

Health-promoting Potential of Parks in 35 Cities Worldwide

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ABSTRACT

Urban parks are important for public health, but the role of specific spaces, such as playgrounds or lakes, and elements, such as benches or sports equipment, in supporting well-being is not well understood. Based on expert input and a review of the literature, we defined six types of health-related activities: physical, mindfulness, nature appreciation, environmental, social, and cultural. We built a lexicon that links each activity to specific elements and spaces within parks present in OpenStreetMap. Using this data, we scored 23,477 parks across 35 cities worldwide based on their ability to support these activities. We found clear patterns: parks in North America focus more on physical activity, while those in Europe offer more chances to enjoy nature. Parks near city centers support health-promoting activities better than those farther out. Suburban parks in many cities lack the spaces and equipment needed for nature-based, social, and cultural activities. We also found large gaps in park quality between cities. Tokyo and Paris provide more equal access, while Copenhagen and Rio de Janeiro show sharp contrasts. These results can help cities create fairer parks that better support public health.

1 Main

As the world's population continues to gravitate towards urban areas, cities are faced with the immense task of creating and maintaining green spaces to foster public health^{1,2}. Urban parks are especially beneficial to vulnerable population groups such as socioeconomically deprived³ and older people^{4,5}. Yet the provision of amenities and facilities that support health-promoting activities has not been systematically analyzed at scale.

Urban green spaces can support health in five main ways. First, they help people stay active, which can reduce obesity and heart diseases^{6,7}. Second, they give people a calm space to rest, reduce stress, and improve focus^{6,8–10}. Third, they bring people together and support social ties¹¹. Fourth, they clean the air, block noise, and cool the city^{6,12}. Last, some green areas expose people to biodiverse forms of life, which may improve the immune system^{13,14}.

Park planners have often focused on practical ways to boost public health, such as adding sports fields, paths, or playgrounds^{15–18}. Despite growing evidence of positive effects, spaces that allowed a diverse range of people to relax or enjoy beauty were often neglected in the past¹⁹. Parks also have the power to build stronger communities²⁰, and many planners now recognize that parks offer clear environmental gains such as cleaner air and lower noise levels¹². During the COVID-19 pandemic, cities saw how vital parks are for public well-being. This led to stronger calls for fair and flexible park design²¹.

Most past studies have treated parks as simple green zones, based on size or distance from homes^{22–24}. Fewer have studied how park layout and equipment affect how people use them. For instance, SOPARC is a tool that tracks how people move through parks and what spaces they use²⁵. Other tools look at what makes parks good for activity, such as access, safety, or looks²⁶. Still others focus on blue spaces such as rivers or lakes²⁷. These tools work well but are time-consuming to implement and hard to scale, and most focus only on physical activity^{28,29}. We still lack a clear understanding of the net benefits of parks, especially when weighing their positive aspects, such as providing spaces for recreation and supporting urban health^{3,30}, with potential downsides, including reinforcing disparities^{31–33} or contributing to gentrification^{34,35}.

Project website: <https://social-dynamics.net/healthy-parks>

Replication Repository: <https://github.com/LinusDietz/Health-Promoting-Parks-Replication>

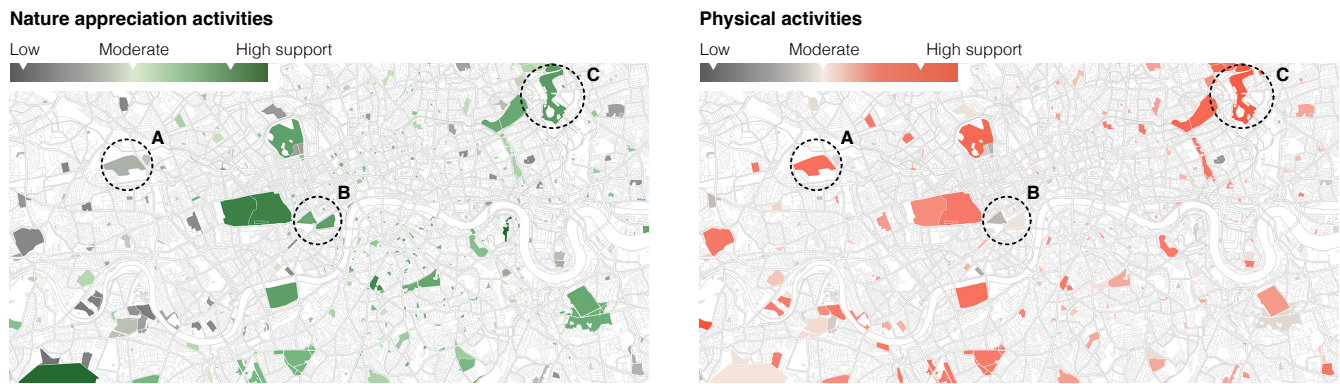


Figure 1. Scores for nature appreciation (left) and physical activities (right) in London parks. Some parks score low on nature appreciation but high on physical activity (A), while imperial-era parks such as Green Park and St. James’s Park, close to the royal palace score high on nature appreciation but low on physical activity (B). Queen Elizabeth Olympic Park, purpose-built for the 2012 Games, scores high across all dimensions (C). Map data from OpenStreetMap <https://www.openstreetmap.org/copyright>

For many cities, there is no easy way to list what parks contain or link these parts to health uses. In this study, we score parks in 35 cities based on how well they support six types of health-related activity. We then ask how these scores relate to fair access to well equipped parks. Our work answers three questions. First, which health-related activities do different park spaces support? Second, how can we measure parks around the world based on this support? Third, where are the biggest gaps in what parks provide?

2 Results

We began by creating a lexicon that linked park spaces and elements to health-related activities using OpenStreetMap (OSM) data. We then scored parks in 35 major cities, which we selected for their geographic diversity and reliable OSM coverage. After validating these scores through statistical comparison and expert review, we analyzed differences in park offerings within and between cities.

2.1 Lexicon of Health-Related Park Features

Step 1: Defining Activities in Parks

An expert panel of three researchers with expertise in urban computing, Earth observation, and computational social science, identified common park activities and organized them into six categories:

- Physical activities:* movement and sport such as walking, biking, swimming, and group exercise;
- Mindfulness activities:* practices like yoga, meditation, and tai chi;
- Nature appreciation:* observing and enjoying the natural environment, including bird watching and picnicking;
- Environmental activities:* community involvement such as gardening and conservation;
- Social activities:* gatherings and group events such as festivals and volunteering;
- Cultural activities:* heritage and arts programs, including performances and exhibitions.

While our 6 categories occasionally overlapped, they captured park activities at a more useful granular level than the typical recreational/physical division. Some overlap is inevitable since certain activities like football (with social and physical aspects) are inherently multi-faceted.

Step 2: Linking Facilities to Activities

We used OSM to collect elements and spaces located within parks in the 35 cities. These included defined areas like forests and ponds as well as features such as benches and sports courts. Each item was described with a tag, which we used to assign the item to an activity category. To scale this process, we trained a classifier based on an large language model (LLM) and validated it with an expert-coded dataset. The full lexicon included 1,441 OSM tags. The ten most frequent tags for each category are listed in Table 3 in Appendix. No OSM tags matched the mindfulness category, so we did not include it in our scoring. Future research may incorporate behavioral data to address this gap.

Table 1. Pearson Correlation Coefficients (PCC) between OSM scores and Flickr activity scores for parks with at least 250 photos.

City	Parks	Mean PCC	Individual Activity Categories PCC				
			Physical	Nature-appreciation	Environmental	Social	Cultural
Amsterdam	25	0.32	0.24	0.36	0.2	0.49	0.29
Auckland	33	0.46	0.38	0.39	0.43	0.47	0.63
Berlin	77	0.34	0.22	0.14	0.53	0.39	0.42
Boston	50	0.4	0.27	0.43	0.36	0.35	0.58
Buenos Aires	54	0.36	-0.04	0.34	0.92	0.15	0.41
Chicago	69	0.41	0.2	0.45	0.35	0.45	0.6
Christchurch	16	0.49	0.27	0.52	0.21	0.72	0.71
Copenhagen	19	0.33	0.31	0.31	0.01	0.22	0.8
Hong Kong	80	0.3	0.38	0.21	0.36	0.21	0.32
Houston	28	0.46	0.36	0.48	0.15	0.61	0.68
London	304	0.44	0.45	0.4	0.32	0.45	0.55
Madrid	42	0.32	0.08	-0.04	0.19	0.66	0.72
Melbourne	59	0.49	0.45	0.63	0.44	0.64	0.29
Montreal	55	0.43	0.31	0.27	0.44	0.49	0.64
Moscow	65	0.34	0.33	0.2	0.34	0.21	0.6
New York	210	0.42	0.41	0.21	0.58	0.45	0.47
Paris	108	0.39	0.42	0.28	0.3	0.39	0.55
Perth	23	0.5	0.18	0.71	0.3	0.68	0.61
Philadelphia	39	0.46	0.43	0.2	0.63	0.32	0.75
Rio de Janeiro	19	0.36	0.26	0.6	0.23	0.41	0.33
Rome	41	0.31	0.43	0.35	0.08	0.16	0.52
San Diego	47	0.44	0.27	0.38	0.61	0.48	0.44
San Francisco	98	0.31	0.17	0.19	0.42	0.32	0.46
Seattle	76	0.38	0.47	0.36	0.09	0.4	0.6
Seoul	52	0.35	0.34	0.36	0.43	0.23	0.38
Singapore	73	0.36	0.14	0.07	0.61	0.39	0.6
St Petersburg	28	0.34	0.17	0.22	0.38	0.39	0.56
Stockholm	50	0.47	0.45	0.32	0.93	0.23	0.42
Sydney	99	0.31	0.42	0.39	0.22	0.14	0.36
Taipeh	107	0.34	0.16	0.22	0.48	0.26	0.56
Tokyo	208	0.31	0.19	0.24	0.37	0.32	0.42
Toronto	111	0.34	0.31	0.3	0.17	0.39	0.51
Vancouver	62	0.44	0.33	0.37	0.33	0.5	0.67
Vienna	40	0.3	0.18	0.08	0.57	0.19	0.5
Washington DC	61	0.52	0.4	0.52	0.56	0.56	0.56
Mean (sd)	72.23 (60.07)	0.39 (0.07)	0.29 (0.12)	0.33 (0.16)	0.39 (0.21)	0.39 (0.16)	0.53 (0.13)

2.2 Scoring Parks for Health Support

We scored each park based on the number of activity-related elements and spaces it contained, normalized by park area. Each park received a score for every activity category. [Figure 1](#) presents an example of these scores for London. In total, we scored 23,477 parks across 35 cities on five continents ([Table 1](#)). Each score reflects how well a park supports a specific activity compared to other parks of similar size in the same city.

Validation with Flickr Data

We validated our park scores using geotagged Flickr images taken within park boundaries. These images included both user-generated and machine-generated tags. We used sentence embeddings to match these tags to our activity taxonomy, allowing us to estimate activity scores for each park based on photo content.

We compared these Flickr-based activity scores with our OSM-derived scores using the Pearson Correlation Coefficient (PCC). Across the 35 cities, the average correlation was 0.39 with a standard deviation of 0.07, indicating moderate but consistent agreement between the two sources. The highest agreement appeared in the cultural ($\mu = 0.53$), social ($\mu = 0.39$), and environmental ($\mu = 0.39$) categories. These types of activities often involve distinctive and photogenic features such as festivals, artworks, or gardens, which are likely to be photographed and tagged.

In contrast, the physical ($\mu = 0.30$) and nature-appreciation ($\mu = 0.33$) categories showed weaker correlations. We believe this may be because users often photograph people or scenery without tagging specific sports or nature-related elements, making it harder to detect those activities in the data.

At the city level, Washington, DC ($\mu = 0.52$) and Perth ($\mu = 0.50$) had the strongest correlations. These cities are in

English-speaking countries where Flickr and OSM usage is more common, which likely led to higher data quality and tag relevance. Cities with lower correlations, including Amsterdam, Hong Kong, and Vienna (each $\mu \cong 0.3$), may have had fewer geotagged images, lower tag accuracy, or less alignment with our English-based taxonomy.

These findings support the use of OSM data to assess park infrastructure for health-promoting activities, especially in categories and regions where online content about park use is widely available.

Validation with Wikipedia

We also validated our activity scores using Wikipedia pages. We identified the top-scoring parks globally for each health-related activity based on our scoring system. For each park, we examined the Wikipedia page to confirm whether the park was known for the corresponding activity type.

