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3D Visibility Analysis for Evaluating the Attractiveness of Tourism Routes Computed from Social Media Photos

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Abstract: Social media is used nowadays for various location-based applications and services, aspiring to use the vast and timely potential of user-generated content. To evaluate the correctness, reliability and potential of these applications and services, they are mostly evaluated in terms of optimization or compared to existing authoritative data sources and services. With respect to route planning, criterion optimization is mostly implemented to evaluate the service effectiveness, in terms of, e.g., length, time or visited places. These evaluations are mostly limited in their effectiveness at presenting the complete experience of the route, since they are limited to a predefined criterion and are mostly implemented in two-dimensional space. In this research, we propose a comprehensive evaluation process, in which a tourism walking route is analyzed with respect to three-dimensional visibility that measures the attractiveness of the route relating to the user perception. To present our development, we showcase the use of Flickr, a social media photo-sharing online website that is popular among travelers that share their tourism experiences. We use Flickr photos to generate tourism walking routes and evaluate them in terms of the visible space. We show that the 3D visibility analysis identifies the various visible urban elements in the vicinity of the tourism routes, which are more attractive, scenery and include many tourism attractions. Since urban attractiveness is often reflected in the photo-trails of Flickr photographers, we argue that using 3D visibility analysis that measures urban attractiveness and scenery should be considered for the purpose of analysis and evaluation of location-based services.

Keywords: social media; geotagged photos; geovisualization; urban attractiveness; visual analysis



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1. Introduction

Smart route planning and navigation solutions are developing fast, aspiring to keep pace with rapid changes and diverse users' requirements. Route planning serves as an important part of location-based services and applications, where the generated route is designed to provide an optimized path through places of interests (targets) by applying certain route constraints. A common formulation of routes can be made from the travelling salesman problem (TSP), the vehicle routing problem (VRP), and the orienteering problem (OP). In the case of route planning designed to calculate tourism routes, it will most likely have to rely on rich contextual knowledge and understanding regarding the urban environment. Increasingly, more and more route planning solutions rely today on the huge volumes of user-generated content existing in online social media repositories [1,2], which are continuously updated and store vernacular information. Flickr, for example, allows users to depict and share their everyday activities and events, including tourism activity, relying mostly on geotagged photos that reflect the exiting visual attractiveness the users experience. Accordingly, including scenic and attractive places documented in Flickr photo-trails that serve as digital footprints, has the potential to significantly enrich the tourism experience. Although visual attractiveness is a subjective quality, one might

argue that some universal attractivity qualities can be deduced when multitude of social media users are photographing a specific site [3], especially when that site is not marked as a tourist attraction on traditional marker platforms, such as TripAdvisor.

Wayfinding is mostly constructed through the visual channel. It is a natural skill that pedestrians do throughout their entire life, helping them to successfully navigate and orientate. Wayfinding involves the integration and assimilation of perceptual and cognitive structures relevant to space into spatial cues that stimulate mental representations ('cognitive map') of the environment that corresponds with the real space [4]. Modelling this process, e.g., identifying environmental architectural and morphological cues, can be used to enhance the traveling experiences. In terms of wayfinding, most route planning algorithms will aim to calculate the shortest or fastest path. These routes will most likely not address users who desire to actively experience the environment, such as tourists. These users will want to include additional environmental cues in their route, such as points of interest, landmarks, and scenery views.

The built environment and its various physical elements and attributes shape how people sense and experience it. These have a direct influence on how people perceive, engage, behave, and act. Nowadays, more and more cities encourage active travel, where pedestrian mobility and walkability are considered an important characteristic of a sustainable and healthy urban environment. As the perception of the urban space is largely influenced by visibility, simulating the visual cues along routes may assist in personalized route choice and qualitatively evaluate the relevance of a route, quantitatively assessing its appropriateness to the specific requirements and preferences of the users [5], such as tourists. This contrasts with existing route evaluation processes that are mostly conducted on a two-dimensional space (e.g., length), overlooking the fact that the routes exist in a three-dimensional reality, and thus should be analyzed and evaluated in this context.

In this study, we showcase the use of Flickr to generate routes having a tourism context, i.e., traveling through attractive and photographed places. To evaluate the effectiveness of these routes, we implement a 3D visibility analysis tool that assesses the visual experience of the calculated tourism route. The tool enables the quantitative measurement of the environmental attractiveness in terms of how the user perceives and experiences the space through which she or he travels. Experimental results are presented for walking routes in Manhattan, New York, USA. The results show that with proper data handling, Flickr can generate rich tourism routes. The geovisualization of the 3D visibility evaluation results validates the tourism route relevance by representing the variant urban typologies and visual components that are visible from it, which affect the perception and experience of the tourist. With today's adoption of Urban Digital Twins, which are complex 3D data models allowing collaborative city-level processes [6], we believe that the 3D visibility evaluation tool can serve as a practical evaluation for various modelling and planning purposes, focusing on location-based services.

2. Related Research

Geospatial big data in social media is used for analyzing and visualizing various aspects related to the urban space. Studies have shown the contribution of crowdsourced geotagged photos for diverse applications, for example, mapping areas that are more calm and more exciting by using big data of geotagged images and audio samples [7], extracting landmarks from geotagged photos by using deep neural network [8], computing pleasant (beautiful and happy) routes in Boston and London [9], and tourism route planning [10,11]. Photography is strongly related to tourism experience [12], meaning that most tourists take photos for documentation purposes as a proof of consuming the experience of travelling a city [4], such that tourism photography is correlated with tourism development [13]. Ref. [14] examined the representations and photographic processes of tourists to be passive consumers of places or of active cultural producers. The authors argue that even though tourists participate actively in the photographic process and produce photos of very personal significance, their photos are still shaped by broader conventions, such as the

cultural construction of places, structural factors, groups of visual social conventions, having structural factors, social and visual elements that influence the tourists' destination photo. Such that the attractiveness of cities implicitly stores geographical information in social media photography [14]. This may give a clue as to how visuals affect the construction of destination image and interpretation [15]. In his book, ref. [3] explains that destination image research has its roots in a variety of disciplines considered as the perception of place for travel and tourism. It should be emphasized that a destination image is built in a complex process, which depends on the characteristics of potential tourists and on the characteristics that are important to them. The image is composed of cognitive, emotional, and conventional components, represented by organic and real substances. In this complexity, the destination image develops and unfolds within personal and social contexts before experienced. Ref. [16] emphasize that the experiences of tourists are a major issue in tourism studies. The authors conducted a walking experiment of a large sample of people traveling within a large-scale urban environment in the city of Jerusalem. They combined high-resolution location data with momentary real-time experience data in the form of objective physiological measures of emotion as well as subjective measures of emotions. The authors provide insights into the personal experience of the individual and the emotional characteristics of the city's tourist attractions, reinforcing the important significance of landmarks, also suggested in our research.

Researchers aspire to describe the complexity of the urban structure with analytical models and tools designed to represent this complexity by measuring the wide range of data available, with its numerous and varied characteristics [17]. Several studies have explored the relationship between the urban space morphology and how the users perceive its experiential qualities, some with 2D and others with 3D visual analysis. Virtual reality (VR) visualization of 3D geographic datasets is immersive and implemented for various applications, such as construction planning, simulation—to name a few [18]. Another usage is related to virtual orientation and wayfinding systems, as was implemented in the campus of Bochum university [19]. There exist various attempts of 3D visibility analysis and representations of three-dimensional isovists, proving their capacity to represent meaningful complex spatial information. The 3D Dynamic visual analysis suggested in [20] simulates and predicts the visual perception of a human moving along an urban path. This analytical model was assessed in an experiment conducted in an immersive virtual environment, using variant urban path morphologies, where the movement velocity was equal for all paths [21]. Ref. [22] carried out an experiment in which users were exposed to visual stimuli, where their route decisions were recorded. The authors showed that pedestrian navigation choices are influenced by specific visibility attributes.

Traditionally, geospatial activity of tourists has been studied using surveys and questionnaires actively filled by tourists ([10,23,24]), or by involving tourists in experiments, as suggested by [16]. Although tourism study that involves active tourists ensures that the collected data is related to tourism only, these approaches are very limited, costly and take time [25]. These documentation methods are nowadays replaced with data collected from GNSS location sensors and online social platforms, which make it possible to document and hence retrieve large volumes of geolocated data [26]. Accordingly, methods are investigated to automatically extract geotagged photos that show tourism context for retrieving knowledge and insights about tourism activity. The increasing diversity of authoritative open-source data (e.g., governmental, municipal) and user-generated personal content (e.g., geotagged locations and photos shared on online social media) has generated an increasing interest in multiple recommendations and planning systems [27]. Accordingly, when handling these data and information, two challenges exist: (1) what can be considered as relevant and informative content—and from what sources, namely requiring the retrieval of the relevant information, such as places of interest (POI), and (2) how to weight and generate routes between the predefined locations and POIs (e.g., [24,28]).

