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Modelling eye-level visibility of urban green space: Optimising city-wide point-based viewshed computations through prototyping

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Abstract. Studies from public and environmental health show strong indication of the importance of visible urban green space. However, current approaches for modelling viewshed based greenness visibility still have high computation costs. As a consequence, comparative studies of city-wide visible greenness, everyday mobility, and individual attention are still at the edge of feasibility. Known optimisations focus on reducing the computation time of single viewsheds. As point-based viewsheds are computed using geospatial data, current approaches seek to accelerate calculation using intelligent data structures or spatial indexes (at the cost of additional memory) or develop approximative heuristic solutions. In contrast, as we aim to process large numbers of viewsheds with fixed parameterisations, we use a prototyping approach preprocessing a single viewshed template to store common prefixes of consecutive lines of sight that can be applied to follow-up viewsheds by a simple offset operation. Our evaluation shows an average improvement of 34% over the benchmark algorithm (RFVS), with even stronger improvements for large viewsheds. We anticipate that these findings lay the groundwork for further optimisation of point-based viewshed computation, improving the feasibility of subsequent comparative studies in the field of public and environmental health.

Keywords. viewshed computation, greenness visibility, urban health, optimisation

1 Introduction: Motivation

Recent research in the field of environmental health reports small but stable positive effects of visual greenness in one's everyday environment on overall self-reported health (Markevych et al., 2017). These range from measurable environmental stressors like air or noise pollution (Lindley et al., 2019) and the encouraging function of a green environment on physical activity and place-bound social cohesion (Markevych et al., 2017) to resilience-building effects like stress recovery and attention restoration (Ulrich, 1983; Kaplan and Kaplan, 1989). Walker et al. (2022) show that adding informed greenness to other indicators such as household and local socioeconomic conditions increases their predictive accuracy notably.

However, informed spatial models of greenspace use parameterisations based on either rough heuristics that are difficult to validate or depend on computationally expensive models (Dadvand and Nieuwenhuijsen, 2019; Labib et al., 2021). Our approach focusses on optimising geospatial methodology to assess the effects of visual greenness on health by introducing a computational approach that significantly decreases computation time of large-scale point-based viewshed analyses.

2 Related Work

Our approach is based on greenspace exposure modelling frameworks developed by Dadvand and Nieuwenhuijsen (2019) and Labib et al. (2021). To account for physical mitigation effects, the mere availability of greenness is estimated by simple map-bound 2D buffer analysis (Lindley et al., 2019). Having access to greenspaces as precondition for active capacity-building requires two components to be modelled: (1) Proximity to greenspaces that can be reached in a reasonable time and (2) structural or legal access that could exclude people from participating from the positive effects of greenspace (Markevych et al., 2017). Whereas proximity can be easily computed by travel-cost-models, structural or legal access as non-disclosed or non-spatial information is hard to obtain, especially for larger areas. Existing combined models of greenness are sufficient to compute exposure time models of everyday activity spaces (Łaszkiewicz and Sikorska, 2020). Nevertheless, involving visibility not only avoids the implicit limitations of accessibility models, but also addresses individual effects in stress recovery and attention restoration (Ulrich, 1983; Kaplan and Kaplan, 1989), presumably better approximating or representing the actual mechanisms involved. As visibility models represent individual perceptions of greenness, they measure immediate and not only long-term effects on individual health at the cost of their demand for more complex solutions.

The exposure to visible greenness can be estimated using street view (SV) images (e.g., Google Street View, Baidu Street View). While this methodology is most commonly used in the literature it has several limitations, such as seasonal inconsistency between SV images and that viewing points are typically limited to roads accessible by car (Li et al., 2015). Furthermore, it is still difficult to accurately classify vegetation from SV images due to many factors, such as shadows and confusion between human-made green features and vegetation (Li et al., 2015).