In the *physical* category, we found that parks such as Centennial Parklands in Australia and Bois de Boulogne in Paris were known for extensive sports infrastructure, including fields for tennis, soccer, and polo. For *nature appreciation*, top parks like La Dehesa de la Villa in Madrid and Guandu Nature Park in Taipei stood out in their cities with large green areas and wildlife. In the *environmental* category, Washington Park Arboretum in Seattle and Kita-no-maru Park in Tokyo included botanical gardens and conservation efforts. *Social* activity leaders like Inspiration Lake in Hong Kong and Toronto Island Park in Canada were cited for hosting gatherings and public amenities. In the *cultural* category, Ueno Park in Tokyo featured museums and historic landmarks, while Seattle Center included concert halls and art venues.

To further verify our assignments, we conducted structured search queries, such as “Tokyo parks for cultural activities” and found that the top-ranked parks by our method consistently appeared in online recommendations and guides. A complete list of these parks, organized by city and activity category, is available in [Table 4](#).

2.3 Cities Differ in Health-Related Activity Support

Our analysis revealed systematic variations in how urban parks support health-promoting activities, with differences occurring both between cities and within individual urban areas. These variations reflect distinct urban planning priorities, geographic influences, and equity considerations that shape park design and resource allocation.

Estimating Park Offerings Through 8-Hectare Model Parks

To compare park features systematically across cities, we constructed statistical models of typical 8-hectare parks: a size representing neighborhood parks and matching our dataset’s average. [Figure 2](#) (top) shows the expected number of elements and area dedicated to each activity type in a *statistically average* 8-hectare park for each city. We computed these values using parameters from linear regression models developed for each city ([Equation 1](#)). While we fitted separate models per city, making raw health scores not directly comparable between cities, the models enabled comparison of hypothetical average parks across urban contexts.

Regional Priorities: European Nature Focus vs. North American Physical Activity

The most notable regional contrast lies in emphasis on physical activity versus nature appreciation, as shown in [Figure 2](#) (bottom). Parks in European cities tended to provide more space for nature appreciation, while North American cities allocated more area to physical activities. These differences reflect broader urban planning patterns and suggest that parks serve different roles depending on regional goals and cultural expectations.

Cultural Features: Universally Limited Support

Across all regions, cultural features appeared least frequently in parks. In terms of elements, nature appreciation appeared most often, followed by social and environmental activities. Cultural features were the least common. This pattern suggests that while nature and movement receive widespread support, cultural health-promoting activities are deprioritized globally in urban park design.

2.4 Park Offerings are Unequally Distributed Within Cities

We examined how park scores vary within cities by grouping parks into quartiles based on distance from city centers, from the innermost 25% (Q1) to the outermost 25% (Q4). This approach allowed us to systematically assess whether proximity to urban centers influences park offerings.

Inner-City Parks Consistently Outperform Peripheral Ones

Across all activity types, parks in central areas scored higher. [Figure 3a](#) demonstrates that park scores dropped steadily with each quartile further from the center. This pattern held across most cities on all continents, with exceptions in Buenos Aires and Rio de Janeiro, where geography and coastal form influence green space layout.

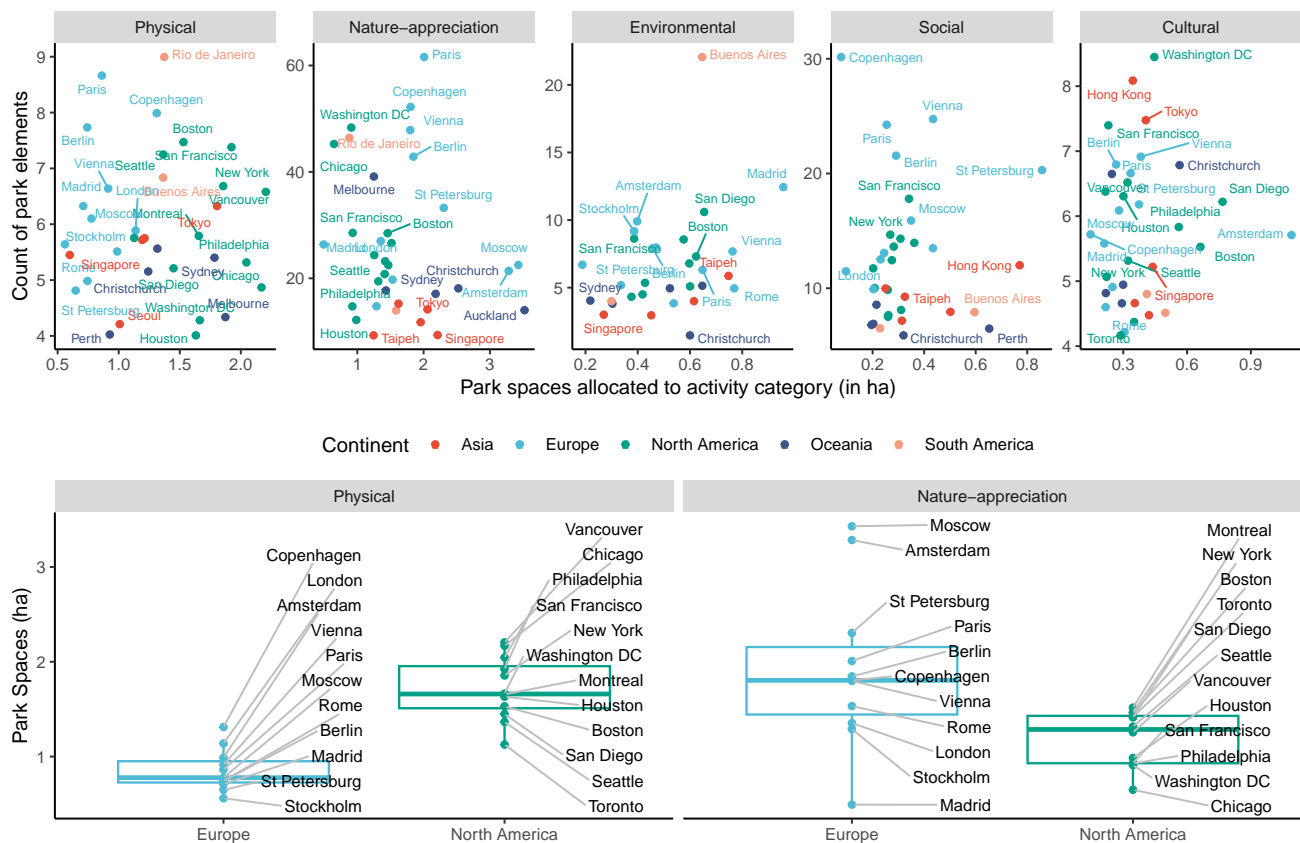


Figure 2. Top: Area of park spaces (horizontal axis) and count of elements (vertical axis) in a typical 8-hectare park by activity and city. Nature and physical activity spaces are the most frequent. Nature-related elements are also the most common across cities. Cultural spaces and elements appear least often. Axes are scaled for clarity.

Bottom: Average space in 8-hectare parks dedicated to nature and physical activities in North America and Europe. North American parks support physical activity more, while European parks provide more space for nature appreciation. Standard box plot with Q1, median, Q3; whiskers at $1.5 \times$ interquartile range.

Nature Appreciation Shows Strongest Distance-Related Decline

The trend was most pronounced for nature appreciation. This finding challenges assumptions that outer areas naturally support greener, more restorative environments and echo Montgomery's concept of the "Savannah Trap"³⁶, where suburban areas include empty, open land that does not support social or ecological use.

2.5 Cities Vary in Ensuring Equitable Park Access

We assessed equity in park offerings within cities using a disparity index (Equation 3) ranging from 0 (complete equality) to 1 (maximum inequality). Box plots in Figure 3b–c show average disparities by activity and region, with detailed values in Table 2.

Activity-Specific Disparity Patterns

Disparities varied by activity type: *physical activities* showed the most even distribution ($\mu = 0.135, \sigma = 0.039$), while *social activities* exhibited the highest disparity ($\mu = 0.222, \sigma = 0.073$), indicating that some parks offer rich social features while others lack them entirely. *Nature appreciation* had moderate average disparity ($\mu = 0.157$) but low variation ($\sigma = 0.032$), suggesting consistent global trends. Overall disparities averaged 0.165, and were similar across continents (0.15–0.19), suggesting that inequality in park design is not limited to one region.

Cities Achieving Balanced Activity Support

Tokyo, Paris, Auckland, Buenos Aires, and Hong Kong demonstrated the most equitable park offerings across activities. Tokyo and Paris particularly excelled, with four or more activity categories showing disparities below one standard deviation from the

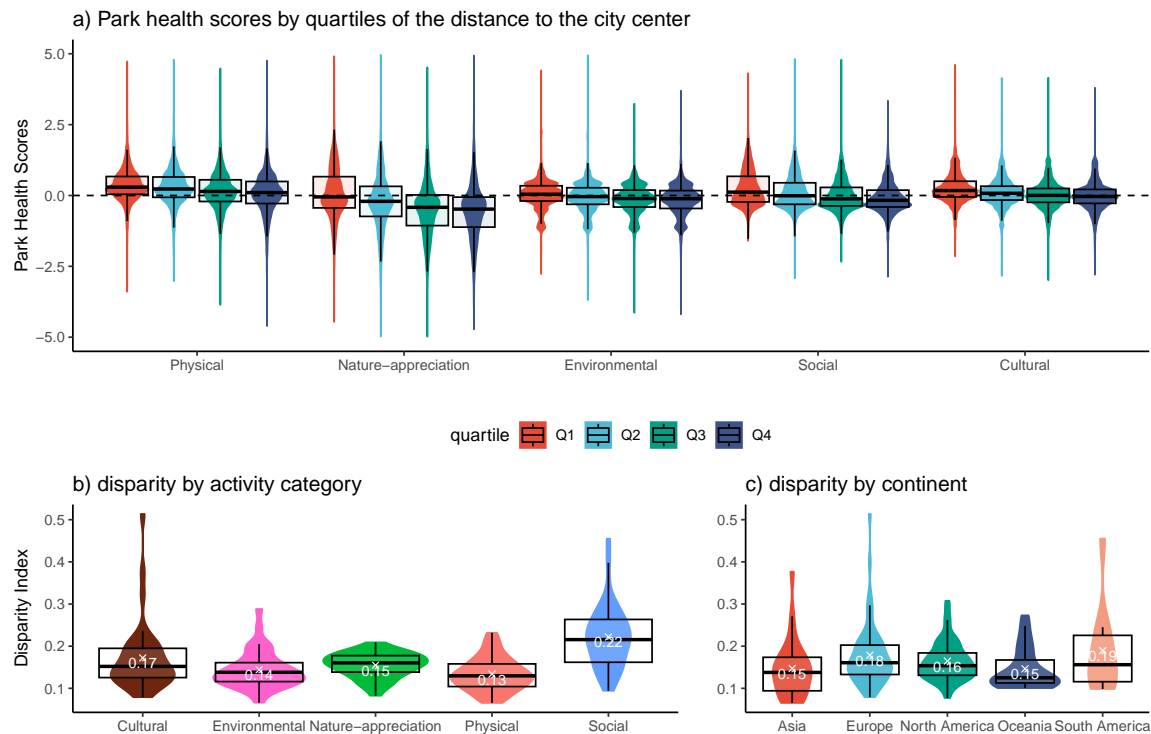


Figure 3. (a) Park scores by distance quartile. Q1 includes parks closest to the city center; Q4 includes those farthest away. Scores decline steadily with distance, especially for nature appreciation. Environmental features show the least decline. Standard box plot with Q1, median, Q3; whiskers at $1.5 \times$ interquartile range. **(b, c) Inequality in park health scores.** Disparities across activities and continents are shown. While total disparity ranges are similar across regions, some activities, such as social and cultural, show much higher inequality than others.

mean. These results may reflect centralized park governance, strong public policy, and active community involvement in cities such as Paris³⁷ and Tokyo³⁸.

Cities with Concentrated Park Resources

In contrast, Moscow, St. Petersburg, Stockholm, Rio de Janeiro, and Copenhagen showed high disparities in park offerings across categories. Stockholm exhibited the highest single-category disparity in cultural features (0.514), suggesting cultural resources were concentrated in a few parks. Copenhagen showed high disparity in both cultural and social categories, potentially reflecting gentrification³⁹. Rio de Janeiro displayed widespread disparities across social, environmental, and cultural categories, aligning with prior findings on spatial health inequality⁴⁰.

These findings demonstrate that while park inequality exists globally, specific cities have successfully implemented more equitable approaches to supporting diverse health-promoting activities through their urban park systems.

3 Discussion

Urban parks offer health benefits that go beyond the usual physical and mental wellbeing. However, our global analysis reveals that urban parks require strategic improvement focused on geographic equity and activity diversity to maximize their health benefits.