Automatic route planning systems aim at providing paths by predefined sets, such as context awareness and personalization, where most route planning solutions are considered

as OP [29]. Ref. [30], for example, provided personalized tourism routes that were based on the interest and preference of the user, while [31] enriched the road database with parameters of density and distribution of user-generated data to plan scenic routes. Ref. [24] generated routes that take under consideration constraints derived from public transit, while [32] suggested generating safe routes by avoiding areas that are considered unsafe and dangerous. Popularity and public interest are commonly considered, where [33], for example, generated routes that pass through known POIs, while relying on predefined start and end points, together with a distance constraint. Others, such as [34], propose a route planning where the POIs are extracted from the clustering of geo-tagged photos on social media, while calculating distance-optimized walking routes using a bi-dimensional nearest neighbor (NN) algorithm. Others, such as [35], combined both travel time and travel comfort to suggest routes, where [36] used the Dijkstra algorithm with weighted popularity road matrix to compute routes. Ref. [37] solved the OP by defining a sequential set of POI data to maximize the traveler satisfaction in the route planning, whereas [38] used a weight graph method for route planning.

In our research, we aim to develop a new approach that uses 3D geovisualization analysis for validating and evaluating tourism routes that rely on implicit geotagged big data stored on social media. Our developed methodology is established on accurate and highly detailed 3D-categorized geographic information, allowing us to visualize, analyze and evaluate the tourism experience.

3. Methodology

Calculating a route that maximizes the tourism experience, we crowdsource geolocations on urban attractivity that are based on the photogenic nature of places mined from Flickr photos. For this, we build on the ideas presented in [39], which will be presented here. Then, we describe the 3D visibility analysis tool used to evaluate the calculated tourism routes.

3.1. Calculating Tourism Routes

3.1.1. Photo Data

Other than the depicted object in the photos, all photos in Flickr store metadata. Figure 1 depicts an example: the background depicts all photos existing for a specific area in Manhattan, NYC, where each point represents the geographic location from which the photo was taken by the user. The table at the bottom depicts part of the metadata of that photo (location depicted in a red circle). The metadata we use for analyzing Flickr photographers' behavior and pattern in the analyzed area are: Location (X, Y), URL (of the photo), Date (time stamp when the photo was taken), and User (ID).

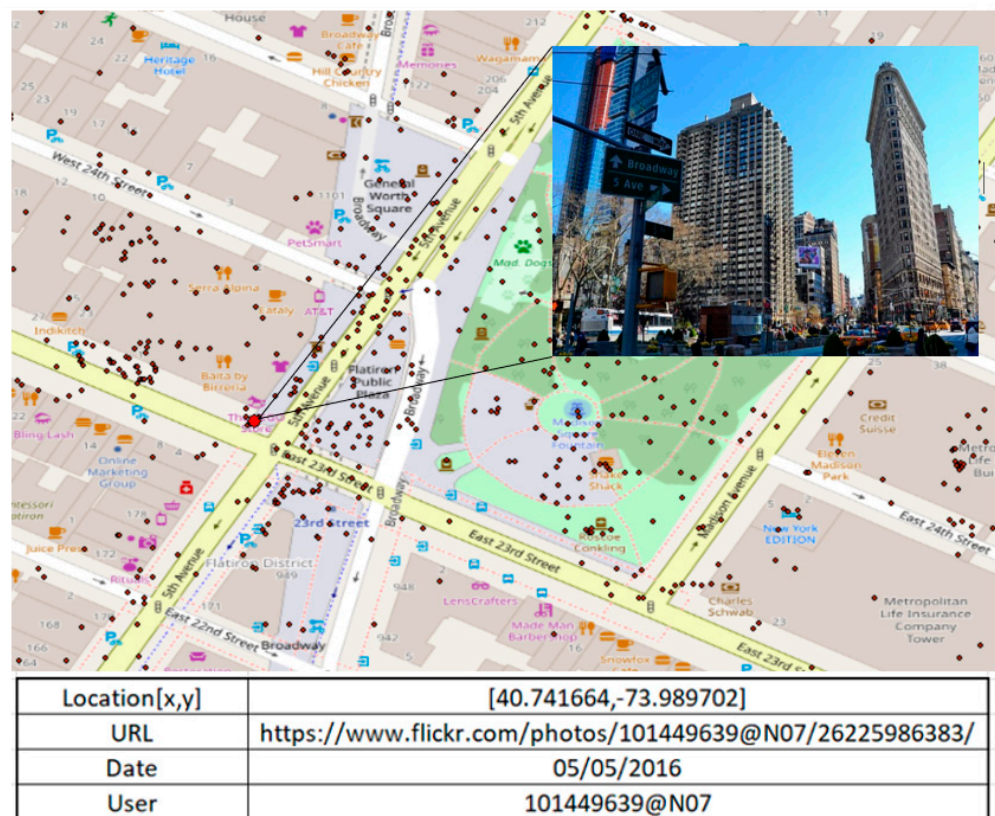


Figure 1. Broadway on 23rd street, Manhattan, NYC, with superimposed Flickr photo locations (depicted as points, background), and metadata of a specific photo (bottom). Background: Google Maps.

3.1.2. Tourism Photographer

Flickr allows users to depict and share their everyday activities and events using photos. Other than analyzing the photos (which will require image analysis), we instead investigate the users' pattern and behavior. Since we aim to calculate tourism routes, we need to retrieve photos that have tourism context, i.e., taken by tourists. This is achieved by identifying photographers that present tourism activity and tourism descriptors according to their photo-trail. According to [40,41], tourists will show comparable tourism consumption for a specific area, such that we employ a set of spatio-temporal adaptive descriptors that characterize tourism activity—and filter other photographers. The adaptive descriptors are:

1. Trip (visit) duration: the trip duration, possibly covering several days, of a single user i between the first (t_s^i) and the last (t_e^i) geotagged photograph timestamp. The average visit duration t_{avg} among n users is defined in Equation (1).

$$t_{avg} = \frac{\sum_{i=1}^n (t_e^i - t_s^i)}{n} \quad (1)$$

2. Number of photos: tourists will most likely take several photos during their trip. We count the number of photos taken by each user, whereas a threshold of at least three distant photos per user is defined (e.g., [10]) as the minimum number of visited locations that represent a photo-trail.
3. Trip distance: the accumulated traveled distance (D_u) of a specific user is calculated. A maximum threshold of fifty kilometers is used to ensure the retrieval of walking activity (as opposed to bicycle and public transportation, for example).
4. Trip speed: a single trip traveling speed V_u , including multi-day trips, is calculated (Equation (2)) according to the accumulated travelled distance D_u divided by the

time interval between the last (t_e) and first (t_s) photo timestamp. Outliers larger than 10 km/h are excluded to ensure walking activity only.

$$v_u = \frac{D_u}{t_e - t_s} \quad (2)$$

By iteratively altering the value of the average trip duration descriptor (t_{avg}), we compute the other descriptor values simultaneously for a specific area, analyzing the differentiation between iterations for defining the most common shared tourism activity descriptors. A photographer validating all descriptors is labeled as a tourist, and we store her or his geotagged photos' metadata in a data structure, depicted in Figure 2, for the consecutive stages.

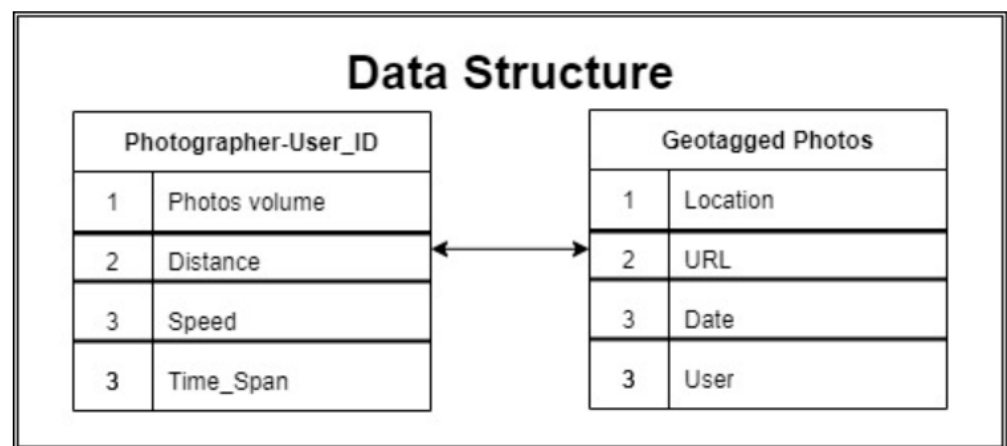


Figure 2. Data structure linking a photographer and her or his geotagged photos.

