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CURRENT ISSUES IN METHOD AND PRACTICE

Using city-bike stopovers to reveal spatial patterns of urban attractiveness

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ABSTRACT

We demonstrate how digital traces of city-bike trips may become useful to identify urban space attractiveness. We exploit their unique feature – stopovers: short, non-traffic-related stops made by cyclists during their trips. As we demonstrate with the case study of Kraków (Poland), when applied to a big dataset, meaningful patterns appear, with hotspots (places with long and frequent stopovers) identified at both the top tourist and leisure attractions as well as emerging new places. We propose a generic method, applicable to any spatiotemporal city-bike traces, providing results meaningful to understand the general urban space attractiveness and its dynamics. With the proposed filtering (to mitigate a selection bias) and empirical cross-validation (to rule-out false-positive classifications) results effectively reveal spatial patterns of urban attractiveness. Valuable for decision-makers and analysts to enhance understanding of urban space consumption patterns by tourists and residents.

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Bike-sharing system; urban space; tourist hotspots; tourist attractiveness; spatial-data; digital footprints

1. Introduction

Identifying urban places attractiveness and quantifying it is of high importance for policymakers, who can better design a city for city users; for the users, who may know which places are attractive; and for the local economy, which can find the optimal locations for their businesses. Yet urban space attractiveness is not at all easy to define, delimit and quantify. Cities are used by various groups, from daily commuters, through local visitors, business travellers, to tourists. Each with various activity patterns, needs, and perceptions of urban space attractiveness. They collectively create complex spatial patterns, dynamically changing with emerging trends and fashions.

In this study, we demonstrate how big spatiotemporal datasets of mobility traces may be used as a proxy revealing the attractiveness of urban spaces. We contribute to the research stream where large sets of aggregated digital footprints are analysed to provide novel insights into how people experience the city (Girardin et al., 2009). By utilizing a relatively less exploited dataset (city bike traces) and exploring its unique feature (so-called stopovers) we reveal meaningful and valuable spatiotemporal patterns.

1.1. Literature review

In this section, we first introduce the notion of urban attractiveness for tourists and local users along with methods to quantify and measure it. Then, we review a variety of recent methods leveraging on

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big datasets of digital footprints and their application to urban attractiveness. Finally, we discuss city-bike systems and a unique feature of digital footprints left by city-bike users – stopovers.

1.1.1. Urban space attractiveness

Following the definition of Biernacka and Kronenberg (2018), the urban space is *attractive*, when one willingly wants to use it and spend her/his time there, and when this space corresponds to one's individual needs, expectations, and preferences. Attractiveness of urban space is not at all easy to define, delimit and quantify (Boivin & Tanguay, 2019), with a substantially different perception of urban space for tourists and locals (Kianicka et al., 2006), notwithstanding both user groups are now better understood thanks to recent studies. For instance, through the indicators to measure urban quality proposed by Garau and Pavan (2018), or with 'City Love Index', lately introduced by Kourtit et al. (2020), which pinpoints attractiveness characteristics based on perceptions of urban quality by residents and their affinity with city life. Residents' urban space consumption is associated mainly with their daily activities (Gonzalez et al., 2008), however, its attractiveness for leisure purposes becomes increasingly significant (Thees et al., 2020), better understood (Johnson & Glover, 2013) and quantified (Biernacka et al., 2020).

Likewise, the tourists' behaviour is better understood (for a thorough review we refer to Cohen et al. (2014)) through a study where various segments (Stangl et al., 2020), activity-based profiles (Fieger et al., 2019), sociodemographic groups (Md Khairi et al., 2019) or groups with specific needs (Lee & King, 2019) are identified. By means of tourist surveying (Jacobsen et al., 2019), stated preference experiments (González et al., 2019), or semi-structured interviews (Kianicka et al., 2006) attractiveness is typically related to a set of site-specific attributes (Estiri et al., 2020) or individual visitors' perceptions (Cracolici & Nijkamp, 2009; Lee & King, 2019). Which, in turn, allows for a refined notion of tourism attractiveness at a national (Mitra, 2020), regional (Cracolici & Nijkamp, 2009), city (Van der Ark & Richards, 2006), or site (Jacobsen et al., 2019) level. Which, however, becomes challenging when within-urban attractiveness needs to be delimited (Zhu, 2020).

While attractiveness at the macro-level can be identified via surveys, observing tourist movements plays a fundamental role in understanding their behaviour within the urban space (McKercher & Lau, 2008). To this end, tourists' spatiotemporal behaviour – encompassing trajectories (movements between activities) (Zakrisson & Zillinger, 2012) and stops (either at attractions, or to eat, rest, do shopping, etc.) (Caldeira & Kastenholz, 2020) – is analysed with implicit assumption that, in general, consumers of urban space spend more time in attractive spaces (Gehl, 2011).

In such context, the movement along the multi-attraction itinerary can be observed (Huang et al., 2020), with participation time (Caldeira & Kastenholz, 2020), time spent per bloc (Espelt & Benito, 2006) or tourism-related intensification patterns (Encalada-Abarca et al., 2021) used as attractiveness intensity indicators. Early attempts to track tourists' movements using mental maps or self-completion diaries and surveys were usually time consuming and thus applied only on small sample sizes (Keul & Kühberger, 1997; Thimm & Seepold, 2016).

1.1.2. Digital footprints

Digital footprints are now available in big volumes from numerous sources (Li et al., 2018) which, coupled with a new kind of tourist that is avid for online content and predisposed to share information on social media, allows for a better understanding of tourist behaviour regarding their spatial distribution in urban destinations (Encalada et al., 2017).

Big volumes of data and its high availability seem to overweight limitations, mainly inherent selection bias (Salas-Olmedo et al., 2018). Consequently, big data in smart tourism (Li et al., 2017) contributes to understanding spatial patterns around urban tourist destinations and, for instance, to differentiate overcrowded places from those with the potential to grow, allowing decision-makers to revisit planning and managing towards a sustainable 'smart' future.

User-generated social media content (photos on *Twitter, Instagram, Flickr*, etc. or recommendations and reviews on *TripAdvisor* or *Booking*) have been widely explored in numerous studies

(Giglio et al., 2019; Hasnat & Hasan, 2018; Kádár & Gede, 2021; Li et al., 2018; Miah et al., 2017; Önder et al., 2016). Recently Martí et al. (2021) used *Instagram* data to reveal a detailed picture of urban areas with the most tourism-related activities – i.e. sightseeing, shopping, eating and nightlife – in Spanish cities.