3.1 Main Findings

By identifying six types of activities people do in parks, we created a detailed taxonomy of park activities and used this to evaluate parks worldwide based on their support for five of the six activity categories (data to evaluate the mindfulness category was not available on OSM). By giving individual scores for each activity, we identified three critical areas that demand attention from landscape architects, urban designers, and policymakers.

Table 2. Disparity scores by city and activity type. Cities are ordered by their overall average disparity. Lower values indicate a more even distribution of features. Scores one standard deviation below or above the mean are marked in gray and bold, respectively.

City	Mean Score	Inequality of each activity category's offering in a city.				
		Physical	Nature-appreciation	Environmental	Social	Cultural
Tokyo	0.089	0.065	0.082	0.066	0.146	0.084
Paris	0.097	0.104	0.101	0.087	0.114	0.079
Auckland	0.121	0.103	0.117	0.105	0.154	0.126
Buenos Aires	0.125	0.172	0.107	0.098	0.137	0.108
Hong Kong	0.125	0.079	0.134	0.197	0.094	0.12
Vienna	0.135	0.13	0.144	0.107	0.17	0.125
New York	0.138	0.113	0.137	0.131	0.177	0.129
Rome	0.138	0.122	0.16	0.116	0.153	0.141
Christchurch	0.138	0.104	0.113	0.101	0.273	0.101
San Francisco	0.14	0.09	0.152	0.116	0.212	0.132
Berlin	0.143	0.131	0.14	0.138	0.152	0.154
Chicago	0.153	0.077	0.178	0.205	0.151	0.153
San Diego	0.153	0.129	0.169	0.124	0.214	0.128
Melbourne	0.155	0.122	0.167	0.124	0.248	0.114
Montreal	0.156	0.126	0.178	0.142	0.215	0.118
Singapore	0.157	0.166	0.14	0.119	0.227	0.133
Perth	0.157	0.132	0.19	0.125	0.21	0.128
Madrid	0.16	0.104	0.163	0.168	0.197	0.167
Sydney	0.16	0.11	0.119	0.153	0.226	0.191
London	0.163	0.134	0.154	0.138	0.23	0.158
Vancouver	0.165	0.102	0.144	0.153	0.216	0.208
Toronto	0.169	0.129	0.178	0.124	0.24	0.172
Houston	0.173	0.139	0.188	0.141	0.218	0.18
Taipeh	0.174	0.082	0.156	0.116	0.138	0.377
Philadelphia	0.175	0.158	0.174	0.122	0.308	0.116
Seattle	0.179	0.132	0.161	0.141	0.265	0.195
Boston	0.186	0.158	0.183	0.147	0.292	0.152
Washington DC	0.191	0.154	0.16	0.173	0.262	0.205
Seoul	0.191	0.177	0.184	0.174	0.271	0.152
Amsterdam	0.197	0.161	0.187	0.153	0.267	0.217
Moscow	0.205	0.232	0.161	0.205	0.236	0.194
St Petersburg	0.213	0.21	0.166	0.288	0.201	0.199
Stockholm	0.247	0.189	0.132	0.105	0.297	0.514
Rio De Janeiro	0.254	0.141	0.193	0.245	0.455	0.236
Copenhagen	0.266	0.209	0.209	0.195	0.398	0.321
Mean (sd)	0.165 (0.039)	0.134 (0.039)	0.155 (0.029)	0.144 (0.045)	0.222 (0.074)	0.172 (0.085)

Geographic Inequities Demand Immediate Action

Our findings show a clear and concerning geographic trend: parks in city centers are better equipped for health-promoting activities than those on the outskirts. This pattern holds across all types of activities, including those that might be expected to be more common in less populated areas, such as nature appreciation or environmental activities. This geographic disparity contradicts basic expectations and creates significant barriers to equitable health access.

This finding aligns with previous research. Wolch et al. found that park distribution often favors more wealthy communities³². Other studies have shown that recent urban development policies have led to significant greening in city centers, while suburban areas have received less investment⁴¹. Our results expand on these works by showing not only reduced access to parks in suburban areas^{32,41}, but also a lack of amenities and spaces for health-promoting activities.

This evidence creates a clear call to action for urban planners to shift their focus to improving suburban parks, as well as parks outside urban centers, where significant and often overlooked recreation gaps are often found⁴². However, creating high-quality urban green spaces can be a balancing act, with potential downsides such as gentrification^{32,35}. Designers must think carefully about the urban context when improving parks in ways that may change their role³⁵.

Activity-Type Inequities Show Mixed but Encouraging Patterns

We also examined disparities in the health potential of parks among cities by activity type. The findings are generally encouraging: overall disparity scores were low and did not show pronounced global variation, in contrast to earlier studies^{43,44}. While previous work has shown high inequality in absolute access to greenery, our results suggest that relative inequality in

access to health-promoting park activities is less severe.

The distribution patterns vary significantly by activity type, revealing both strengths and critical gaps. Physical activity infrastructure was the most evenly distributed, likely reflecting its prominence in public health discourse and urban policy¹⁸. This aligns with the medical literature's emphasis on physical activity benefits (Table 7). In contrast, facilities for social activities were the most unequally distributed, revealing a key area for improvement⁴⁵.

The global nature of this challenge is evident from our data: the five cities with the greatest disparities in park offerings span four continents, indicating that uneven provision of well-equipped parks is not a concentrated issue. This suggests that just urban planning is not only a matter of financial resources but also one of municipal priorities and community engagement^{37,46}. A positive trend can be observed in the Asian countries of our study and Oceania, which have the most fair provision of park facilities.

Our Findings Provide Actionable Insights for the Design of Well-equipped Parks

To understand the relevance of our work for urban planning, we conducted 30-minute semi-structured interviews with domain experts. We reached out to experts who received their professional education on different continents: a lecturer and urban designer (E1, Hong Kong), an urban designer and master planner (E2, Canada), and a municipal park development manager (E3, United Kingdom). The experts confirmed that our quantitative approach offers significant practical value for urban design decisions. They identified several ways our findings could support urban design: reducing reliance on subjective park assessments (E1), serving as a quantitative baseline for master planning (E1 and E2), and providing an evidence-based alternative to institutional knowledge and practice-specific heuristics (E1). All experts emphasized that the visualization of park scores is already useful to “*identify the gaps regarding what is present in terms of offerings in a district (E1)*”, especially when aiming to ensure fair access to parks²⁴. This was echoed by the park manager, who said they would use the park scoring to guide development priorities, and as supporting evidence to gain leadership backing or external funding. When shown the taxonomy of activities, they noted that most of their projects addressed physical and nature-appreciation activities, and “[*the activity taxonomy*] helps us think about what it is we’re doing and how and how some categories have been neglected (E3).”

The experts also highlighted the importance of the way our scores are normalized to the specific context of each city. Our park scores are normalized to reflect the unique context of each city, making direct comparisons between cities hard. While this limits inter-city comparisons, it avoids drawing misleading conclusions across culturally, geographically, and climatically diverse settings. For example, E1 cited culturally different approaches to park provision in the form of “three-dimensional parks” in high-density environments like Hong Kong, while E2 brought up the challenges in adopting urban transformation manuals from Western cities in regions with extreme climates such as the Middle East.

3.2 Limitations and Future Directions

Despite the well-known benefits of parks, lack of fair access to urban green spaces remains a common theme in academic literature^{2,32,41,43,47}. We focused only on urban parks, excluding other types of urban green spaces such as gardens, street trees, and green roofs, which also contribute to urban health. Parks were selected because they support a wider range of activities than more specialized spaces, are generally publicly accessible, and are typically maintained by municipal administrations, making any identified shortcomings more actionable for policy and planning.

Relying on map data limits our analysis to activities that can be linked to specific elements and spaces within parks. While some studies explored the relationship between open spaces and their use⁴⁸, we avoided making assumptions about such usage to reduce the risk of cultural bias in our park evaluations. As a result, we excluded mindfulness activities like yoga from our main analysis, as they often do not require designated areas in city parks. Likewise, our data does not account for temporary cultural events, such as music festivals held in parks.

Park offerings were scored under the assumption that the presence of facilities and spaces enabling certain activities is a necessary condition for realizing specific health benefits. However, their presence alone may not be enough to deliver these benefits in practice. Furthermore, not all activities are directly tied to specific infrastructure, and OSM cartographic data alone cannot capture the intensity of use. We did not distinguish between the quality of maintenance or design of individual elements, such as benches being equipped with backrests, or the size, layout and species of trees and other plants.

Like all urban spaces, parks are in constant flux, which raises the question of how parks have evolved over time². This became clear during the COVID-19 pandemic, when many cities had to rethink their strategies, possibly leading to big changes in park facilities with major social justice effects⁴⁹. Looking at historical data from OSM is challenging, as it is difficult to distinguish between actual changes in park facilities and the increasing completeness of the OSM database.

A key direction for future research is to examine how park offerings directly influence health outcomes. While collecting global medical data to evaluate the health impact of individual parks is impractical, more targeted investigations may be feasible in specific contexts. For instance, prescription data available in some countries could be used to estimate the prevalence of certain medical conditions⁵⁰, and to explore potential causal links between changes in park infrastructure and improvements in public health over time.

We showed that the OSM park scores are closely linked to activities captured in Flickr photos, but other data could also be used to approximate park usage. For instance, detailed mobile traffic data could offer interesting insights into how parks are used^{31,51}. This could also help reduce biases inherent in social media data sources like Flickr and OSM, which rely on actively submitted contributions from tech-savvy users rather than passive observations of citizen behavior.

Finally, by focusing on health-promoting activities, our work introduces avenues for health-related behavioral change^{20,52}. For instance, our activity-based approach could support context-aware recommendations⁵³, such as identifying the most suitable times to engage in specific park activities when conditions like temperature, air quality, or crowdedness are most favorable.

4 Methods

4.1 Data

OSM is a globally encompassing geographic information database based on crowdsourced contributions. While accessible through a map interface at <https://openstreetmap.org>, its primary value lies in being an indispensable source for open mapping data both in commercial and scientific applications^{54–56}. Thanks to its permissive licensing, OSM has fostered a large ecosystem of individual and professional contributors. As a result, the project has achieved comprehensive worldwide coverage, with near-perfect mapping quality across the western world⁵⁶, while retaining remarkable detail in the global south⁵⁵. In this study, we utilized OSM data from fall 2023.

OSM employs a tagging system with key-value pairs to categorize and describe all these map objects. Each map object is typically associated with multiple tags that describe its purpose, but may also include additional information, such as opening hours, or data source references. To avoid the complexities of the OSM data model, for our tasks, it was sufficient to focus on two key map objects related to parks: *park elements* and *park spaces*. *Park elements* are 0-dimensional points representing objects like benches, individual trees, and statues. On the other hand, *park spaces* refer to areas within the parks, such as meadows, lakes, and forests.

Flickr (<https://flickr.com>) has established itself as one of the most prominent platforms for sharing photography. Since its inception in 2004, the platform has gained considerable popularity, accumulating billions of images. Notably, many of these images have been precisely geo-located, thanks to the utilization of the (phone) camera's GPS module.

We utilized a substantial dataset comprising geo-located images posted between 2004 and 2015. This extensive dataset offered us a valuable secondary perspective on activities taking place within the parks of the world. By intersecting these images with the park outlines from OSM, we identified 10,788,686 pictures captured within the boundaries of parks in our study cities. To extract the depicted content from these images, we used user-assigned tags in conjunction with automatically-generated computer vision labels^{57,58}.

4.2 Study Area

Our research focused on 35 cities listed in [Table 1](#), which we selected using three criteria to make our analysis broad yet robust.

First, we selected major cities worldwide with populations of at least 650,000. This threshold includes many of the largest urban areas, such as major European capitals and other densely populated regions where parks play a vital role in public well-being. To improve representation in Oceania, however, we made an exception for Christchurch, New Zealand, which has a smaller population. This first criterion allowed us to examine parks in cities from various parts of the world, each affected by its own climate, history, and cultural background.

Second, we only looked at cities in countries where at least 80% of the population has access to the Internet⁵⁹. This ensured we had enough online data (like tags on OSM or photos on Flickr) for our study. Since there is no detailed global data on Internet use in cities specifically, we used the country's overall access to the Internet as our guide. We decided on this threshold upon our preliminary analyses, finding that in many cities in Africa and South America, there was not enough digital information for our approach, which relies on social media and collaborative mapping data.

