Greenness visibility using viewshed analysis: A pilot study in Manchester

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Summary

Assessment of green visibility exposure is challenging for a large spatial extent and in a complex built environment. In this study, we demonstrated an innovative application of viewshed-based greenness visibility index (GVI) modelling at a fine spatial resolution for each location within the study area. We validated our GVI against a commonly used index based on randomly sampled locations with available Google Street View (GSV) images. We observed very strong positive, significant correlations between our GVI values GSV-based index ($r = 0.943$, $p = 0.001$). Our method allows accurate, efficient and comprehensive greenness visibility assessment, not just along roads.

KEYWORDS: Greenspace; Visibility Exposure; Viewshed; Street greenery; GIS

1. Introduction

The connection between human health and the natural environment is widely recognised. Many recent studies have indicated that exposure to the natural environment, particularly blue and green spaces, has positive health benefits along multiple pathways (Lindley et al., 2019; Markevyche et al., 2017). The conceptualisation of exposure to nature or greenness can be broadly classified into three categories; availability, accessibility, and visibility of blue and greenspace, hereafter referred to as 'greenness' (Labib et al., 2020a). Availability and accessibility are most widely studied in the literature because availability and accessibility metrics can be measured with greater efficiency and accuracy from the satellite images (e.g. NDVI) or GIS data (e.g., land use) (Labib et al., 2020b). However, availability and accessibility metrics have limited abilities in capturing the ways that humans experience nature, in part due to their calculation from a top-down 'bird's eye' view in 2D space (x, y). Visibility, on the other hand, is calculated in 3 dimensions (x, y, z) (Larkin and Hystad, 2019; Jiang et al., 2017), permitting a more representative measure of the human experience of greenness.

Traditionally, environmental psychologists used photographs or questionnaires to understand how the visibility of natural features influences attention restoration or stress recovery (Kaplan and Kaplan, 1989). However, photographs limit the understanding of the visibility of nature in a spatial context, and can be prohibitively time consuming for large cohorts. Alternatively, several recent studies have used street view (SV) images (e.g., Google Street View, Baidu Street View) to measure visibility of nature, particularly in urban areas (Helbich et al., 2019; Wang et al., 2020). Coupling with artificial intelligence methods (e.g. deep learning), SV-based visibility measurements are becoming increasingly common in the literature. However, SV images are not available in many locations that are not accessible to the vehicles used to capture the images (Rzotkiewicz et al., 2018), such as back gardens, the inside of community parks and public rights of way. Therefore, the estimation of neighbourhood level greenness visibility is only achievable from certain locations using this approach. Existing studies usually sample SV images within a neighbourhood along the roads and average the resulting neighbourhood visibility based on the sample locations (Lu, 2019; Lu et al., 2019). A traditional GIS-based approach such as viewshed analysis, on the other hand, can provide a comprehensive estimation of greenness visibility, as it can be used to measure visibility at any location in the landscape, not just along the streets (Qiang et al., 2019). For example, Nutsford et al., (2016; 2015) used a viewshed-based vertical visibility index to measure greenspace visibility, but they limited their measurement only to neighbourhood centroids for a single observation point, which is clearly unable to capture the overall greenness visibility for the entire spatial unit (e.g., neighbourhood).

Viewshed-based approaches have been long established as the most popular method in the field of GIS for analysing visibility (Qiang et al., 2019). Considering the availability of recent high-resolution digital elevation data (e.g., LiDAR-based digital surfaces), this research explores how greenness visibility can be measured effectively using a viewshed approach in order to establish a Greenness Visibility Index (GVI) for every pixel in a surface. We present our method in a small case study area, before providing a statistical comparison against a Google Street View (GSV) -based visibility index in order to validate our approach for locations where GSV available (i.e., along streets).

2. Methods and materials

2.1 Data

The method developed for this research study was applied to a case study area (approximately 3.9 km^2, 156,600 cells of 5 m resolution) in Manchester (Figure 1a), UK. We used three spatial datasets: digital surface model (DSM); digital terrain model (DTM), and a land use and land cover-based binary greenness surface. The DSM and DTM used in this study are processed from point cloud data captured by LiDAR systems by the Environment Agency (2019a, b), and are resampled to 5 m resolution (Figure 1c, d). Previously Qiang et al., (2019) indicated 5 m resolution is sufficient to model visibility because such resolution is adequate to portray outlines of major obstacles (e.g., buildings) key for visibility analysis. The greenness data used in this study was obtained from Dennis et al., (2018) land cover data (Figure 1b), re-sampled to 5 m resolution and reclassified into a binary surface of ‘green’ and ‘not green’ (Figure 3b).