While such data may reveal spatial patterns, it does not track tourist movements, which requires geo-location data from personal devices (mobile phones) or vehicles (e.g. rental cars, scooters or bikes). GPS traces were used e.g. by Girardin et al. (2009) to provide insights into the attractiveness of urban space in NYC; by Orellana et al. (2012) to explore visitor movement patterns in the Dwingelderveld National Park; by Smallwood et al. (2012) to understand distance decay in destination choice. Zheng et al. (2017) used GPS to predict the next destination within a Summer Palace in Beijing and Ferrante et al. (2018) tracked cruise passengers at the destinations.

1.1.3. City-bike mobility traces

Lately, bicycle sharing has become increasingly popular around the world, making usage datasets big enough to study urban dynamics and aggregate human behaviour (Froehlich et al., 2009). City-bike systems store records of trips with their origins, destination, and travel times in publicly available big databases, which allows for a rich understanding of mobility patterns (Cantelmo et al., 2019). Number of recent studies have used city-bike data e.g. to identify potential locations for new stations, estimate bicycle flows and usage, understand social and demographic context or predict usage in real-time (Caulfield et al., 2017; Eren & Uz, 2020; Frade & Ribeiro, 2014; Imani et al., 2014; Salon et al., 2019; Tran et al., 2015; Wang & Akar, 2019). Parallel studies investigate how bike trips are affected by urban space factors such as: the number of retail stores and business offices near bike stations (Lin et al., 2020), demographic features (Wang & Lindsey, 2019) or land-use (Kutela & Teng, 2019).

How city bikes are used by tourists was also studied. Vogel et al. (2011) identified that stations dominating between noon and afternoon were located directly near tourist hotspots, Brinkmann (2020) has shown differences in city-bike usage between tourists and frequent users in Rio de Janeiro and Miami Beach. Buning and Lulla (2020) revealed different usage patterns between local residents and visitors, showing that visitors primarily use city bike for leisure-based urban exploration, while residents' use bikes mainly to commute. However, up to our knowledge, the unique feature of city-bike traces – stopovers was not exploited so far.

1.2. Study overview

Core of the proposed method lays in the concept of a *stopover* (introduced in Banet (2021)), a short stop made by a city-bike user during her/his trip. Bicycle is not returned at the station but stays with the user during a stopover. Stopovers are typically short, since for longer stops users typically return bicycles to the docking station due to the time-based fare scheme. Stopover is not related to traffic, as we explicitly filter traffic-related stops e.g. at traffic lights. With such a notion of stopover we may limit it to non-commuting trips since commuters rent bikes to quickly reach the destination rather than to have stopovers.

Users may stopover for a variety of reasons. The actual interpretation of the stopover depends on the user type. We introduce *city-bike users* typology in Figure 1. Since the user details are missing, we cannot distinguish commuters (using city bike to reach their workplace), from local recreational users (having a weekend tour around green areas of the city), from business visitors (using city bike to reach the dinner with a client) and tourists (using city bike to visit recommended tourist destinations).

Nonetheless, we hypothesize that if a city-bike user stops where she/he does not need to, it is mainly due to the place's attractiveness, which may be either touristic, recreational, commercial or of any other kind. We further hypothesize that places where stopovers are frequent and long (following Gehl (2011)), denoted urban *hotspots*, are attractive. Such hotspots may be both isolated

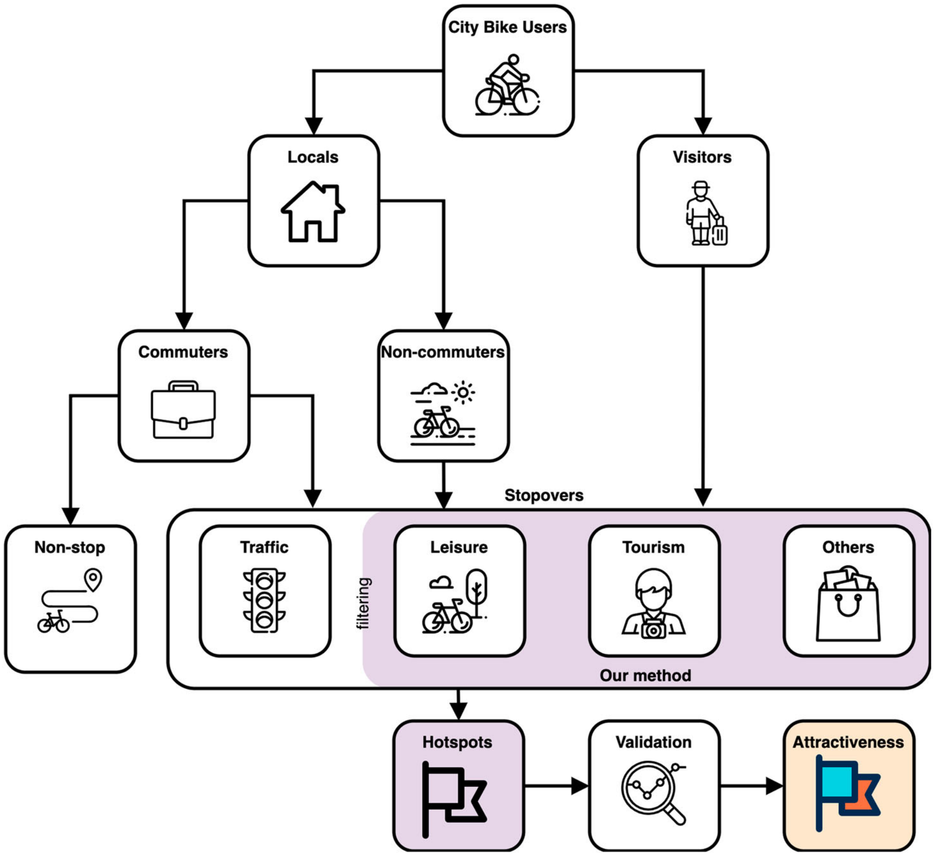

Figure 1. City-bike users classification. While local commuters stop mainly due to traffic, other user groups are likely to stopover during their trip. Both visitors and local non-commuters may stop at attractive leisure and touristic places, as well as to supply some of their needs (e.g. shopping). Places with frequent and long stopovers (hotspots), after empirical validation, may be used as a proxy of urban space attractiveness.

destinations (e.g. Wawel Royal Castle), as well as part of the cluster (e.g. Kazimierz Jewish District) or corridor (e.g. Vistula Boulevard) where several attractive places are located, collectively creating a complex spatial pattern composed of multiple identified hotspots.