An alternative method for assessing greenness visibility from eye-level perspective uses GIS-based viewshed analysis. Recent studies have demonstrated the use of city-wide scale viewshed-based greenness visibility as a highly accurate alternative to SV-based visual exposure (Tabrizian et al., 2020; Labib et al., 2021; Cimburova and Blumentrath, 2022). Such methodologies are not dependent on the availability of SV-images and can be scaled to large areas with little effort. However, high computation time remains the major limitation of this methodology, because a single, point-based viewshed for each observer location is required. Recent studies reported total computation time for the Greater Manchester region and Oslo as 11.5 and 5.6 days, respectively (Labib et al., 2021; Cimburova and Blumentrath, 2022).

Optimising viewshed algorithms has been subject to prior research. While the well-known R3 algorithm achieves high accuracy, it has low efficiency and is therefore only practical for small datasets (Franklin and Ray, 1994). The sweep-line algorithm (Van Kreveld, 1996) has accuracy equivalent to the R3 algorithm with reduced computation time. In essence, a sweep line rotates around the observer's position. All cells intersected by the current sweep-line are active. Visibility is only computed for those cells whose centerpoints were passed by the sweep-line on the last rotation step by comparing their slope to all active cells closer to the observer. Ferreira et al. (2013) reduced computation time by implementing a parallel sweep-line algorithm utilising multiple CPU cores which does not modify the algorithm per se. While the aforementioned methods calculate visibility from an observer to the centre of a cell, the RFVS algorithm uses a relaxation of the problem such that a target may be considered visible if any part of the cell is visible (Franklin and Ray, 1994). As this algorithm is only an approximation with reduced accuracy, it is very computationally efficient. Ferreira et al. (2016) further reduced computation time by optimising the sort order of the cells relying on spatial indexes. Also in this case, technical improvements through parallel processing have been achieved using GPUs (Zhao et al., 2013; Hao-Nguyen et al., 2018). However, as with parallel computing of the original sweep-line algorithm, this does not reduce the complexity of the problem. Cimburova and Blumentrath (2022) report that simply reducing the sampling rate by a factor of four does not lead to a significant drop of accuracy in the resulting greenness visibility.

In this study we aim to present a fast and novel algorithm suitable for large sets of single point-based viewsheds by implementing a viewshed prototyping approach that makes use of shared processing steps between all individual viewsheds. In addition, we allow for basic CPU multi-threading by computing viewsheds from multiple vantage points simultaneously. We build on the work of Labib et al. (2021) by presenting the easy to use R package GVI (Brinkmann and Labib, 2021) that enables fast computation of greenness visibility for large-scale areas. Whereas previous approaches mainly aimed at reducing computation time of a single viewshed, our goal is to reduce the aggregated computation time for a large number of viewsheds and thereby enable a scaling-up of spatial coverage and resolution for greenspace visibility modelling.

3 Method

3.1 Viewshed and Greenness Visibility

The Viewshed Greenness Visibility Index (VGVI) (Labib et al., 2021) expresses the ratio of visible greenness to the total visible area. This is derived from geospatial datasets of elevation and binary greenspace (e.g., green, no-green). Elevation and greenspace data are typically represented by high resolution elevation models and Land Use and Land Cover (LULC) maps, respectively. Our operationalisation of green space depends on the classification of the LULC raster. Using LULC data with a 2 m resolution, our approach is not sensitive enough to capture objects below that threshold. As visual qualities are represented by LULC data values, other visibility metrics such as bluespace-, or tree-visibility can be calculated in the same manner. To calculate eye-level visibility for an observer we used a viewshed based on the RFVS algorithm as it has high computational efficiency whilst still maintaining sufficient accuracy. The height of the observer is derived using ground-level elevation from a Digital Terrain Model (DTM) and the observer height offset (e.g., 1.7 m). Height within the viewshed is evaluated using a Digital Surface Model (DSM) to account for obstacles such as trees. The VGVI algorithm is described in detail in Labib et al. (2021).