Third, we chose cities where, on average, parks have at least one-eighth of park areas are annotated with health-related tags on OSM. Since our analysis relied heavily on OSM data, this criterion ensured a minimum level of information on the platform for our study. We settled on this one-eighth threshold after observing that, below this level, the lack of contributor-added tags limited our ability to extract meaningful information. This primarily excluded cities where most tagging was done predominantly automatically through earth observation that was not accompanied by manual tagging of OSM contributors. This was mainly the case in China, where non-governmental mapping is restricted⁶⁰.

4.3 Identifying Health-promoting Activities in Urban Greenery

We identified and categorized park-based activities using input from an expert panel consisting of three co-authors of this study. We compiled a comprehensive list of activities commonly undertaken in urban parks. To collect relevant papers, we used two specific queries of Google Scholar: “(urban) AND (parks OR greenery) AND usage” and “(activities in urban) AND (parks

OR greenery)”. From this process, we retrieved the top 50 scholarly articles for each search phrase, resulting in a total of 91 unique papers. We reviewed each article and collected all activities, resulting in a diverse set of activity descriptions varying in granularity. For example, the literature included both broad terms such as *leisure activities* or *recreation*, as well as more specific categories like *physical* and *social* activities. We also noted plenty of individual activities like *walking*, *performing street theater*, *fishing*, and *playing all kinds of different sports*. Subsequently, we convened to categorize the identified activities, with a particular focus on their potentially different impact on health and on ensuring a consistent level of specificity across categories. Broad terms such as recreation were deemed too general to be analytically useful, whereas distinctions like physical versus social activities were considered meaningful. This process ultimately yielded six distinct categories: physical, mindfulness, nature-appreciation, environmental, social, and cultural activities.

4.4 Annotating Park OSM Tags with Activities Using LLM Classifiers

To associate different park elements and spaces with health-promoting activities, we annotated OSM tags describing those elements and spaces with activities. This turned out to be a challenging task. OSM is a collaborative platform with some governance and guidelines (https://wiki.openstreetmap.org/wiki/Map_features) for tagging, but the flexible tagging system offers the crowdsourcing contributors substantial freedom. As a result, the data can be inconsistent and fragmented, necessitating thorough cleaning. Each map object, such as park elements and spaces, can be tagged with an unlimited number of tags, offering in-depth descriptions. As a result, we encountered over 30,000 unique key–value pairs associated with park elements and spaces. Since our primary focus is on the core functional aspects of these elements, we conducted a data cleaning step (detailed in Appendix [Section B.3](#)) to remove irrelevant metadata associated with the map objects. This filtering allowed us to focus exclusively on tags relevant to activity-related features, thereby making the annotation process more pertinent to our study.

Using Large Language Models for Annotation

Even for domain experts, linking these tags unequivocally to health-related activities was difficult. For instance, a bench might relate to socializing, enjoying nature, or resting after physical activity. Choosing one activity over another often depended on personal experience, as many tags could plausibly refer to multiple activities. Given the large number of items and the specialized nature of the task, we chose an LLM classifier as an alternative to expert annotation or crowdsourcing.

Using LLMs as classifiers offers several advantages as they provide a more objective and consistent approach to annotation, can handle large volumes of data quickly, and do so at relatively low cost. In some cases, LLM classifiers have even outperformed crowdworkers⁶¹, who may themselves rely on machine learning tools to complete tasks⁶². Research also suggests that LLM-based annotations can match the quality of those made by domain experts⁶³. Given these benefits, we established a benchmark in our domain to evaluate the feasibility of using LLMs to map OSM tags to health-promoting activities. Three experts manually annotated the 100 most frequent tags, and final labels were selected by majority vote. We then used this expert-labeled dataset to assess the accuracy of the labels generated by different LLM classifiers. The details of the LLM annotation benchmark can be found in the Appendix, [Section B.4](#). The outcome indicated that GPT-4, set at a temperature of 0.9, yielded the best annotation performance of an F_1 score of 0.77.

Operationalization of the Taxonomy

Using the taxonomy with six categories of health-promoting activities in [Table 7](#), and GPT-4 as the best-performing annotation model, we ran the annotation of OSM tags describing *park elements* and *park spaces*. These tags were then labeled with one of the health-promoting activities, or “none” if they didn’t support a particular activity. In doing so, we established a lexicon of *park elements* and *spaces* linked to health-promoting activities ([Table 3](#)). We had to exclude the mindfulness activities category at this stage, as none of the OSM tags found in parks were primarily associated with it.

4.5 Computing Park Health Scores by Aggregating OSM Tags

The core method to characterize parks in terms of their potential for health-promoting activities is based on counting the respective *park elements* and *spaces*. These counts are then combined to give each park an overall score for each health-related category. This score represents the potential health benefits of each park.

Counting Health-promoting Elements and Spaces in Parks

In our process of assigning health-promoting activity scores to each park, we first gathered *park elements* and *spaces* within each park using the *osmium* library. We then assigned health-promoting activities to these *elements* and *spaces* based on the lexicon created in the previous step ([Table 3](#)). We discarded any *elements* or *spaces* whose tags did not match an activity category. In a few instances, *park elements* or *spaces* could fall into more than one health-promoting activity category. For example, apple trees are annotated in OSM with the tags [natural=tree, produce=apple]. In our lexicon of park elements and spaces, we map natural=tree to the nature-appreciation and produce=apple to the environmental category. To account for this overlap, we proportionally assign the element as 50% nature-appreciation and 50% environmental. More

generally, when multiple tags are matched to different categories, we proportionally count the resource based on the number of matched tags, ensuring that its contributions are accurately accounted for.

Transforming Counts into Health Scores

After tallying up the *park elements* and *spaces* within the park, we measured the overall effect of the park in promoting healthy activities within a city. This score should account for the park's size and the range of facilities it offers for different activities. Our proposed scoring method is based on the following considerations.

1. *Amount of Health-Promoting Elements and Spaces*: The number and area of health-promoting facilities determine how much offering there is for each activity.
2. *Area of the Park*: The character of a park depends on the concentration of health-promoting facilities. Larger parks must offer more to obtain a high score.
3. *Diminishing Returns with Increased Count*: We posit that as the count of these elements and spaces increases, the associated benefits exhibit diminishing returns.
4. *City-specific Normalization of Park Health Scores*: The value of a park's facilities for a certain activity is relative to similar facilities in other parks throughout the city.

To reflect these assumptions into our scoring, we proposed a linear regression model to compute the park health scores shown in Equation 1. We used the idea of an “average park” in each city to compute a baseline and used the distance of each park to the average park line, i.e., the residual, as a score. The average park baseline was determined by computing separate linear regression models for *park elements* and *spaces* in each city, estimating the expected amount of facilities relative to the park area.

$$E_{Act}(\log_2(\text{count}(Act))) = i + s \cdot \log_2(\text{park area}) \mid Act \in \text{Activity Categories}, \quad (1)$$

where i and s represent the intercept and slope of the regression lines, respectively. To obtain regression models for each activity category and both *park elements* and *park spaces*, we utilized the binary logarithm to account for the diminishing returns of an increase in park size. For each city, separate regression models were calculated for each activity category, as well as for *park elements* and *park spaces*. See Section B.5 for details on the modeling.

By analyzing the residuals, we identified parks that exceeded expectations (positive residuals) and those that fell short (negative residuals) in providing health-promoting resources for a given activity. We made the linear model dependent on park area so that the resulting scores for health-promoting *elements* and *spaces* reflected their density. To reduce the influence of extremely large parks with high amounts of facilities, we applied the binary logarithm. We calculated these scores separately for each city, rather than using a single global model, to ensure that the results reflected each city's local context. To illustrate this method, we plotted the linear models and the individual park scores in the *log-log* space for London, UK (Figure 4). The regression lines denote expected health scores based on park size. The modest R^2 values showed that the number of health-promoting facilities could not be explained by park size but instead reflected different design priorities and the needs of local citizens. Park scores for *park elements* and *spaces* are residuals from this *average park line* in the model, adjusting for park size when determining health scores.

Combining Scores from Park Elements and Spaces

The regression models gave us individual scores for *park elements* and *park spaces* for each activity. To verify the impact of combining these scores into one combined health score, we examined the co-occurrences of *park elements* and *spaces* and found that they represent orthogonal concepts in practice, as outlined in Section B.6. Based on this finding, we computed a combined score by first normalizing the scores of *park elements* and *spaces* using the z-score transformation, considering all parks in a city. This normalization allowed us to standardize the scores, making them comparable despite being on different scales. Then, we linearly combined these z-scores by averaging them together to create the overall score for the park according to Equation 2.

$$\text{Score}(P_{Act}) = \frac{z(\text{residual}_{\text{elements}}(P_{Act})) + z(\text{residual}_{\text{spaces}}(P_{Act}))}{2}, \quad (2)$$

where P denotes an individual park, Act is one of the activity categories, the residual scores for elements and spaces stem from Equation 1, and $z()$ indicates the z-score transformation.

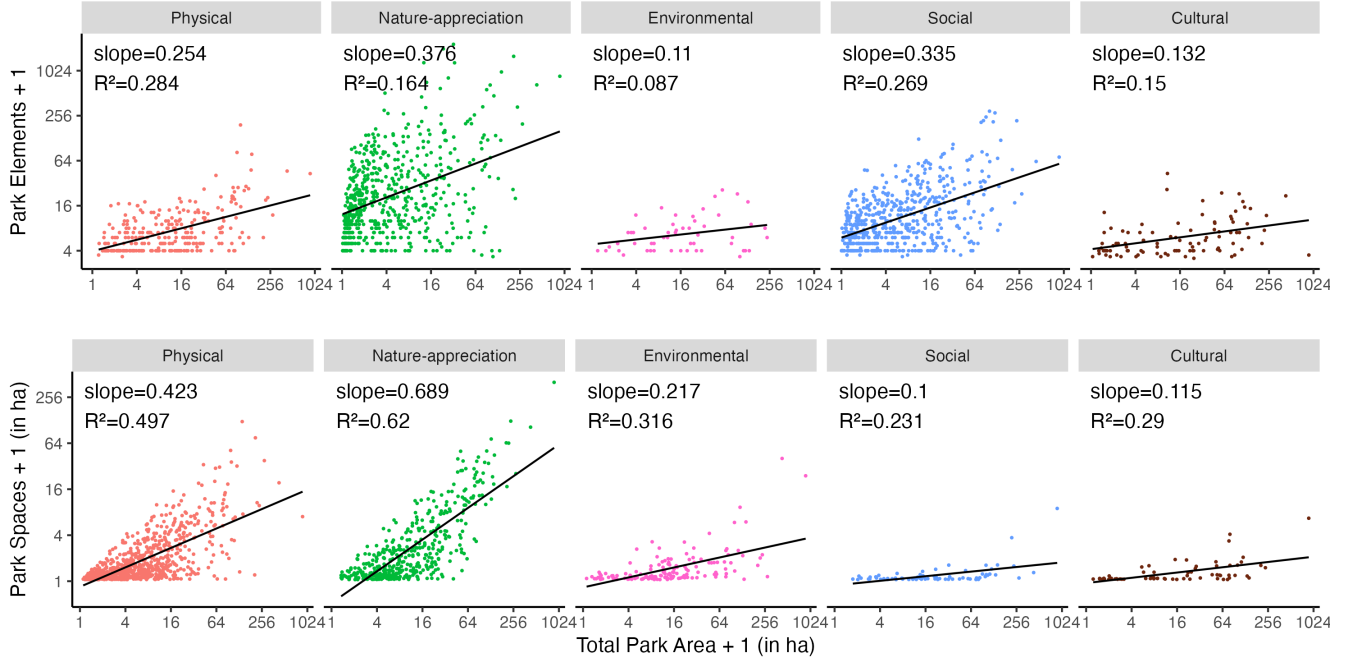


Figure 4. Visualization of the scoring method. The linear regression models for determining the park health scores for the *park elements* (top) and *park spaces* (bottom) in London, UK. The horizontal axis denotes the park's area (\log_2), while the vertical axis represents the count of *park elements* (\log_2) and the area occupied by health-promoting *park spaces* (\log_2). The modest R^2 values are anticipated, highlighting the variety among parks.

The combined and normalized scores of *park elements* and *spaces* represent a comprehensive and unified measure of the park's health-promoting amenities and facilities, accounting for both individual elements and cultivated areas. The combination process accounted for the relative importance of each aspect, leading to a more meaningful overall score that represents how well a park is equipped to support performing health-promoting activities. Since the scores are based on z -score-normalized residuals, a value around 0 indicates average support for a given activity, while a score of ± 1 means the park is 1 standard deviation above or below the city-wide average.