While we argue that the identified hotspots are meaningful and valuable, we refrain from naively interpreting them as attractive urban hotspots. Like any other automated classification method, the accuracy of our method is not perfect, as we illustrate with the confusion matrix in Figure 2(a). The wrong classifications are either when our method fails to identify actually attractive places (e.g. places not accessible with a bike, or outside of the city-bike system) or when it identifies places which are not attractive (where stopovers were not due to attractiveness, but for other reasons). We argue that *validation* of our results is straightforward, since each identified place may be examined against its true attractiveness relying either on the expert knowledge, other sources (social media, other digital footprints or Volunteered Geographic Information), or a field visit.

1.3. Research problem, gap and contribution

We contribute to the stream of research aiming to reveal spatial patterns of urban attractiveness. Identifying tourist hotspots and determining their dynamically changing attractiveness level is of crucial importance for decision-makers, who can now design the city better with attractiveness

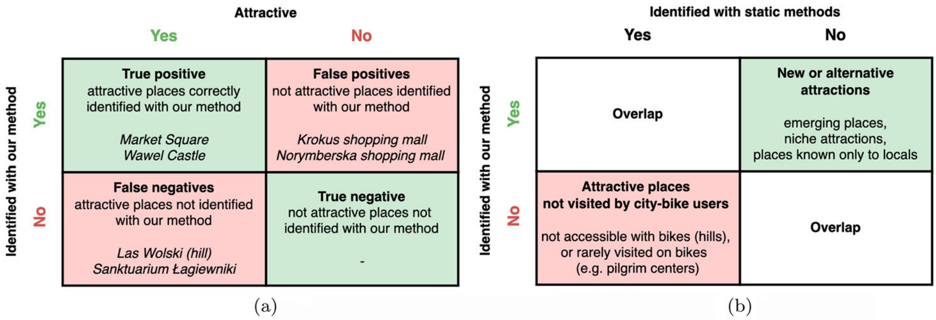

Figure 2. Accuracy of our classification against actual attractiveness (left) and classic static methods (right). (a) validating results of our method (rows) against actual space attractiveness (columns) and (b) comparing our classification with classic static rankings.

perception of residents and tourists in mind. Thus, in rapidly changing urban landscape, we need a dynamic method adapting to the recent trends and fashions of tourists (Dunne et al., 2011) and residents (Kourtit et al., 2020). Classic methods relying on expert knowledge and costly surveying fail to provide the detailed picture and are inherently static. Recently, number of methods were proposed, where big volumes of digital footprints were applied to reveal behaviour of residents and tourists in urban areas. Consequently, the delimitation of attractive urban spaces has become more detailed and underpinned by users' behaviour (observed via their digital footprints) and perception (understood thanks to surveying). The objective of this paper is to demonstrate how this picture can be improved by using a new source of data and its unique features.

In this paper, we exploit the potential of stopovers to reveal the spatial patterns. We hypothesize that the stopovers are related to the space attractiveness and verify it with acase study. Nonetheless, observing stopovers is challenging. Stopovers cannot be read from social media data, even geotagged, which does not provide a participation time and, since it requires users' action, content is not posted from all places perceived as attractive. Detailed spatiotemporal digital traces are needed to reveal stopovers, and only the active travel modes (walking, scooters, bicycles, etc.) allow for unrestricted stopovers. Cars are used by urban space consumers to a limited extent and most of the attractive places are not accessible with a car. Cars can be traced only to their parking spot and public transport passengers up to their bus stop.

Pedestrians exploring urban space are the least restricted to make spontaneous stopovers. However, tracing pedestrians typically raises privacy issues and big volumes of personal mobile location data are not easily available. The privacy issues are partially overcome in a station-based system, which does not contain sensitive personal data. Consequently, the stopovers may be easily observed on a large scale only from shared systems like scooters and city bikes, which is their unique feature. In this study, we exploit its potential.

Mining stopovers from detailed trajectories is not trivial. To this end, we propose a novel method which allows first to identify stopovers from spatiotemporal trajectories and then to filter stopovers clearly not related to attractiveness. While the results of the method need to be validated against external sources and local knowledge (as illustrated in Figure 2(a)), the revealed pattern accurately reproduced tourist hotspots of Kraków. The proposed method works with unlabelled data, yet the results may be refined when extra labels (sociodemographics or user type) are available.

Applying our method to the case of 35 thousand traces from Kraków has revealed a surprisingly meaningful and correct spatial pattern (Figure 3). Not only the main tourist attractions were properly identified, but also other insightful findings appeared. We identified a number of hidden gems, known only to locals, as well as newly emerging places, recently gaining popularity and often not yet listed on tourist websites. Such places are unlikely to be timely identified via static studies, relying on expert knowledge (like in Faracik et al. (2008)), or surveys (like (Kianicka et al., 2006)) as

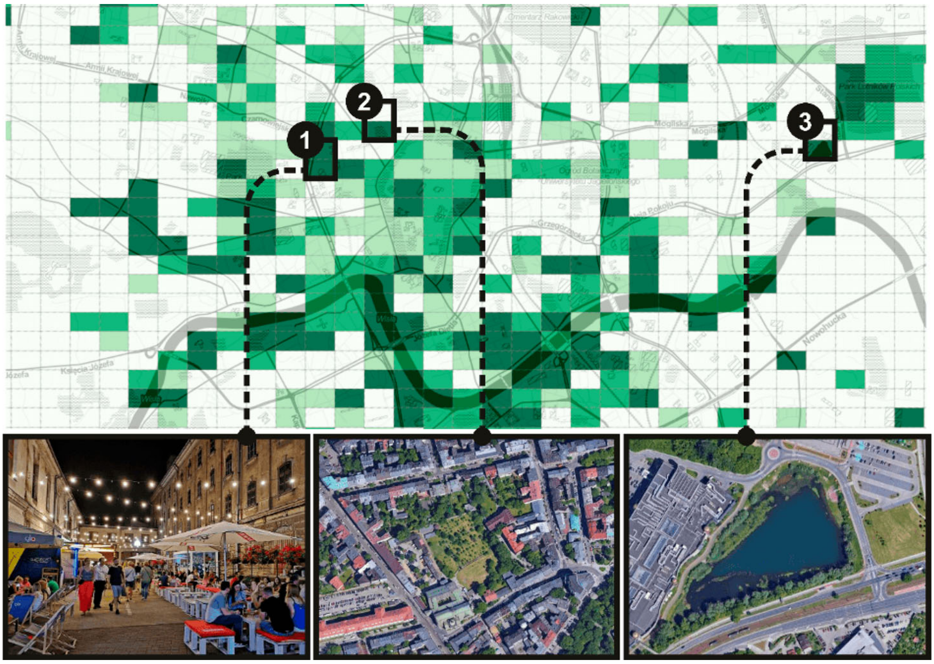

Figure 3. Urban space attractiveness in Kraków, Poland. Identified hotspots were not only the classic points of any tourist itinerary, but also emerging places not mentioned in travel guides, e.g.: (1) the Dolnych Młynów pubs and clubs, (2) Karmelicka str. gardens and (3) the Dąbski Pond.

we illustrate in Figure 2(b), which is a central contribution of the paper. We demonstrate this with three examples in Figure 3.