3.1.3. Popular Places Identification

We divide the analyzed area to equal sized cells to retrieve the main popular and frequently traversed locations (places of interest, POIs) visited by the photographers. Using cells allows fast and intuitive clustering of photos for each cell in the analyzed area. We use a cell size of 250×250 m (e.g., [42,43]), assuming this size represents the common grid structure of city streets, and the fact that it is rare to find adjacent attractive locations within this distance. Since we analyze walking routes that are at least several hundreds of meters, the grid cell approach ensures that each cell will have a POI, overcoming alternative clustering processes that use non-adaptive Kernel values (e.g., density-based) that can lead to numerous dispersed photos clustered to a single POI—instead of several ones (e.g., [44]). A smaller grid cell size allows the retrieval of local attractive places to compute more tuned routes; still, these routes can be less natural in terms of walkability, producing more walking deviations and detours due to the concertation of nearby numerous POIs that show lesser popularity. A centroid calculation is implemented on all the photos that fall in the cell's extent to identify the POI location. The POI should depict the physical location of the tourism attraction (e.g., landmark, site, viewpoint) that photographers documented during their trip, meaning that most photos in that cell were taken in its vicinity. For each cell, we construct a popularity measure that includes the number of photographers traversing it during their trip and the number of photos. Figure 3 depicts an example of the outcome of this process. The cell popularity is measured (ranked) according to the number of unique tourism photographers traversing the cell; in case there are no tourism photographers, the number of accumulated photos taken in that cell is used as a criterion of popularity. Cells with a higher volume of visiting tourism photographers are considered more attracting, enabling better understanding of the actual tourism consumption in the area, in terms of patterns and activities.

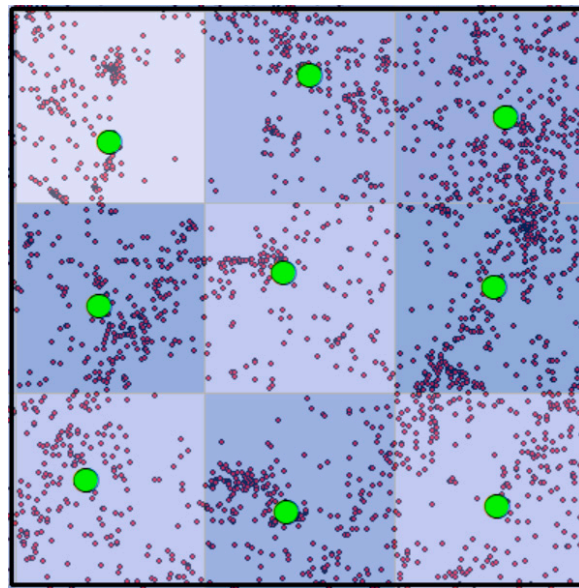


Figure 3. Photo locations are depicted in red dots, and photo centroids (POIs), depicted in green, are computed and saved in the cell data structure.

3.1.4. Route calculation

We employ a greedy heuristic route calculation algorithm that maximizes the popularity score of the recommended route based on the predefined ranking of tourism photographers and number of photos. The approach ensures fast and intuitive implementation according to the minimum distance constraint between a predefined origin and destination points, while enriching the tourism experience by traversing popular cells.

A routable graph between the origin point (S) and the destination point (T) $S \rightarrow T$ is defined as a directed graph $G = (V, E)$, where V is a set of vertices and E is a set of edges. Each vertex V_i represents a centroid of the geotagged photos in a cell. Each edge E_i indicates the transition from one cell to an adjacent cell according to the popularity transition defined from the ranking. Routing is performed from the origin point to the destination point (forward)—and vice versa (backward), whereas both routes might not geometrically coincide due to the ranking used. We employ the shortest distance to the destination point constraint, together with removing the visited cells from the data structure. Using the heuristic greedy approach will ensure crossing the cells that are the most popular along the shortest route constraint. Accordingly, a popularity score test is conducted on the forward and backward calculated routes, and the route with the highest popularity score between the two is chosen as the tourism route.

Route popularity score f for a given graph $G = (V, E)$ is defined in Equation (3), where n is the cell index, and N is the number of tourism photographers in the cell.

$$f(\text{popularity}_{score}) = \sum_{i=1}^n N_n(\text{number of tourism photographers}) \quad (3)$$

After computing the tourism route between consecutive extracted waypoints in the graph, the algorithm uses Google Maps API to consider the pedestrian road network by applying walking travel mode route computation between the waypoints (i.e., POIs).

3.2. Visibility Analysis

The tourism route evaluation relies on the Dynamic 3D Visibility Analysis model presented in [20]. This model simulates the way pedestrians would potentially observe and experience the urban environment, while allowing us to consider various characteristics and types (typologies) of the built environment, the integrated effect of the geometry of

the environment, as well as the variant elements of the view, such as surfaces, trees and vegetation, buildings and building types, roads, water bodies and the distant sky.

To carry out the analysis, we first build a detailed 3D model of the analyzed area. A Rhino 3D model of Manhattan is compiled based on a detailed 3D model acquired from CADMapper (<https://cadmapper.com/> accessed on 2 February 2021), which includes the topography, buildings/structures, parks, and water bodies. To differentiate among the various urban features for geovisualization analysis, we have distinguished by color the different elements of feature categories of the area (e.g., land use, landmarks, buildings, trees). Vegetation, i.e., small size parks and single trees, were obtained from NYC Open Data census (<https://data.cityofnewyork.us/Environment/2015-Street-Tree-Census-Tree-Data/pi5s-9p35> accessed on 2 February 2021); landmarks, land use and feature (building) categories were obtained mainly from foursquare (<https://foursquare.com/> accessed on 2 February 2021) and Zola (<https://zola.planning.nyc.gov/about/> accessed on 2 February 2021); street-level commercial facades were obtained from Google Street View. The resulting 2D representation of this process is depicted in Figure 4 (top), where Figure 4 (bottom) depicts the Rhino 3D model of the area with the urban fabric; in both images, the colors represent the different object categories used in our analysis. For example, orange depicts residential buildings, purple depicts commercial buildings, pink depicts landmarks, and green depicts trees and parks.

The 3D visibility analysis tool is implemented in Grasshopper, where according to the evaluated route, consecutive viewpoints are placed in an interval of 10 m on the sidewalks. From each viewpoint, multiple lines of sight (LOS) are spatially evenly dispersed to simulate the viewshed observed by the pedestrian, depicted in Figure 5. The LOS are created by drawing virtual lines from the viewpoint to a grid of points that are projected on a curved plane in the direction of movement along the defined path. The LOS are intersected by the first spatial opaque element or surface they meet, and their length (distance) is measured and recorded. LOS 3D distance is limited to 1 km, assuming the visible distance in an urban fabric. In case of non-intersection with objects, the LOS is defined as intersected with the sky category. The square root of the distance of the lines from the observer to the object is calculated, presuming that the closer the element, the stronger its perception and experience impact on the observer (pedestrian), and on the pattern of visibility, assuming this becomes closer to reality. Higher and wider objects have a stronger impact on the observer experience, whereas they are seen from many more LOS and viewpoints. The objects' category color is recorded, which are accumulated and stored for geovisualization analysis in terms of aggregated visibility LOS for each viewpoint on the route, in our case in terms of tourism attractiveness. The dynamic movement of walking along the tourism route—and urban path in this example—is represented as the accumulated visibility calculations of consecutive viewpoints along that path directed towards the target (destination) point. This is represented through geovisualization graphs documenting distance and intensity of visibility for each viewpoint. As formulated in Equation (4), category visibility score is defined as the accumulated LOS distance (D) between each viewpoint (i) along the path to each category object (j). The visibility analysis process in Grasshopper is done automatically, including the creation of the visibility graphs, whereas the computation time needed for each viewpoint analysis takes approximately 3 min to complete.

$$\text{Category Visibility Score} = \sum_i^n \sum_j^m \sqrt{D_{ij}} \quad (4)$$



Residential Commercial Offices Hotels Public Buildings Landmarks Trees and Parks Water Ground Sky