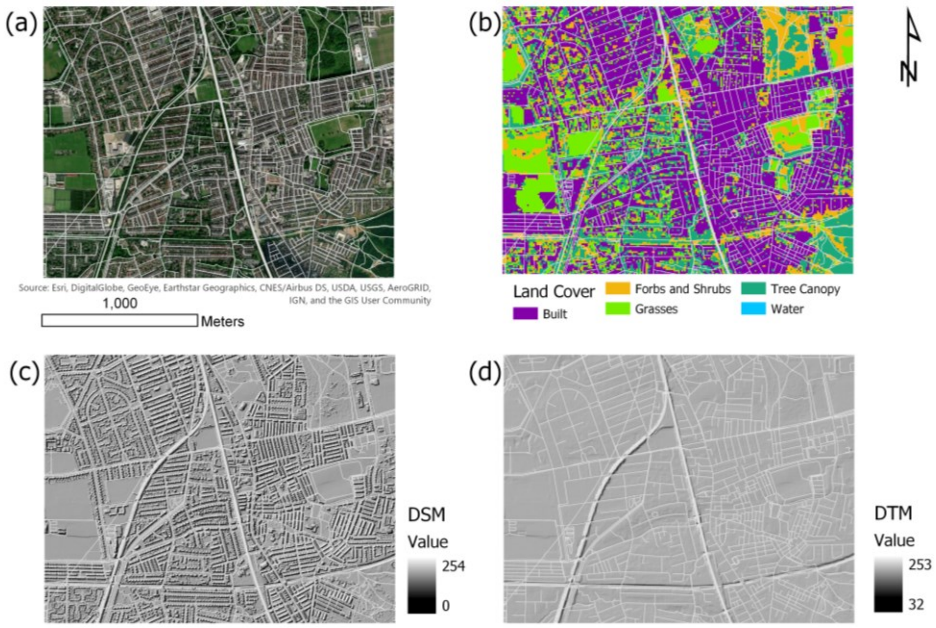

Figure 1: (a) High-resolution satellite image of the study area (Source: ESRI, 2020); (b) Land cover data (Source: Dennis et al., 2018); (c) Digital surface model; (d) Digital terrain model. Overlaid with OpenStreetMap road network dataset.

2.2 Calculating Greenness Visibility Index (GVI)

We used a Python implementation of a viewshed algorithm to calculate the greenness visibility index (https://github.com/jonnyhuck/green-visibility-index). In this case, we applied the Midpoint circle algorithm to calculate an arc of 1/8 of the circle at the desired radius from the *Observer* cell (Figure

2a), then transformed this 8 times in order to identify each cell describing circle radius. As each cell is identified, we use Bresenham's line algorithm to cast a ray to it from the *Observer* cell, with a fixed observer height of 2 m (approximate eye level). The binary visibility of each cell on the ray is calculated using the DSM in order to account for buildings and trees etc. We finally calculated the number of green cells among the visible cells (Figure 2b), and used eq.1 to determine the GVI for each cell:

$$GVI = \frac{Total\ Visible\ Green\ Cells}{Total\ visible\ Cells} \tag{1}$$

In this pilot test, we used a radius of 100 m, because previous studies indicated that visibility of greenness, and presence of greenspace in close proximity has a stronger influence on health outcomes (Nutsford et al., 2016; Labib et al., 2019; Hystad et al, 2014).