4.6 Quantifying Disparities of Park Scores

One goal of our study was to quantify disparities in health benefits offered by different parks within a city. To measure the disparities in the presence of amenities and facilities associated with health-promoting activities within a city, we propose the following disparity index. The metric essentially quantifies the inequality of the park health scores, as generally, one could expect that good park management would provide for a similar amount of features and facilities in all parks of a city. Since the park health scores could be negative, we can not directly use a standard inequality metric, such as the Gini Index, but had to min-max normalize the park score before computing the Gini Index (Equation 3).

$$Gini_{Act}(\{X'_{Act} | X_{Act} : P \in C\}), \quad (3)$$

where X_{Act} is the score of activity category $Act \in [\text{physical, cultural, etc.}]$ of a park P in city C , and

$$X' = \frac{X - X_{max}}{X_{max} - X_{min}} (\text{min-max normalization}),$$

and the Gini index was computed in a standard way:

$$Gini = \frac{A}{A + B},$$

where A is the area between the Lorenz curve and the line of perfect equality and B is the area beyond the Lorenz curve⁶⁴.

4.7 Semantic Matching of Flickr Labels and OSM Tags

In our validation, we leveraged a global dataset of 10.7 million geotagged Flickr images taken within parks across 35 cities. Each image came with user-generated tags, partially annotated by computer vision algorithms. To semantically match these Flickr labels to OSM tags, we used text embeddings, treating the task as an asymmetric semantic search problem. To overcome language diversity in the Flickr labels, we detected the top three non-English languages per city and translated the labels into English using machine translation models. To further improve embedding quality, we enriched OSM tags with concise definitions from the OSM mapping guidelines. The embeddings were generated using the `all-mpnet-base-v2` S-BERT model, and matching was done based on cosine similarity, with a threshold of 0.7 to ensure quality. The methodological details are described in [Section B.7](#).

This process yielded 2,171 Flickr-to-OSM matches, with 1,432 corresponding to health-promoting features. To assess accuracy, three experts reviewed the 20 most frequent label-tag matches for London. We aggregated their responses using majority voting. The experts' annotation agreed with 82% of the matchings, which is highly accurate considering they are based solely on individual tags.

Having assured that the matchings are accurate, we proceeded to profile the parks based on the activities associated with the matched OSM tags, following the same scoring approach as what we used for the OSM *park elements* and *spaces* ([Equation 1](#)). In our validation, we chose a minimum of 250 images from each park and at least 15 parks in each city. This criterion was established to secure a robust number of images for each park, thus ensuring the accuracy of our analysis. This was a mitigation against potential biases that could have been introduced by individual photographers if a park had only a few images.

Data availability

The replication package contains tables of the park health scores in the cities: <https://github.com/LinusDietz/Health-Promoting-Parks-Replication>. The original OpenStreetMap data used for scoring the parks is publicly available and can be best obtained from one of the third-party download servers, for example from <https://download.geofabrik.de>. The Flickr dataset for the validation can not be shared due to the terms of conditions of this dataset.

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Code availability

The Python and R code to compute park health scores is available at <https://github.com/LinusDietz/Health-Promoting-Parks-Replication>.

Author contributions statement

L.D. conceived and conducted the experiments and co-drafted the manuscript with S.S. K.Z., A.F.Z. and D.Q. conceived the experiments and edited the manuscript. All authors analyzed the results and reviewed the manuscript.

Ethics declarations

Competing interests

The authors declare no competing interests.

Appendix

A Supplementary Results

A.1 Lexicon of Elements and Spaces for Health-promoting Activities in Parks

We display the top 10 most frequent tags for each activity category in [Table 3](#) and have published all 1441 entries of the lexicon in the replication package.

Table 3. Lexicon of *elements* and *spaces* for health-promoting activities in parks. We show the 10 most frequent tags per activity category. The full lexicon of 1441 elements and spaces is available in the replication package.

Activity Category	Elements	Spaces
Cultural	information=board, tourism=artwork, historic=memorial, artwork_type=sculpture, artwork_type=statue, board_type=history, historic=monument, memorial=plaque, memorial=war_memorial, memorial=bench	tourism=artwork, tourism=attraction, religion=christian, leisure=bandstand, historic=memorial, denomination=anglican, building=church, historic=building, tourism=museum, amenity=theatre
Environmental	waste=trash, produce=plum, amenity=recycling, fruit=apple, produce=damson, leisure=garden, man_made=beehive, produce=apple, amenity=watering_place, man_made=monitoring_station	leisure=garden, landuse=flowerbed, landuse=allotments, building=greenhouse, landuse=orchard, landuse=farmland, building=farm_auxiliary, landuse=farmyard, garden:type=community, garden:type=residential
Nature-appreciation	natural=tree, amenity=fountain, tourism=viewpoint, board_type=nature, tourism=picnic_site, amenity=shelter, natural=shrub, attraction=animal, board_type=wildlife, waterway=weir	natural=wood, natural=water, natural=scrub, water=pond, natural=heath, landuse=forest, heath=bracken, natural=grassland, natural=wetland, amenity=shelter
Physical	amenity=bicycle_parking, highway=crossing, amenity=drinking_water, leisure=fitness_station, barrier=cycle_barrier, sport=fitness, leisure=pitch, sport=orienteering, orienteering=marker, leisure=playground	leisure=pitch, leisure=playground, sport=soccer, sport=tennis, highway=footway, golf=bunker, sport=basketball, highway=pedestrian, area:highway=footway, golf=tee
Social	amenity=bench, tourism=information, leisure=picnic_table, amenity=cafe, board_type=notice, amenity=telephone, amenity=fast_food, playground=playhouse, amenity=restaurant, advertising=board	amenity=cafe, building=pavilion, building=retail, amenity=community_centre, leisure=outdoor_seating, amenity=school, amenity=restaurant, building=kiosk, amenity=kindergarten, building=terrace

A.2 Top Parks by City

The following [Table 4](#) lists the best-equipped park of each city by their scores on each activity category.

A.3 Geographic Influence on Park Scores

[Figure 5](#) complements the findings from [Section 2.4](#) regarding geographic influences on park health scores. The plot provides additional insights subdivided by continents.

Using a correlation analysis between the distance to the city center (discounted using the binary logarithm) and the park health scores, we aimed to provide an additional quantification of the decay in park scores moving away from the city center. Plotting the PCC for each city individually in [Figure 5](#), we observe mostly low to moderate negative correlations.

A.4 Disparities of Park Scores

[Figure 6](#) provides a visual representation of the data tabulated in [Table 2](#) emphasizing the continent of the cities. This figure supplements the findings in [Section 2.5](#).

A.5 Validating the Overall Ranking of Parks through an Online Survey

As an additional means for validating the park scores, we conducted a survey in one city, London, UK. In an online questionnaire, we asked London citizens about suitable parks for performing activities. The main set of questions was phrased as: “*Can you name several parks suitable for **physical activities** (e.g., sports)?*”

Table 4. Top parks of the cities by activity category

City	Physical	Nature-appreciation	Environmental	Social	Cultural
Amsterdam	Sloterpark	Sloterpark	Park Frankendael	Westerpark	Amstelpark
Auckland	Lloyd Elsmore Park	Point England Park	Panekke / Radonich Park	Ambury Regional Park	Albert Park
Berlin	Tempelhofer Feld	Landschaftspark Johannisthal/Adlershof	Gärten der Welt	Tempelhofer Feld	Treptower Park
Boston	Franklin Park	Charles River Esplanade	Temple Street Park	Charles River Esplanade	Georges Island
Buenos Aires	Parque Indoamericano	Parque de la Memoria	Paseo Arzoumanian	Parque de las Ciencias	Parque Avellaneda
Chicago	Lincoln Park	Northerly Island	Grant Park	Lincoln Park	Grant Park
Christchurch	Canterbury Agricultural Park	Bottle Lake Forest Park	Hagley Park North	Avon River Precinct	Hagley Park North
Copenhagen	Fælledparken	Østre Anlæg	Husum Bypark	Enghaveparken	Østre Anlæg
Hong Kong	九龍仔公園 Kowloon Tsai Park	藝術公園 Art Park	佐敦谷公園 Jordan Valley Park	迪欣湖活動中心 Inspiration Lake Recreation Centre	灣仔臨時海濱花園 Wan Chai Temporary Promenade
Houston	Hermann Park	Hermann Park	Wright-Bembry Park	Hermann Park	Hermann Park
London	Old Deer Park	Russia Dock Woodland	Bushy Park	Richmond Park	Alexandra Park
Madrid	Parque Agustín Rodríguez Sahagún	Dehesa de la Villa	Parque del Retiro	Finca Vista Alegre	Parque del Retiro
Melbourne	Albert Park	Grant Reserve	Fitzroy Gardens	Albert Park	Carlton Gardens
Montreal	Parc Jean-Drapeau	Parc Angrignon	Jardin botanique de Montréal	Vieux-Port	Parc Jean-Drapeau
Moscow	Парк Останкино	Бирюлёвский дендропарк	Выставка достижений народного хозяйства	Тимирязевский парк	Выставка достижений народного хозяйства
New York	Pelham Bay Park	Prospect Park	Bronx Park	Brooklyn Bridge Park	Fort Tilden
Paris	Bois de Boulogne	Bois de Vincennes	Jardin des Plantes	Bois de Boulogne	Bois de Boulogne
Perth	Altone Park	Kings Park	Hyde Park	Christ Church Grammar Playing Fields	Victoria Gardens
Philadelphia	East Fairmount Park	East Fairmount Park	East Fairmount Park	Race Street Pier	Fort Mifflin
Rio De Janeiro	Aterro do Flamengo	Quinta da Boa Vista	Largo da Carioca	Campo de Santana	Praça Luís de Camões
Rome	Villa Borghese	Villa Glori	Parco Agricolo di Casal del Marmo	Riserva Naturale dell'Acquafredda	Villa Borghese
San Diego	Balboa Park	Mission Bay Park	Balboa Park	Balboa Park	Balboa Park
San Francisco	Presidio of San Francisco	Lake Merced Park	Golden Gate Park	Presidio of San Francisco	Golden Gate Park
Seattle	Warren G. Magnuson Park	Seward Park	Washington Park Arboretum	Seattle Center	Seattle Center
Seoul	올림픽공원	매봉산공원	서울숲	송파나루공원	경복궁
Singapore	Changi Business Park	Windsor Nature Park	Singapore Botanic Gardens	The Lawn@Marina Bay	Singapore Botanic Gardens
St Petersburg	парк Героев-Пожарных	Парк-дендрарий Ботанического сада Петра Великого	Летний сад	Приморский парк Победы	парк Лесотехнической академии
Stockholm	Årstafältet	Kungsträdgården	Sveaplan	Karlaplan	Humlegården
Sydney	Centennial Park	Centennial Park	Sydney Park	Lawrence Hargrave Reserve	Clarks Point Reserve
Taipeh	大安森林公園	關渡自然公園	士林官邸公園	天母運動公園	中正紀念公園
Tokyo	若洲海浜公園	上野恩賜公園	北の丸公園	上野恩賜公園	上野恩賜公園
Toronto	Centennial Park	Sunnybrook Park	Highland Creek Ravine	Toronto Island Park	Don Valley Brick Works Park
Vancouver	Connaught Park	Stanley Park	Stanley Park	Hastings Park	Morton Park
Vienna	Augarten	Draschepark	Schlosspark	Schlosspark	Schlosspark
Washington DC	East Potomac Park	National Mall	Schönbrunn National Mall	Schönbrunn National Mall	Schönbrunn National Mall

Study Information

We recruited the participants using the first author's institutional research recruitment portal as well as mailing lists within scientific institutions in London. The participants were informed about the voluntary nature of their participation and that no personally identifiable information about them was collected. For these reasons, age was collected using 7 age groups ("Below 18", "18–24", "25–34", "35–44", "45–54", "55–64", "65 and over") and as a privacy mechanism only the postal area (e.g., N1) instead of the full postcode was requested. Furthermore, we asked participants how long they have been living in London ("I don't live in London." – "Less than 1 year." – "1 to 5 years." – "More than 5 years."). Finally, as a means

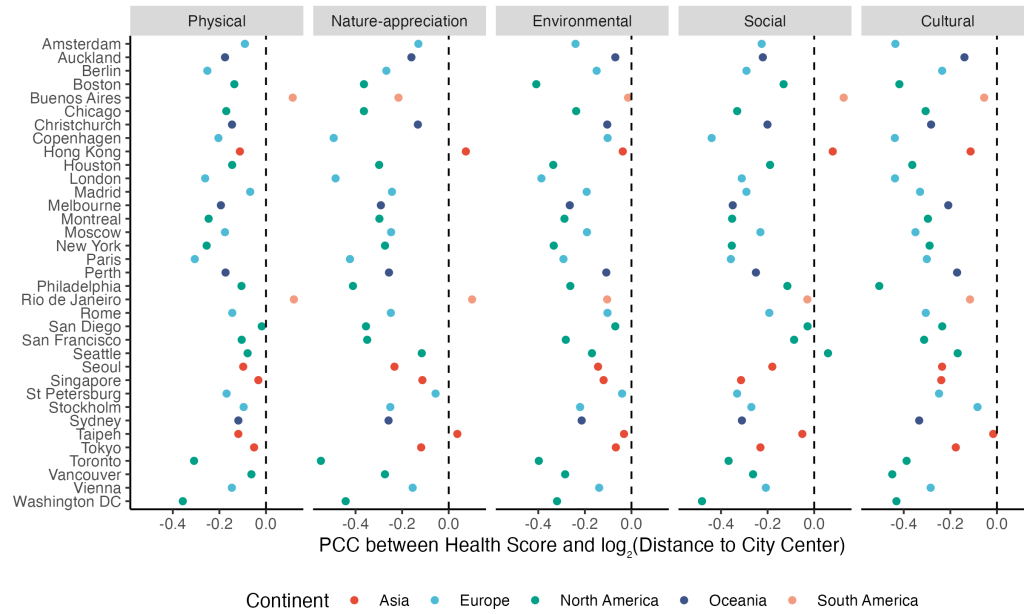


Figure 5. Pearson correlations between park health scores and the distance to the city center (\log_2) by city.