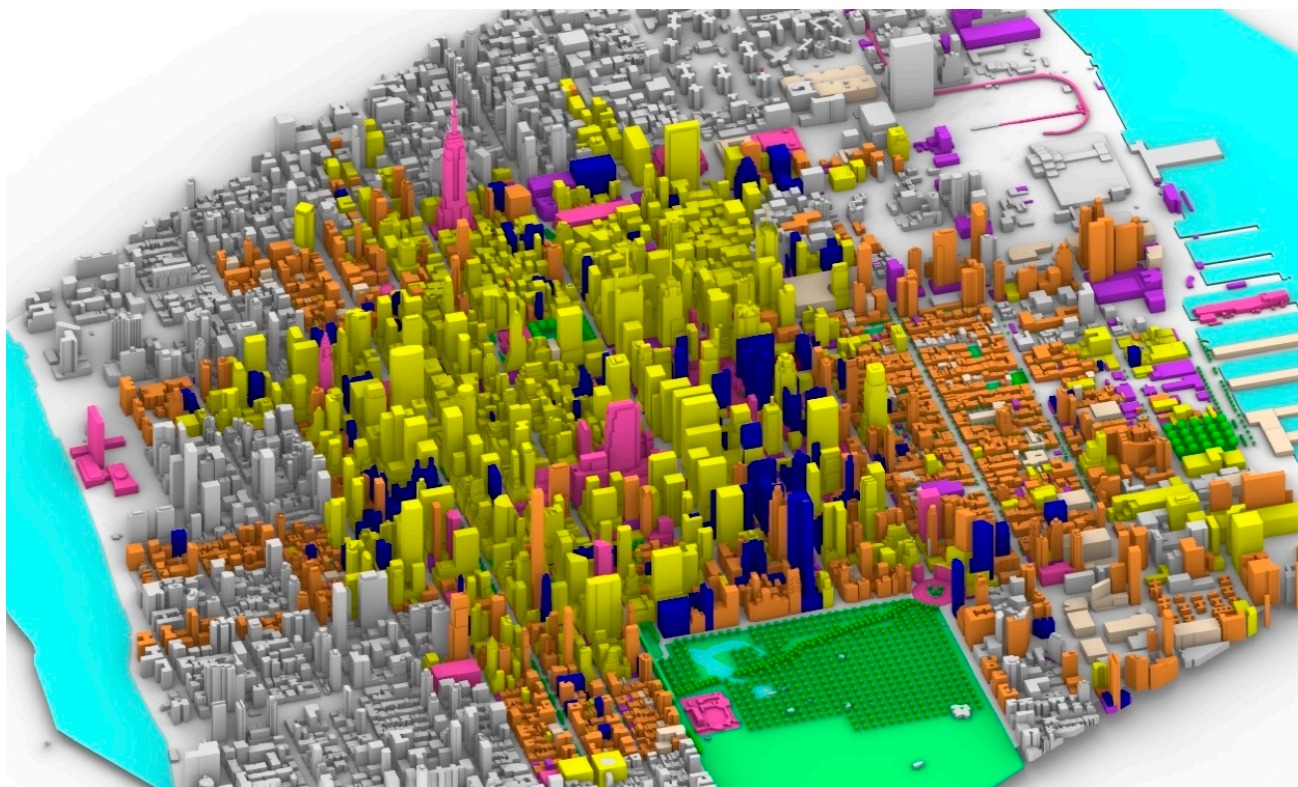


Figure 4. Colored features of different element categories in Manhattan, NYC (**top**), and the Rhino 3D model of the same area depicting the urban fabric colored according to the different element categories (**bottom**).

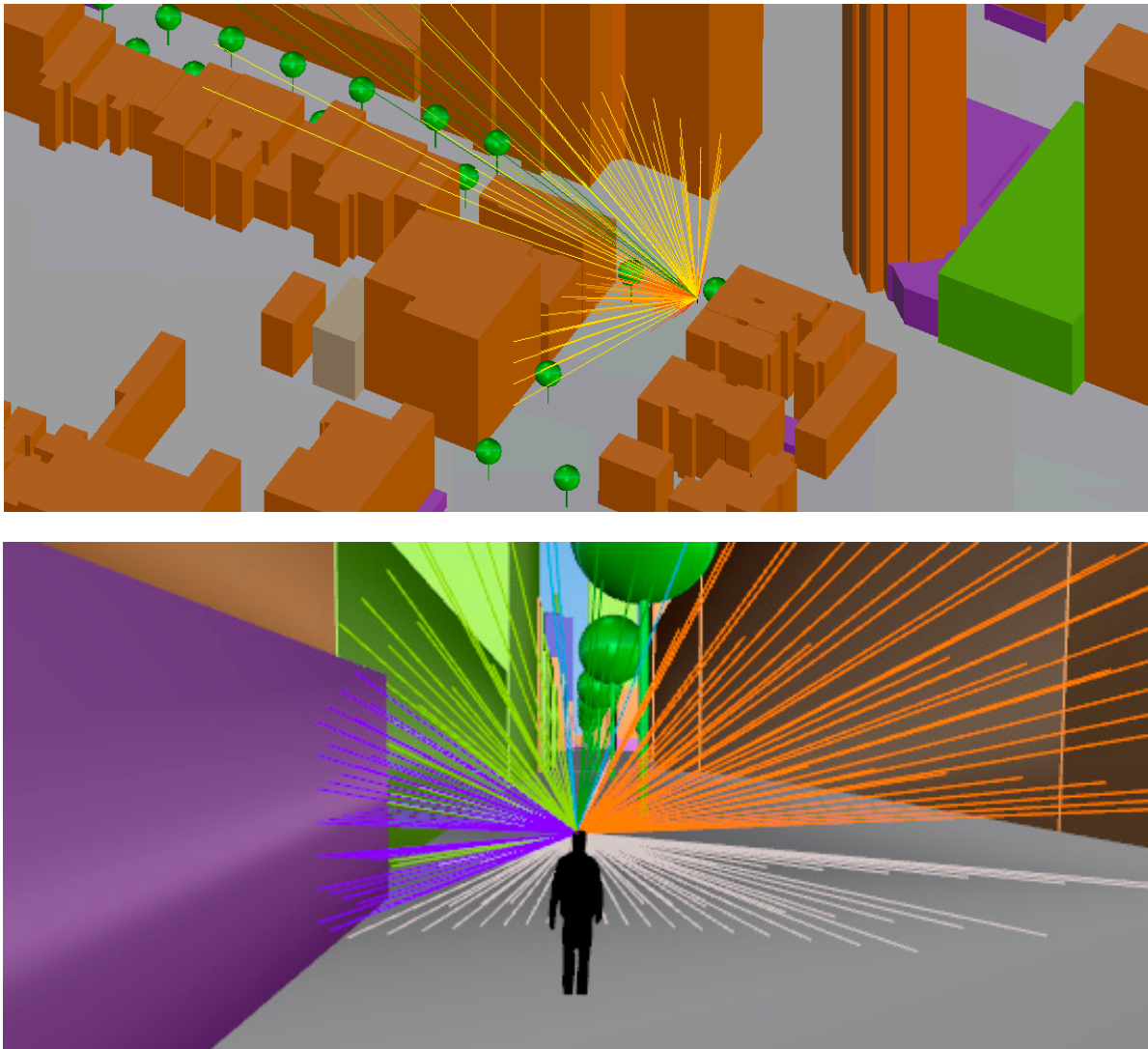


Figure 5. Simulating the visibility from a single viewpoint along the route: perspective view (**top**) and street-level view (**bottom**). LOS are depicted as straight lines in different colors according to the urban fabric element category they meet.

4. Experimental Analysis

Evaluation is made for Manhattan, NYC, USA; Flickr photos were downloaded for a period of 6 years, from 2010 to 2016. Table 1 depicts the main statistics of the Flickr photo data used.

Table 1. Main Flickr photo data statistics for Manhattan.

	Number of Users	Area (Sq. Km)	Photo Volume
Manhattan	22,665	14 × 15	358,691

4.1. Tourism Photographers

A minimum route distance value of 1 m and a minimum time interval of 1 s of photographer trajectory were defined to filter irrelevant and meaningless data. Using these two thresholds, the number of users (photographers) has decreased by more than 50% to 9026. After the preliminary filtering, the adaptive descriptors presented in Section 3.1.2 are computed iteratively and simultaneously, extracting the shared tourism activity related to the tourism photographers' travel trajectories in Manhattan. The volume of photographers per trip duration is decreasing, whereas most photographers exist for between one and five

days. Additional parameters statistical analysis, such as the average travel trip distance and the average photo number, shows that their values do not change substantially on this time duration.