The paper is organized as follows. In the next section, we introduce a generic method to identify stopovers in mobility traces and apply it to the city-bike datasets. We introduce a set of filters to calibrate the method before we synthesize the data on the spatial grid. In Section 3, we illustrate the method using the example of Kraków, where stopovers identified in 35,000 bike trips yielded a grid that was validated against actual tourist hotspots. Finally, in Section 4, we synthesize the results and discuss the potential applications and limitations of the proposed method.

2. Method

We first formalize how stopovers are identified in the raw dataset, followed by a filtering rule, after which only meaningful stopovers remain in the dataset. Consequently, we aggregate the stopovers over a spatial grid and classify the cells into four levels of attractiveness, the outcome of the method. The code to read the data from gpx files, identify stopovers and compute attractiveness grid is publicly available[1] and was originally proposed in Naumov and Banet (2020), further developed in Banet (2021) and finally refined in the light of the general method proposed here.

2.1. Stopovers

We analyse trip tracks, i.e. chronologically ordered sets of track points:

$$Track = \{TP_i\}, \quad i = 1, \ldots, N_{TP}, \tag{1}$$

where each track point TP is defined as the time t and position:

$$TP = \langle t, lon, lat \rangle \tag{2}$$

For convenience, we use a dual definition, where a trip becomes a set of trip segments:

$$Track = \{TS_j\}, \quad j = 1, \ldots, N_{TS} \tag{3}$$

and TS_j is the j-th trip segment of the journey track defined by the couple of neighbouring track points TP_o and TP_d:

$$TS = \{TP_o, TP_d\} \tag{4}$$

For each trip segment, we read: t_s – the travel duration for the trip segment [h]; d_s – the distance, calculated with haversine formula [km]; and v_s – the average travel speed, defined as the distance d_s divided by the travel duration t_s [km/h]. Consequently, the raw trip data now becomes:

$$Trip = \langle ID, Track, t_{tr}, t_{idle}, d \rangle, \tag{5}$$

where ID is the unique number identifying a trip in the dataset; $Track$ is the reference to the object representing the GPS track as a set of track segments; t_{tr} is the total travel time according to the track points data (the difference between the time moments when the last and the first track points in the track were read) [h]; t_{idle} is the total idle time during the journey [h]; d is the travel distance [km].

The total idle time is defined as the sum of travel durations for those travel segments for which the location has not been changed:

$$t_{idle} = \sum_{TS_{idle}} ts, \; TS_{idle} = \{TS_j{:}d_j = 0\}, \quad j = 1, \ldots, N_{TS}, \tag{6}$$

where TS_{idle} is a set of all segments within the trip that have zero travel distance.

Stopovers, the central element of the proposed method, are identified as set of consecutive segments of a trip for which the distance was null:

$$Stopover = TS_{idle}\{TS_k, TS_{k+1}ts\}, \quad 1 \leq k \leq N_{TS}. \tag{7}$$

Note that, according to the definition, more than one stopover could be defined within a trip, if travel segments with zero distance are not consequent segments. We illustrate three selected rides with various number of stopovers in Figure 4.

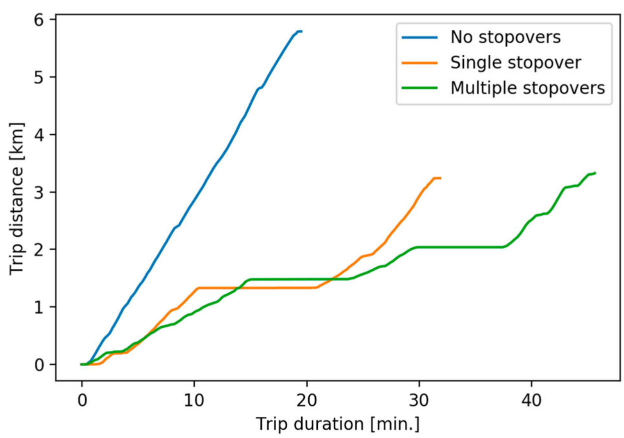

Figure 4. Typical spatiotemporal traces of city-bike trips with various number of stopovers. Commute trips typically are with no stopovers (orange) while leisure or touristic trips are more relaxed and are often intermitted with stopovers.

2.2. Filtering

Data filtering method which is used in the paper was described by Naumov and Banet (2020) and then developed in Banet (2021) and here we adjust in the light of findings from our case study. The method allows the dataset to be filtered to ensure that it only includes user stopovers that were not related to e.g. traffic issues or locking and unlocking the bike at the rental station.

(1) The dataset was first cleansed of corrupt records related to signal failures in GPS transmitters. Trip data points were dropped if the GPS signal was not received for at least 5 min;
(2) In the second filtering stage the remaining trips with an average speed of 0 km/h were eliminated, i.e. trips with a null duration or distance. These trips were highly probably related to situations where the bike user unlocked the bike, but did not take it out of the stand, but locked it again, e.g. due to a technical problem;
(3) Subsequently, we removed very short trips, e.g. when the bike user discovered a technical issue soon after renting the bike and finally decided not to travel with the bike.

On such filtered samples, we identified stopovers using the method proposed above. For each recorded trip, stopovers were identified with (Equation (7)) with their location and duration. Yet, a heatmap visualization of obtained stopovers revealed a need for further filtering, presumably leveraging on the abundance of available volunteered geographic information (e.g. location-based social media, or digital-terrain models). In our case study, for the second stage of filtering, we used spatial metadata from OpenStreetMap using a method originally presented by Banet (2021) and adjusted for the needs of the case study, as follows:

(1) **Bike rental/return stops.**
Most evident was the need to filter stopovers in the proximity of BSS stations, where what our method identified as stopovers were in fact unlocking and locking the bike and checking its technical condition. We identified a threshold of 7 m around BSS station to efficiently eliminate trip starts and ends from stopovers. Naumov and Banet (2020) explored the cumulative number of stops as a function of distance from origins and found a natural cut-off point at 7 m, after which the number of stops stabilized;
(2) **Stops at traffic lights.**
Obviously, most of the time when city-bike users stop is not for sightseeing, but at traffic. This had to be filtered with care to obtain meaningful results. Importantly, in the vicinity of most of Kraków's tourist attractions, there are no traffic lights, so we could safely assume that stopovers around traffic lights are not due to attractiveness. Our analysis revealed that the number of stops stabilized at a radius of 30 m; adopting a greater radius would lead to discarding stopovers unrelated to the presence of a pedestrian crossing or intersection;
(3) **Railway crossings stops.**
Despite there being just a handful of single-level railway crossings in Kraków, stopovers in their vicinity (definitely non-attractive places) biased the emerging picture. Since those were just a few points, it was easy to identify them and manually filter at the 30 m threshold;
(4) **Short, traffic-related stopovers.**
While the above filters were spatial, we decided to apply also a temporal filter, which we found efficient in filtering short, traffic-related stops. Namely, we found that the vast majority of stopovers below 30 s were around unsignalized pedestrian crossings. So we filtered stopovers in the vicinity of pedestrian crossings shorter than 30 s.