Table 5. Park health scores by quartiles determined using the distance to the city center. Q1 are the inner city parks, and Q4 are the parks that are most distant to the city center. On the left, we show the mean health scores for each quartile; on the right, we show the p -values determined using a two-sided t-test for each null hypothesis $H_0 : Q_i = Q_j$ stating that the mean scores for two subsequent quartiles i and j are equal. All null hypotheses can be refuted with high significance levels ($p < 0.001, ***$), with the exception of the difference between Q3 and Q4 in the environmental category, where the significance is $p = 0.003, **$. We confirmed the normal distribution of the scores using QQ-plots.

Activity Category	Mean Health Scores				p -values of H_0		
	Q1	Q2	Q3	Q4	Q1 = Q2	Q2 = Q3	Q3 = Q4
Physical	0.382	0.297	0.160	0.068	0.000	0.000	0.000
Nature-appreciation	0.107	-0.211	-0.497	-0.580	0.000	0.000	0.000
Environmental	0.020	-0.076	-0.156	-0.186	0.000	0.000	0.003
Social	0.289	0.137	-0.004	-0.088	0.000	0.000	0.000
Cultural	0.260	0.096	0.010	-0.022	0.000	0.000	0.001

to identify low-quality responses, we asked people for a park close to their homes, which we could use as an instructional manipulation check in conjunction with the reported postal area. The data collection was registered as a minimal-risk study at the first author's institutional review board (King's College London Research Ethics Office, ID: MRA-22/23-38802).

Results

The metric we used to quantify how well the citizen response aligned with our health scores is the average percentile-ranking^{1,2}, which captures how highly the selected park was placed in the overall ranking of parks for the corresponding activity. A value close to 1 means parks with the highest scores were selected, whereas 0.5 would represent a random selection. The results demonstrate a clear alignment between the freely recalled parks by the participants and the rankings derived from our health scores. As shown in Table 6, the median and mean values of the average percentile-ranking for the parks named by citizens were consistently high. For nature-appreciation, physical activities, cultural activities, and social activities the median scores are above 0.89, highlighting a strong concordance between citizens' perceptions of the park and the quantitative rankings derived from our proposed park profiling method.

The result for environmental activities is subpar compared to the other activities, with a mean and median average percentile-ranking of 0.50. Only 57.5% of the respondents could name an environmental park, and on average, 1.8 parks were named in this category by each person, which indicates that parks for environmental activities are harder to think of compared

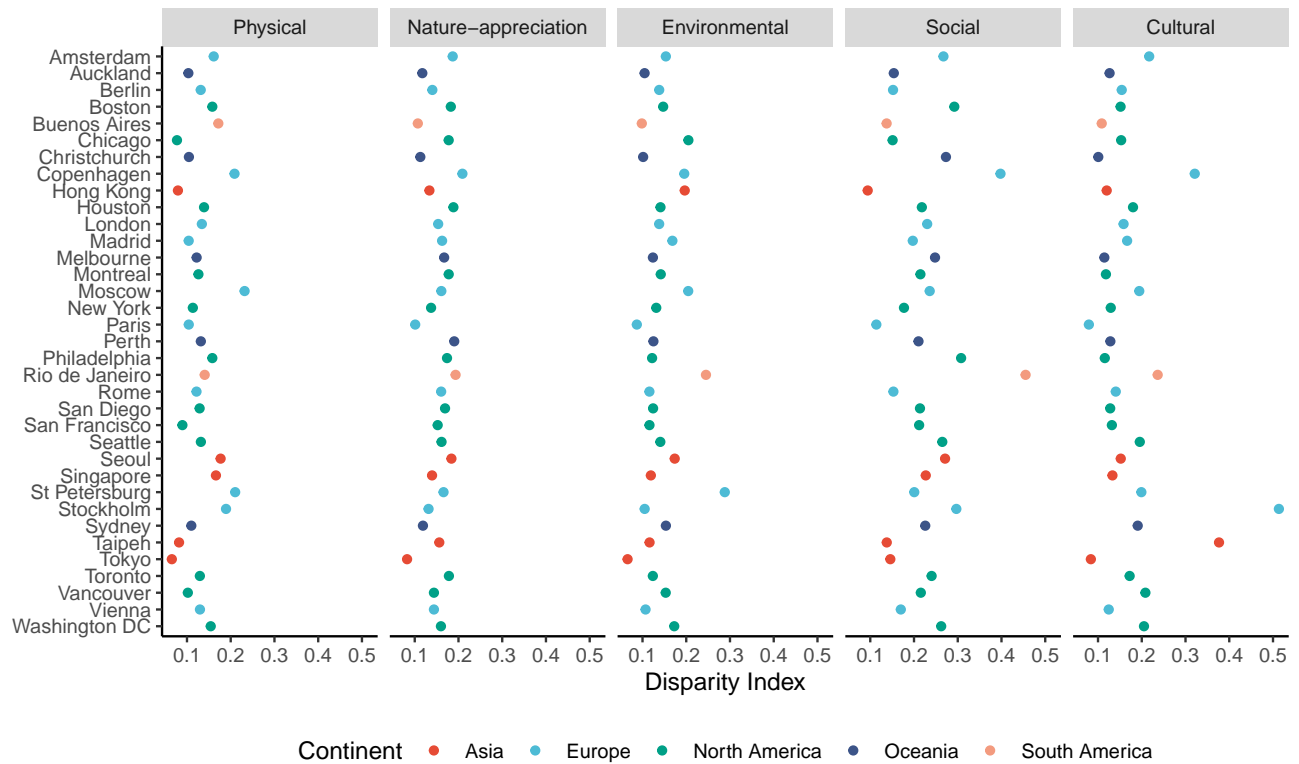


Figure 6. Inequality of park scores in the cities. Overall, nature-appreciation activities show the lowest disparities, whereas the largest differences can be observed in the social activities category.

to the other activities. Another explanation for the low scores in this category is that while urban gardening and conservation can be done in many parks, they typically do not occupy much *spaces*, environmental activities are less mainstream in cities, and the number of *park elements* for this category is comparatively low in London’s parks impeding high activities scores.

The overall alignment between Londoners’ perceptions of parks and our health scores underscores the effectiveness of our approach in accurately capturing and evaluating the health-promoting potential of parks.

B Supplementary Material

B.1 Scoping Review to Map Activity Categories to Health Benefits

Next, our goal was to collate and map health-prompting activities in parks discussed in prior studies. Considering between a systematic and scoping type of review, the scoping review was a better fit for our task because we only needed to map activities discussed in the literature, and we did not need to focus on the types and quality of data collected in those studies, which is a task for systematic reviews. Specifically, we turned to using the well-established PRISMA method³, which is designed to

Table 6. Result statistics of the online survey. Citizens were asked to name parks that are suitable for the activities. The first three columns show the statistics of the average percentile-ranking of the named parks. **AR** is the answer rate of the respective category, i.e., how many respondents were able to name at least one park), **N** is the number of non-empty responses, and **MR** is the mean number of parks that were named per respondent.

Activity category	median	mean	σ	AR	N	MR
Physical	0.91	0.84	0.17	97.5%	78	4.26
Nature-appreciation	0.95	0.85	0.19	95%	76	2.75
Environmental	0.50	0.50	0.31	57.5%	46	1.80
Social	0.93	0.87	0.13	96.2%	77	4.94
Cultural	0.89	0.75	0.25	81.2%	65	2.27

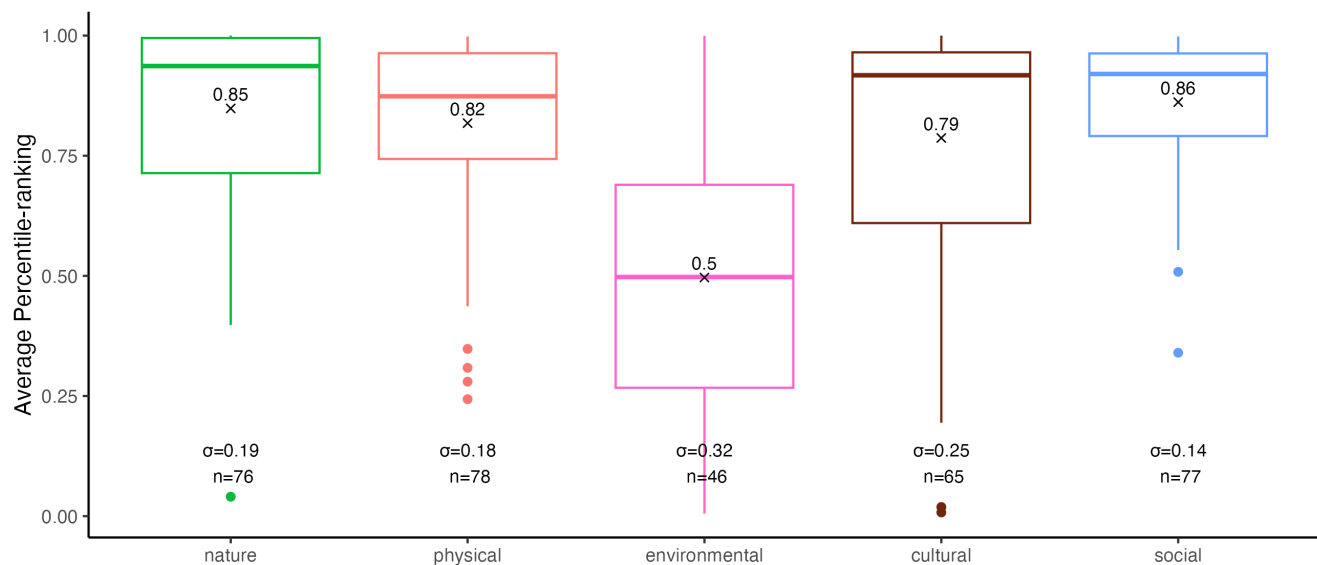


Figure 7. The online survey results as box-whisker plots. Standard box plot with Q1, median, Q3; whiskers at $1.5 \times$ interquartile range. The values indicated with the x represent the mean values.

facilitate transparent reporting of reviews, and it has been designed primarily for reviews of studies that evaluate the effects of health interventions, irrespective of the design and strength of effects found in the included studies.

The overarching research question was: “Which are the health benefits of activities in urban greenery?” Our focus on urban greenery instead of only parks was to ensure both the *comprehensiveness* and *generality* of the taxonomy, as future studies might look beyond urban parks. We used the WHO’s definition of urban greenery to determine the scope of our survey: “[...] urban green space is defined as all urban land covered by vegetation of any kind. This covers vegetation on private and public grounds, irrespective of size and function, and can also include small water bodies such as ponds, lakes, or streams (“blue spaces”)⁴.”

