Using Social Media Data to Understand People's Activities in Urban Green Spaces (UGSs)

GEO 511 Master's Thesis

Author
Anjing Zhang
21-741-756

Supervised by
Dr. Inhye Kong

Faculty representative
Prof. Dr. Ross Purves

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Department of Geography, University of Zurich

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Department of Geography, University of Zurich

Abstract

Urban green spaces (UGSs) are essential for outdoor recreation in urban areas, providing ecosystem services and public benefits. Understanding people's activities in UGSs is crucial for increasing UGSs use and enhancing human well-being. Previous studies have mainly focused on investigating activities in urban parks and drivers of park use. Many other green spaces, such as sports fields and street green spaces, have not been thoroughly examined. Therefore, this study examined the use of various types of UGSs in Zurich using geo-tagged Flickr photographs. Firstly, Google Cloud Vision API and hierarchical clustering analysis were employed to identify people's activity types within UGSs. Then, Generalised Linear Models (GLM) were used to analyse relationships between spatial variables and various activities. Further, the impacts of spatial variables on activities in different UGSs categories were analysed. Results showed that four activity types were found: 'Flora & Fauna', 'Water activity', 'Sports & Recreation' and 'Cityscape'. All four activities were almost equally prevalent in Parks. 'Sports & Recreation' was the dominant activity type in Sports fields, while 'Cityscape' was the most popular activity in Street green spaces and Other green spaces. 'Water activity' was the least common activity in all types of UGSs except for the Park. Regression models showed that road density exhibited a significant positive correlation with the popularity of 'Sports & Recreation' and 'Cityscape' activities while displaying a negative association with 'Flora & Fauna' and 'Water activity'. Other variables such as area, distance to Zurich Lake, average elevation, and population density had varying impacts on these activities. The findings of this study can assist policymakers in enhancing the planning, construction, and maintenance of various UGSs.

Keywords: activities; urban green spaces (UGSs), image classification;

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1 Introduction

1.1 Importance of urban green spaces

Over the past few centuries, urbanization rates have experienced a swift increase on a global scale, resulting in more than half of the world's population currently residing in urban areas (Ritchie and Roser, 2018). This proportion is expected to continue increasing in the following decades (Angel et al., 2011). Rapid urbanization has brought various urban environmental issues, such as air and water pollution (Saucier et al., 2023), land degradation (Abu Hammad and Tumeizi, 2010), and so on. Along with environmental degradation, urbanization has brought a sedentary and stressful lifestyle (Pinchoff et al., 2020). Researchers have indicated that urbanization is associated with the epidemic of non-communicable diseases (NCDs), such as diabetes, obesity, cancer, and mental disorders (Howell et al., 1997, Schaefer et al., 2009). Therefore, large-scale urbanization in many countries worldwide has become a significant health concern.

Many studies have proven that Urban green spaces (UGSs) can improve the urban environment and help urban dwellers prevent diseases. UGSs are spaces mainly covered by natural elements. Potential UGSs include parks, green street spaces, sporting fields, riverside greenbelts, cemeteries, squares and plazas, public and private gardens, school and community gardens, waterways and wetlands (Mukherjee and Takara, 2018, Shen et al., 2017). On the one hand, UGSs present valuable opportunities for mitigating urban heat, enhancing air quality, reducing traffic noise (Grote et al., 2016, Nowak et al., 2018), and improving urban water management (Mukherjee and Takara, 2018). To achieve sustainable and resilient urban development, it is essential to understand the utilization of UGSs under global change, such as rapid urbanization, ecological environment deterioration, and extreme weather. Utilizing this knowledge can enhance the development of effective planning strategies that promote the optimal utilization and maintenance of green spaces (Kabisch et al., 2021). On the other hand, UGSs offer opportunities for dog walking, cycling, jogging, social gatherings with family and friends, and the appreciation of natural beauty, and other activities (Coombes et al., 2010, Razak et al., 2016). There is substantial evidence for various benefits of UGSs, including reducing stress (Neuvonen et al., 2007, Roe et al., 2013, Tyrväinen et al., 2014), increasing happiness (MacKerron and Mourato, 2013), enhancing physical health and mental health (James et al., 2015, Pretty et al., 2005, Zhang et al., 2020), and promoting social well-being (Hough, 2013, Keeler et al., 2019, Keniger et al., 2013). For example, a comprehensive systematic review and meta-analysis conducted by Twohig-Bennett and Jones (2018), which encompassed 143 studies, found compelling evidence supporting the positive impact of UGSs exposure on various health outcomes. Their results indicated significant associations between green space exposure and decreased heart rate, reduced risk of type II diabetes, and lower all-cause mortality. According to a study conducted by Huerta and Utomo in Mexico City, urban residents who frequented UGSs at least once a week during the pandemic reported significantly higher subjective well-being scores, with an increase of 8.7%, compared to those who did not visit UGS at all (Huerta and Utomo, 2021). Therefore, analysing the usage of UGSs and gaining insight into the factors that contribute to the usage of UGSs can provide valuable guidance for the development and management of UGSs. This understanding becomes particularly crucial in meeting the needs of a growing urban population and understanding human-nature interaction in urban areas.

UGSs is a broad term, including parks and many other urban vegetated areas. Most previous studies focus on examining urban parks. A series of studies have investigated the use of urban parks using social media (SM) data, such as measuring visitation patterns of urban parks (Song et al., 2020b, Wood et al., 2013), identifying recreational activities (Huai et al., 2022, Song et al., 2020a), analysing visitors' emotions or preferences (Mondschein et al., 2020, Plunz et al., 2019, Wan et al., 2021, Zhu and Xu, 2021), assessing factors influencing park use (Donahue et al., 2018, Zhang and Zhou, 2018) and evaluating cultural ecosystem services (CES) of parks (Depietri et al., 2021, Huai et al., 2022, Oteros-Rozas et al., 2018). It is widely known that urban residents enjoy nature almost exclusively in urban parks, but many other kinds of green spaces also contribute to our daily exposure to nature. However, few studies have examined other types of UGSs using SM data. People can enjoy nature from different types of UGSs, like green street spaces and private gardens (Xiao et al., 2016), which can significantly supplement locations in which public parks are lacking (Hanson et al., 2021). For example, Dennis and James (2017) investigated the connections between public green spaces and gardens and their impacts on local health disparities in the North West of England. Their findings suggested that domestic gardens had a greater positive effect in mitigating health deprivation compared to public green spaces, underscoring the significance of private gardens as an essential health asset. Wang et al. (2022) found a positive association between the presence of green street spaces and the reduction of negative emotions. This suggests that higher levels of green spaces along urban streets are linked to a potential improvement in emotional well-being and a decrease in negative effects among individuals.

1.2 Research gap

The global population's escalating shift toward urban living is driving the expansion of cities, resulting in not only environmental degradation but also a rise in physical and mental health challenges among individuals. UGSs can improve the urban environment, for example, by providing habitat for wildlife, reducing noise, improving air quality, etc. UGSs also offer opportunities for physical activity, stress reduction, and mental well-being, enhancing urban residents' overall health and quality of life.

However, most previous studies have primarily focused on the usage of urban parks. Many other types of UGSs, such as private gardens, street green spaces, sports fields, and green squares, have received limited attention. This knowledge gap highlights the need for a more comprehensive understanding of the utilization patterns associated with these diverse forms of UGSs. By addressing this limitation, a more holistic and inclusive perspective can be achieved in developing effective strategies for the utilization of all types of UGSs in urban settings.

1.3 Research questions

Based on the limitations stated before, this study aims to investigate recreational activities in various types of UGSs and analyse how spatial factors affect various recreational activities within UGSs using geo-tagged Flickr images covering 2009 to 2019 for Zurich.

Research Question 1: What activities do people perform at different types of UGSs?

- Identifying types of activities based on Flickr images and auto-content identification

- Analysing recreational activities in different UGSs categories

Research Question 2: How do potential spatial variables affect various activities within different UGSs categories?

- Examining relationships between spatial variables and various types of activities

- Examining relationships between spatial variables and activities at different UGSs categories

This study expands research efforts to encompass a broader range of UGSs and provide valuable insights into their contributions to environmental sustainability, public health, and urban livability. It aims to offer a more holistic comprehension of the wide array of urban green spaces and how they impact environmental sustainability, public health, and urban planning. This study highlights the potential of using SM data to inform evidence-based urban planning and management decisionmaking. The findings of this study will contribute to a more inclusive and informed approach to UGS development and management, ensuring that the needs of urban populations are met across various types of green spaces. In addition, this study utilizes social media data to swiftly evaluate the utilization of urban green spaces, offering a cost-effective alternative to conventional surveys. This approach has the potential to enhance public green space management by delivering precise insights into user behaviour and the values of urban residents in a resource-efficient manner.

1.4 Thesis structure

This paper is structured in the following manner: Chapter 2 examines the background of applying SM data to analyse the use of UGS, especially urban parks. In this section, there is a general summarization of the literature on UGSs and geo-tagged SM data, including measuring UGSs visitation, identifying recreational activities in UGSs, and analysing factors influencing park visitation. Chapter 3 introduces data and methods used in this study to process data. Chapter 4 provides a comprehensive description of the results obtained from the data exploration and primary analysis conducted in this study. The subsequent Chapter 5 examines the implications of these findings, addressing the research questions. In Chapter 6, a summary of the entire thesis is presented, encompassing a review of the results, establishing connections with relevant literature, a discussion of any limitations encountered, and offering recommendations for future research endeavours.

2 Literature review

2.1 Analyzing visitation patterns of UGSs using geotagged SM data

2.1.1 Counting visitation frequency

Measuring UGS use is essential for understanding the human-nature interaction in urban areas. Collecting comprehensive data on the usage of UGSs continues to present an ongoing challenge (Heikinheimo et al., 2020). Traditional survey approaches primarily rely on on-site observations and questionnaires (Priess et al., 2021, Sreetheran, 2017). The advantage of these methods is the questionnaire design to obtain specific information according to the research objectives. However, the responses provided by the participants can be affected by many factors, such as the interviewees' ages, genders, races, and incomes and the phrasing of survey questions (García-Díez et al., 2020, Scholte et al., 2018). Additionally, observations and questionnaire surveys often suffer from limited sample sizes, time and space constraints, and potential limitations in representing the broader public (Arnberger and Eder, 2015, Wright Wendel et al., 2012). These methods are very time-consuming and money-consuming (Tenerelli et al., 2016). In addition, observation data is valuable for gathering statistics on visitor utilization frequency and preferences for physical activities due to its abundance of information. However, it is not well-suited for spatial analysis due to the lack of geographical knowledge. Considering the advantages and limitations of traditional data, there is a growing need for new data sources that can effectively map and measure visitation, taking into account both spatial and non-spatial information (Shoval and Ahas, 2016).

Considering the limitations associated with traditional techniques, there has been a growing interest in utilizing geo-located SM data as a novel approach to analysing the usage of UGSs. SM data typically comprises real-time contributions from active users, encompassing elements like reviews, images, hashtags, and check-in (Chen et al., 2018, Martí et al., 2019). SM platforms like Flickr, Twitter, Instagram and Weibo are most frequently used in previous studies (Cui et al., 2021). These platforms facilitate individuals in sharing their experiences and viewpoints by publicly uploading either textual data (such as words, and tags) or non-textual content (including pictures and videos) on the internet (Norman and Pickering, 2019). Twitter, established in 2006, is a popular platform for the public to express their thoughts while providing a valuable geo-tagged text source. Users can tweet messages with precise geographic coordinates on Twitter. This combination of textual content and location data within tweets presents a unique opportunity to extract valuable insights and gain a deeper understanding of the spatial aspects of people's experiences and perspectives (Cui et al., 2021). Similarly, photo-sharing websites like Flickr, established in 2004, offer a means for individuals to share their photos, resulting in an extensive collection of freely accessible user-generated data resources. Instagram, launched in 2010, is a platform for sharing self-generated and user-generated content (Tenkanen et al., 2017). Weibo, also named Sina micro-blog, is China's largest social networking website. It allows users to disclose their locations when they publish micro-blogs (Gu et al., 2016). This data type includes intricate spatiotemporal details and highly visually appealing content, providing significant value in analyzing visitors' spatial and Landscape preferences across a wide range of dimensions (Schirpke et al., 2021).

It has become increasingly evident that geo-tagged SM data can represent a valuable source of information for understanding tourism and visitor patterns. Given the widespread adoption of SM and the convenient accessibility and affordability of its data, many studies have demonstrated that geotagged SM data can be a reasonable proxy for recreational visitation in national parks, protected areas, and urban parks (Ghermandi, 2022). By comparing visitation rates estimated by geo-tagged images from Flickr and empirical data at 836 recreational sites worldwide, (Wood et al., 2013) firstly demonstrated that geo-tagged photos are a suitable proxy of visitation. Ever since the first comprehensive study was published, the correlation between actual visitor statistics and the number of geotagged photographs was revealed. It has become evident that geotagged photos from Flickr have significant potential for understanding tourism visitation patterns. Subsequently, some studies have expanded the scope of data sources to other media-sharing platforms, such as Instagram, Twitter, and Weibo. Extensive research that analyzes this field has expanded to various typologies of sites, including national parks and national reserves to urban parks. Sessions et al. (2016) compared survey data with SM data for 38 National Parks located in the western United States. They found that the monthly count of photos posted within a park is a dependable indicator of visitor numbers during that particular month. After analysing geo-tagged pictures from Instagram and Flickr in a National Park in South Africa, Hausmann et al. (2017) pointed out that no noteworthy distinction was observed between the preferences expressed by tourists in surveys and the preferences uncovered through content shared on SM. Heikinheimo et al. (2017) conducted a study comparing systematically collected survey data and geo-tagged SM data content in Finland's most famous national park. Their study indicated the successful utilization of SM data in identifying the most popular sub-regions within the park and extracting pertinent information regarding visitors' activities in this national park. Hamstead et al. (2018) compared the visitation frequency measured by Flickr photographs and tourists' surveys in National Parks across the western United States. The results of their analysis support the notion that the monthly count of geotagged photos within a park can serve as a reliable indicator of the number of visitors during the corresponding month. Song et al. (2020a) indicated that geotagged SM data would more accurately depict visitors' preferences compared to their park visit frequency. To support this assertion, he conducted a comparative analysis with household surveys conducted in urban parks across Singapore. Therefore, regarding urban parks, the utilization of SM data has predominantly focused on analyzing visitation patterns rather than assessing the accuracy and reliability of such data as a proxy for actual visitation.