After the above stages of filtering, meaningful spatial patterns started to emerge, with heatmaps now clearly resembling tourist attractiveness, rather than a traffic map. Notably, in the above, we did not need to map-match traces, which makes the methods light and generally applicable.

2.3. Aggregation

For meaningful and quantifiable visualization, we divided the analysed area into a number of rectangular fields of a given size S. We used a spatial grid that can be represented as the following matrix:

$$Grid = ||Field_{ij}||^{S\times S}, \quad i = 1 \ldots S, \quad j = 1 \ldots S, \tag{8}$$

where $Field_{ij}$ is the rectangular field representing the part of the analysed area; S is the grid size (the greater number of cells, the more detailed results). For each field we get:

$$Field = \{n_{st}, t_{st}, t_F\}, \tag{9}$$

where n_s is the total number of stopovers in the field; t_{st} is the total duration of all the stopovers in the field [h], and t_F is the mean stopover time (calculated only for cells with more than three records):

$$t_F = \begin{cases} 0 & n_{st} < 3 \\ t_{st}/n_{st} & \text{otherwise} \end{cases} \tag{10}$$

All are potentially useful to reveal the spatial attractiveness. As we demonstrated for our case study in the next section, we decided to base attractiveness on the mean duration of stopovers rather than their number or total duration. To sharpen the emerging picture, we classified grid cells into four attractiveness classes, representing quartiles of mean stopover duration (t_F), where 3rd class represents the highest attractiveness and 0th lowest. The final outcome of the method is a spatial grid with rank (from 0 to 3) of urban space attractiveness for each field.

3. Results

We illustrate the proposed method with the case of Kraków, Poland, one of the emerging tourism centres in Europe. With its rich history and unique cultural heritage, the city has attracted a growing number of tourists in the last decade. For Kraków, tourism is not just an important source of revenue, but also a major social phenomenon that shapes its urban identity. Tourism in Kraków has long been concentrated around the historic city centre (Old Town, Wawel Castle, Kazimierz), i.e. the urban complex inscribed in the UNESCO World Heritage List. Yet now it extends to neighbouring areas, such as Kleparz, Krowodrza, Zabłocie, Stare Podgórze, and Nowa Huta, due activities aimed at decentralizing tourist traffic (Tracz & Semczuk, 2018). Visitors are becoming increasingly heterogenic, spanning from John Paul II-related pilgrims, to city-breakers focused on nightlife, from high-school pupils visiting their national royal Castle for the first time, to frequent visitors looking beyond the top-10 sights. These dynamics and diversity yield rapid and complex patterns which are hard to trace and quantify.

We used the data from the local city-bike system, 'Wavelo'. The system was launched in 2008 and, constantly evolving, was in operation until 2019. The input data records covered one week of the high tourist season in 2017, i.e. from 31st of May to 7th of June, when the weather was favourable for bike traffic and leisure with mean temperatures between 16°C and 21°C and barely any rainfalls.

The first step was to cleanse the dataset provided by the city-bike system. First, we eliminated all data corrupted by GPS transmission failures (a total of 5946 trips). At the second stage, 40 trips with a null duration and 635 trips with null distance were removed. The third stage, which involved filtering out short trips, identified 421 trips with a distance shorter than 50 m. Once these were eliminated, the final sample consisted of 27,927 routes.

The number of stopovers in the cleansed sample was 54,143, with a mean stopover time around 80 s. After the last filtering stage, the number of stopovers dropped to 5791, while their mean duration rose to a little over 6 min; only 25%, however, were longer than 5 min 35 s (Table 1). The largest drop in the number of stopovers was recorded after the first step, which involved eliminating those

Table 1. Number of stopovers and their statistics in the subsequent filtering stages.

Stage	# stops	Time [s]							Sum
		Mean	Std	Min	25%	50%	75%	Max	[h]
raw	54143	79.17	291.63	1	15	25	65	27,350	1190.77
1st	9639	280.93	559.30	1	85	90	255	8290	752.20
2nd	6277	335.83	647.13	1	85	155	275	8290	585.56
3rd	6219	337.74	649.78	1	85	160	275	8290	583.45
4th	5791	361.80	667.09	31	85	170	335	8290	582.00

within a radius of 7 m from the trip's origin. Further decreases were less steep, but a clear relationship could still be observed between the increase of the mean duration and the lower number of stopovers in the sample.

After each filtering stage, we visualized the dataset for verification of the obtained results. The unfiltered sample was dominated by punctual stops near rental stations. The first filtering stage allowed us to identify stops that were not related to the trip origin or destination. After the first stage, the map still contained punctual hotspots related to stopovers at junctions and level crossings, which were successfully filtered in the subsequent filtering stages. Finally, most stopovers were identified in the touristic and leisure places like Vistula Boulevards, Old Town, and the Main Market Square.

To quantify the results, we created a grid where each field was assigned the corresponding number of stopovers and total stopover time (Equation (9)). In the case at hand, the area delimited by the outer geographical coordinates of the recorded stopovers was divided into 10,000 fields of the same geographical longitude and latitude, i.e. $0.0015^\circ \times 0.0036^\circ$. Figure 5 shows values on the grid of: number of stops (a), total stopover time (b), mean stopover time (c) and mean stopover time in four classes (d). Based on the emerging patterns, it was evident that the mean stopover time provides a meaningful proxy to identify urban hotspots. Other ones yielded both false-positive as well as true-negative errors, where the identified hotspots were not attractive and attractive hotspots were not identified, respectively.