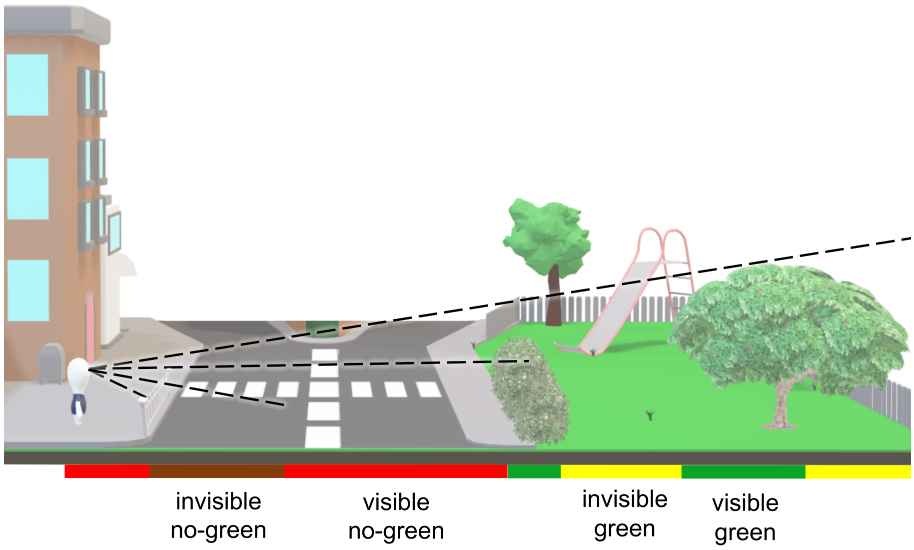

Figure 1. Representation of a single line of sight. Dichotomous visibility (e.g. visible, not visible) and intersected greenness values (e.g. green, no-green) are evaluated along the line of sight.

In brief, we use a raster map representation of the study area. We applied the Midpoint Circle Algorithm (van Aken, 1984; Cao et al., 2020) to calculate an arc of 1/8 of the perimeter of a circle with a fixed radius r (e.g., 800 m) from the observer location catching all intersecting pixel cells. We then applied Bresenham's line algorithm (Bresenham, 1965, 1977) to cast a line of sight (LOS) to each perimeter cell. The 8-way symmetry property of a circle was used in order to project the LOSs eight times to identify LOS for all cells within the circle. A single LOS can be described as a sequence of cells $(c^0, c^1, ..., c^i, ..., c^k)$ where $k \leq r$, and c^0 is the observer location and c^k a cell at the circle's perimeter. As visualised in Fig. 1, dichotomous visibility (e.g., visible/not visible) for each cell on a LOS is evaluated with simple geometry by calculating the slope α^i from the observer cell c^0 to each LOS cell c^i. Let μ be the highest slope so far, then c^i is visible if and only if $\alpha^i > \mu$. Finally, the VGVI was calculated as the proportion of visible green cells to the total visible area. All values are summarised using a user-selected distance decay function (e.g., exponential or logarithmic) to account for the reduced visual prominence of an object in space with increasing distance from the observer. The estimated VGVI values range between 0 and 1, where 0 = no green cells are visible, and 1 = all of the visible cells are green.

3.2 Viewshed Prototyping

VGVI is often calculated for a large number of observer locations. Computation time per point can be reduced by creating a viewshed prototype prior to viewshed computation that pre-calculates shared processing steps between all individual viewsheds. On average, the calculation of LOS paths accounts for 25% of total computation time. However, as the coordinates of all LOS cells are relative to the observer location in the centre and the viewing distance is assumed constant for all observers, this step can be generalised for all viewsheds.

An observer with synthetic coordinates is generated and the circle's perimeter cells and LOS paths are calculated. When applied to an actual observer location, the LOS cells only need to be reprojected to true pixel coordinates and visibility can be calculated as described in section 3.1.

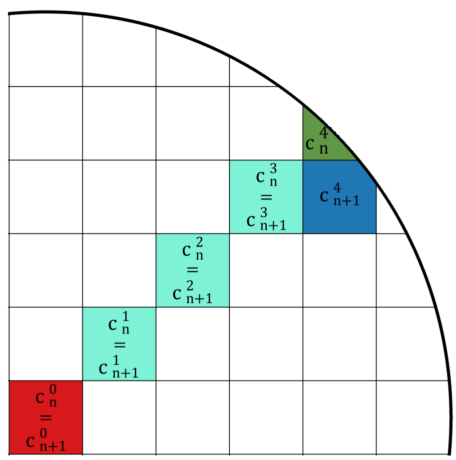

Figure 2. Reuse of shared path segments of consecutive lines of sight (LOSs) visualised in the first quadrant of a viewshed. Red: Observer cell in the centre. Green: Last cell of the first LOS. Dark blue: Last cell of the consecutive LOS. Light blue: Shared prefix between both LOSs.