2.1.2 Spatial-temporal patterns of visitor activity

Geotagged SM data has also been used to reveal the spatial and temporal patterns of visitor activity (Lyu and Zhang, 2019). Barros et al. (2019) conducted a comprehensive analysis of visitor behaviour in Spain's most famous national park by integrating geotagged photographs from Flickr, GPS tracks, and official data. Their study examined the origins of visitors, spatial distribution, and monthly visitation patterns. The findings demonstrated that data from SM proved to be a valuable resource for analyzing visitor behaviour patterns in national parks. Liang and Zhang (2021) utilized multiple SM data to analyze the temporal and spatial patterns of urban park visitation in Shanghai. Their findings revealed that park visitation in Shanghai exhibited spatially and temporally uneven distribution. They also observed a preference for parks in downtown districts and a higher inclination to visit parks during the spring season and on non-workdays. Cui et al. (2022) examined the spatiotemporal changes in utilising various UGSs in London during the COVID-19-related lockdowns by analysing geotagged Twitter data. Their study showed differences in spatial and temporal patterns of UGSs visitation before and during the COVID-19 breakout. Chen et al. (2018) used SM real-time Tencent user density data to measure the use of 686 urban parks of Shenzhen and revealed the temporal visitation patterns of parks in Shenzhen: on work days, the peak hour shifts to 13:00 and 19:00 to 20:00, corresponding to the time when individuals who are employed have opportunities to explore urban parks. However, during rest days, the peak hour for urban park visits typically takes place between 15:00 and 17:00. A notable difference becomes evident: 13:00

stands out as the busiest hour on workdays but as the least active hour during days off. Interestingly, between 0:00 and 8:00, there is minimal variation in urban park usage between work and rest days. For spatial patterns, they found that parks located in more developed areas were usually more frequently visited. Rizwan et al. (2018) used Sina Weibo check-in data to investigate users' behaviour in 10 districts of Shanghai, revealing a noteworthy trend of increased SM usage among female users. Moreover, they detected notable differences in people's behaviour in different districts when comparing weekdays and weekends. Additionally, there was an observed increase in check-ins during nighttime compared to the morning hours. Huang (2023) developed a framework and formal procedure to analyze visitor activity patterns in national parks using SM data. This framework explores various dimensions, including the annual and monthly trends in visitor activity times, the movement patterns of park visitors, and the connections between Points of Interest (POIs). The study took four highly visited U.S. national parks as examples. The results from the case study indicated that walking durations tend to be more extended during the spring and fall seasons, while stationary periods peaked in the winter. However, due to differences in climate, landscape features, and geographical positions, the seasonal variations in visitor activity times differed notably among these distinct parks.

2.1.3 Visitor characteristics

A number of studies have explored the visitation patterns of different groups of tourists. Sessions et al. (2016) evaluated the reliability of utilizing crowd-sourced online photos to provide insights into the behaviours and preferences among international visitors, out-of-state tourists and in-state tourists. Their assessment involved a comparison of empirical data with photographic data sourced from the online platform Flickr for 38 Western United States National Parks. They found that access rates derived from surveys and Flickr data were comparable. However, they found that estimates based on SM data tended to exaggerate the presence of international tourists while minimizing the number of out-of-state visitors, with an error margin ranging from 5% to 20%. This overestimation of international visitors in the photographs may be attributed to the possibility that international tourists were more inclined to share their experiences through photos, potentially indicating a more profound and memorable experience for them. Huai et al. (2022) analyzed the spatial behaviour patterns and landscape preferences of both tourists and residents in the urban parks of Brussels using SM images and computer vision techniques. They observed that tourists were more focused on the place's identity, particularly emphasizing landmark statues and constructions, whereas locals displayed a greater interest in native flora, flowers, insects, birds, and wildlife.

2.2 Analyzing activities in UGSs

2.2.1 Geo-tagged text

Utilizing location-based SM data offers a significant advantage in determining activity purposes. Various geo-tagged SM data, such as hashtags, reviews, check-in data, and photos, have been applied to identify human activities. Hashtags can reflect the subjective perceptions of an individual user, which can be used to recognise visitors' activities. Grzyb et al. (2021) discovered nine main categories of activities in UGSs of central Poland by aggregating Instagram hashtags, including 'nature in general', 'natural elements', 'health', etc. By using user-generated photo tags from Flickr, Schirpke et al. (2021) recognized 12 different cultural ecosystem services in the lakes in the European Alps, including landscape features, aesthetic experiences and recreation, tourism, nature observation, education, the sense of place, culture, heritage, etc. Huang (2023) analysed Flickr photos tags and derived four basic activity types for parks' visitors, which were stationary, walking, riding, and flying namely.

Location-based check-in services within different SM applications enable individuals to share their activity-related preferences, presenting a valuable source for identifying human activity. Check-in data provides a brief link to the original location-based service provider. By querying the location-based service provider, various activity categories can be classified based on the types of location (Hasan et al., 2013). By categorising different activity categories based on the kinds of visited sites, (ibid) identified six types of activities within three US cities: home, work office, eating, entertainment, recreation, and shopping. In another study conducted by Hasan and Ukkusuri (2014) in New York City, two additional types of activities were identified: social service and education.

Utilizing georeferenced text from platforms like Twitter, researchers can use detailed temporal and spatial data about visitors of UGSs, which can help address the question, 'What activities do people engage in when they visit UGSs?'. For example, to categorize Twitter postings and identify people's activity types, Roberts (2017) manually screened tweets and calculated word frequencies to identify sports-related tweets, identifying seven distinct types of physical activity, including running, walking, biking, etc. This research illustrated the potential of geo-tagged SM data in investigating peoples' physical activities in UGSs, bridging gaps in conventional research methodologies. Sim et al. (2020) applied text mining to analyse the changes in human activities by month. For example, activities such as biking and walking were frequently mentioned in April, along with events like free jazz nights, while during the period from December to February, park users commonly referenced activities like walking and lighting. Salloum et al. (2017) employed text mining techniques to extract visitors' behaviour types in UGSs from unstructured tweets. They calculated word frequencies to identify various park activities and conducted sentiment analysis. Their study revealed that SM data can capture significant activities in parks, such as 'nature', 'sports', 'eating', etc., which is hard to distinguish in traditional questionnaire responses. By applying text mining to Twitter data in 10 functional categories of UGSs in London, Cui et al. (2022) identified six main groups of UGS activities, which were art, leisure, nature, physical, picnic, and social respectively.

2.2.2 Geo-tagged photos

A photograph is worth more than a thousand words. Researchers typically search the tags, captions, or other textural photo descriptions generated by the users or the SM applications to extract the semantics of SM images (Spyrou and Mylonas, 2016). However, textual data may often be unavailable or may describe an image context that is unclear, incomplete, or hard to interpret (Koylu et al., 2019). Photographs have the ability to convey objective information and contain a great deal of detail about a visitor's interests or emotional state at a specific moment and location (Angradi et al., 2018, Sinclair et al., 2018). Some studies have applied manual classification to classify geo-tagged photos and recognize people's activities in UGSs. For example, Heikinheimo et al. (2020) conducted manual content categorization of a subset of SM images from Flickr and Instagram, and ultimately identified activities including physical activity, diet, water activities, etc.

Advancements in high-performance computing and deep learning have greatly enhanced the effectiveness and precision of computer vision algorithms when it comes to classifying images and detecting objects (Koylu et al., 2019). Richards and Tunçer (2018) introduced an innovative approach to assessing the ecosystem services of parks by utilizing an automated image-content classification algorithm of SM photographs. This method involved employing Google Cloud Vision, an online image identification algorithm, to analyze a dataset of over 20,000 photos captured in Singapore parks. Hierarchical clustering was subsequently applied to categorize these photographs, resulting in the identification of seven distinct clusters: transport, plants, animals, water, etc. To evaluate the precision of the combined image recognition and hierarchical clustering process, a quantitative assessment was conducted by comparing it with a manual evaluation. The analysis revealed an impressive overall accuracy rate of 85% for the classification of photos. Despite slight discrepancies observed when comparing the automated image recognition algorithm to the human manual type, the approach remains valid for rapidly assessing the ecosystem services values of parks. Huai et al. (2022) used another photo classification algorithm to identify parks' CES values. Their study showed that locals prefer natural elements like plants, flowers, and birds, while tourists showed more interest in remarkable sculptures and constructions in Brussels urban parks. In the study conducted by Song et al. (2020b), SM data was used to examine landscape preferences among various groups of park users, employing geo-tagged photos and automated image identification algorithms. The researchers categorized park photographs into ten distinct groups, including birds, plants and vegetation, food, etc. Substantial disparities were identified in both the quantity and categories of park photographs taken by tourists in contrast to local residents. These variations were also evident among distinct user groups delineated by the content of their photos.

2.3 Factors influencing urban park visitation

Extensive research has examined the impacts of various physical and socio-cultural factors on urban parks' visitation. Three main categories of factors have been found that may affect the popularity of urban parks: park attributes, accessibility, and surrounding environment. Park attributes usually include park size, vegetation coverage, sports fields, children's playgrounds, presence of water body and lawn, distance to waterbody, toilet number, road length, and parking lots. After using SM photos to investigate the visitation rate of Shen Zhen urban parks, (Chen et al., 2018) found no relationship between park size and park attendance. However, in a study focusing on parks in Wuhan, park size presented a significant correlation with park visitation (Lyu and Zhang, 2019). In addition, Song et al. (2020a) found that park attributes like lawns and natural vegetation, the footpath length, and the waterfront area contributed to the higher popularity of parks in Singapore. Accessibility is considered to have a significant impact on park use. Good accessibility makes it easy for people to visit the park (Dallimer et al., 2014). Indicators like the number of bus and metro stops, road density, distance to the city centre, and number of public transport nodes are regular indicators for the accessibility of a park (Dallimer et al., 2014, Zhang and Zhou, 2018). Zhang and Zhou (2018) found that the number of bus stops and distance to the urban centre significantly affect park use in Beijing. Parks farther from the city centre and have fewer bus stops receive fewer visits. However, some studies found that indicators like the bus and metro stop density, and road node density have no significant relationship with the park's popularity (Chen et al., 2018, Lyu and Zhang, 2019). The surrounding environment features are usually structured by population density, building density, restaurants, recreational facilities, and household income (Donahue et al., 2018, Song et al., 2020a). People were likely to visit parks with convenient services and facilities, which meant that when choosing a park to visit. Donahue et al. (2018) employed SM data to analyze visitation patterns in urban and peri-urban green spaces within the metropolitan area of the Twin Cities, Minnesota, USA. Their results indicated that the presence of nearby water attractions, the count of park facilities, the length of trails, and the population density of the neighbouring community positively impact visitation rates of parks. In a study conducted in Wuhan parks, Lyu and Zhang (2019) discovered that accessibility demonstrated a positive association with park usage. However, the impacts of accessibility were comparatively lower than that of surrounding environment characteristics and park attributes on the visitation of parks in Wuhan. Chen et al. (2018) found that increasing bus and metro stop density and road node density did not significantly impact park usage in Shenzhen. In other words, accessibility had a minimal effect. However, the study found that park attributes, such as the presence of children's playgrounds, density of toilets, availability of shopping and restaurant (POIs), presence of parking lots, and park grade, were significantly associated with park usage. By applying automated image identification algorithms Song et al. (2020a) categorized geotagged photos in Singapore urban parks into five groups, including water&sky, recreation, plants, etc. They found that parks with an extended waterfront and location near a beach are associated with a higher frequency of photos of water &sky and recreation. This suggests that coastal recreational activities hold significance for many park visitors in Singapore.

Previous research has examined a wide array of variables to assess their relationship with park utilization. However, the key determinants influencing park usage show variations across different research studies. This divergence can be attributed to the likelihood that the variables influencing park use may differ depending on the specific characteristics of the green space, the demographics of the user group, or the urban context being studied (Donahue et al., 2018, Lyu and Zhang, 2019).

3 Data and method

3.1 Study area

Zurich is the largest city in Switzerland and manages 12 districts. It is the economic centre of the German-speaking part of Switzerland. During the period from 2012 to 2021, Zurich's population has a consistent growth, experiencing an increase from 376,990 to 428,700 residents (SFS). It suggests that Zurich is experiencing an escalating level of urbanization pressure. Meanwhile, Zurich has acknowledged the significance of its public green spaces in enhancing the life quality for its residents (Seeland et al., 2009). Zurich's high quality of life is globally recognized, consistently ranked as the world's most livable city by Mercer, a prominent human resources consulting organization, since 2000 (Xu et al., 2019). A crucial contributing factor to this accolade is its outstanding public space system, which plays a pivotal role in its ongoing selection (Xu et al., 2018). Figure 1 shows the general situation of Zurich. The built-up areas are mainly in the area surrounding the lake and in the northern part.

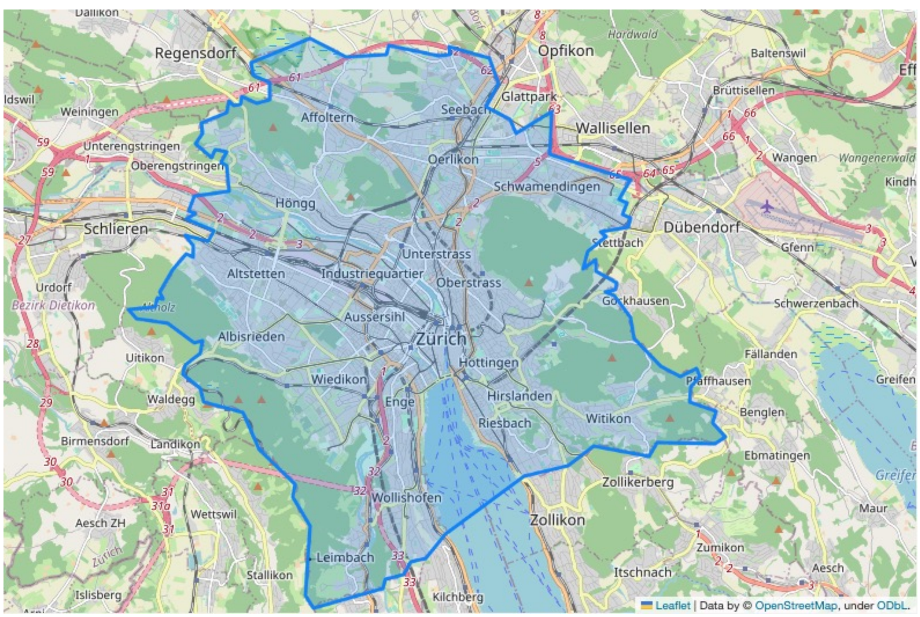

Figure 1: Study area: Zurich.