Accordingly, we have defined a value duration of five days to define the walking tourism activity and travel characteristics of the analyzed area in Manhattan. This value was cross-referenced with official reports from Manhattan, whereas a survey made by the Alliance for Downtown New York (<https://www.seatehcity.com/nyc-tourism-facts-statistics/> accessed on 2 February 2021) in 2018 found that the average number of days tourists stay in Manhattan is 5.5. This supports our assumption regarding the tourism activity in our analyzed area, validating our holistic approach to work with adaptive calculated values.

Analyzing the tourism photographers' trajectories distribution reveals that most are clustered around the city centers—a pattern that is not associated with residents of the area—which corresponds to the findings of [45]. The speed threshold helped to exclude photographers traveling long distances over a short time, which should resemble a travel mode other than walking. As a result, approximately 20% of all the users (photographers) were identified as showing tourism characteristics.

4.2. Popular Places

We use Moran's I for the validation of popular places retrieval. Moran's I is a spatial analysis tool used to measure the global and local spatial autocorrelation of data [46]. Local Moran's I is used to analyze the data distribution and difference between spatial clusters of photos and photographers based on the number of features in each group, while relying on the grid cell partition of space. We implement the spatial autocorrelation (Moran's I) according to the feature-based analysis using the Global Moran's I statistics. The global test checks the complete spatial patterns distribution of all data. This test examines whether the data is clustered, dispersed, or randomly distributed.

Global Moran's I analysis is implemented, with the results of the hypothesis test detailed in Table 2, indicating that the null hypothesis (z-score) is rejected for photos and photographers, which means that the positive value for Moran's I index of both photos and photographers indicates that spatial clusters exist in 99% confidence.

Table 2. Statistical results of Global Moran's I correlation test for photo- and photographers-based popularity score.

Variable	Photos	Photographers
Moran's Index	0.45	0.39
Expected Index	0	−0.0006
Variance	0	0
Z-score	252.09	117.67
p-value	0	0

The Anselin Local Moran's I is implemented to examine the spatial correlation of the examined feature of interest [47]—in our case, the popularity score of photos vs. photographers. If no outliers are detected, the popularity score is statistically clustered. The cluster and outlier analysis (Anselin Local Moran's I) tool in ArcGIS is used for the analysis.

Figure 6 depicts the cluster analysis based on Moran's I Anselin local analysis. The left image depicts our approach, in which only the tourism photographers are clustered, while the right image depicts all photo clusters exist in the area. The left image presents a clear distinction among different neighboring cells having varying values, making it easy to identify more popular locations in the area that are highly clustered—High-Low outliers (hot-spots). It is also easy to identify less popular locations that are tagged as Low-

High outliers (cold-spots). Unlike, the right image is much more homogenous, showing relatively similar cluster values for neighboring cells represented by High–High clusters, distributed uniformly in the central area of Manhattan, which makes it hard to identify the more popular locations. This proves that using tourism photographers, instead of photos, helps in revealing the popularity and attractiveness of different areas that are derived from tourism photographers’ activities and patterns.

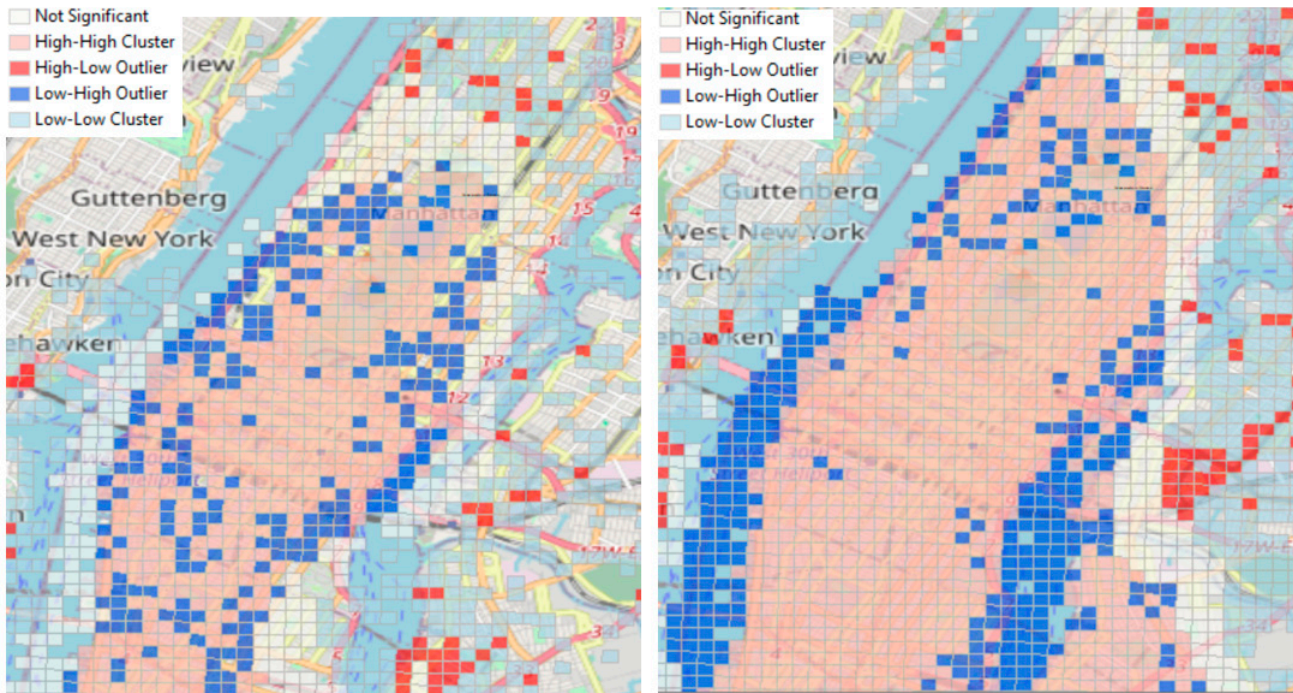


Figure 6. Heat map cluster analysis comparison (based on cluster Moran’s I analysis): tourism photographers-based (left) and photo-based (right) (background: OpenStreetMap).

4.3. Case Study I

4.3.1. Route Calculation

Applying our algorithm for cell-trajectory analysis, we retrieve a map depicting cells and areas that are more popular than others, defined by the number of tourism photographers that traverse each cell. Using Google Maps geospatial map layer, the user selects the origin and destination points for which she or he would like to calculate the walking tourism route. Our algorithm automatically computes and recommends a comprehensive walking route for the user that maximizes the tourism popularity score. Two case studies are investigated and evaluated, depicting two routes that are characterized by well-known and popular locations in Manhattan, NYC. Although both routes traverse central Manhattan, they are different in terms of their environmental and urban fabric setting, allowing us to validate and examine the 3D visibility analysis approach for a variety of category classes of tourism walking routes. Case study 1 is defined between Grand Central Terminal and Manhattan Cruise Terminal, a more homogenous east–west route in central Manhattan that traverses some of the most popular tourism landmarks in the area (e.g., Times Square). Case Study 2 is defined between Central Park Zoo and the Empire State Building, a north–south route in central Manhattan that is considered more heterogeneous, traversing popular shopping streets and tourism attractions—as well as scenery with open green spaces.

For case study 1, the forward route is considered more touristic due to its higher popularity rate: 568 accumulated tourism photographers, with respect to 282 in the backward route, validating that the optimal tourism route passes through more popular cells

(maximum f-popularity score). Figure 7 depicts the resulting walking routes computed by the algorithm, which for comparison purposes—the shortest route generated by Google Maps—were approximately 5.2 km and 3.0 km in length, respectively. The figure shows that the tourism route passes through the main attraction locations in the area existing between the defined origin and destination points. These main attractions are commonly presented and highly ranked in tourist guidebooks and websites, such as TripAdvisor. Although location 6 does not appear in TripAdvisor, it does not mean that it is not an attraction; on the contrary, the popularity measure shows that this location—Hell’s Kitchen and a photographing opportunity of the area—is very popular among tourists, attracting many photographers, such that it can be included in the planned route.