We further reduced computation time by applying a prefix cache algorithm on subsequent LOS paths. As shown in Fig. 2, neighbouring LOS paths may be overlapping. In a viewshed with radius r, let L_n be the n-th LOS in a clockwise order with a sequence of cells $(c_n^0, c_n^1, ..., c_n^i, ..., c_n^k)$ where $k \leq r$. Let L_{n+1} be its consecutive LOS with $(c_{n+1}^0, c_{n+1}^1, ..., c_{n+1}^i, ..., c_{n+1}^k)$ there exists

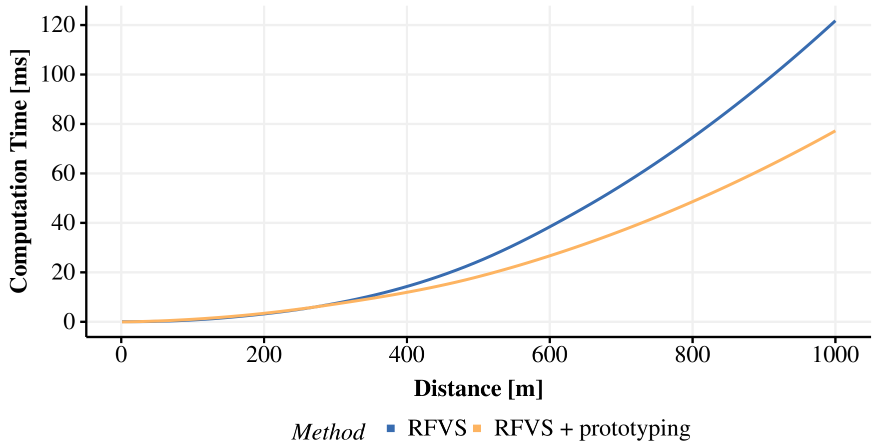

Figure 3. Computation time [ms] per viewshed parameterized by viewing distance [m] from the observer location. Blue: the benchmark RFVS algorithm. Orange: RFVS algorithm with prototyping.

a certain threshold j with $0 \leq j < r$ where $c_n^i = c_{n+1}^i$ for all $0 \leq i < j$. When calculating visibility for L_n we temporarily store the maximum slope μ at each cell c_n^i in the array υ at the position υ_i. When calculating visibility for L_{n+1} we begin at c_{n+1}^{j+1} and use $\mu = \upsilon_j$ from the previous LOS as the maximum slope so far. As demonstrated in the example (Fig. 2), when calculating visibility for L_{n+1} we begin at c_{n+1}^4 and use $\mu = \upsilon_3$, consequently taking only one instead of four processing steps. As part of the pre-computed prototype we store the specific threshold j for each LOS referencing the longest prefix for the preceding LOS.

4 Results

We implemented our algorithm in C++ with g++ 4.6.2 using OpenMP (Dagum and Menon, 1998) for parallel processing on the CPU. Our experimental platform was an AMD Ryzen 9 3900X 12-core with 64 GB RAM running Windows 10. We have built an easy to use R package (R Core Team, 2021) around the C++ code. Reproducible workflows have been provided on GitHub and our data freely available (10.5281/zenodo.6421424).

We measured computation time (a) for the raw viewshed calculation excluding the greenness visibility step to promote comparison with other viewshed algorithms, and (b) for the complete VGVI algorithm simulating a large-scale study. For testing the algorithms we used LiDAR derived DSM and DTM (Natural Resources Canada, 2019) with 1 m spatial resolution of the Vancouver metropolitan area (area: 528 km^2). Publicly available LULC data has been acquired by Metro Vancouver (31.11.2019) at 2 m resolution and reclassified to a binary greenness raster (0=no-green; 1=green).