3.2 Research flow

This study uses geo-tagged SM photographs to analyze people's activities at UGSs. It also examines the factors influencing different types of activity and activities within different UGSs categories, taking Zurich as an example. Firstly, after preprocessing, 708 UGSs and 7614 Flickr images were left. Then, Google Cloud Vision API and hierarchical clustering techniques were employed to identify and categorize the Flickr images based on their contents. These types of Flickr images are used to represent visitors' activities within UGSs. Following this, the study investigates the relationship between predictors and different types of activities. Further, the study explores potential factors that influence different kinds of activities within a particular UGSs category. The whole technical workflow can be found in Figure 2.

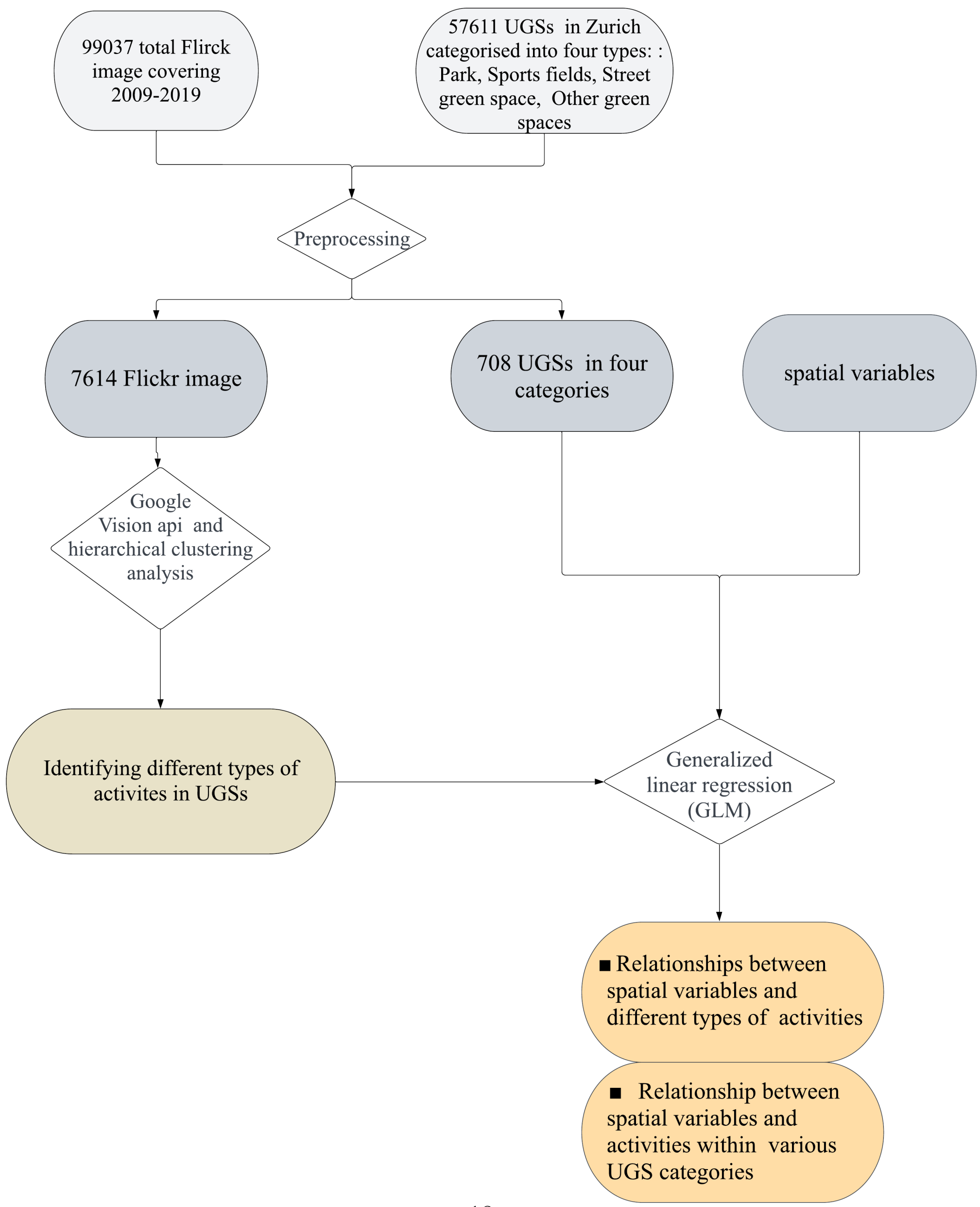

Figure 2: Rresearch flow

3.3 Data

3.3.1 UGSs in Zurich

UGSs data for Zurich is downloaded from `https://data.stadt-zuerich.ch/dataset/geo_gruenflaechen` in 23ch, March 2023. These data are provided by the Zurich Area Management System (FMS). They are based on the official cadastral survey of the City of Zurich, aerial photographs, and orthophoto maps. The raw UGS data for Zurich is categorized into four main categories and consists of 19 specific types:

- Parks: '611 Parks';
- Cemeteries: '623 Graveside services', '624 Cemetery facilities';
- Sports and swimming facilities: '631 Sports facilities', '632 Swimming facilities';
- Other open space: '641 Street trees', '642 Street greenery', '643 School Green', '650 School Grey IMMO', '651 Social buildings IMMO', '652 Administrative buildings IMMO', '653 Cultural buildings IMMO', '654 Factory buildings IMMO', '660 Housing estates LVZ', '661 Residential properties LVZ', '662 Stream maintenance ERZ', '663 Green space maintenance VBZ', '664 Green space maintenance EWZ', '690 Billable services'.

Considering the aims of this study and sample sizes, I merged the UGS categories of 'Cemeteries' and 'Other green space'. The reclassified UGSs types are listed below:

- Park: '611 Parks';
- Street green space: '641 Street trees', '642 Street greenery';
- Sports fields: '631 Sports facilities', '632 Swimming facilities'
- Other green spaces: '623 Graveside services', '624 Cemetery facilities', '641 Street trees', '642 Street greenery', '643 School Green', '650 School Grey IMMO', '651 Social buildings IMMO', '652 Administrative buildings IMMO', '653 Cultural buildings IMMO', '654 Factory buildings IMMO', '660 Housing estates LVZ', '661 Residential properties LVZ', '662 Stream maintenance ERZ', '663 Green space maintenance VBZ', '664 Green space maintenance EWZ', '690 Billable services'.

The distribution of UGSs is shown in Figure 3

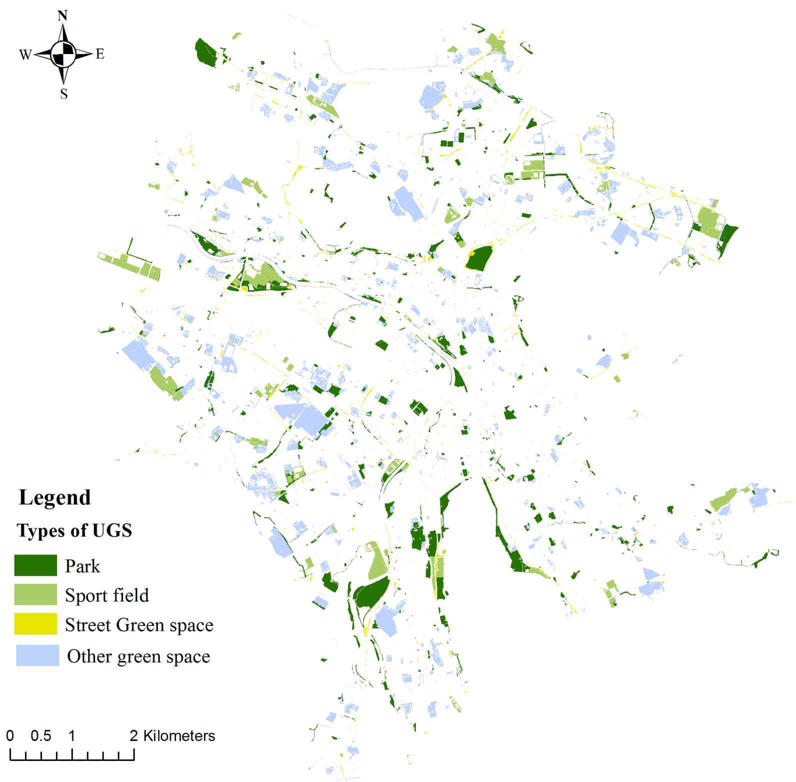

Figure 3: Spatial distribution of UGSs for four different types

3.3.2 Flickr images from 2009 to 2019

Flickr is an online photo-sharing platform that has gained significant popularity and recognition since its launch in 2004. It provides photographers, enthusiasts, and individuals a platform to show their work, explore creative inspiration, and connect with like-minded communities. With its extensive user base and diverse content, Flickr has become a valuable resource for researchers, enabling them to access and analyze visual data in social sciences, urban planning, tourism, and environmental studies. The platform's API (Application Programming Interface) allows developers to access and utilize Flickr's data and services, opening up possibilities for innovative research applications and analysis (Fox et al., 2020). This study downloaded 97,762 Flickr images around

Zurich City, covering the period from 2009 to 2019. These images offer valuable visual insights into different facets of the city, providing a rich resource for studying and understanding Zurich city. From Figure 4, the maximum value was 3619.63 images per 2500 m^2, minimum was 0. The areas with the higher image density were located mainly in Lake Zurich, Zurich's Old Town, the Zurich Zoo and the northeast corner of the city.

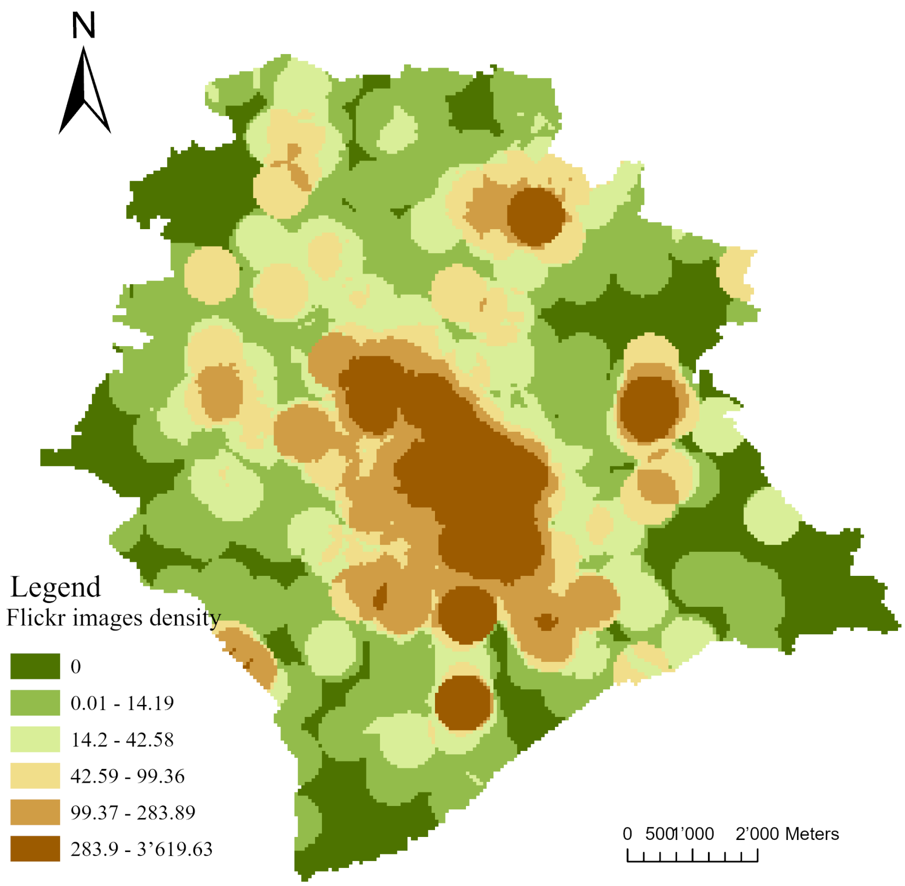

Figure 4: The density map of Flickr images in Zurich from 2009 to 2019.

The annual count of Flickr images in Zurich from 2009 to 2019 can be found in Figure 5. The number of annual images peaked in 2014, followed by a sudden drop, fluctuating between 4,000 and 6,000 from 2015 to 2019. This may be due to the fact that Flickr was gradually replaced by other SM platforms after 2014. In addition, the number of images per month peaks in August, meaning that Zurich UGS is mainly visited in August. In contrast, January and February saw fewer visits.

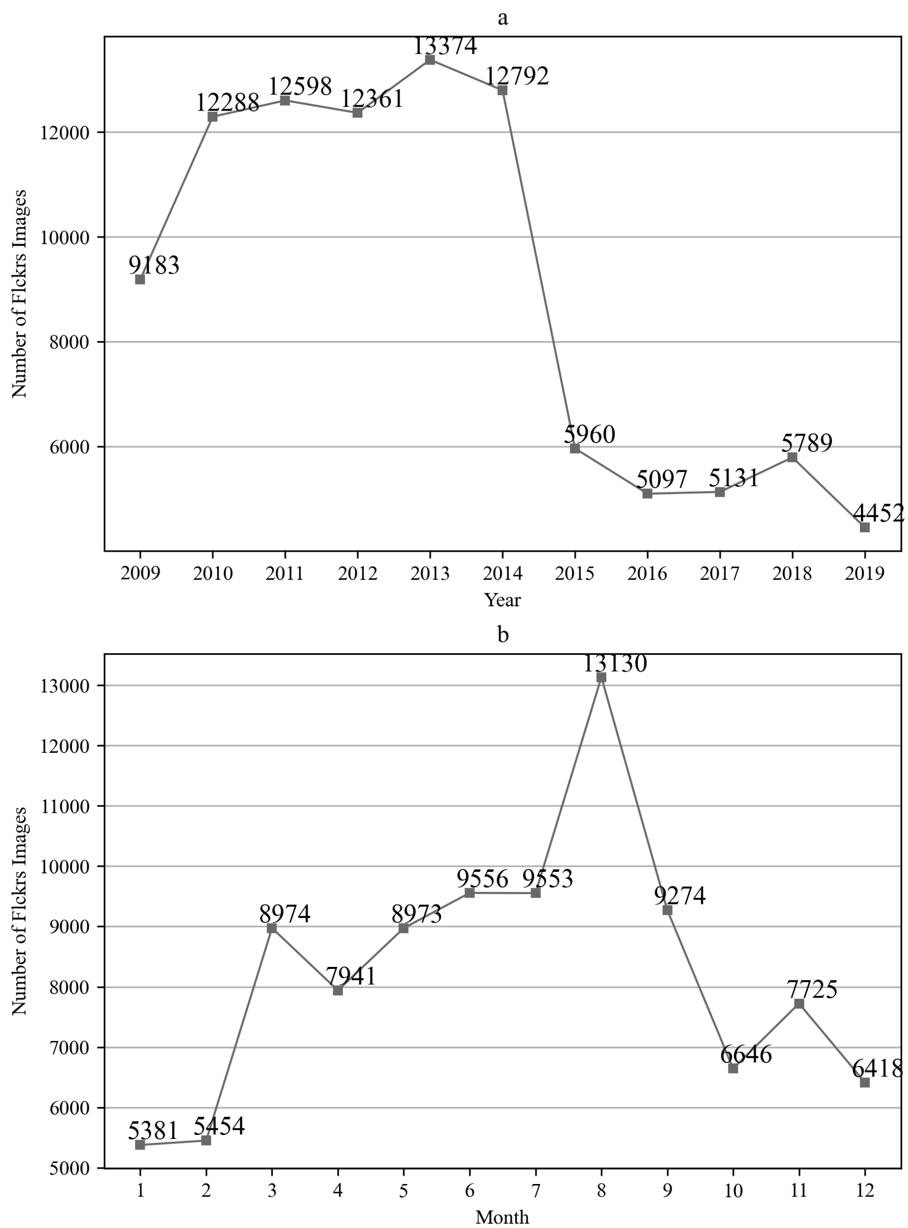

Figure 5: (a) Annual count of Flickr and (b) Monthly count of Flickr images.