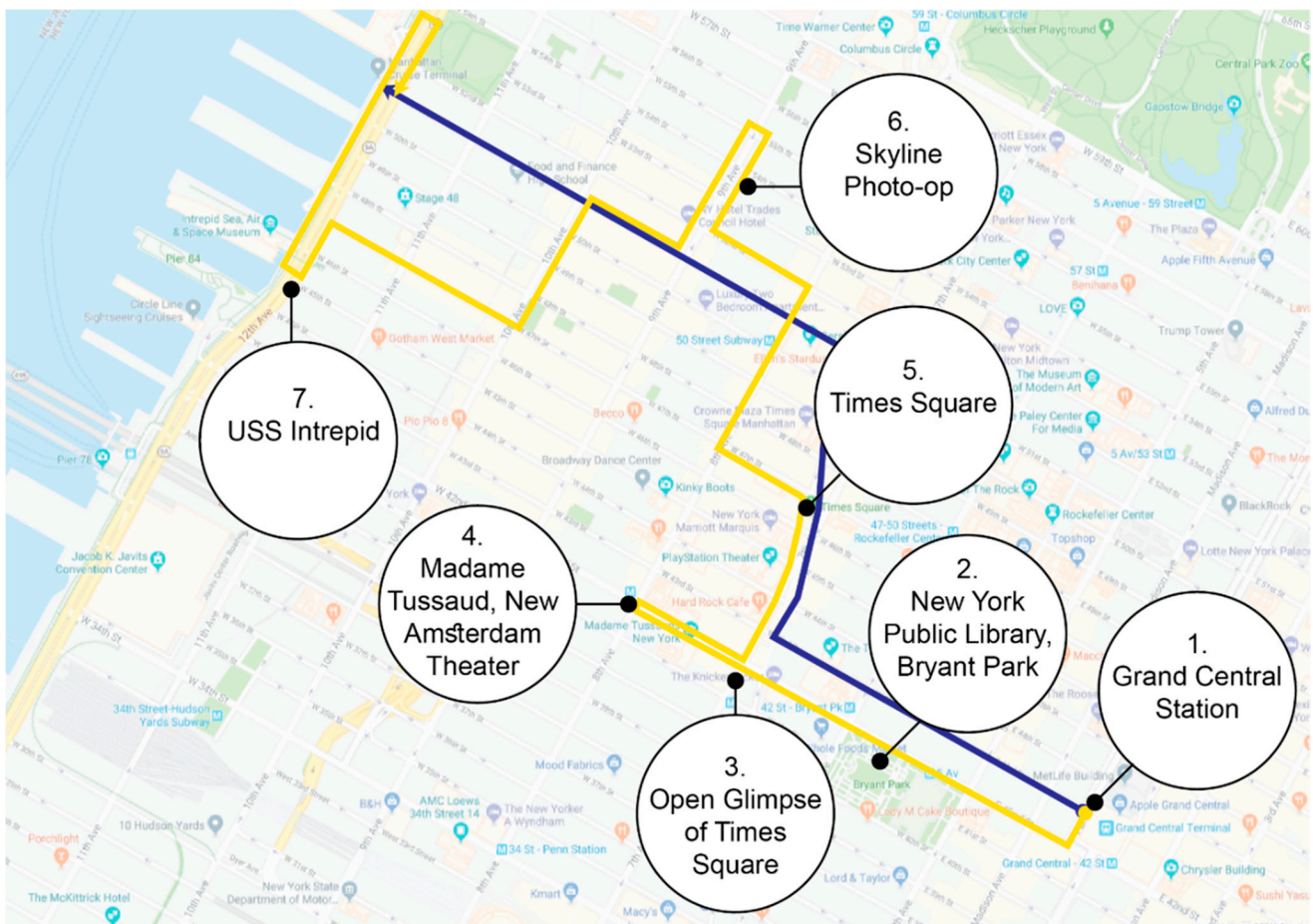


Figure 7. Tourism walking route in Manhattan (case study 1) computed by our algorithm (yellow) and the shortest path according to Google Maps (blue), with the identified landmarks and attractions along the routes (background: Google Maps).

4.3.2. Quantitative 3D Visibility Evaluation

To validate the proposed tourism route planning methodology and results, we carry out a quantitative evaluation with the 3D visual analysis tool, which comparatively analyzes and assesses the visual experience of a user walking in the tourism route. To quantitatively understand and visualize the outcome of the 3D visual analyses, we geovisualize all object category types by graphs, depicted in Figure 8, where the X-axis is the accumulated walking distance of the viewpoints along the path (route), and the Y-axis is the square root of the distance of the lines from the observer to the object. For comparative purposes, we also present the shortest route. The shortest path has 275 viewpoints, half the length of the tourism route, having 547 viewpoints. Figure 9 depicts the landmark category type (depicted in pink), where we can see that the tourism route has seven land-

mark peaks, which correspond to the landmarks depicted in Figure 7, dispersed along the route, meaning that it is rich with these objects, having a high peak -sequence and -magnitude; the shortest Google Maps route depicts a single landmark, which is Times Square. The geovisualization of the 3D visibility analysis validates that the overall impact and experience of landmarks is very high in the tourism route, giving the pedestrians a heterogeneous and attractive walking experience, which is the result of the accumulated knowledge retrieved from the Flickr tourism photographers’ trajectories.

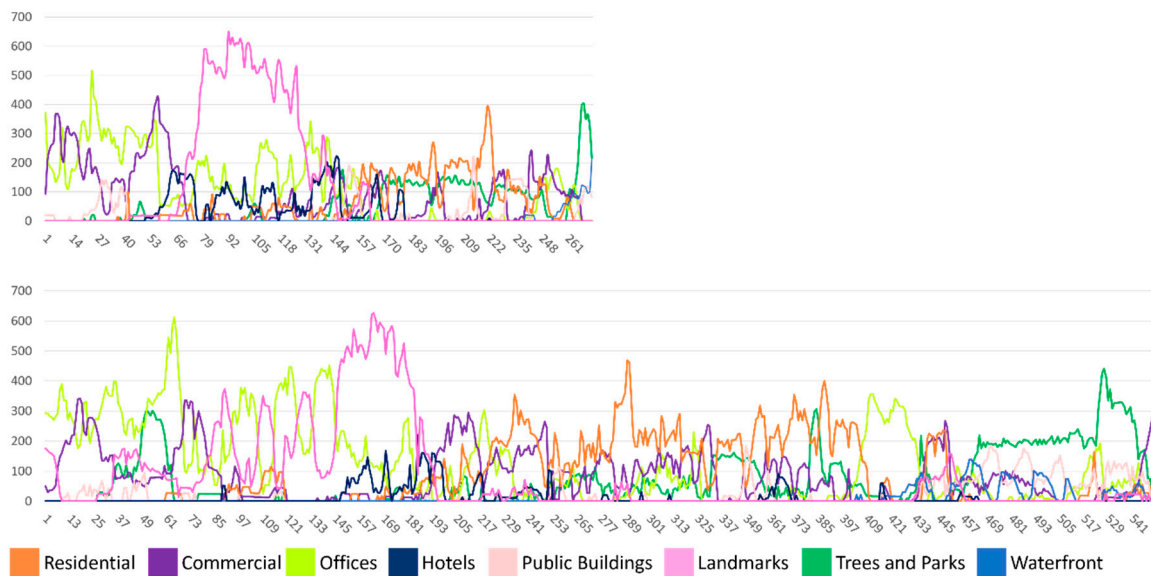


Figure 8. Geovisualization graphs of case study 1 generated by the 3D visual analysis tool for all feature category types, produced for the shortest route (**top**) and the tourism route (**bottom**).



Figure 9. Cont.

