenness at the neighborhood level. This index helps to calculate that greenness and walkability at the neighborhood level have different effects on different age-gender groups of people.

In addition to GVI and SVF, collecting a fine scale of microclimate data can help to determine how physical characteristics (e.g., solar radiation, albedo, vegetation) contribute to human exposure to the ground and air temperatures. However, urban microclimate measurement poses substantial challenges as data taken from specific areas may not be representative of the district or city level. Many areas across the city have different levels of heat because of variation in impervious surfaces, vegetation and heat wasted from vehicles and buildings. Furthermore, fixed weather stations cannot be installed and deployed at multiple places due to increase in cost. Thus in continuation to this research, University of Ottawa in collaboration with Centre for Entrepreneurship and Engineering Design (CEED) and WSP are designing a mobile measurement bicycle. This bicycle will be coupled with a thermocouple unit, hygrometer unit, and camera. The GPS unit will collect latitude, longitude and speed, and provided timestamp to calculate sky view factor. This bicycle will permit movement from space to space within a city to assess the physical and thermal properties of microclimates incoming and outgoing short- and longwave radiation and ground surface temperature. All of the equipment will take a reading once every second and will store it to an onboard solid state hard drive.

Assessing human exposure to high temperature will require understanding both how average temperatures are expected to shift with global warming and how local temperatures are modified by the urban heat island effect. Estimating the ground surface and air temperatures with machine learning and bicycle based field measurement system supports preventative programs at the neighborhood-level like cooling centers or the planting of street trees to reduce temperatures.