3.3.3 Spatial variables

As Table 1 shows, ten variables from three categories were selected in this study. 1) Seven park attributes — park area, vegetation coverage, distance to Zurich Lake, average elevation, length of footpath and cycleway, tree number and fountain number were used to describe the park's attributes. 2) Two independent variables, road density and transport nodes, were used to evaluate UGSs accessibility. 3) One variable, population density, was used to describe the surrounding environment features. These variables are derived from publicly available geospatial data, without the need for costly and time-consuming field surveys.

Table 1: Descriptions for spatial variables used in this study.

Types	Variables	Description	Data Sources	scale
Attribute	Area (m^2)	Calculated from the polygon shapefile in ArcGIS 10.6	Zurich open data	Park level
	Vegetation coverage	mean NDVI of each UGS	Zurich open data	
	Distance to Zurich lake (m)	Nearest Euclidean distance from the park edge to lake edge	Zurich open data	
	Fountain number	Number of fountains within each UGS	Zurich open data	
	Length of cycleway and footpath (m)	Polyline shape files included the categories 'cycleway', footway', 'pedestrian', 'path', 'track', 'steps', and 'bridleway'; Cycleways and footpaths within 10 m beyond polygon boundaries were included.	Open street map	
	Average elevation (m)	Average elevation of each UGS	GeoVITe	
	Tree number	Number of trees within each UGS	Zurich open data	
Accessibility	Road density (m/m^2)	Polyline shape files include the categories 'primary', 'secondary', 'tertiary', 'residential', 'service', 'motorway', 'trunk', 'living street' 'unclassified', as well as related 'link' roads. Road density is calculated by dividing the total length of these roads by the 100-meter buffer zone.	Open street map	Neighbourhood-level (within 100 meter buffer)
	Transportation stops	Number of bus and tram stops within neighbourhood	OpenStreetMap	
Surrounding environment	Population density	mean population density within 500-meter buffer	Zurich open data	Neighbourhood-level (within 500m buffer zone)

Details of each variable can be found below:

Area

The area of each UGS was calculated based on the polygon shapefiles using ArcGIS10.6. (Unit: m^2)

Vegetation coverage

Vegetation coverage is represented by the Normalized Differential Vegetation Index (NDVI), which is a vegetation index that provides information about the presence and health of vegetation based on the difference in reflectance between near-infrared (NIR) and red light. The NDVI values range from -1 to +1, with different ranges indicating different characteristics. Negative values (-1 to 0): These values typically represent water bodies, clouds, or other non-vegetated surfaces, as they have low reflectance in both NIR and red wavelengths; Values close to zero (0 to 0.1): These values indicate shallow vegetation cover or sparse vegetation, such as barren land or areas with little or no vegetation; Low to moderate values (0.1 to 0.3): These values represent areas with medium vegetation cover, such as grasslands, shrublands, or agricultural lands with crops in early stages; High values (0.3 to 0.7): These values indicate dense vegetation, such as forests, dense crops, or areas with lush green vegetation; Very high values (0.7 to 1): These values are rare and often associated with thick, healthy foliage, such as tropical rainforests (Carlson and Ripley, 1997).

The Zurich NDVI data was downloaded in `https://data.stadtzuerich.ch/dataset/geo_orthofoto_2010_bund___sommer___quasi_true___ndvi`. It was generated by a Digital Surface Model (DOM) obtained from ADS80 aerial image strips during the summer survey of 2010 conducted by Swisstopo. The resolution is 25 centimetres. The zonal statistics tool in QGIS was applied to measure the average NDVI in each UGS.

Distance to Zurich Lake

ArcGIS10.6 was used to calculate UGS's distance to Zurich Lake. Zurich Lake polygon was extracted from the Waterbody area (downloaded from `https://data.stadt-zuerich.ch/dataset/ktzh_av_gewaesser__ogd_`). The nearest Euclidean distance from the park edge to Zurich Lake represented the distance to Zurich Lake. (Unit: m)

Fountain number

Zurich fountain data can be downloaded from (`https://data.stadt-zuerich.ch/dataset/geo_brunnen`). There are 12000 fountains in Zurich, including wells from the water supply and other service departments in Zurich and private wells. This study calculated the number of fountains within each UGS boundary. This data was updated on April 13 2023.

Length of cycleway and footpath

Zurich road data was obtained from OpenStreetMap (OSM). Established in 2004, the OSM project has garnered significant attention in recent years. It is one of the most notable sources of Volunteered Geographic Information (VGI) on the Internet, accumulating a wealth of data. The project's growth and the extensive data it offers have contributed to its rising prominence and popularity. Unlike platforms like Wikipedia and Flickr, which primarily rely on user contributions to specific topics or images, the OSM project focuses on gathering detailed information about elements such as streets, roads, transportation nodes, points of interest, and buildings. OSM emphasises including precise geographic references in the collected data, providing a comprehensive and geographically oriented database (Neis and Zipf, 2012). The Zurich OSM dataset was downloaded from `https://download.geofabrik.de/europe/switzerland.html` on March 9 2023. I only used Zurich road polygon data and transportation nodes point data.

In the OSM road polyline data, there are 27 types of roads in Zurich OSM data: bridleway; cycleway; footway; living_street; motorway; motorway_link; path; pedestrian; primary; primary_link; secondary_link; residential; secondary; tertiary_link; track; service; steps; tertiary; track_grade 1; track_grade 2; track_grade 3; track_grade 4; track_grade 5; trunk; trunk_link; unclassified; unknown. Polyline shape files included categories: 'pedestrian', footway', 'path', 'track', 'steps', and 'bridleway'; Cycleways and footpaths are recognised as footpaths. Polyline shape file categories as 'cycleway' is recognised as the cycleway. Cycleway and footpath polyline shape files within 10 meters beyond UGS polygon boundaries were included. (Unit: m)

Average elevation

A digital elevation model (DEM) is a three-dimensional representation of a terrain's surface created from terrain elevation data. Zurich (DEM) data is downloaded from `https://geovite.ethz.ch/DigitalElevationModels.html`. This data was uploaded in 2019. The average elevation for each UGS is calculated by the Zonal statistics tool in QGIS. (Unit: m)

Tree number

Zurich tree data was downloaded from `https://data.stadt-zuerich.ch/dataset/geo_baumkataster`. The number of trees within each UGS was calculated by ArcGIS10.6.

Road density

Polyline shape files include the categories 'primary', 'secondary', 'tertiary', 'residential', 'service', 'motorway', 'trunk', 'living street', 'unclassified', as well as related 'link roads' are recognized as the main road. The road density of a UGS was calculated by dividing the total length of main roads within its 100m buffer zone by the area of its buffer zone. (Unit: m/m^2)

Transportation stops

Transportation node data is also obtained from OMS. It contains 731 bus stops and 411 tram stops. Transportation nodes within 100 meters beyond the UGSs polygon were included.

Zurich population density

Zurich population density dataset was downloaded from `https://data.stadt-zuerich.ch/dataset/ktzh_raeumliche_bevoelkerungsstatistik__ogd_`. The dataset comprises spatial data with a resolution of 1 meter, providing information on population distribution, age structure, gender composition, and the proportion of foreign residents. (Unit: $person/m^2$)

Figure 6 and Table 2 show the general statistic description of each variable.

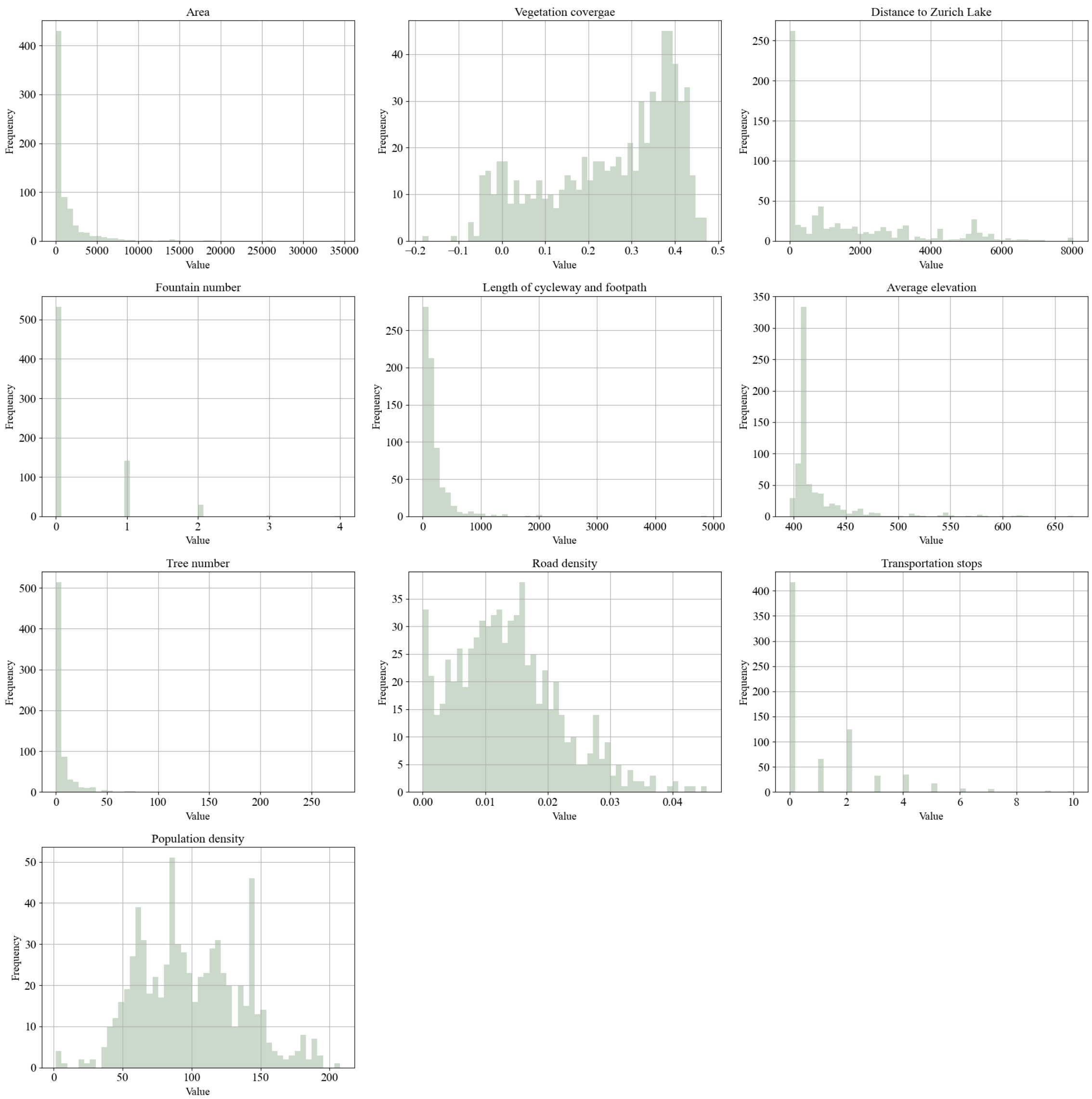

Figure 6: Histgram of spatial variables.

Table 2: General statistic description of spatial variables.

Type	Spatial variables	Max	Min	Mean	std.
Attributes	Area	34503.47785	20.85216002	1379.403618	2726.324234
	Vegetation coverage	0.473698326	-0.183076554	0.252990539	0.149532243
	Distance to Zurich Lake	8046.232943	0	1587.608162	1884.513922
	Fountain number	4	0	0.305084746	0.594769392
	Length of cycleway and footpath	4886.224871	0	197.9553739	294.7311953
	Average elevation	667.8959079	395.9512665	422.0201261	33.78830257
	Tree number	278	0	6.504237288	16.49392273
Accessibility	Road density	0.045471298	0	0.013541257	0.008447744
	Transportation stops	10	0	1.06779661	1.646540999
Surrounding environment	Population density	207.55	1.666666667	99.56312373	37.03817946

3.4 Method

3.4.1 Data preprocessing

Figure 7 introduced the data preprocessing workflow. Firstly, I used spatial joins between 57611 UGSs and 99073 Flickr images, resulting in 10573 geo-tagged photos in 1820 UGSs. Then, a scene recognition model (Places365-ResNet18) was applied to filter outdoor images. Places365-ResNet18 model is downloaded from `https://github.com/CSAILVision/places365` (Huai et al., 2022, Zhou et al., 2018). This resulted in a final dataset of 8697 outdoor images. This step is due to the presence of museums or concerts in certain parks, which has led to many indoor photos on SM platforms. Finally, these outdoor images and 1820 UGSs are spatially joined again, leading to 1622 UGSs and 8697 images left. As the proportions of various activities within each UGS are required in this study, UGSs with only one image are removed. As is shown in Figure 8 (a), 771 UGSs left after removing UGSs with less than two images. Then, to improve the data representativeness, I decided to only use the major part of the data according to the area of UGS. As Figure 8 (b) shows, UGS with an area less than 20 m^2 were removed. Finally, only 708 UGSs and 7614 Flickr images were left.