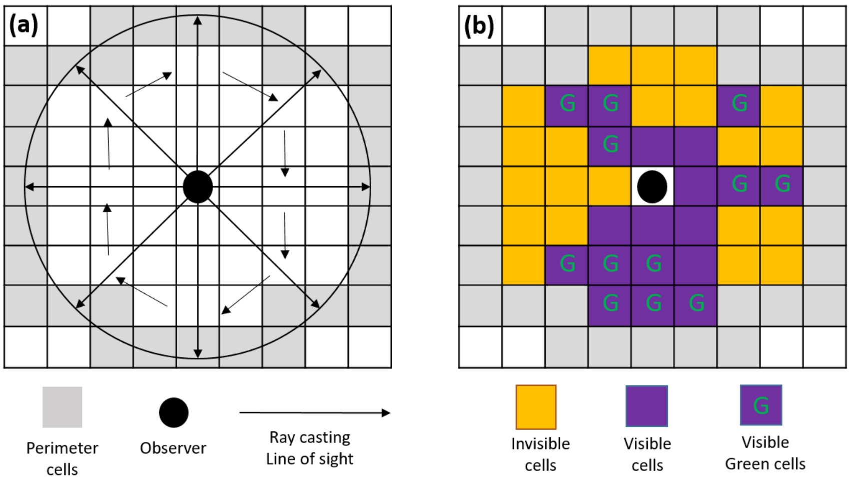

Figure 2: (a) Line of sight algorithm for viewshed analysis for a given buffer distance, (b) viewshed outcome for observer cell; for this example, *GVI = 12/19 = 0.631*.

2.3 Validity tests

In order to assess the validity of our new GVI measure, we compare our results to GSV image-based green view index measurements at 20 randomly selected locations along roads where GSV images were available. The street-view based index computes the ratio of the number of green pixels per image summed over six cardinal directions to the total numbers of pixels per images over the same directions (details in Li and Ghosh, 2018; and Li et al., 2015). Pearson's correlation coefficients were calculated to assess the relationship between our GVI measure and GSV-based GVI measure. In addition, we also explored our GVI measure visually by creating a 3D virtual representation of the study area using OS MasterMap Building Height Attribute (OS MasterMap, 2019) and a tree database (City of Trees, 2011).

3. Results and discussion

Calculation of the GVI for the test study area took approximately 1.5 hours on a 3.1 GHz Intel Core i7 laptop with 16GB RAM. In the processing, 156,600 viewsheds were calculated to cover 3.9 square kilometre area, and each viewshed calculation required approximately 0.036 seconds. The outcome of this analysis produces a greenness visibility map for the study area (Figure 3a), where 0 represent the lowest level of green visibility, and 1 indicates the highest greenness visibility.

Comparing Figure 3a and 3b, we observed visibility of greenness showed a similar distribution to the green and no-green binary map of the study area, however, closer examination identified that, in many locations despite the presence of greenness on a 2D map, the GVI score was lower as the visibility of the green spaces was obscured due to presence of features such as buildings. As we examined the GVI in 3D (Figure 3c), it becomes clear that the presence of buildings is a crucial variable in greenness visibility. There are many obvious instances in Figure 3c where buildings are obscuring the vegetation cover and so keeping the GVI low even though the greenspace is in close proximity.