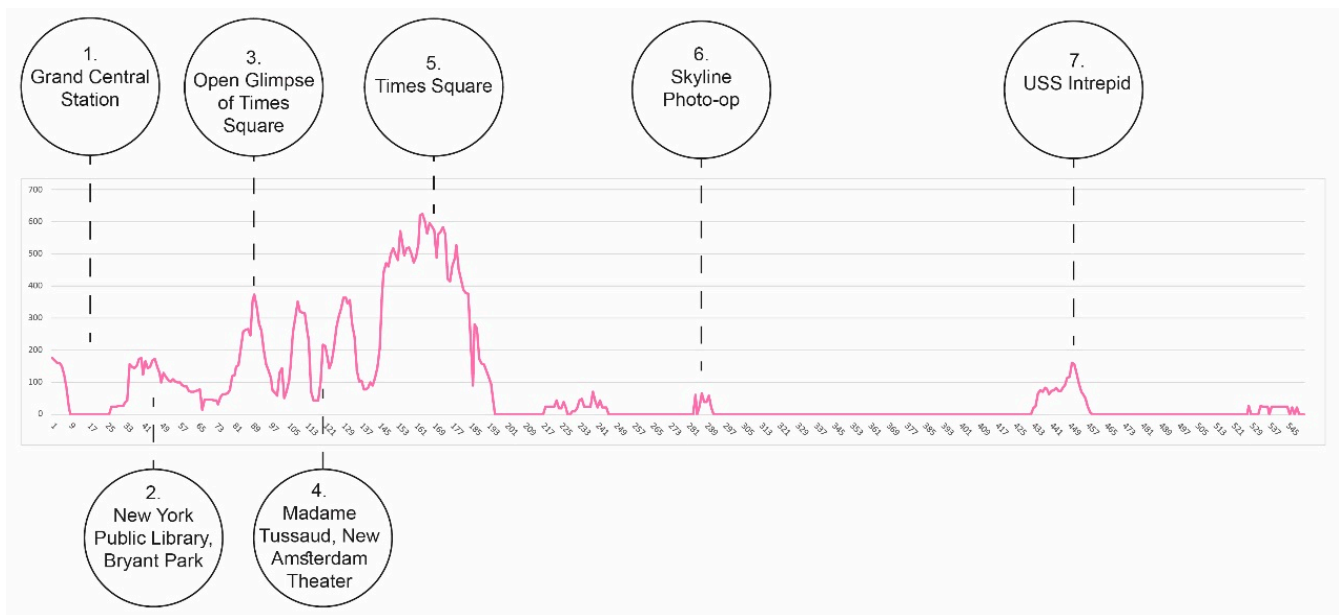


Figure 9. Geovisualization graphs of case study 1 showing the landmark category type (pink) visible from both routes: the shortest route (**top**) and tourism route (**bottom**). A simulation of the 3D visualization scenery from the pedestrian perspective in Times Square is depicted on the right.

Other than landmarks, we can see that a tourist walking the tourism route perceives a rich and attractive overall walking experience. This is depicted in Figure 10 that shows the magnitude and sequence of green areas and open views that is perceived from trees, parks, and waterbodies (waterfront in Manhattan). This further proves the potential of 3D visibility analysis that generates a more comprehensive understanding on the user experience, by quantifying additional elements that have a positive affect and are observed by the user. This also means that the tourism route traverses lower buildings density that allows better view options on the surrounding area. Accordingly, the 3D visibility tool delivers a comprehensive understanding on the built environment and the corresponding relevance of the route, in which other evaluation processes could not provide.

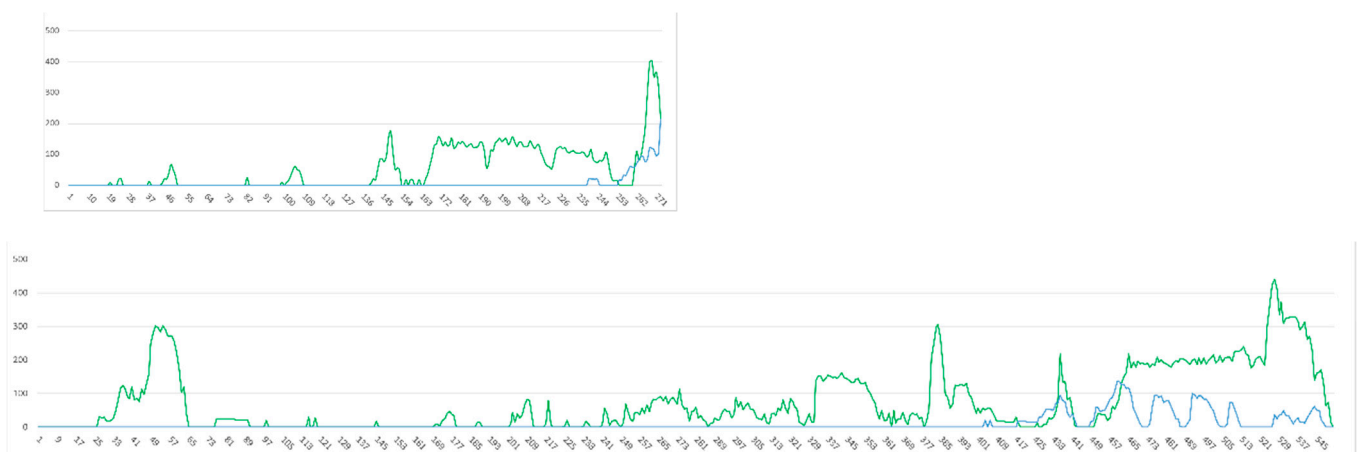


Figure 10. Geovisualization graph of case study 1 showing the green objects category type (green) and open sky category type (blue). The shortest route (**top**) and the tourism route (**bottom**).

4.4. Case Study II

4.4.1. Route Calculation

The origin point is Empire State building, and the destination point is Central Park Zoo. Figure 11 depicts the resulting tourism walking route, which passes through main landmark and attraction locations in the area existing between the defined origin and destination points, validating that it traverses more popular cells using the maximum f-popularity score. The attractions include the Chrysler Building, Grand Central Terminal, view to Rockefeller Center building, 5th Avenue, and Bryant Park. Furthermore, in its north part, the tourism route makes a detour inside Central Park, revealing a scenery view route that is traversing through main popular POIs inside the park—a detour calculated thanks to the popularity measure generated from the existing photos.

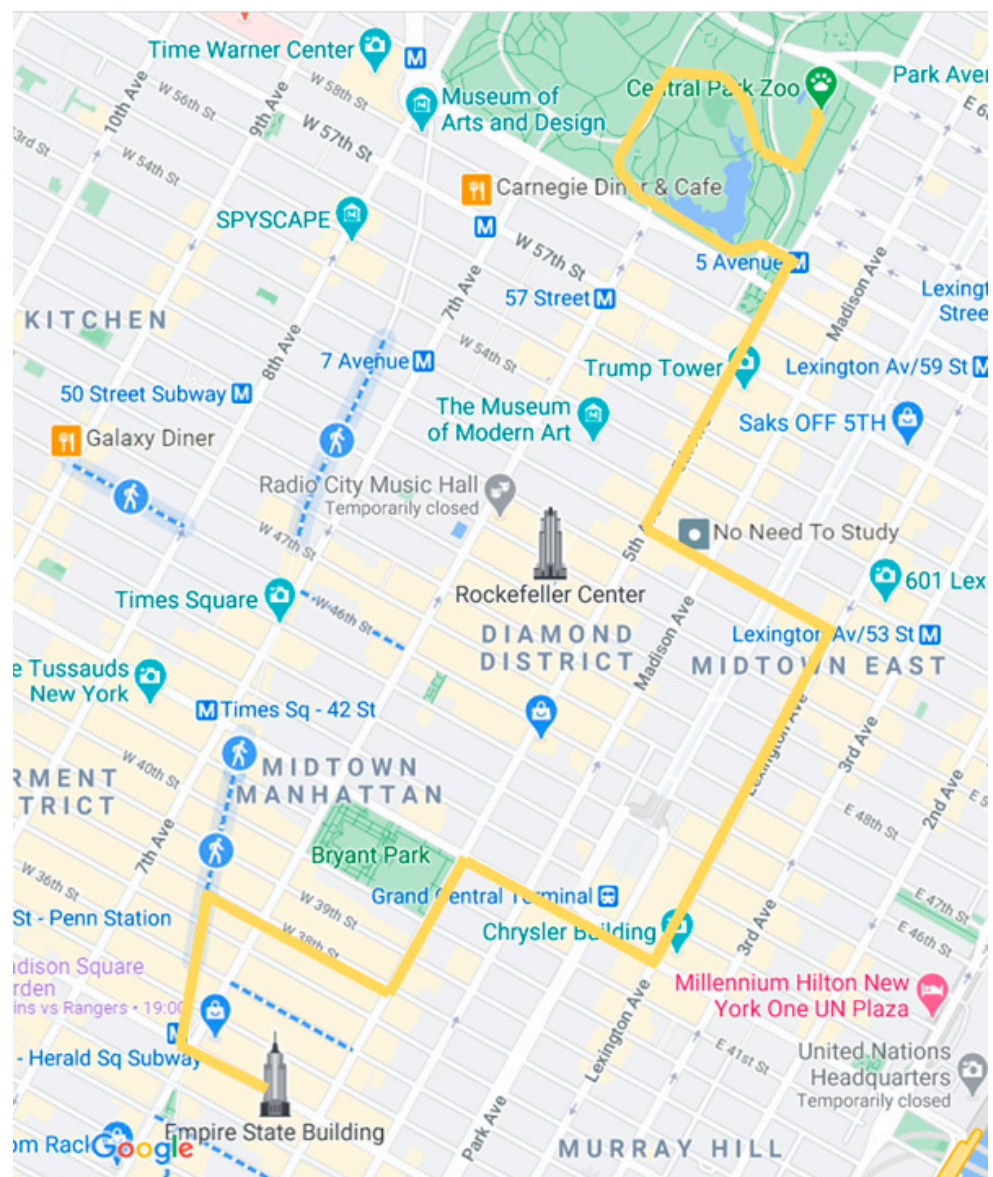


Figure 11. Tourism walking route for case study 2 traversing the main landmark and attraction locations in the area (background: Google Maps).