The distribution of left UGSs can be found in Figure 9. The area of each UGSs and image count within each UGSs by type are shown in Table 4 and Table 3. There are 461 Parks, 62 Sports fields, 52 Street green spaces and 133 Other green spaces. There are 5792 images in Parks, 921 in Sports fields, 214 in Street green space and 687 in Other green spaces. The Sports field had the highest average number of images at 14.8548 and the biggest mean area at 2667.6668 m^2, while Street green space had the lowest average number of images at 4.1154 and the smallest average area at 469.4194 m^2.

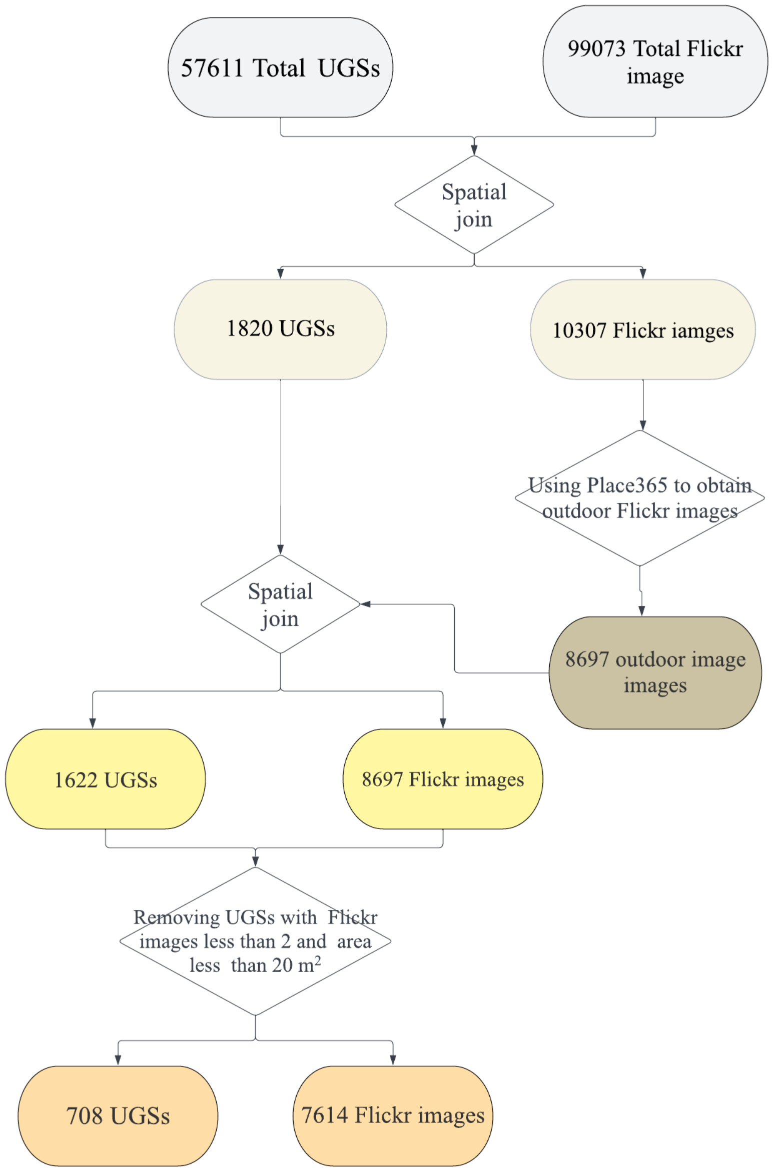

Figure 7: Workflow for data preprocessing.

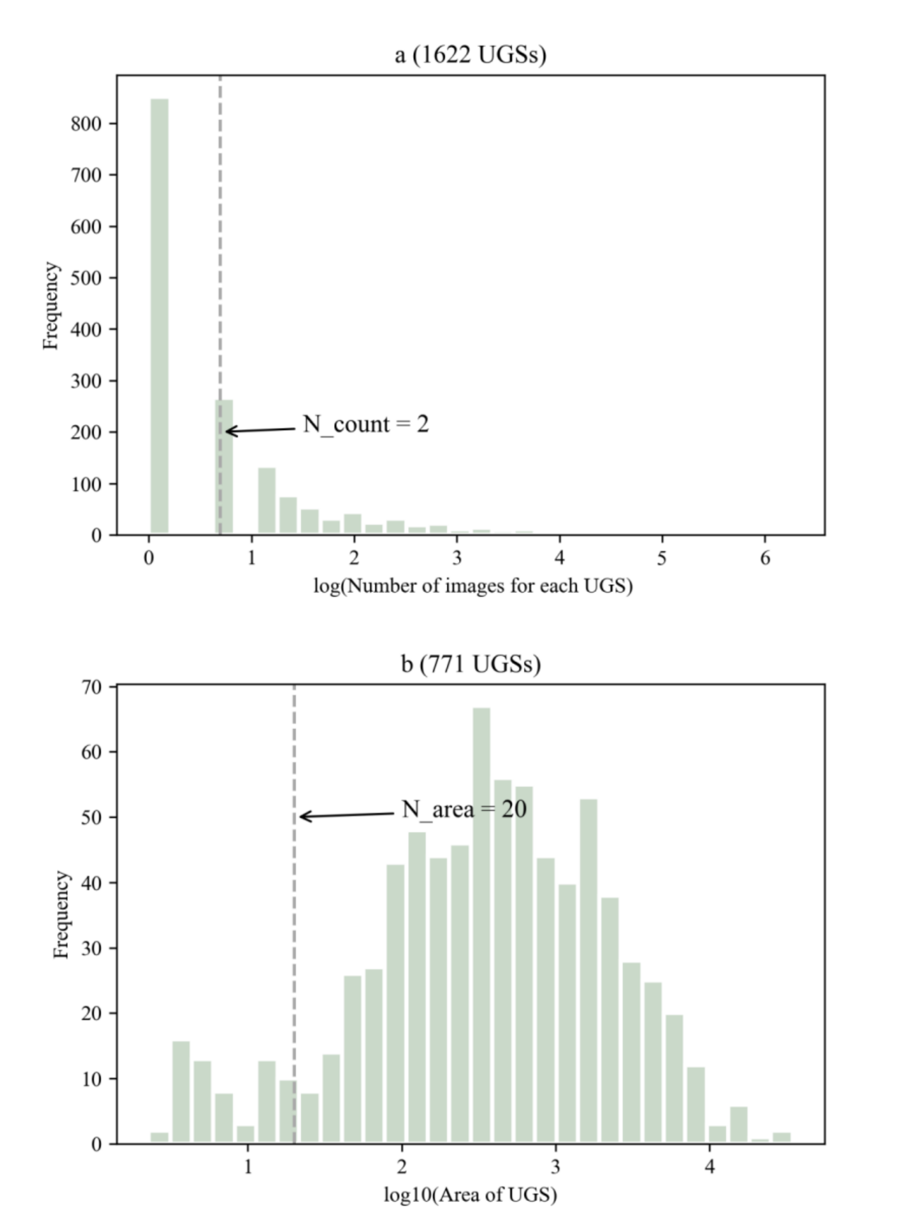

Figure 8: (a) Removing UGSs with less than two images, then 771 UGSs left. (b) Removing UGSs smaller than 20 m^2, only 708 UGSs left.

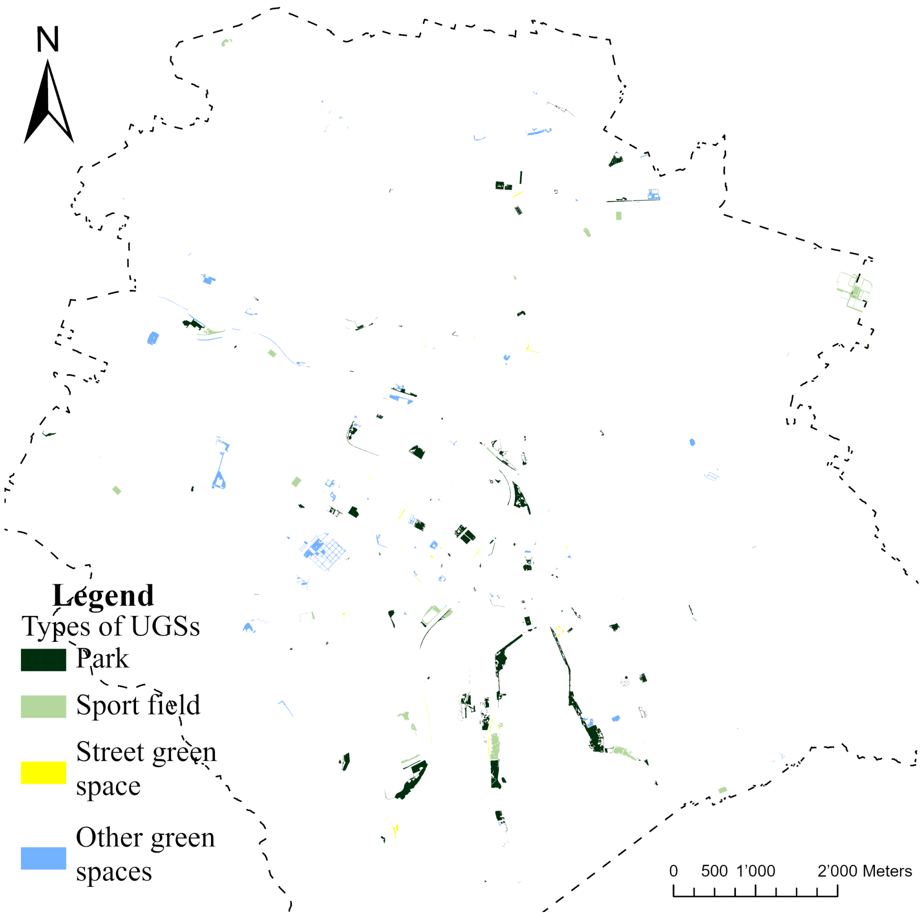

Figure 9: Distribution of left UGSs after data preprocessing.

Table 3: Statistic description of the image count within each UGS by types.

Type of UGSs	count	mean	max	min	total
Park	461	12.5640	528	2	5792
Sports fields	62	14.8548	277	2	921
Street green space	52	4.1154	15	2	214
Other green spaces	133	5.1654	37	2	687

Table 4: Statistical description of the area of each UGS by type.

Type of UGSs	count	mean	max	min	total
Park	461	1227.5619	34503.4779	20.9860	565906.0276
Sports fields	62	2767.6668	26129.1859	42.9475	171595.3411
Street green space	52	469.4194	2163.1578	27.6704	24409.8103
Other green spaces	133	1614.3352	19182.5518	20.8522	214706.5825

3.4.2 Image classification

In this study, Google Cloud Vision was used to classify images. Computer vision (CV) is a rapidly advancing and intricate field of research that has experienced significant growth in recent decades. It encompasses the scientific and technological aspects of machines capable of capturing and analyzing images or videos, primarily extracting valuable information from processed visual data. Many CV algorithms and image recognition techniques have been developed in recent years, such as Google Cloud Vision, Microsoft Azure Computer Vision API, etc. (Mulfari et al., 2016). This study employed Google Cloud Vision, a machine learning algorithm designed for image analysis, to examine the elements present within the photographic images. Google Cloud Vision API is a cloud-based image analysis service provided by Google Cloud Platform. Introduced on December 2, 2015, Google Cloud Vision has experienced continuous growth and development. It allows for exploring labels, text, landmarks, logos, and attribute information of images based on large-scale image training of machine learning models (Lee and Son, 2023). In this study, image content interpretation was conducted using the "Label detection" function offered by the Google Cloud Vision API. This feature generates multiple labels along with their respective probabilities for an image. The service is underpinned by cutting-edge Deep Neural Network Machine Learning algorithms that rely on pre-trained models drawn from extensive libraries. In this study, Python code was developed to process all images by the Google Cloud Vision API platform requiring user authentication. Thus, several keywords were automatically generated to describe the content of the images (Zhou and Ushiama, 2020). Figure 10 shows a sample result of image recognition conducted by Google Cloud Vision API.

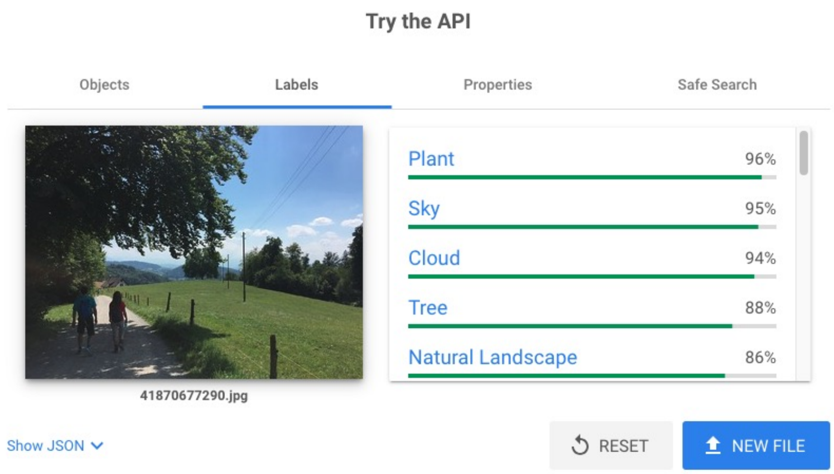

Figure 10: An example of Google Cloud Vision API.

1485 unique keywords were generated from UGSs photographs. The 20 most frequently appearing keywords are shown in Figure 11

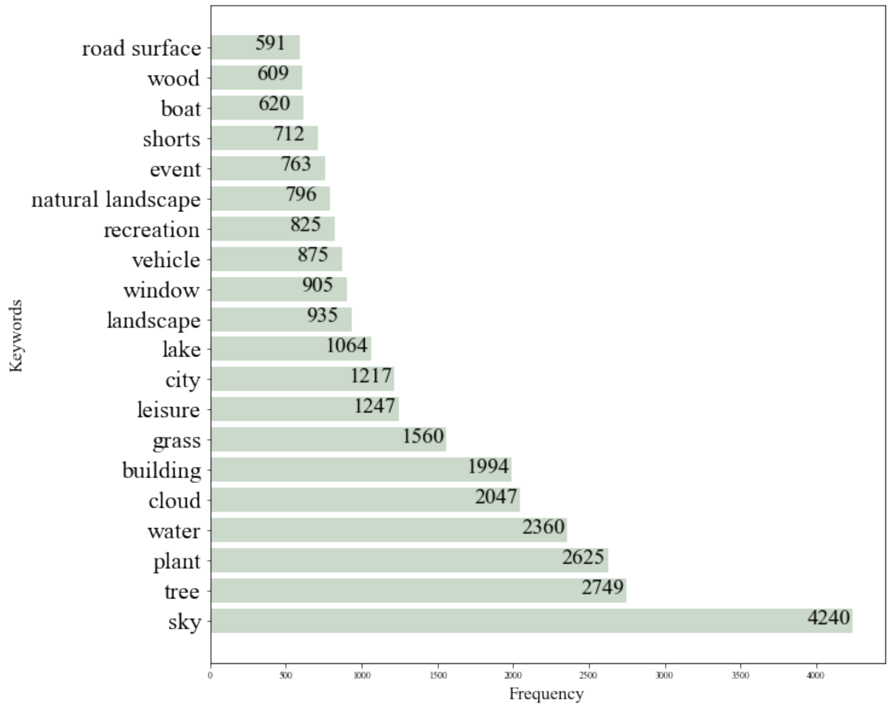

Figure 11: The most 20 frequent keywords.