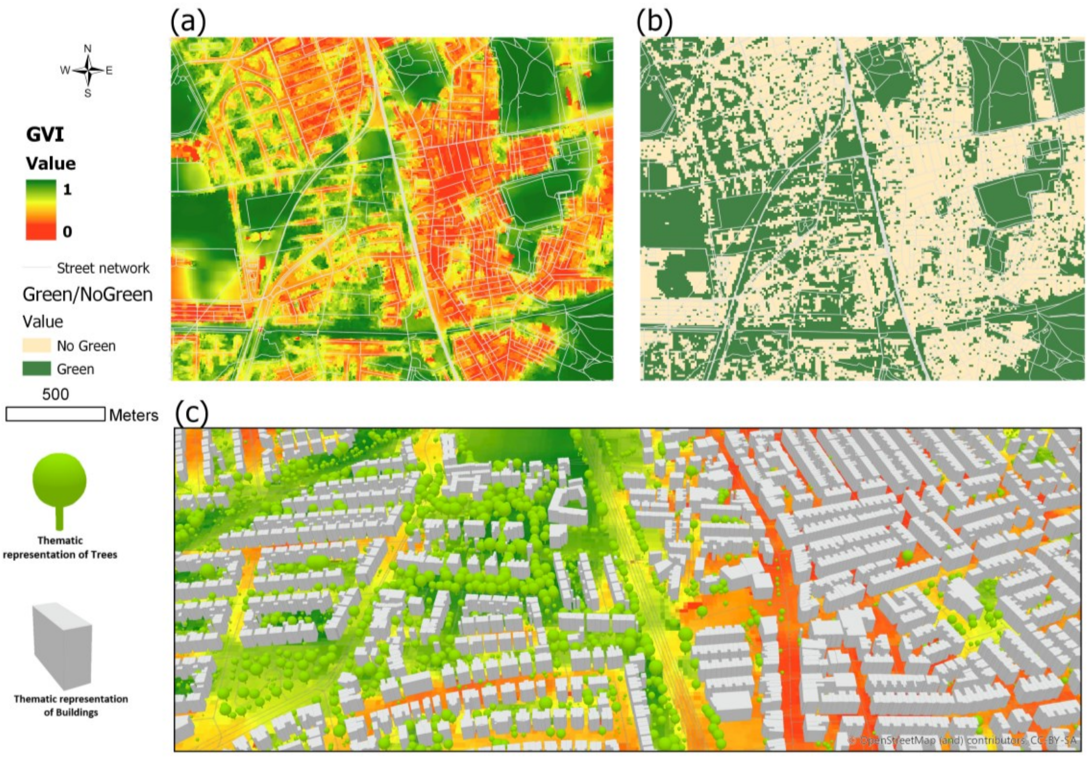

Figure 3: (a) Greenness visibility index for the case study area; (b) Binary green, no-green map indicating greenness in study area; (c) 3D virtual representation of buildings and trees on the GVI map (*detailed animated overview:* [*https://youtu.be/71xdj7hv2HE*](https://youtu.be/71xdj7hv2HE)).

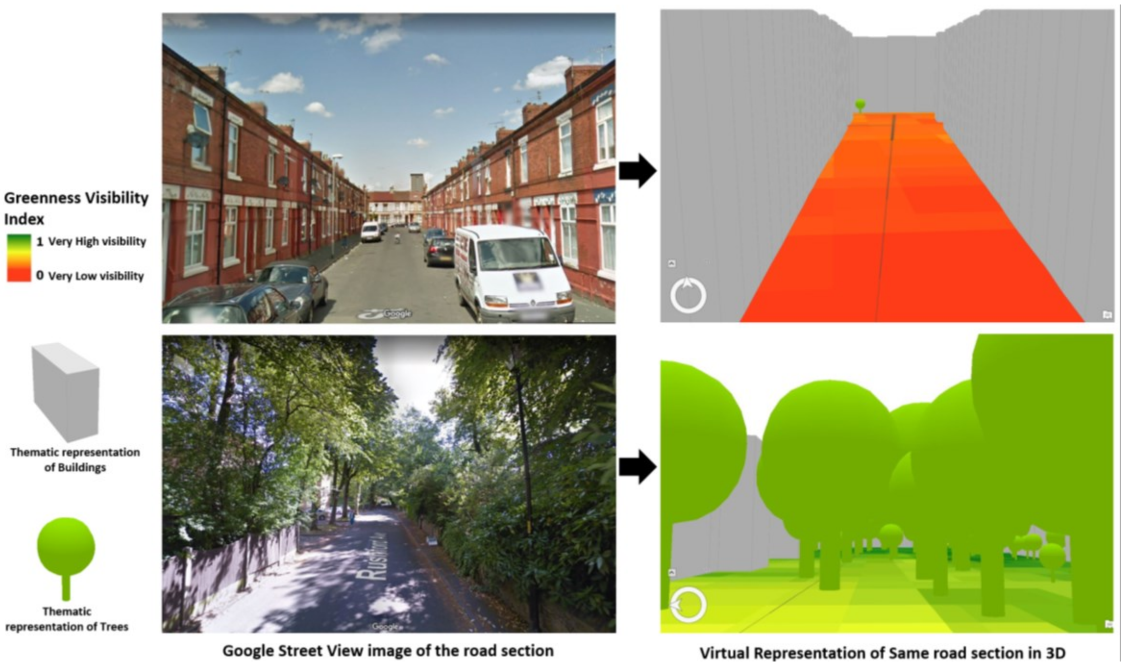

Figure 4: Comparisons of Google street view based greenness with GVI within the virtual representation.