Most fields in the attractiveness identification grid, i.e. 94.74%, have a rating of 0, but the most attractive areas of the city, such as the Old Town, the Vistula Boulevard, the Benedictine Abbey in

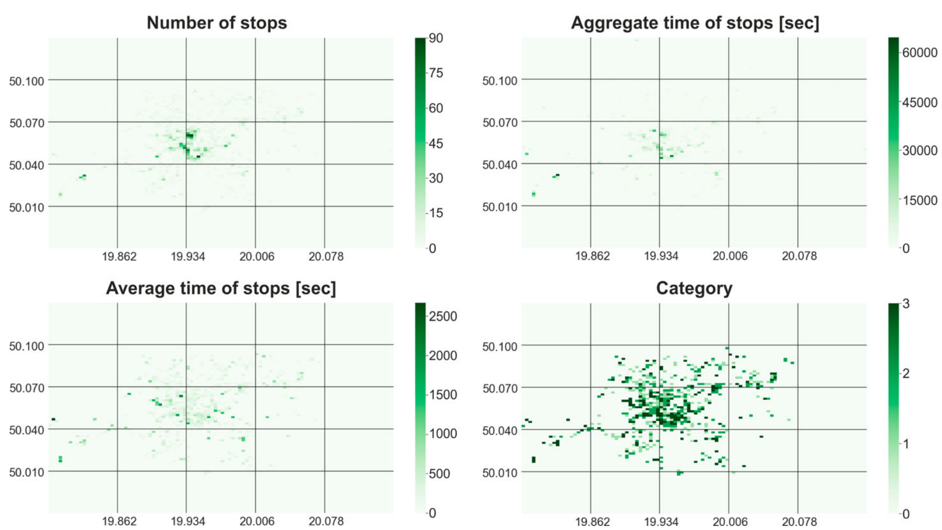

Figure 5. Values on the 100×100 grid of (a) number of stopovers, (b) aggregated (total) stopover time, (c) average stopover time and (d) average stopover time in four classes. Clearly the last one shows the most evident patterns resembling the actual structure of Kraków's tourist and recreational attractiveness.

Tyniec, the Kolna kayaking centre, the Polish Aviators' Park, Bagry Lake or Nowa Huta Lake, achieved a high attractiveness score. Table 2 shows the number of fields in each attractiveness category and their percentage share in the total number of fields in the attractiveness identification grid.

3.1. Validation

Since the proposed method is explorative and aims for more complete identification of previously unrevealed attractive urban hotspots, its' validation is not straightforward. Nonetheless, to demonstrate its capabilities, we validated our results against typical sources of tourist attractiveness. Faracik et al. (2008) evaluated urban space in terms of its tourism attractiveness, which was later adopted as an official and the latest tourism policy by the Mayor of Kraków. In the comprehensive study, they relied on their expert knowledge to select the natural, cultural, accommodation and services factors in the assessment process and, similarly to our study, classified the city space into four classes, as shown in Figure 7.

Most of the hotspots identified by our method overlap with those mentioned in the literature. Figures 8 to 11 zoom in the attractiveness grid in selected areas of Kraków and discuss them. By comparing Figure 7 with Figures 8 to 11 one can see greater details of hotspots locations and complex, yet clear patterns resulting from our method. Complexity of revealed patterns refers to both the spatial distributions, where stops are unevenly located across the city, as well as their relative importance (as measured with the proposed four-step scale).

In Table 3 we compare the most important official tourist attractiveness (highly ranked in Faracik et al. (2008)) with our method results. Our method managed to correctly identify all tourist attractions from the official sources of attractiveness (compare our findings on Figure 6 with official attractiveness in Figure 7), with two exceptions, both poorly accessible by bike.

The first one is the pilgrims centre in Łagiewniki (south), which is typically visited by elder tourists who rarely use city bikes and is poorly accessed by bicycle (as it is located on the hill). The second was the Wolski Forest, with the ZOO and the Piłsudski Mound. While considered as one of the most attractive spots in the city, for topographical reasons, this place is popular among mountain bikers rather than Wavelo users.

On the other hand, some places classified as attractive with our method were clearly not touristic shopping malls. Shopping can be perceived attractive by tourists and locals, several of the shopping malls in Kraków are the attractive ones. They are located near the Old Town (Galeria Krakowska) and Kazimierz (Galeria Kazimierz). However, the two examples that we use: the Krokus mall and a shopping centre in Norymberska street are clearly not attractive and used by locals to supply their basic needs. Our method failed to filter them out, yet manual post-processing with a basic background field knowledge allowed us to effectively interpret such false-positive cases.

4. Conclusions and discussion

We proposed a generic method applicable for any spatiotemporal data from city bikes, which, since city bikes are nowadays present in most of the metropolises worldwide, makes it applicable to explore the spatial patterns of stopovers in a broad range of cities. The light and replicable method, relying on standard spatiotemporal trip tracks allows to identify hotspots – places with

Table 2. Attractiveness classes of attractiveness identification grid fields.

Class	# Fields	Share
0 (lowest)	9474	94.74%
1	183	1.83%
2	183	1.83%
3 (highest)	160	1.60%

Table 3. Most attractive tourist places according to official listing (Faracik et al., 2008) compared with our classifications. Italics denote places either not identified or wrongly classified as attractive to our method.

Place	Rank: Official	Our	Accuracy[a]	Comment
	Central (Figure 8)			
the Main Market Square	3	3	TP	
Wawel Castle and the Vistula Boulevards	3	3	TP	
Kazimierz quarter	3	3	TP	
the city beach in the Courland Boulevard	–	3	TP	Recently opened
Błonia and the Rudawa Valley	2	3	TP	
the Jordan's Park	2	3	TP	
	South-west (Figures 9, 10)			
Cricoteka	1	3	TP	
Schindler's Factory and the MOCAK	2	3	TP	
the Krakus Mound	2	3	TP	
ZOO and Piłsudski Mound	2	0	TN	Poorly accessible by bike
Bagry Lake	–	3	TP+	Primarily for locals
the Vistula Boulevards in Stare Dębniki,	2	3	TP	
Pilgrim center Łagiewniki	3	0	TN	Poorly accessible by bike
the Vistula Boulevards in Ludwinów	2	3	TP	
Zakrzówek	1	3	TP+	Primarily for locals
the kayaking trail in Tyniec	2	3	TP	
the Benedictine Abbey in Tyniec	3	3	TP	Distant yet bike-accessible
shopping mall at Norymberska street	–	3	FP	Hardly attractive
	East (Figure 11)			
Centralny Square	2	3	TP	
the Polish Aviators' Park	1	3	TP+	
Nowa Huta Lake	2	3	TP	
Nowa Huta Meadows	–	3	TP+	Picnic spot for bike trips
Krokus shopping mall	–	3	FP	Hardly attractive

[a]TP – true positive, TP+ – added-value to the official sources, TN – true negative, FP – false positive (compare with Figure 2).

frequent and long stopovers. Which, as we demonstrate are a good proxy of the space attractiveness. By assuming that most of stopovers identified with the method are related to tourism and/or leisure, we identified complex and meaningful spatial patterns, clearly pointing towards city's most attractive urban hotspots. The results showed that the most frequent stopover locations of Wavelo bike users were, concentrated in the proximity of the most attractive cultural and natural assets. With the proposed automated manual filtering, not relying on local field knowledge, one can reveal number of valuable findings, both in terms of identifying unknown places as well as quantifying well-known ones. While the local knowledge may refine the results and make it a reliable indicator of urban attractiveness. Results of our case study proved that the method effectively identified most of the established Kraków tourist attractions. The recent dynamism in behaviour of tourists, shifting from well-known paths to exploring newly emerging sights, was evident from the emerging patterns. Our method managed to cover it and quantify those changes.