3.4.3 Hierarchical clustering analysis

This study used the Hierarchical clustering method provided by Song et al. (2020b) and can be downloaded from `https://github.com/xp-song/photo-classify`. This method categorizes the photographs into groups based on content types using keyword labels generated by Google Cloud Vision. The similarity between each pair of unique photos was computed by considering the number of shared keywords. This method eliminates the subjectivity often associated with manual classification and allows for categorising photographs into discrete groups using hierarchical clustering, even when there is overlapping content (Song et al., 2020b).

3.4.4 Regression analysis

Generalized linear regression (GLM) models of the negative binomial family were used to examine the impacts of spatial variables on activity types in UGSs. When the conditional variance exceeds the mean value, it suggests an over-dispersion of the variable. Thus, it is proper to use negative binomial regression in this study, which is suitable for dealing with count variables exhibiting over-dispersion. Before building the GLM model, I used the procedures of Hosmer Jr et al. (2013) to reduce the input parameters shown in Table 1. Highly positively or negatively correlated (Pearson $r > 0.5$) parameters were eliminated to avoid multicollinearity. Then all predictor variables were scaled to 0-1.

To build regression models, I first developed regression models for different activity types. The response variable was the proportion of Flickr images related to a specific activity within each UGSs. Subsequently, I generated models for each particular activity within different UGSs categories. In these subsequent models, the response variable was the activity ratio within a specific UGS type.

4 Result

4.1 Image classification and activity clustering

After utilizing Google Cloud Vision and hierarchical clustering on 7614 Flickr photos, nine distinct types of images were identified (as shown in Figure 12).

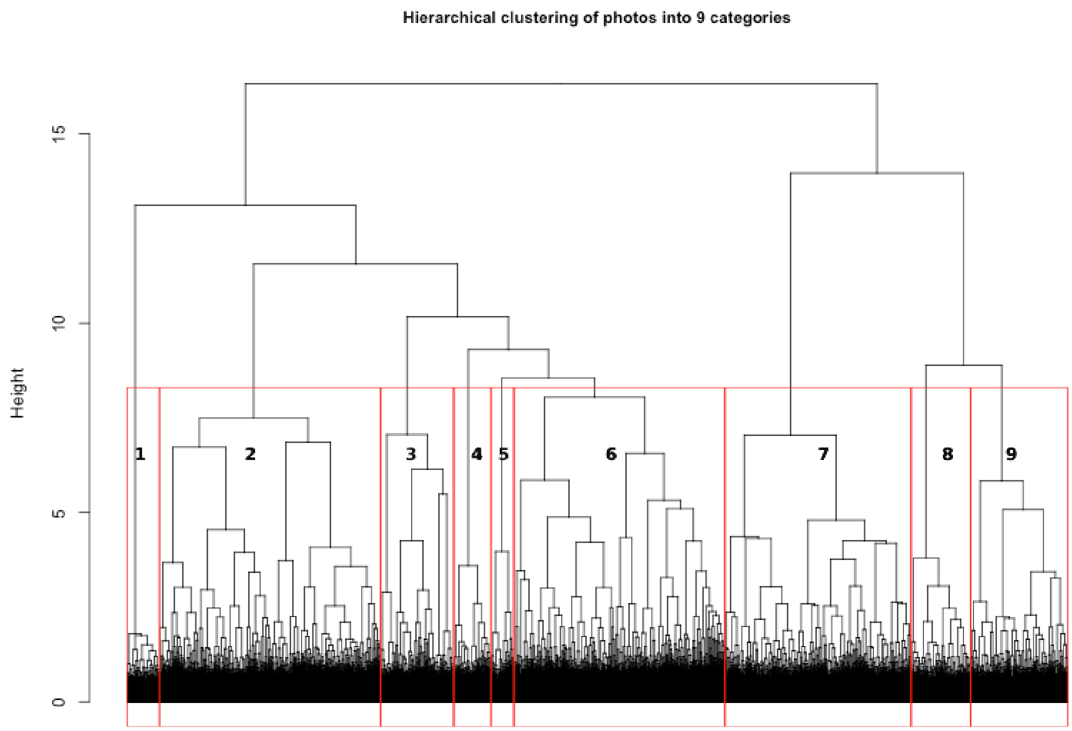

Figure 12: Nine categories of Flickr photographs and their label.

The group labels, the most frequently associated keywords and the number of photos in each group are listed in Table 5. For the convenience of discussion and comparison, these nine groups were merged into four main types of recreational activities.

Table 5: Categorising nine groups of labels into four types of activity and the most frequent 10 keywords for each group.

Recreational activities	Group label	Number of photos	The most 10 frequent keywords and their frequency
Sports & Recreation	1	1786	{'event,': 838, 'sky,': 800, 'leisure,': 616, 'tree,': 545, 'recreation,': 533, 'shorts,': 404, 'cloud,': 332, 'plant,': 330, 'water,': 321, 'travel,': 320}
	9	300	{'ball,': 502, 'sports': 368, 'player,': 362, 'equipment,': 311, 'football,': 300, 'shorts,': 295, 'soccer,': 286, 'grass,': 239, 'soccer': 237, 'ball': 165}
Flora & Fauna	4	1735	{'plant,': 2164, 'tree,': 1406, 'grass,': 1170, 'landscape,': 1072, 'sky,': 956, 'leisure,': 637, 'natural': 621, 'road': 414, 'surface,': 414, 'recreation,': 400}
	8	190	{'bird,': 265, 'beak,': 204, 'water,': 151, 'feather,': 124, 'ducks,': 110, 'geese': 106, 'swans,': 105, 'waterfowl,': 99, 'lake,': 93, 'wing,': 79}
Water activity	3	512	{'water,': 628, 'boat,': 520, 'watercraft,': 506, 'sky,': 444, 'lake,': 444, 'vehicle,': 394, 'cloud,': 252, 'boats': 208, 'boating–equipment: 208, 'supplies,': 208}
	7	795	{'water,': 897, 'sky,': 810, 'landscape,': 684, 'cloud,': 610, 'lake,': 592, 'natural': 439, 'tree,': 377, 'plant,': 334, 'dusk,': 261, 'horizon,': 261}
Cityscape	2	1429	{'building,': 1576, 'sky,': 1415, 'city,': 985, 'window,': 857, 'tree,': 742, 'cloud,': 661, 'facade,': 600, 'urban': 590, 'water,': 589, 'plant,': 581}
	5	563	{'vehicle,': 865, 'bicycle': 567, 'tire,': 559, 'wheel,': 516, 'automotive': 453, 'motor': 294, 'sky,': 267, 'tree,': 238, 'car,': 229, 'plant,': 190}
	6	304	{'sculpture,': 401, 'art,': 311, 'statue,': 304, 'sky,': 205, 'tree,': 194, 'monument,': 177, 'plant,': 174, 'grass,': 120, 'cloud,': 95, 'leisure,': 77}

Group 1 and Group 9 were combined and renamed as 'Sports & Recreation', Group 4 and Group 8 were merged and renamed as 'Flora & Fauna', Group 3 and Group 7 were combined and renamed as 'Water activity', and Group 2, Group 5, and Group 6 were merged and named as 'Cityscape'. As a result, there are four types of activities: 'Sports & Recreation', 'Flora & Fauna', 'Water activity', and 'Cityscape'. Figure 13 shows the number of photos contained in each activity. In the 'Sports & Recreation' activity, the most frequent keywords include 'event', 'sky', 'leisure', 'tree', 'recreation', 'shorts', 'cloud', 'plant', 'water', 'travel', 'ball', 'sports', 'player', 'equipment', 'football', 'shorts', 'soccer', 'grass', 'soccer', 'ball'. There are 2086 photos related to this activity, occupying almost 27 % of the total images. For the 'Flora & Fauna' activity, the most frequent keywords are 'plant', 'tree', 'grass', 'landscape', 'sky', 'leisure', 'natural', 'road', 'surface', 'recreation', 'bird', 'beak', 'water', 'feather', 'ducks', 'geese', 'swans' 'waterfowl', 'lake', 'wing'. It has 1925 relevant images, accounting for 25.2 % of the Flickr image dataset. For 'Water activity', keywords include 'water', 'boat', 'watercraft', 'sky', 'lake', 'vehicle', 'cloud', 'boats', 'boating–equipment', 'supplies', ‘water’, ‘sky’, ‘landscape’, ‘cloud’, ‘lake’, ‘natural’, ‘tree’, ‘plant’, ‘dusk’, ‘horizon’. It has the least images, and 1307 water-related images occupy 17 % of the dataset. In the last activity, ‘Cityscape’, the most important keywords are ‘building’, ‘sky’, ‘city’, ‘window’, ‘tree’, ‘cloud’, ‘facade’, ‘urban’, ‘water’, ‘plant’, ‘vehicle’, ‘bicycle’, ‘tire’, ‘wheel’, ‘automotive’, ‘motor’, ‘sky’, ‘tree’, ‘car’, ‘plant’, ‘sculpture’, ‘art’, ‘statue’, ‘sky’, ‘tree’, ‘monument’, ‘plant’, ‘grass’, ‘cloud’, ‘leisure’. It has the most relevant images at 2296, holding 30% of the whole image dataset (Figure 13).

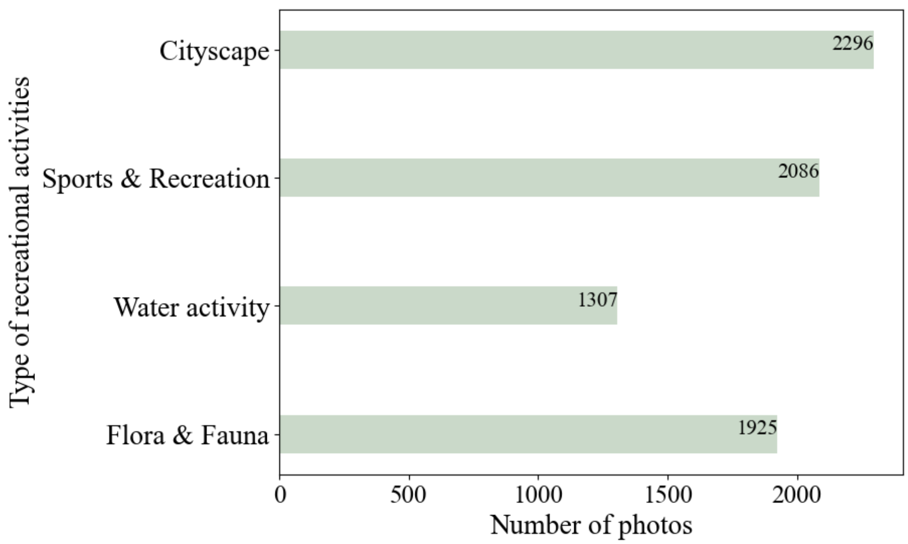

Figure 13: Number of photos for each activity type.

Figure 14 displays the distribution of photos related to different types of activity. Most of the photos of ”Water activities” were relatively centrally located around Lake Zurich, while the distribution of photos related to the other three types of activities was relatively decentralized.

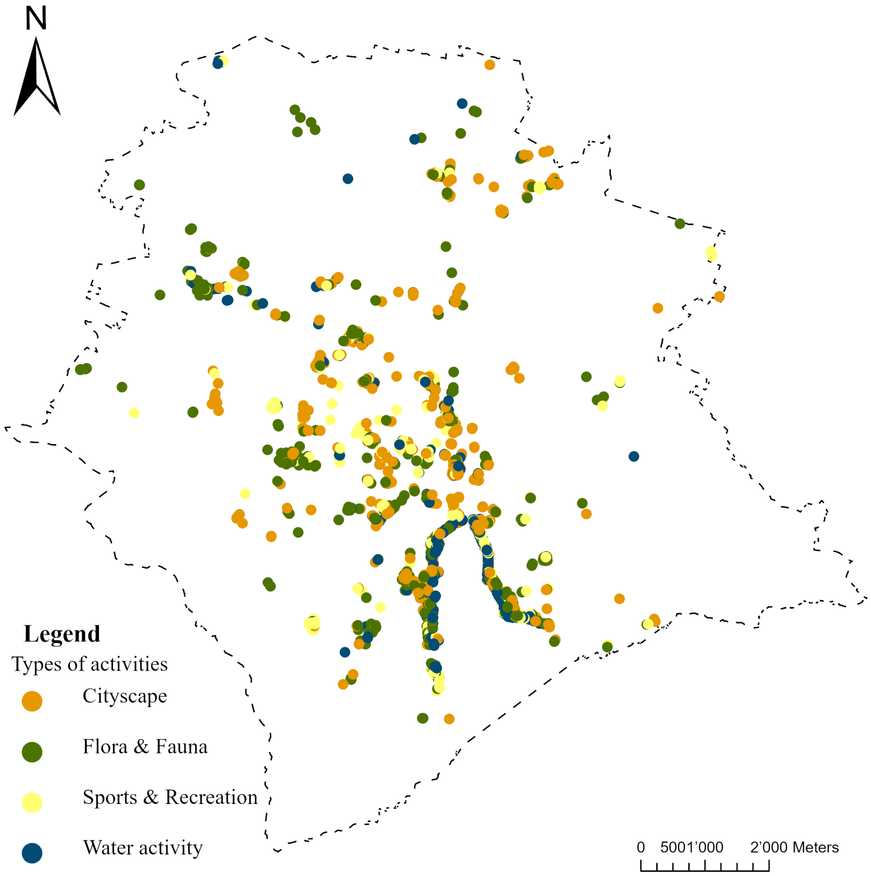

Figure 14: Distribution of photos related to different activity types.

4.2 Comparison between the distribution of Flickr image and UGSs

From Figure 15, there were overlaps between regions of the greatest concentration of Flickr images and UGSs used in this study, such as areas around Zurich Lake and Old Town, the north-east corner of Zurich city, except the Zurich Zoo which is one of the most popular places among photographers. This is because the Zurich Area Management System (FMS), which provides the Zurich UGSs data, did not recognize zoos as a type of UGS. In addition to the Zoo, almost all the urban green spaces were located in eye-catching areas.