When compared with GSV-based green view index, we observed a very strong positive and significant correlation between our GVI values and street view based GIV value ($r = 0.943$, $p = 0.01$, Figure 5). Visual comparisons of GSV images and our GVI value along with 3D virtual representation (Figure 4), indicates that our new GVI measuring captured similar representation of greenness observed in street view images. Considering these, we conclude that our GVI score is an effective method for the calculation of greenness visibility, with the added benefits of simplicity, speed and improved spatial coverage in comparison with SV-based approaches.

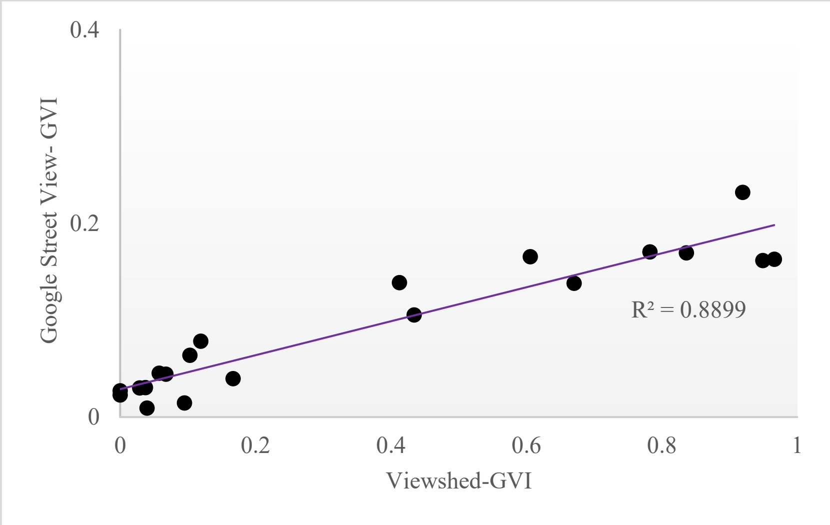

Figure 5: Correlation (*r = 0.943, p = 0.01*) between viewshed greenness visibility index and Google Street view green view index.

Our GVI index improves upon single observer, fixed search distance viewshed approaches (e.g., Nutsford et al., 2015). Additionally, our new method complements existing street view greenness visibility analysis methods when images are available (Helbich et al., 2019; Li and Ghosh, 2018; Li et al., 2015), and we improve visibility assessments by providing visibility measurements at locations where street view images are unavailable, such as backyards, parks, and public rights of way. Our method is simpler than the artificial intelligence algorithms deployed for SV-based visibility indices, and there are no privacy issues when using SV-images.

Further research will address several limitations of this study. First, we only considered visibility within 100m around each cell, but visibility and visual significance can extend to the horizon (Qiang et al., 2019). In future studies, multiple distances need to be incorporated to measure the visual impact of distant greenness. Second, we modelled overall greenness visibility by combining different greenness types. While our method is cable to model visibility for different types of vegetation (e.g., grass, trees), the application we presented in this pilot study, limited the understanding of the visibility of different vegetation types. Third, we did not consider the self-obscuring nature of vegetation in our model. The effects of self-obscuring vegetation should be considered in future development. Fourth, while our method is efficient for large observer locations, the viewshed computation method is still resource-intensive. Possible optimisations and improvements in the algorithm also require additional investigations. Finally, greenness visibility does not indicate accessibility to greenspaces. In future studies, visibility and accessibility should be combined to achieve a comprehensive measurement of greenness exposure.

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GVI software relies upon the Fiona (https://github.com/Toblerity/Fiona) and Rasterio (https://github.com/mapbox/rasterio) Python libraries, which themselves rely upon the GDAL/OGR software libraries (https://github.com/OSGeo/gdal); as well as the Numpy Python library (https://github.com/numpy/numpy).

5. Biographies

S.M. Labib is a final year PhD student at the University of Manchester, with research interests in applications of GIS and remote sensing in environmental epidemiology, urban ecosystem, and environmental processes.

Jonny Huck is a lecturer in GIS at the University of Manchester, with research interests in the representation of vague geographical entities in geographical information science and the application of emergent technologies to geographical problems, particularly in the provision of healthcare in the global south.

Sarah Lindley is a Professor of Geography at the University of Manchester, with research interests in environmental processes and geographical information science.

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