As we were interested in the intersection of urban greenery and medical studies, we performed a set of queries on PubMed and SpringerLink to identify papers that linked the usage of urban greenery with health benefits. An article was deemed relevant if the results evidenced that one or more activities typically done in public urban green spaces had a health benefit. To obtain a comprehensive overview of each activity category, we used a total of 6 queries. Upon our preliminary experiments, we employed a collection of keywords for our queries that included both those commonly encountered in the initial set of studies and those formulated by our experts. This approach enabled us to discover a diverse range of papers relevant to each category of activity. The queries were:

Physical activities: (urban greenery) AND (health) AND (sports OR exercise)

Nature-appreciation activities: (urban greenery) AND (health) AND (nature) AND (exposure)

Environmental activities: (urban greenery) AND (health) AND (garden OR planting OR conservation)

Social activities: (urban greenery) AND (health) AND (social OR social cohesion OR social capital OR social contacts)

Cultural activities: (urban greenery) AND (health) AND (culture) OR (cultural ecosystem)

Mind-body activities: (urban greenery) AND (health) AND (mindfulness OR meditation OR yoga OR tai chi OR breathing techniques)

Following the PRISMA statement depicted in Figure 8, out of the initially *identified* 762 articles, 417 were duplicates, leaving us with 344 unique articles. Next, we *screened* these articles and discarded 5 conference proceedings and 17 articles that were perspectives or study protocols, successfully retrieving the remaining 322 articles. In the *Eligibility* step, we determined whether these articles were relevant to our search. We found that 114 articles were relevant, while 208 were not. Most articles were excluded because they were not about urban green spaces or because there was no significant link between the activities

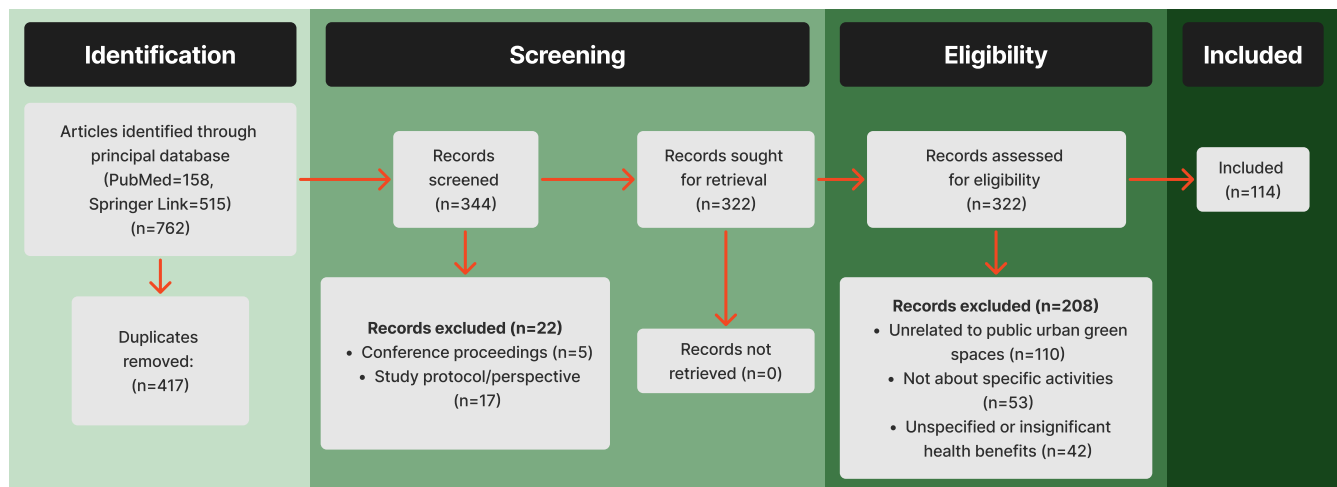


Figure 8. Our PRISMA Statement: Process of identification, screening, and determining eligibility for articles in our literature survey.

and health benefits. When analyzing the *included* articles, we recorded each activity category alongside the general health aspects and specific health benefits the article evidenced (Table 7).

Results

As can be seen in Table 7, most research has focused on the benefits of *physical activity* in parks. Out of 79 studies on the health benefits of exercising, 46 underscored positive outcomes like weight loss^{22–24}, cardiovascular improvements^{52,54}, metabolic activity^{30,31}. Additionally, these activities demonstrated positive effects on mental health (16 articles), well-being (7 articles), and social health (6 articles).

The second most studied category is *nature-appreciation*, with 68 articles. These activities significantly boost mental health (34 articles), primarily in reducing stress^{9,75} and anxiety^{67,70} and preventing depression^{14,15,17,18,67–69}. They also contribute to physical health (14 articles) and overall well-being (12 articles).

In our review, we found that *social* and *environmental activities* received less attention in conjunction with urban parks, with only 33 and 28 articles covering them, respectively. Despite this, both contribute to all identified health aspects. Social activities enhance social and mental health, fostering a sense of belonging^{111–113} and improving mood¹⁰⁵. Environmental activities, such as gardening, offer diverse benefits, including cognitive restoration⁹³ and improved general health⁶³.

Finally, *cultural* and *mindfulness activities* are relatively under-researched regarding their health benefits in the context of urban parks. Cultural activities often fell outside the scope of our review, which required a connection to urban parks, while more general cultural activities were studied. However, their health benefits are likely underreported given the presence of cultural facilities in parks (e.g., historic monuments or arts venues). Likewise, mindfulness activities and nature-based therapeutic interventions, such as forest therapy¹¹⁸ provide health benefits, but have not been studied in the context of urban parks, highlighting a potential gap in the scientific literature that warrants future exploration.

B.2 Determining the Threshold Values for Computing the Linear Models

Figure 9 and Figure 10 depict histograms of park elements and park spaces. The plots supplement the determination of thresholds for excluding parks with insufficient activity data in Section 4.5, *Transforming Counts to Health Scores*.

B.3 Data Cleaning of OSM Tags

This section describes the steps we undertook to exclude OSM tags that are not useful for our analysis.

The first step of the data cleaning process was not specific to annotating health-promoting activities. Instead, the focus was on removing any extra information not necessary for understanding the main purpose of the map object. For example, to identify a bench on a map, one just needs to look for the label `amenity=bench`. However, a bench can also have additional tags like `inscription`, `operator`, `material`, and `backrest`, which offer more specifics about the bench. When it comes to identifying the object's primary purpose for health-promoting activities, this extra information is not only unnecessary but could also lead to confusion. To remove these irrelevant labels, three of the authors created lists of keys and values that were only used to provide extra details when combined with other labels. All co-authors carefully reviewed, discussed, and agreed upon these lists. If there was any doubt about whether to exclude certain labels, they were kept and left for subsequent

Table 7. Activities in urban parks linked to health benefits. Specific health benefits evidenced in the respective articles are grouped by health aspects.

Activity Category	Health Aspect	Specific Health Benefit
Physical	Cognitive health	dementia prevention ⁵
	General health	longevity ^{6,7}
	Mental health	stress reduction ^{8–12} , depression prevention ^{12–19} , anxiety reduction ¹⁶ , various ²⁰ , mood improvement ²¹
	Physical health	weight reduction ^{6,22–28} , increase of physical activity ^{9,11,15,17,29–51} , blood pressure reduction ¹⁸ , diabetes prevention ^{6,52} , various ²⁰ , increase of leisure activities ⁵³ , hypertension ⁶ , cardiovascular health improvements ^{26,52,54–56} , bone development ²⁶
	Social health	various ^{20,57} , social cohesion ^{15,18,58,59}
	Well-being	increase restorative capacity ⁶⁰ , enhanced social interactions ⁶¹ , quality of life ^{5,17,39,46,56}
Nature-appreciation	Cognitive health	attention fatigue reduction ⁶²
	General health	lower morbidity ⁶³
	Mental health	positive emotions ^{64,65} , depression prevention ^{14,15,17,18,66–69} , anxiety reduction ^{67,68,70,71} , suicide prevention ^{72,73} , mood improvement ^{21,62,69,74} , relaxation ⁶⁵ , mindfulness ⁶⁵ , calmness ⁷¹ , stress reduction ^{9,62,67,68,74–80}
	Physical health	mood improvement ⁷⁴ , improved ghq-12 scores ⁸¹ , blood pressure reduction ^{18,74,82} , antenatal health ⁸³ , respiratory health ⁸⁴ , increase of physical activity ^{9,15,17,48,81,85,86} , blood oxygen saturation ⁷⁴
	Social health	increased social capital ⁸⁷ , social loneliness reduction ⁸⁸ , various ⁵⁷ , social cohesion ^{15,18}
	Well-being	stress reduction ^{67,74,79} , quality of life ^{17,66,67,79,89–91} , blood pressure reduction ⁷⁴ , increase restorative capacity ⁹²
Environmental	Cognitive health	restorative effect against cognitive failures ⁹³
	General health	lower morbidity ⁶³
	Mental health	stress reduction ^{78,94} , anxiety reduction ^{95,96} , improved sleep ^{95,96} , depression prevention ^{66,96}
	Physical health	cardiovascular health improvements ⁹⁷ , inflammation reduction ⁹³ , respiratory health ⁹⁷ , access to healthy produce ⁹⁸ , immune system improvement ⁹⁹ , increase of physical activity ^{31,100} , improved sleep ⁹⁵
	Social health	access to healthy produce ⁹⁸ , social cohesion ^{94,98}
	Well-being	nutritional diversity ¹⁰¹ , quality of life ^{66,95,102,103} , improved sleep ⁹⁵ , increase restorative capacity ¹⁰⁴
Social	Cognitive health	dementia prevention ⁵ , restorative effect against cognitive failures ⁹³
	General health	longevity ⁷
	Mental health	mood improvement ¹⁰⁵ , depression prevention ^{12,13} , various ¹⁰⁶ , improved mental health inventory (mhi-5) scores ¹⁰⁷ , stress reduction ^{12,94}
	Physical health	access to healthy produce ⁹⁸ , various ¹⁰⁶ , inflammation reduction ⁹³ , increase of physical activity ^{46,51}
	Social health	social cohesion ^{58,59,94,98,105,108} , various ⁵⁷ , access to healthy produce ⁹⁸ , increased social capital ¹⁰⁹ , social loneliness reduction ¹¹⁰ , improve sense of social belonging ^{111–113}
	Well-being	increase restorative capacity ¹⁰⁴ , quality of life ^{5,46,114} , enhanced social interactions ⁶¹
Cultural	Cognitive health	dementia prevention ⁵
	General health	various ¹¹⁵
	Physical health	increase of physical activity ¹¹⁶
	Well-being	quality of life ^{5,114,116}
Mindfulness	Mental health	stress reduction ⁷⁶ , anxiety reduction ¹⁶ , depression prevention ^{16,19}
	Physical health	increase of physical activity ⁵¹
	Well-being	quality of life ¹¹⁷

annotation. The goal was to make sure that only necessary and relevant labels were kept for categorizing *park elements* and *spaces* into health-promoting activity categories.

In the process of cleaning the data, 1926 keys were omitted. These included keys such as `name`, `operator`, and `source`, which cannot provide insight into the object’s activity. In addition, 11 values were also left out because they only described metadata and did not help in understanding the primary function or essence of the map object. Examples of such values include `yes/no`, `unknown`, or `Bing`. A full list of these omitted keys and values can be found in the replication repository. This initial data cleaning step significantly reduced the number of tags to 2118, which were the ones we needed to map to health-promoting activities, or none if the object did not support any of them. This streamlined dataset provided a more focused and relevant basis for the subsequent annotation and classification of *park elements* and *spaces*.

B.4 Benchmarking LLM Classifiers

To evaluate the suitability of LLM classifiers as annotators for OSM tags, we created a high-quality, expert-annotated gold standard set consisting of the 100 most frequent tags. To ensure accuracy and reliability, three co-authors independently labeled these 100 items with health-promoting activities or none, and we used the majority voting strategy to aggregate the individual opinions into one final outcome label. In cases where conflicts arose, i.e., where the three annotators provided different labels, a discussion was held to resolve the discrepancies. Through this rigorous annotation process, we established a robust and reliable

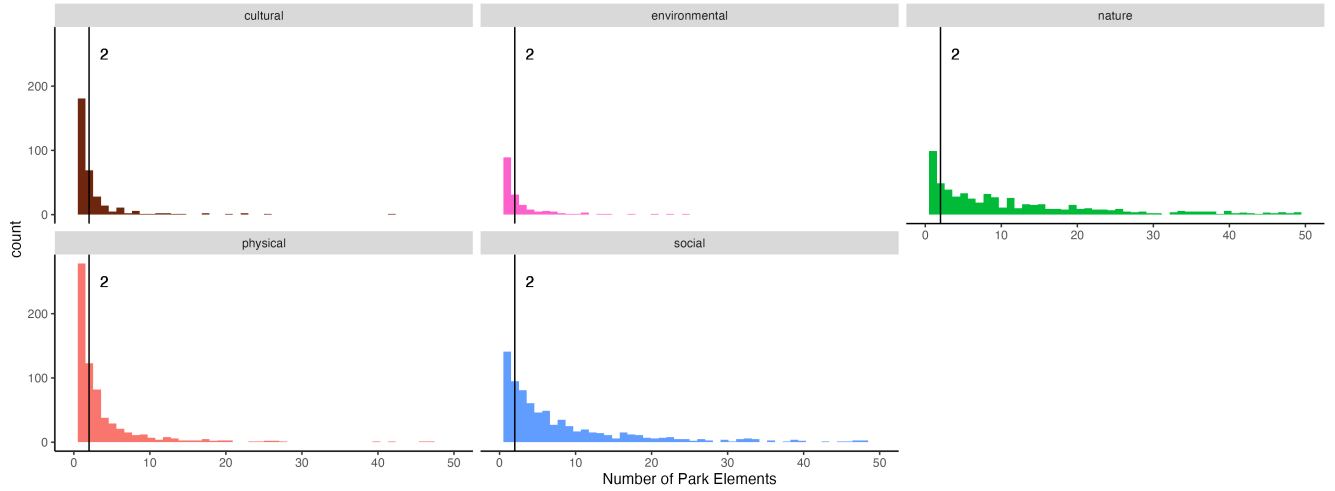


Figure 9. Histogram of park elements. We set 2 as the minimum number per activity category.