Despite relying on personal and potentially sensitive data, we find the method transparent and ethical. Even though the precise spatial path is recorded, it always starts and ends at the city bike station, rather than at personally sensitive home or workplace. While the users' ID is not stored in the dataset, his sociodemographic attributes may be disclosed, which would enable more detailed analysis differentiating locals from visitors, young from older users, etc. The proposed method has potential in real-time monitoring and can be potentially automated to report the attractiveness and its relative changes over time. Making it an efficient tool for policy makers to monitor shifts in tourist behaviour.

Importantly, in the post-COVID context, our method offers an efficient and inexpensive monitoring framework allowing us to understand how the pandemic changes impacted the consumption of urban space by tourists, locals and visitors. Allowing to quickly identify the most visited, possibly crowded, places where intervention may be needed to stop virus spreading.

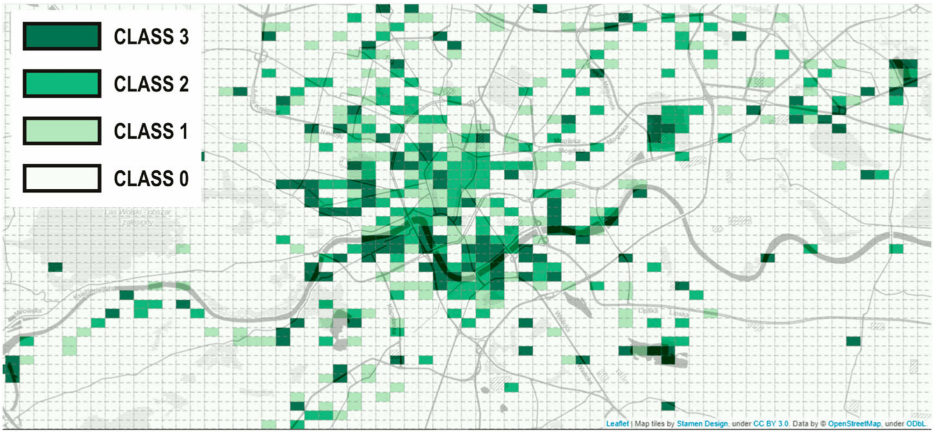

Figure 6. Four classes of urban attractiveness in Kraków based on the mean stopover times of city-bike users.

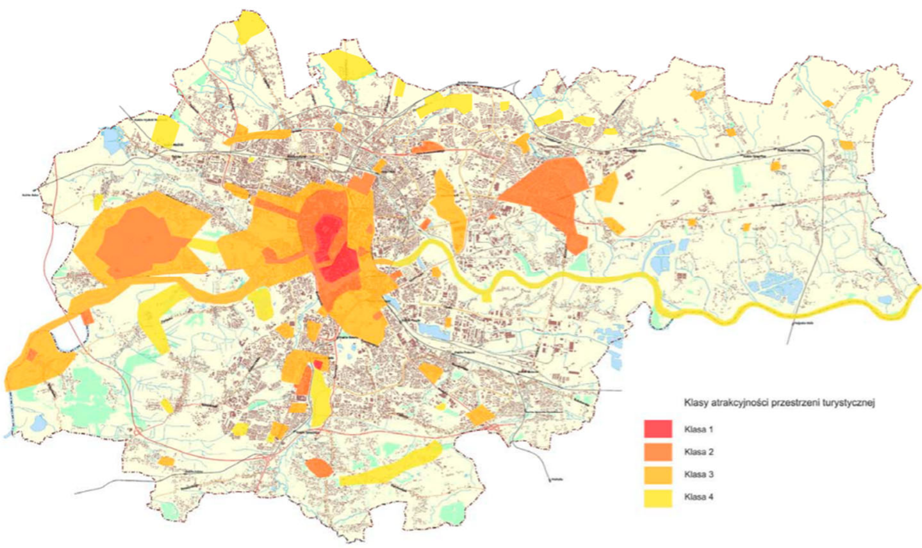

Figure 7. Four classes of tourist attractiveness in the official policy of Mayor of Kraków (Faracik et al. (2008)).

Clearly, our method has some limitations. It relies on a sequence of filters, where thresholds need to be manually parameterized (e.g. cut-off distance from traffic lights, or from station). While it effectively filters commuting trips, as long as the user type remains unknown, the leisure remains indistinguishable from tourism, and local residents from visitors. This shall be further enhanced with labelled data. While the city-bike systems are often limited in space and rental stations are not evenly distributed everywhere in the city. This was not the case for Kraków, yet in cities where the coverage is not complete, this may obscure the overall image and fail to yield a complete spatial pattern.

Finally, to verify the results before drawing the conclusions a basic field knowledge is needed. In the case of Kraków, some definitely non-attractive shopping malls were misclassified with our method. Yet in any case, a virtual or physical site visit may always verify its actual attractiveness. For instance, for us, the locals of Kraków, the data revealed the place that we were not aware of

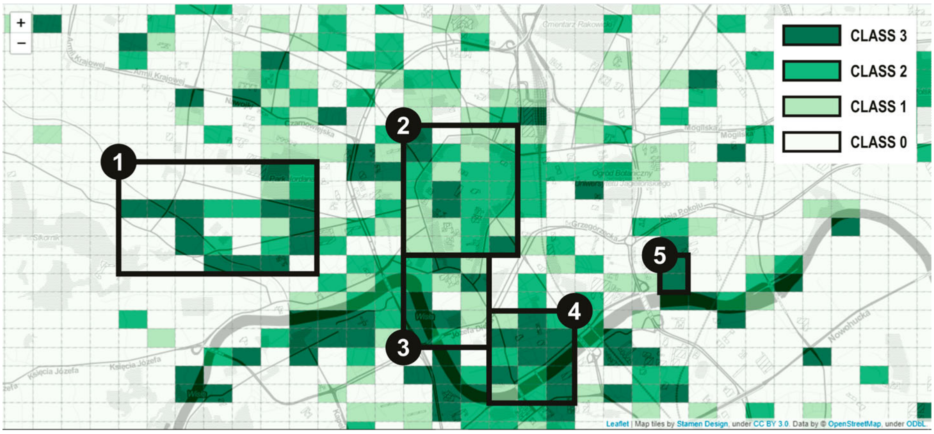

Figure 8. Selected highest-rated spots in Central Kraków: (1) Błonia with the Rudawa Valley and the Jordan Park, (2) the Old Town with the Main Market Square, (3) Wawel Hill with the Vistula Boulevards, (4) Kazimierz with the Vistula Boulevards, (5) the city beach area, highly popular among locals is the new riverside and not listed in official guides. The old town (2) is now more detailed, making the most attractive spots visible.