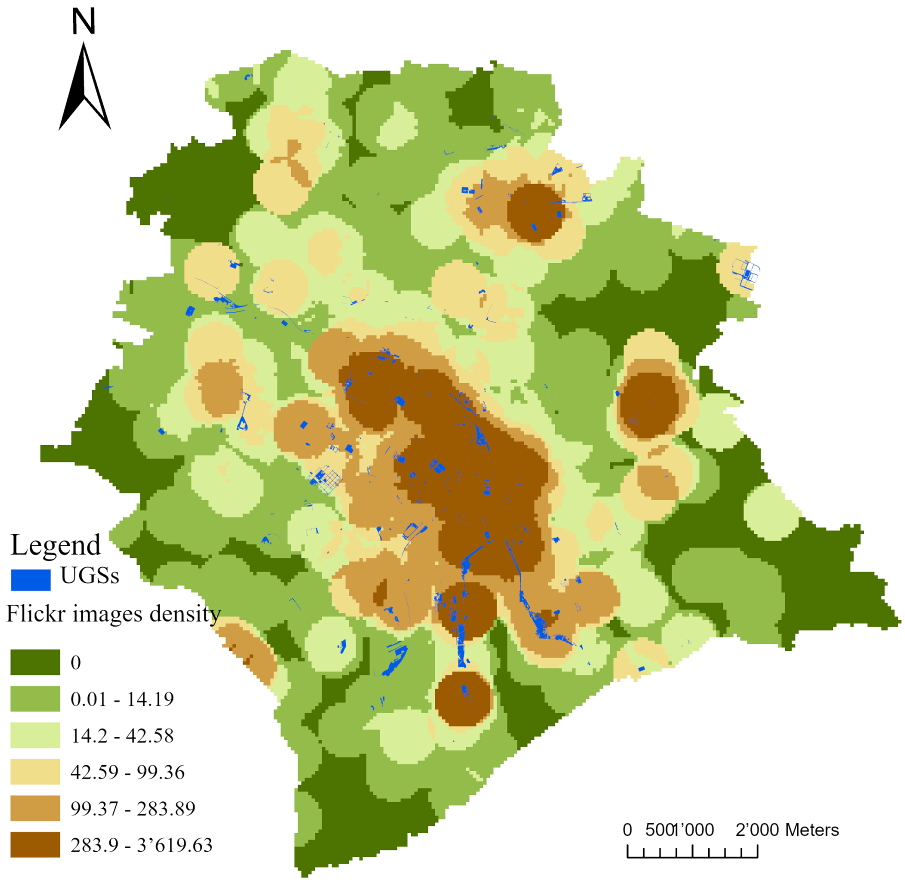

Figure 15: Distribution of UGSs after preprocessing and the density map of the whole Flickr image dataset before preprocessing.

4.3 Relationship between activity types and UGSs types

As is shown in Figure 16, Parks had the most Flickr photos, meaning it is the most critical type of UGSs for people. Around 5792 photos were located in Parks, accounting for 76 % of the whole image dataset. 12.7% of photos are located in the Sports Fields. The proportions of photos in Street green space and Other green spaces (green areas in schools, private buildings, etc.) were 3 % and 9 %. In each UGS category, the distribution of activities varied, shaping the essence of these spaces. For example, in Parks, there was a relatively balanced ratio of activities: 22% was dedicated to 'Sports & Recreation', 20% to 'Water activity', 31% to 'Cityscape', and 26%

to ‘Flora & Fauna’. ‘Sports and Recreation’ activity was dominant with regard to Sports fields, encompassing a significant 70 % share of the photographs in it. In contrast, the remaining activity types found their place with more modest proportions: ‘Water activity’ at 9%, ‘Cityscape’ at 8%, and ‘Flora & Fauna’ at 13%. Street green spaces presented an entirely different scenario. The visual narrative was predominantly captured by ‘Cityscape’, composing 56 % of all images. ‘Flora & Fauna’ claimed its significance as the second most prevalent activity, constituting 20% of the images. On the other hand, ‘Water activity’ was relatively infrequent, accounting for merely 6 % of the photographs, making it the least represented activity within street green spaces. In the realm of Other green spaces, the activity ‘Cityscape’ predominated again, constituting the largest share at 38 % in terms of captured images. ‘Flora & Fauna’ followed closely behind, encapsulating 34 % of the visual narratives. Meanwhile, ‘Water activity’ remained at the periphery, holding the smallest share with only 6% of photos.

These findings indicated the significance of types of UGSs in catering to various recreational activities. Park emerges as the most favoured choice for the surveyed activities, emphasizing their central role in providing recreational opportunities within urban environments. But other types of UGSs can still provide places for people to enjoy nature and recreation.

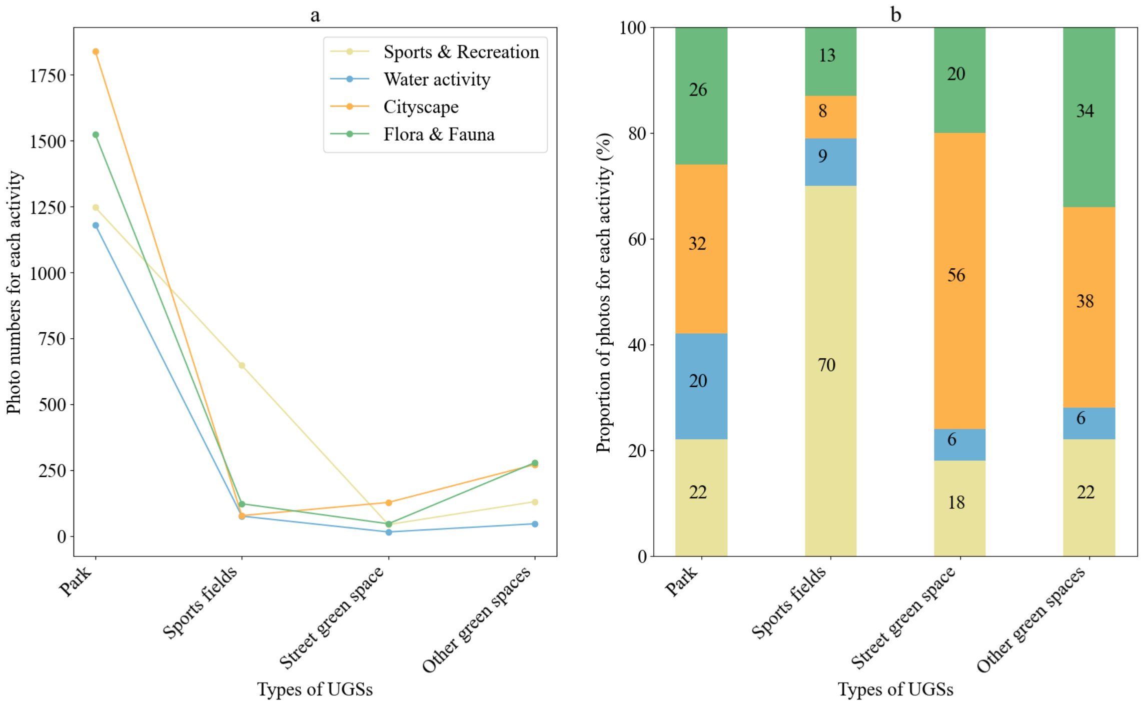

Figure 16: (a) Number of photographs associated with an activity type in each UGS category. (b) The proportion of photographs associated with an activity type in each UGS category

4.4 Influence of spatial variables on activity types

4.4.1 All UGS types

After identifying four types of activity, the proportions of images related to a specific type of activity within each UGSs were measured. The general statistic description of these four dependent variables can be found in Figure 17. The average proportion of 'Flora & Fauna' photos stands at 35%, 'Water activity' images average at 16%, 'Sports & Recreation' images come in at an average of 18%, and 'Cityscape' images have an average representation of 31%.

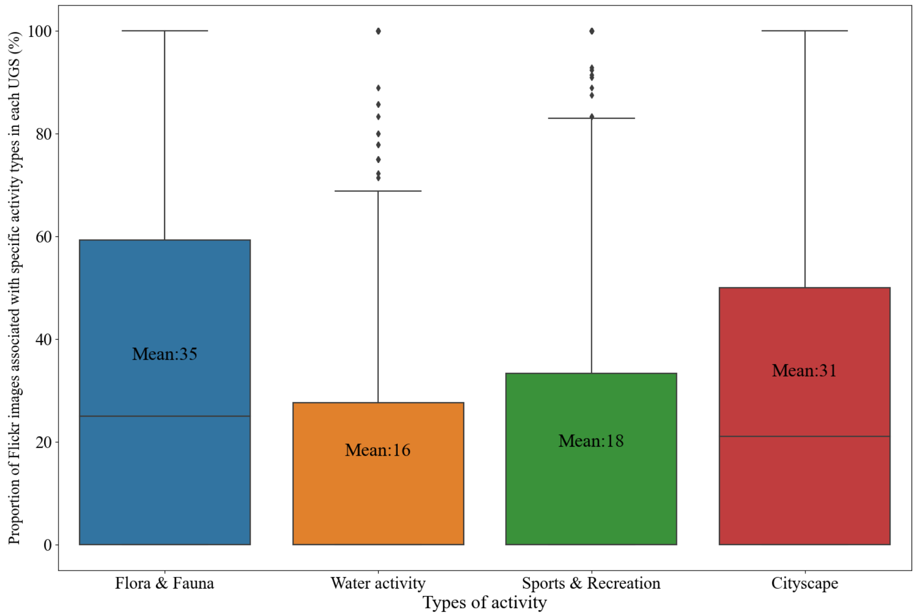

Figure 17: General statistic description of four dependent variables (Dependent variables were measured by the proportions of images related to a specific type of activity within each UGS) .

Factors influencing various activities at all types of UGSs are shown in Table 6. The spatial variable significantly associated with all activity was road density. It had a negative relationship with the proportion of activities 'Flora & Fauna' and 'Water activity', but had a positive relationship with that of 'Sports & Recreation' and 'Cityscape'. UGSs with smaller sizes usually had more images related to 'Water activity' and 'Cityscape' and fewer images related to 'Sports & Recreation'. UGSs closer to Zurich Lake usually had more 'Water activity' and 'Sports & Recreation' images and fewer 'Cityscape' photos. The average elevation was significantly negatively related to the proportion of 'Water activity' and 'Sports & Recreation' but was significantly positively associated with that of 'Flora & Fauna'. In neighbourhoods, UGSs with higher population density often had more 'Flora & Fanua' pictures and fewer 'Water activity' and 'Cityscape' images. Additionally, higher vegetation coverage had a positive relationship with photos of 'Flora& Fauna', while it had a negative correlation with the presence of 'Cityscape'. Fewer transportation stops in nearby areas were correlated with fewer photos of 'Water activity' within UGSs.

Table 6: Relationships between spatial variables and various activities in the whole UGSs. (N_sample = 708)

Types of activity	Flora &Fauna	Water activity	Sports & Recreation	Cityscape
R^2	0.08504	0.319	0.07463	0.1065
Area	0.6219	-3.3583**	2.3135**	-1.5323**
Vegetation coverage	0.8173**	-0.2606	-0.1641	-0.4979**
Distance to Zurich Lake	0.1467	-0.5172**	-0.4502*	0.6562**
Fountain number	0.1015	0.1252	-0.4669	0.1114
Length of cycleway and footpath	0.9278	0.7812	-0.5324	0.1877
Average elevation	0.7554*	-1.5784**	-1.0139**	0.1758
Tree number	-0.6252	-0.1763	-0.2671	0.7535
Road density	-0.5948*	-2.1902**	1.0009**	1.089**
Transportation stops	-0.4075	-0.7999**	-0.1737	0.398
Population density	1.0808**	-1.6271**	0.215	-0.6689**

* $p < 0.05$, ** $p < 0.01$

4.4.2 Variables influencing activities at different UGS types

The relationships between spatial variables and specific activities within the different categories of UGS were shown in Table 7. The spatial variables associated with a higher ratio of 'Flora & Fauna' photos across all UGS categories was higher vegetation coverage. Another influential factor was population density, which showed a negative relationship with the presence of 'Flora & Fauna' at Sports fields and a positive correlation with that at Park and Other green spaces. Other green spaces at higher elevations and less transportation nodes had more 'Flora & Fauna' photos, while Sports fields at lower elevations and Street green space with more transportation nodes had more 'Flora & Fauna' photos.

For the 'Water activity', all types of UGSs with fewer people living in the neighbourhood were associated with a higher ratio of photos related to it. Park and Sports fields closer to Zurich Lake had more images associated with 'Water activity', while the reverse was found in Street green spaces and Other green spaces. The size of UGS and road density was significantly negatively related to the presence of 'Water activity' photos at Park, Sports fields and Other green spaces. Average elevation had a negative correlation with the proportion of 'Water activity' pictures at Park, Street green space and Other green spaces. Sports fields with more fountains had a higher ratio of pictures related to 'Water Activity', while the situation was reversed for Street green space and Park.

As for the 'Sports & Recreation' activity, Sports fields and Street green spaces at higher elevations tended to have more relevant images. Conversely, Park and Other areas at lower elevations exhibited a higher prevalence of relevant photos. Sports fields with bigger sizes and short lengths of cycleways and footpaths were associated with the presence of 'Sports & Recreation' pictures. However, bigger sizes were related to fewer 'Sports & Recreation' images in Street green space and Other green spaces. Shorter lengths of cycleways and footpaths were correlated with fewer pictures related to it in Park and Street green space. Road density and population density had a positive relationship with the presence of 'Sports & Recreation' photos.

Finally, Sports fields with more people living around had more 'Cityscape' images. By contrast, Park and Other green spaces located in neighbourhoods with lower population density were associated with a lower proportion of photos related to 'Cityscape'. Additionally, smaller sizes and greater distances from Zurich Lake were spatial factors associated with a higher occurrence of 'Cityscape' imagery in both Park and Sports fields.