4.1 Viewshed

To evaluate our algorithm performance, we measured computation time for (a) the original algorithm without prototyping, (b) our novel algorithm utilising only one, and (c) utilising 10 CPU threads in parallel. We generated 1000 random observer locations across the complete study area. Viewsheds for all points have been calculated at multiple distance levels from 1 m to 1000 m. We measured total runtime at each distance level and scaled it to computation time per viewshed (total runtime / 1000). The times represent the average of 10 runs and are given in milliseconds, the results are visualised in Fig. 3. Overall, mean single-core computation time per viewshed was improved by 34.2% (± 20.9%) using our novel algorithm. Indifferent (but not lower) results were measured for small viewsheds (r < 300 m), using a larger radius (r > 300 m) led to an improvement of 40.5% (± 15.7%). Compared to our single-core algorithm, we achieved speeds up to 9 times faster when using 10 concurrent threads.

4.2 Greenness visibility

To demonstrate runtime for a large-scale greenness visibility study we estimated city-wide VGVI at 5 m intervals, resulting in 17,329,345 observer locations. As suggested by Labib et al. (2021), we assumed an eye-level observer height of 1.7 m and used an exponential distance decay weighting function with a viewing distance threshold of 800 m. The result of the city-wide VGVI calculation is mapped in Fig. 4. For a rough evaluation of our approach with other aforementioned studies, we do not compare complexity, rather computation time. Total runtime time using 20 CPU threads was 20.3 hours, equivalent to computation time per observer of 84 milliseconds.

To compare our algorithm with other results by Labib et al. (2021) and Cimburova and Blumentrath (2022) respec-