4.4.2. Quantitative 3D Visibility Evaluation

As in case study 1, the 3D geovisualization of the 3D visibility analysis proves that the overall impact and experience of landmarks is very high in the tourism route. Depicted in

Figure 12 (top), the tourism route is passing through many landmarks that are distributed along the route, revealing a rich and attractive overall walking experience. In addition, as depicted in Figure 12 (bottom), the magnitude and sequence of green areas and open views, specifically where the route traverses through Central Park in its final segment, emphasizes the scenery and attractiveness of the route that is clearly identifiable by the geovisualization of the 3D analysis, contributing to the overall user experience that have a positive effect.

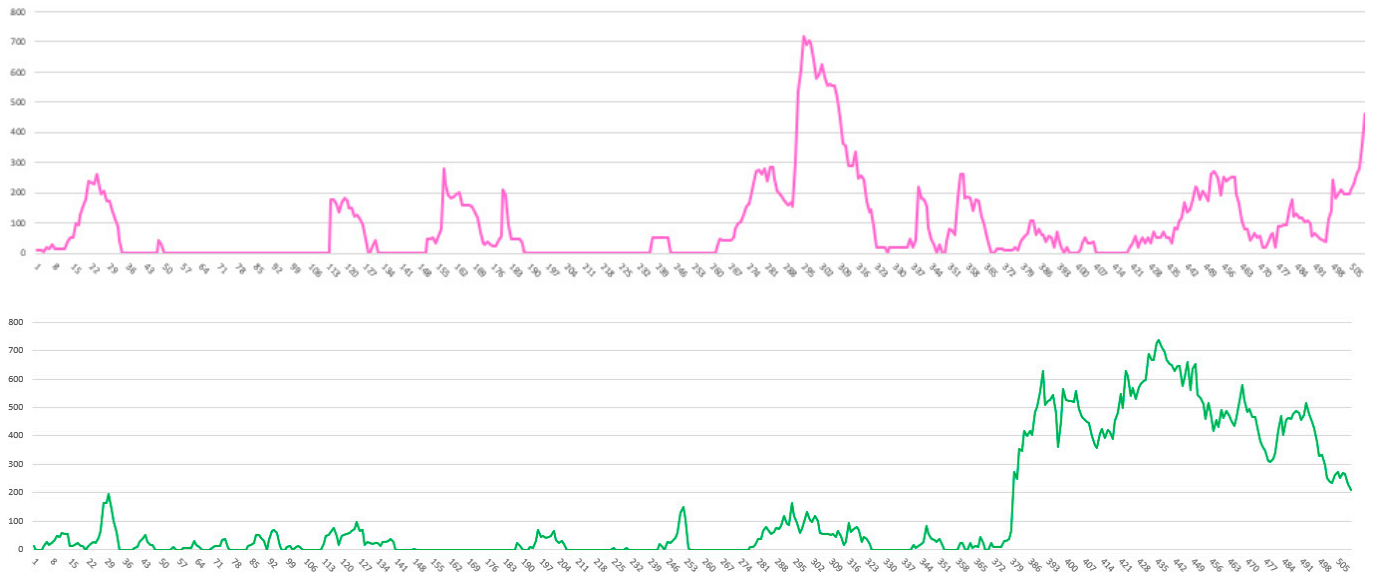


Figure 12. Geovisualization graph showing the landmark category type (pink, **top**) and the green objects category type (green, **bottom**) visible from the tourism route of case study 2.

Strong correlation between the 3D visibility analysis and the extent of urban attractiveness of pedestrian routes commonly travelled by tourists was found. The 3D visibility analysis model clearly demonstrates its potential to identify high visibility indices of elements associated with tourism and leisure (such as visibility to landmarks and views of greenery, trees, and bodies of water). It also further validates our assumption of using crowdsource social media photo data that can generate attractive qualities, especially for areas and sites that are not marked as tourist attractions on traditional tourism platforms. Moreover, the 3D visibility analysis was found to provide with qualitative prediction related to the extent of attractiveness of urban pedestrian routes. Based on this model, location and sequence of attractive pedestrian routes may be planned for the comfort of urban tourists.

5. Discussion and Future Work

This research proposes an innovative alternative evaluation for tourism route planning, where we consider the user experience thorough visual perception, which shapes the travel experience. The route evaluation tool relies on 3D visibility that allows quantitative analysis of the frequency and magnitude of the visibility to specific urban spatial element types, or a combination of such elements (heterogeneity versus homogeneity). This allows a better understanding on a particular spatial experience that is unique to a given route.

To evaluate the tool, we explored the use of crowdsource social media photos, Flickr in our case, as a source for aggregating urban attractiveness to compute rich tourism walking routes. Based on the Flickr photo dataset, a set of spatiotemporal descriptors was developed to identify photographers that present tourism activity. Using this information allowed us to automatically retrieve popular POIs that were used to calculate tourism routes according to origin and destination points defined by the user. Adequately deducing trajectories of photo trails serves with information on the visual appeal of the urban environment. We

chose Manhattan, NYC, as a case study, which presents a mixed urban fabric that is very rich and vibrant, having many tourism attractions. The computed routes pass through the main popular landmarks, attractions, and sights existing between the user-defined origin and destination locations, making sure the user has a tourism experience while walking in an unfamiliar area. The quantitative 3D visibility evaluation confirmed that the visual experience of the recommended tourism route is worthwhile, crossing well-known tourism attractions and unmarked attractive locations, as well as traveling in less dense areas (low buildings), enriching the user with views and parks and overall tourism experience. This additional information on the route quality and experience could not have been retrieved otherwise.

Tourists and locals are two main pedestrian groups that take photos to describe their experience in the urban environment. Each group can be divided to subgroups, whereas the division can be oriented by different perspective and approaches, e.g., cultural and scenery. Although in this research we treated photos taken by locals as noise, still, locals' activity and behavior can provide more comprehensive global experiences of a large number of general users who see the attractiveness in specific urban settings, discovering new and less familiar places, leading first time visitors to scenic routes between major attractions. A more comprehensive investigation should be conducted with the aim to correctly integrate both groups, which can contribute with more comprehensive tourism consumption to effectively improve recommended tourism routes. We also plan to analyze the tourism score as part of the 3D visibility analysis calculation for improving the weighted visibility score of our geovisualization analysis and use space syntax indices to adjust the visibility score compatibility to the urban vicinity.

Traditional tourism routes evaluation can be limited, relying on surveys, which are costly, timely and limited, or simply counting the number of visited landmarks. This research is a step towards the utility of 3D visibility and attractivity analysis as a valid method to define effective walking routes for tourists. Integrating 3D geovisualization analysis with crowdsourced user-generated content for computing and evaluating tourism walking routes allows us to generate a more comprehensive and up-to-date depiction of tourism perception and consumption in urban spaces. The results of this study can contribute to tourism consumption and urban planning, mainly since contributed user experience in online social media are becoming customary, storing information that might not exist elsewhere, together with the fact that the update-rate is very high. Overall, we believe that the results obtained, and insights gained from this research are very promising, having the capacity to assist urban planners to plan new attractions in different locations in their cities by better understanding the existing tourism activities, exposing areas that are less frequently visited. Furthermore, the results can help in developing transportation infrastructures and advertisement services to better connect tourists to different attractions. Tourists will be able to navigate and tour in unfamiliar destinations with no a-priori knowledge, while timely and relevant tourism data stored in online crowdsource social media will contribute to and support the development of context-aware tourism routes attuned to their interests and criteria. The 3D visibility analysis tool can contribute to the sustainability of cities, promoting new pedestrianism and walkability. With today's unprecedented use of complex 3D databases and models, the use of Virtual Reality and adoption of Urban Digital Twins, this tool can become the foundation for experiential location-based services carried out by policy makers and urban designers and planners as part of the smart city vision.

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