Table 7: Relationships between spatial variables and various activities in different UGS types (N_parks=461, N_sports fields=62, N_street green spaces=52, N_other green spaces=133)

Types of activity	Types of UGS	R^2	Area	Vegeta-tion coverage	Distance to Zurich Lake	Fountain number	Length of cycleway and footpath	Average elevation	Tree number	Road density	Transportation stops	Population density
Flora& Fauna	Park	0.0793	1.0699	0.6326**	0.2456	0.0764	0.8356	0.3058	-0.9084	-0.5864	0.0826	1.3162**
	Sports fields	0.3752	-5.7569**	2.5489**	1.2342*	-1.0034	4.3051	-6.6887**	3.4511	2.3623*	1.9952	-2.2416*
	Street green space	0.6652	32.7861	6.4262**	-1.9052	3.0051*	26.6541**	-0.3234	-18.1725**	-0.584	1.3959*	0.6286
	Other green spaces	0.265	2.696	0.918*	0.5252	-0.4089	0.377	2.2926**	-0.3268	-0.0621	-3.4326**	2.2154**
Water activity	Park	0.227	-2.7914**	-0.0942	-0.7345*	-1.0372**	-0.6282	-1.3059*	-0.1499	-0.8741**	-0.3089	-1.2516**
	Sports fields	0.7874	-7.3457**	-1.3438	-3.0477**	2.1324*	1.9889	-0.3755	9.2561	-5.6907**	-8.6167**	-5.1252**
	Street green space	0.8642	11.9545	6.4968**	2.3512*	-6.9134**	-11.9222	-10.1269**	-21.7643*	-0.4909	1.7416	-5.5152**
	Other green spaces	0.5535	-5.3985**	-2.3154**	2.5805**	0.2775	2.9421*	-6.2051**	1.7993	-2.8285**	0.4843	-3.8055**
Sports & Recreation	Park	0.1072	0.7016	-0.3547	-0.4571	-0.6528	2.7118*	-2.2639**	-0.1003	1.4765**	-0.4622	-0.304
	Sports fields	0.4174	5.9363**	-1.3933*	0.0972	1.4487	-7.7565*	5.2951**	-1.2615	-0.3173	0.8478	3.7242**
	Street green space	0.7081	-58.0421**	-1.5736	-9.1523**	2.6217*	22.7357*	5.0426**	15.3083**	2.1502*	-0.6415	5.254**
	Other green spaces	0.202	-3.624*	-0.0773	-1.0857*	0.4944	-0.4307	-1.8909**	1.8109	0.5482	2.0488**	0.1414
Cityscape	Park	0.1196	-1.9039*	-0.0015	1.5573**	0.5298	1.1109	-0.0582	0.6983	0.9614**	-0.0827	-1.3444**
	Sports fields	0.4937	-7.6657**	-1.3895*	1.4041**	-1.409	0.8265	-7.8573**	22.8832**	1.9382	3.0273**	2.1*
	Street green space	0.2289	-15.6684	-1.8914**	-0.1282	-0.238	-8.0386	0.9214	-4.2563	-0.5055	0.273	0.0557
	Other green spaces	0.1382	0.1767	-0.91*	0.2091	-0.6648	0.3095	-0.9339	-3.0265	0.8246	0.9863	-1.2262*

* $p < 0.05$, ** $p < 0.01$

5 Discussion

This study used geo-tagged Flickr photos to investigate people‘s activities within UGSs and assess how different spatial variables influenced these activities. Additionally, it explored the relationships between spatial variables and activities across four distinct UGS categories. By using automated image identification and hierarchical clustering, four activities were identified within Zurich UGSs: ‘Flora & Fauna’, ‘Water activity’, ‘Sports & Recreation’ and ‘Cityscape’. Results indicated that all four activities were nearly equally popular in Park. ‘Sports & Recreation’ took precedence in Sports fields, while ‘Cityscape’ emerged as the most favoured activity in Street green space and Other green spaces. Notably, ‘Water activity’ was the least prevalent activity across Sports fields, Street green space, and Other green spaces. Regression models showed that road density significantly positively correlated with the popularity of ‘Sports & Recreation’ and ‘Cityscape’ activity but negatively related to that of ‘Flora & Fauna’ and ‘Water activity’. Other important variables, including the size of the UGS, distance from Lake Zurich, average elevation, and population density, affected the partial activity differently.

5.1 Activities in UGSs

In this study, four main activities were identified, which were ‘Sports & Recreation’, ‘Flora & Fauna’, ‘Water activity’, and ‘Cityscape’. All four activities are popular in the Park. Previous studies that explored human activities at UGSs have also mainly focused on parks. For example, Song et al. (2020a) analyzed photos from Flickr and Instagram in Singapore urban parks and categorized them into six types: birds, wildlife, plants, flowers, recreation, and water/skyscapes. Using geo-tagged social media photos and computer vision method, Huai et al. (2022) identified ten landscape feature categories, corresponding to 4 CES categories in urban parks of Brussels. Urban parks are essential places for various outdoor recreation in cities. Therefore, it is reasonable that people can enjoy all four activities in Parks. Regarding Sports fields, there is no doubt that ‘Sports & Recreation’ is the most common activity as it provides most sports facilities. In the case of Street green space, it is usually along the street or road and is generally smaller in size. As a result, photographs taken within its setting are typically associated with artificial features, often characterized as ‘Cityscape’. As for the ‘Water activity’, it was the least common activity in all UGSs types except for the Park. It may be because the waterbody was not a typical natural landscape in urban areas, and the main waterbody in the study area is Zurich Lake, located in the central part of Zurich and is mainly surrounded by parks.

5.2 Important spatial variables affecting activities in UGSs

This study revealed that a lower road density in the surrounding neighbourhood corresponded to a reduced number of images associated with 'Flora & Fauna' and 'Water activity' but more 'Sports & Recreation' and 'Cityscape' photos. This finding is consistent with Song et al. (2020a), whose study also demonstrated that an increased road density correlated with a lower number of photographs depicting flora and water features. This may be due to the fact that built-up areas are less appropriate for nature photography and more for artificial landscapes and people-oriented activities. But in Sports fields, road density was positively correlated with the occurrence of 'Flora & Fauna'. This may be explained by the fact that most areas within the playing fields are artificially constructed, and plants are usually distributed as landscaping along the nearby roads.

This study also found meaningful associations between UGS size and the number of Flickr images. Hamstead et al. (2018) demonstrated that the size of parks in New York City was positively associated with the frequency of social media posts, including those on platforms like Twitter and Flickr. In a study of Wuhan, Lyu and Zhang (2019) employed a dual dataset approach, incorporating Baidu heat maps and Weibo check-in data, to analyse the park use. Their research highlighted a significant correlation between park size and the level of park utilization, underscoring the influence of park sizes on park popularity. Zhang and Zhou (2018) also substantiated this trend, investigating the volume of check-ins on the Weibo platform, specifically within parks located in Beijing. However, this trend was not found by Song et al. (2020a) in their study conducted in Singapore, as well as by Donahue et al. (2018) in their investigation carried out in the USA. The outcomes of household surveys performed by Schipperijn et al. (2010) revealed that the frequency of visits to larger parks increased significantly only when these parks were situated near residents' residences. This study found that as the UGSs size increased, there was a rise in the number of 'Sports & Recreation' images but a decline in the amount of 'Water Activity' and 'Cityscape' images. This may be because of the need for a particular size area for sports activities and the holding of events. Artificial features are more common in small UGSs, typically the street green space. Additionally, in smaller UGSs, water features are usually relatively more prominent because they may be more visible in a limited space. This makes it easier for people to notice water features and photograph them.

In this study, I also found that UGSs closer to Zurich Lake were associated with a higher proportion of photos related to 'Water activity' and 'Sports & Recreation' but a lower ratio of 'Cityscape' images. It suggests that the water feature is essential in Zurich to enjoy UGSs. By analyzing 1622 questionnaires, Kienast et al. (2012) indicated that waterbodies correlate with higher use in the neighbourhood green spaces in cities and towns in Switzerland. Song et al. (2020a) also found that the length of waterfronts and the distance to the coast were associated with water or sky recreation in parks. These associations may be linked to inherent human preferences for water and vast landscapes, topics that have been explored in the fields of evolutionary and environmental psychology Hartmann and Apaolaza-Ibáñez (2010). For instance, individuals often gravitate towards water-rich environments for leisure, as these waterscapes have positively impacted people's emotional well-being (Meert et al., 2014). UGSs that are further away from the lake are usually located in busy parts of the city and may be surrounded by more buildings and roads, making them more suitable for scenes related to city life. However, the distance to Zurich Lake was significantly positively associated with 'Water activity' images in Street green space and Other green spaces.

Results also showed that elevation had a positive relationship with the occurrence of 'Flora & Fauna' images but a reversed relationship with that of 'Water activity' and 'Sports &recreation' photos. As is known, plants and animals are common on hills where the average elevation is higher, while lakes are in low-lying areas. For humans, the city's built-up areas are usually centred on gentle, low-lying terrain.

Population density also has impacts on activities within UGSs. Lyu and Zhang (2019) indicated that population density negatively impacted park use in Wuhan. Zhang and Zhou (2018) also found a similar trend in the usage of Beijing Parks. The primary factor is the high quality of accessibility of transportation in Wuhan, which encourages people to visit parks located at a certain distance from their homes. Residents thus may not necessarily utilize or appreciate the parks in close proximity to their residences. As a result, living in the immediate vicinity of urban parks is not necessarily a determining factor. This city-wide study revealed that a higher population density in the surrounding neighbourhoods was associated with a decrease in the prevalence of 'Water activity' and 'Cityscape' images while concurrently witnessing an increase in the frequency of 'Flora & Fauna' photographs. One possible explanation is that 'Water activity' and 'Cityscape' photographs are usually taken in parks or UGSs in commercial districts, where population densities are generally low. While in densely populated residential areas, people may be more likely to enjoy nature provided by small gardens, greenbelts, etc.

Vegetation coverage was significantly positively correlated with the occurrence of 'Flora & Fauna' photos but negatively correlated with that of 'Cityscape' photos. This suggests that natural landscapes play an essential role in the photographs shared by park visitors, especially in capturing plants and wildlife. In contrast, in well-built areas where natural landscapes have almost disappeared, people can almost only enjoy city life.

5.3 Implications

This study used SM data to investigate people's activities at UGSs and the impacts of different spatial variables on these activities. Recognizing that local governments frequently confront resource limitations in conducting extensive surveys, social media could provide supplementary data or alternative methods for consistently measuring park use patterns. Results revealed the mix of activities within different categories of UGSs. It shows people's actions in less common urban green spaces, such as playing fields and street green spaces. As urban populations continue to expand, the importance of providing access to well-maintained city parks and other public spaces becomes increasingly evident. The results imply that urban planners should also take into account the significance of urban green space systems beyond just traditional parks.

The regression models showed that road density was positively related to the occurrence of 'Sports &recreation' and 'Cityscape' photos but negatively related to that of 'Flora & Fauna' and 'Water activity' photos. Accordingly, when the public is more keen to enjoy nature, urban planners need to consider reducing the accessibility of UGSs. However, the situation is reversed when the public is more inclined to enjoy urban life. Given the inherent trade-offs in accommodating various needs, conducting a neighbourhood-specific analysis like this can offer more detailed insights into the factors that should be taken into account during UGSs planning. Notably, critical spatial variables, including UGSs size, vegetation coverage, distance to Zurich Lake, elevation and population density, were also found to have significant impacts on the use of UGSs. These discoveries enhance our comprehension of variations in UGSs usage within Zurich City.

5.4 Limitations

This research paper employed geotagged Flickr images to understand the activities at UGSs, with Zurich as the focus of the study. Unlike conventional surveys, which demand considerable time and effort, this approach is more time-efficient and provides broader spatial coverage. Nevertheless, it is essential to acknowledge that this method has limitations. For instance, individuals visiting cultural relic parks and expansive urban parks may have a higher propensity to share photos, while this tendency might be lower at sports fields. This potential variation among UGSs can introduce uncertainty when analyzing the impacts of influencing factors. Therefore, there are inherent biases within geotagged Flickr images. Spatial bias in geo-located data is a big issue. The size of social media content is likely to be highly biased toward popular tourism destinations. For instance, numerous studies have pointed out that overactive users with too many uploads and over-concentration on famous sites also lead to problems in social media data (Gupta et al., 2020). The mismatches between user tags and the image content are another issue. Social media data is self-published by users. While the photographer's position may usually be relatively close to the photo's subject, especially in a UGS, it has been found that the locations of social media photographs can be influenced by users' preferences (Cui et al., 2021). Some individuals have a tendency to geotag photos with the location of the subject in the photo, such as a renowned building, rather than the photographer's own position (Song and Zhang, 2020). In addition, after evaluating the users of six platforms in Great Britain by questionnaire, Blank and Lutz (2017) found that Twitter users tend to have a younger age profile and higher levels of education. Compared to older visitors, young visitors to parks are more willing to post their natural experiences online (Heikinheimo et al., 2017). Women are likelier to share their experiences on social media than men (Hausmann et al., 2017). The representativeness of social media data, thus, is a big problem as it cannot represent all demographic groups. Therefore, social media data contains inherent bias and only partially reflects the opinions and behaviours of people in the real world. The reliability and usefulness of the Flickr image data should be further validated when UGSs authorities publicly disclose visitor statistics in the future.

Several other spatial variables influencing the utilization of UGSs have not been factored into this analysis. These include individual socioeconomic indicators like income, occupation, education, age and gender, previously identified in the introduction as potential determinants of park visitation. Moreover, psychological factors like interest levels and safety perceptions are also known to influence park usage. The spatial distribution of these characteristics among SM users could potentially explain variations in park visitation patterns, but quantifying them geospatially currently presents a considerable challenge. Regrettably, gathering sociodemographic data from SM users, unlike traditional visitor surveys, proved unattainable, thus constraining a more thorough investigation into the connection between park visitation and user-related factors.

6 Conclusion

This study applied Flickr photos to examine peoples' activities at Zurich UGSs. Google Cloud Vision API and hierarchical clustering were used to identify activity types at UGSs according to the contents of Flirck images. Then, GML models were employed to analyse the impacts of spatial variables on various activity types. Further, relationships between variables and activities at different UGSs categories were analysed. The outcomes of our study have shed light on the factors driving the preferences of different activity types at UGSs in Zurich, enhancing our comprehension of UGSs use. These findings have substantial importance for the planning and administration of UGSs.

Four activities were recognized according to the content of geo-tagged images: 'Flora& Fauna', 'Water activity', 'Sports & Recreation' and 'Cityscape'. This city-wide analysis of social media photographs at UGSs across Zurich has shown the variations of activity preferences in different types of UGSs. The study results also indicated that road density, UGS size, vegetation coverage, average elevation, and population density are essential factors in determining the popularity of various activities within the UGSs. Considering the type of activity and UGSs, one factor may have very different impacts on the popularity of an activity. Consequently, urban planners should apply diverse criteria to meet varying needs.

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Personal declaration I hereby declare that the submitted Thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the Thesis.

Zurich, September 25, 2023

Anjing Zhang

Anjing Zhang