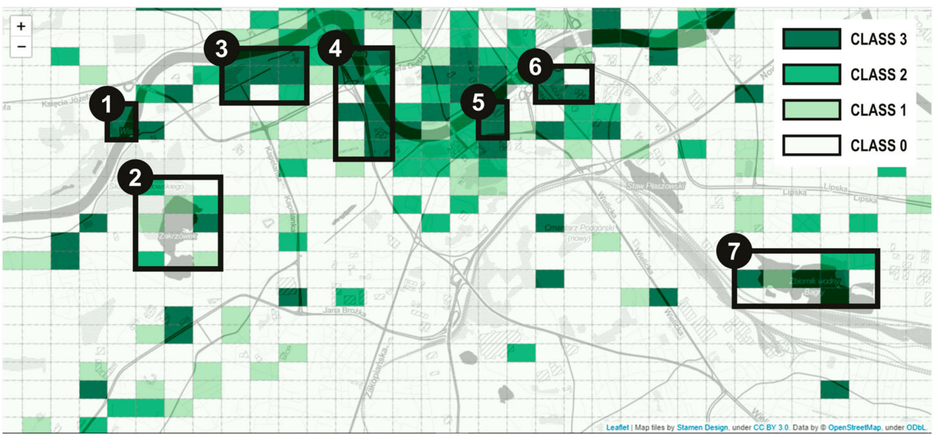

Figure 9. Selected highest-rated spots in South Kraków: (1) the kayak rental station, (2) Zakrzówek lake, (3) the Vistula Boulevards in Stare Dębniki, including the Dębnicki Park, (4) the Vistula Boulevards in Ludwinów, (5) the area of Cricoteka and the Podgórski Market Square, (6) the area of Schindler's Factory and the MOCAK, (7) Bagry Lake. Pilgrims centre Łagiewniki (to the south), highly ranked in official guides, not identified in our method due to low bike accessibility. The shopping mall at Norymberska street (down from hotspot 2) was identified as attractive, which is clearly a false-positive case that has to be filtered manually.

(hidden garden at Karmelicka street). Notably, this may be partially mitigated with the use of abundance of available Volunteered Geographic Information (VGI), which can be used to refine and validate the results.

We believe that with this method we fill some of the gaps in research on the urban space attractiveness for residents and tourists.

Note

1. https://github.com/naumovvs/city-bikes-analysis.

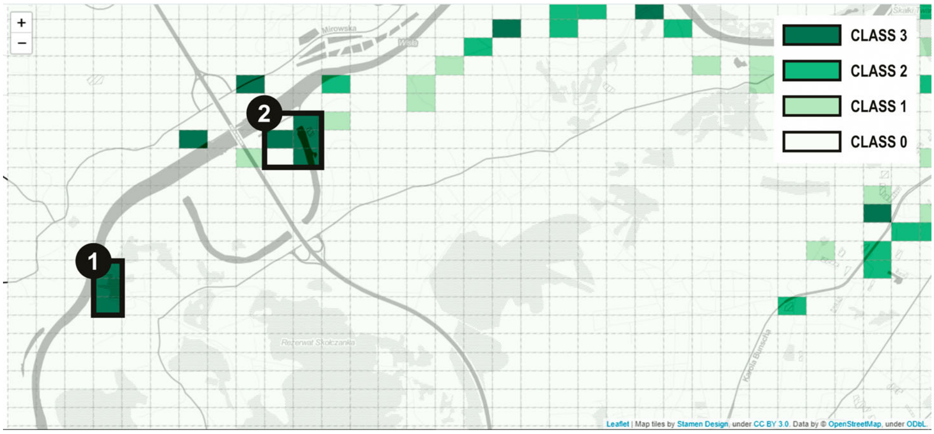

Figure 10. Selected highest-rated spots in West Kraków: (1) the Benedictine Abbey in Tyniec, (2) the kayaking trail in Tyniec. Both attractive yet distant, which leaves a trace of short breaks along the highly popular bike path stretching by the river between old town and Tyniec.

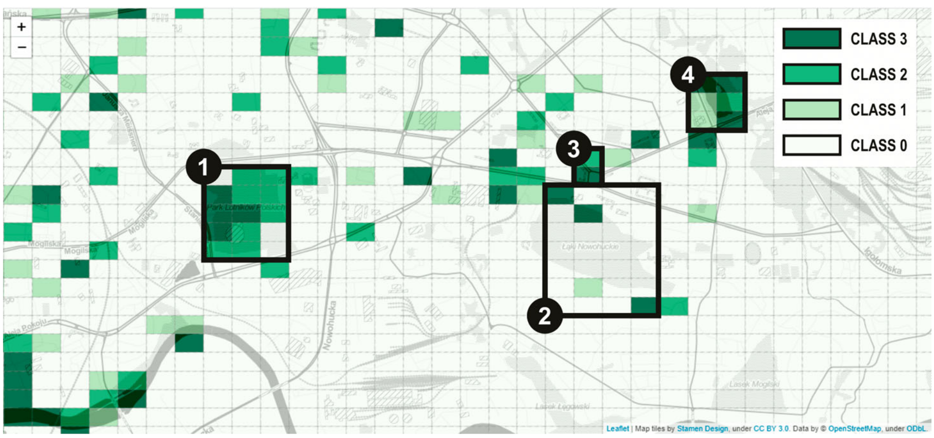

Figure 11. Selected highest-rated spaces in East Kraków: (1) the Polish Aviators' Park, (2) Nowa Huta Meadows, (3) Centralny Square with Aleja Róż, (4) Nowa Huta Lake. The old Nowa Huta area marked as one equally attractive spot in official guidelines (Figure 7) is now depicted with more detail, making it evident that attractive places concentrate around Plac Centralny and the Lake.

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