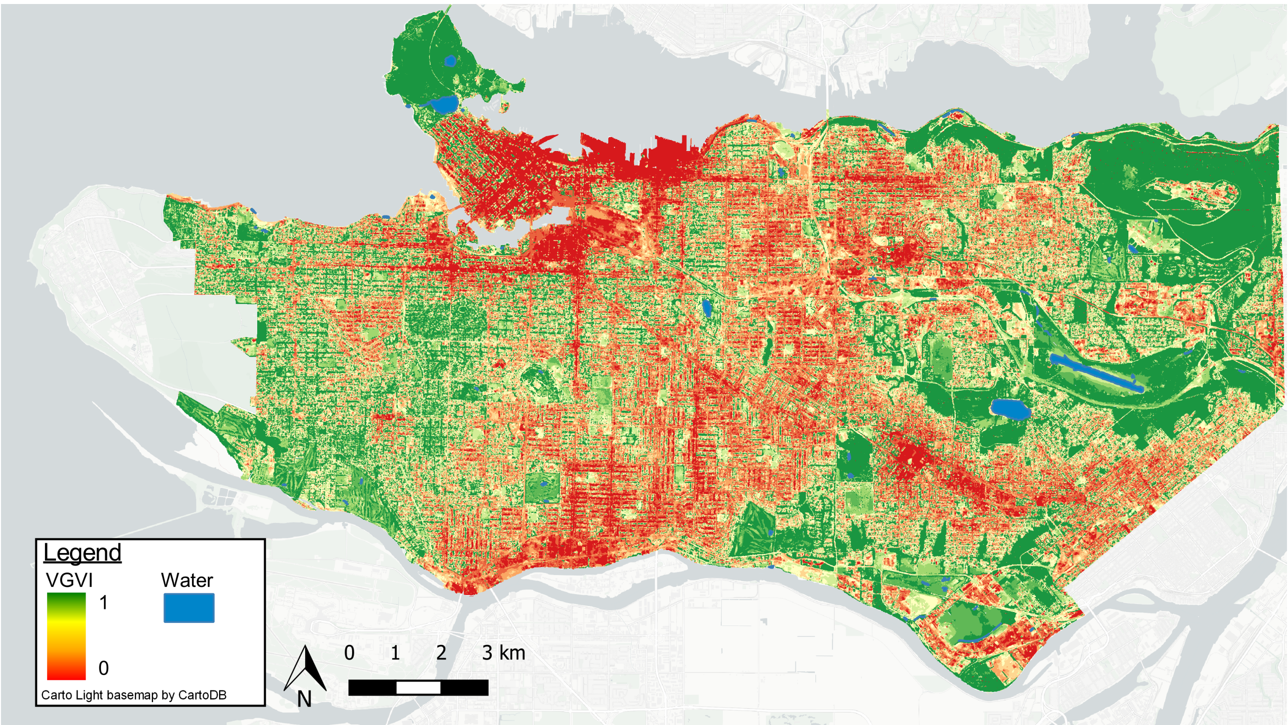

Figure 4. Example Viewshed Greenness Visibility Index (VGVI) map of Vancouver, Canada. An interactive version of the complete study area is available online from https://bit.ly/3r6IyNR.

tively, we also computed VGVI with 5 m resolution of elevation models and 800 m viewing distance, and 1 m resolution of elevation models and 100 m viewing distance. Both studies used parallel CPU computation to estimate city-wide VGVI. Computation time per point using our novel algorithm was 5 and 2 milliseconds, compared to reported 0.8 seconds (Labib et al., 2021) and 80 milliseconds (Cimburova and Blumentrath, 2022), respectively.

5 Discussion

Our results indicate that, in addition to the advances already made in optimisation of the algorithmic processing of single viewsheds, there remains a significant potential to enhance city-scale viewshed-analysis through improvement of the computational algorithms. By using prototyping of the viewshed computation process, we outperform the original RFVS algorithm in any parameterization for 1000 random observer locations on a city map, starting to produce significant gains from a 250 m viewing distance. By that simple technique, we also outperform the parameterization of recent optimisations regarding computation time of VGVI. In addition, by reusing preprocessing steps for all viewsheds, our approach will take further advantage from the combination with Ferreira et al. (2016) and Cimburova and Blumentrath (2022).

The quality of the results highly depends on the input data used. LULC data is not available in equal quality for all regions. For our model we used a DSM with 1 m resolution. Future research will analyse the effect of aggregation (larger cells of the DSM) on accuracy of greenness visibility. In our study, we used a simple distance decay function to account for the decreasing salience of an object in space with increasing distance from the observer. Furthermore, as a general limitation of viewshed computations, the 2.5D character of DSM data does not allow for multiple height values. Only the largest height value is stored for each pixel. Therefore, looking underneath objects like trees or power cables is not represented correctly. However, further detailed evaluation comparing real-world experiences with our model is needed.

These optimisations are a precondition for the efficient use of viewshed based computations on large numbers of observer locations in the field of environmental health. A model of city-wide visibility of urban green spaces allows for an efficient computation of location based services utilising them, e.g. measuring the impact of everyday mobility on public health. Further work will take advantage of it to evaluate effect sizes of greenness visibility on attention data (e.g., in virtual environments: Tabrizian et al., 2020), the relative impact of close and distant-range vision, and different categories of vegetation (Schreyer et al., 2022). To facilitate using our novel algorithm in the context of urban health geography we provide the easy-to-use R package GVI (Brinkmann and Labib, 2021).

6 Conclusion

Studies from public and environmental health show strong indication of the importance of visible urban green space. However, computation time of current models of city-wide viewshed based greenness visibility are still not sufficient to leverage large-scale comparisons of visible greenness, everyday mobility and individual attention in the field. In addition to existing concepts to optimise computation time of single viewsheds, we propose a prototyping approach sharing as many computation steps as possible between viewshed computations for a large number of observer locations. Our evaluation shows an improvement over the benchmark algorithm (RFVS), especially for large viewsheds. We anticipate that by combining these results with known optimisation steps for point-based viewshed computation (e.g., intelligent pre-sorting, spatial indices, and heuristic sampling), we will improve the feasibility of subsequent comparative studies in the field of public and environmental health.

Author contributions. Project conceptualisation (BBW, STB, DK); literature review and monitoring (STB, DK); data acquisition/preprocessing (STB); data modelling (STB); interpretation of results and manuscript preparation (STB, DK, BBW). All authors read and approved the final manuscript.

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