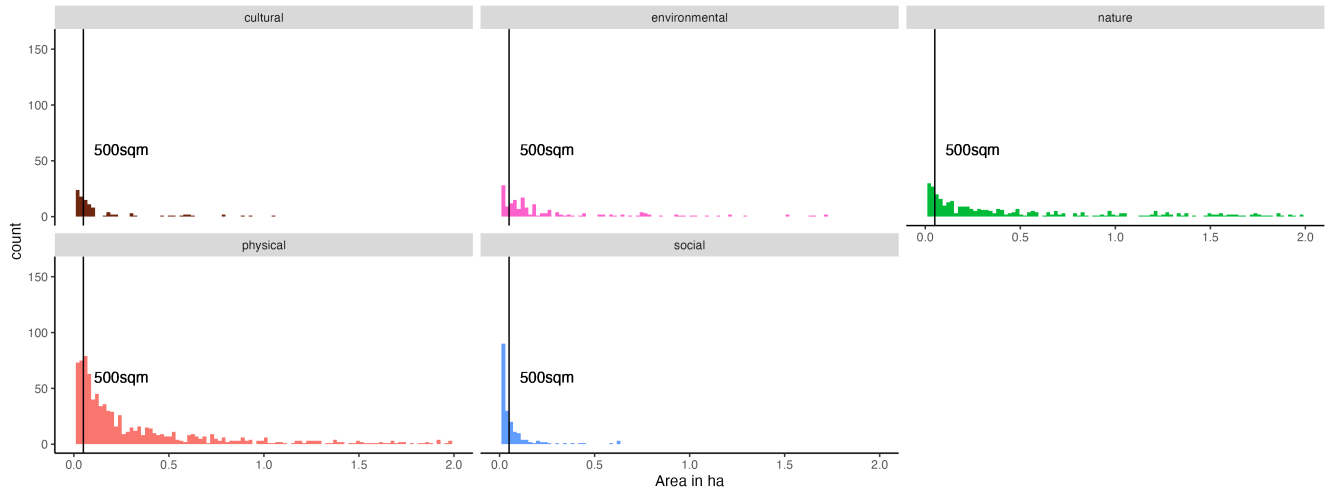


Figure 10. Histogram of park spaces. We set 0.05ha (500 m²) as the minimum size per activity category.

“gold standard” dataset of 100 items. This dataset serves as a benchmark to assess the accuracy of the labels provided by the LLM classifiers.

For generating the annotations, we conducted a systematic exploration of the configuration settings of two LLMs, GPT-3.5-turbo¹¹⁹ and GPT-4¹²⁰ using the OpenAI API¹²¹. Our goal was to identify the best-performing setting in terms of the weighted F_1 score, which is the harmonic mean of precision and recall in this multi-class classification task. The independent variables were *i*) the large language model, i.e., gpt-3.5-turbo or gpt-4¹²⁰, *ii*) the temperature parameter $t \in \{0.3; 0.6; 0.9\}$, which controls the randomness of the models’ completions, and *iii*) the prompt, for which we tested two versions, one with and without providing a brief definition of the OSM tag taken from the OSM wiki. The full prompt is shown in Figure 11.

Figure 11 shows a specific sequence of prompts designed to elicit a main activity and a secondary activity for each OSM tag. The reason behind this approach was our hypothesis that certain OSM tags could support multiple health-promoting activities, as demonstrated by the example of benches that could be argued to be annotated with social, nature-appreciation, or physical activities. Additionally, we obtained a reliability score for each of the model’s annotations. These reliability scores offer an indication of the model’s confidence in its assigned activities, which could serve as a threshold to actually use the annotations, as low scores might indicate that the annotation is more speculative. By incorporating these main activities, secondary activities, and reliability scores from the LLM models, we hoped to gain a more nuanced insight into how these amenities and facilities in parks can be used. This detailed information allowed us to account for the potential multi-functionality of certain OSM tags and provided data for the evaluation using the proposed benchmark.

Furthermore, we followed the guidelines¹²² to optimize the performance of the LLMs annotations. We assigned a system

Table 8. Results of LLM Benchmarking. The highest performance is achieved with GPT-4, using a temperature of 0.9 and not providing definitions for the tags. Annotating a secondary activity did not improve the F_1 scores.

LLM	Definitions	Temperature	F_1 -score Main Activity	F'_1 -score Weighted Combination
gpt-4	✗	0.9	0.772	0.772
gpt-4	✗	0.6	0.770	0.770
gpt-4	✓	0.3	0.764	0.764
gpt-4	✗	0.3	0.755	0.755
gpt-3.5-turbo	✗	0.6	0.747	0.747
gpt-4	✓	0.6	0.740	0.740
gpt-3.5-turbo	✗	0.9	0.728	0.728
gpt-3.5-turbo	✓	0.3	0.726	0.726
gpt-4	✓	0.9	0.713	0.713
gpt-3.5-turbo	✓	0.6	0.710	0.710
gpt-3.5-turbo	✗	0.3	0.704	0.708
gpt-3.5-turbo	✓	0.9	0.689	0.689

persona, i.e., ‘*You are an expert in urban planning and public health, with a specialization in urban parks. [...]*’, gave definitions of the six activities with exemplary activities, and provided several correct completions of items as means to few-shot learning. Finally, we provided a clear specification of the desired output format.

To determine the highest agreement between the human-annotated benchmark and the annotations of the LLMs, we used the F_1 score, which is the harmonic mean of the precision and recall. One complication in the evaluation was that the benchmark only comprised one activity label, whereas we asked the LLM annotator for a main and secondary activity for each tag. Thus, we report two F_1 scores: one that uses the label from the main category only and another that is a weighted combination of the main activity category and the secondary activity category. The weighted F'_1 score is computed by slightly altering the impact of each element of the confusion matrix as follows:

$$TP' = TP_{main}^i \cdot reliability^i + TP_{2nd}^i \cdot (1 - reliability^i) \quad (\text{true positives}) \quad (4)$$

$$FP' = FP_{main}^i \cdot reliability^i + FP_{2nd}^i \cdot (1 - reliability^i) \quad (\text{false positives}) \quad (5)$$

$$FN' = FN_{main}^i \cdot reliability^i + FN_{2nd}^i \cdot (1 - reliability^i) \quad (\text{false negatives}) \quad (6)$$

$$reliability^i = \frac{mean(reliability_{main}^i)}{mean(reliability_{main}^i) + mean(reliability_{2nd}^i)} \quad (\text{Ratio of reliability between main and secondary category}) \quad (7)$$

Intuitively, this means that we use the reliability scores stemming from the LLM annotations to estimate the LLM’s confidence that a label is correct, thus creating a comparable metric that allows for comparing two annotations for one item to one human-annotated ground truth.

We tested various settings to see which would deliver the best performance, which was GPT-4, set at a temperature of 0.9, and without providing definitions for tags. To give you a clearer picture, we’ve compiled the results of the top-performing configuration in Table 8. The F_1 scores tabulated in the tables show the best results of systematically adjusting the reliability scores for primary and secondary categories from 0 (using any label, regardless of its reliability) to 1 (annotate “none” in all cases). Generally, GPT-4 outperformed its predecessor, GPT-3.5. Adding definitions actually had a negative effect on label quality, possibly due to misleading keywords in the tagging instructions. When it came to the temperature setting, there was no consistent impact, with minimal differences between otherwise equivalent configurations. Interestingly, adding a secondary activity label didn’t improve the annotation quality (cf. last column of Table 8). In fact, the best results were achieved when the

Table 9. The correlations between the scores for *park elements* and *park spaces* are low. This property allowed us to linearly combine them into a unified score.

Activity Category	Mean Pearson Correlation
Physical	0.16
Nature-appreciation	0.05
Environmental	0.18
Social	0.06
Cultural	0.18

reliability threshold of the secondary annotation was close to 1, rendering all secondary annotations to “*none*”, thus being equivalent to only using the main activity label. This suggests that the primary labels generated by the system are already of high quality, so putting any weight on a secondary label actually harms the overall score. Based on these findings, we decided to use GPT-4, set at a temperature of 0.9 and without definitions, to label all OSM tags and not impose any threshold on the reliability score.

B.5 Modeling Average Park Offerings

To model average park offerings, we used independent regression models for *park elements* and *spaces*. During the computation of the regression models, parks with very low activity counts in a specific category were excluded. This exclusion was necessary to prevent artificially flattening the regression lines due to close-to-zero values, which would distort the normalization. The specific threshold for excluding parks with low activity counts was determined empirically by analyzing the histograms of the values. This approach enabled us to identify an appropriate cutoff point for excluding parks with insufficient activity data, ensuring the reliability of the regression models. For a visual representation of the exclusion process and the determination of the threshold, refer to [Figure 9](#) and [Figure 10](#).

B.6 Orthogonality of Park Elements and Spaces

Park elements include points of interest, individual trees, benches, and similar items. *Park spaces*, however, include areas like forests, sports fields, and buildings. There can be cases where a park area is broken down into its individual parts, like a playground with separately mapped features like swings, slides, or spinning equipment. But these cases are pretty rare in OSM mapping. Likewise, unless a tree is particularly important, areas tagged as `natural=wood` should not include individual trees according to the mapping guidelines¹²³. Based on these observations, we hypothesized that it would be acceptable to combine scores from park features and areas linearly, as they contribute differently to the overall offering of facilities for health-promoting activities.

To validate the assumption that *park spaces* and *park elements* are orthogonal, we calculated the pairwise correlation coefficients of their respective scores in all cities and averaged them, as presented in [Table 9](#). The low Pearson Correlation Coefficients supported our observation that the scores of *park spaces* and *park elements* indeed capture largely independent concepts, with all correlations being slightly positive but below 0.2. Consequently, we combined them into one overall score for the park.

B.7 Semantic Matching of Flickr Labels and OSM Tags

In our validation, we used a global dataset of geotagged photos from Flickr, from which we selected all 10,711,513 images that were taken within one of the parks from 35 cities in our study. These images came with user-generated labels and were also partially annotated with computer vision labels from a computer vision algorithm^{124,125}. To obtain semantically equivalent representations of Flickr labels and OSM tags, we employed Sentence-BERT (S-BERT¹²⁶) for text embeddings. We formulated this task as an asymmetric semantic search problem, where the Flickr label was the search term, and the goal was to find the closest matching OSM tag. Given the worldwide reach of our study, the multiple languages present in the user-generated Flickr labels created a challenge in mapping them to the corresponding OSM tags, which were all in English. To address this, we identified the top three languages besides English used in the tags of each city, using the Google MediaPipe¹²⁷ Language Detection Model¹²⁸. To ensure that the language detection was accurate and to eliminate named entities, we only used labels where the language detection indicated a confidence of 50% or more. We then translated those tags to English using the respective OPUS machine translation models¹²⁹.

To further improve the quality of embeddings, we augmented the OSM tags with short definitions sourced from the OSM mapping guidelines¹²³. For instance, the OSM tag `sport=table-tennis` was augmented with the definition “A bat and ball game played over a table.” We were able to expand 66% of the OSM tags with these descriptions. The remaining tags were

left without descriptions primarily because of the unregulated nature of tagging in OSM, which led to many undocumented tags or multiple values within one tag, like `sports=soccer;rugby`. Note that these tags were still used for mapping, albeit with less information.

After embedding the OSM tags using S-BERT's `all-mpnet-base-v2` model, we proceeded to match each Flickr label to the closest OSM tag in the embedding space, using the cosine distance as similarity measure. To ensure that the matches were of high quality, we set a strict threshold: the cosine similarity score had to be at least 0.7. We arrived at this value after noticing that when the similarity score was lower than 0.7, the matches became less reliable based on manual inspections. This allowed us to avoid matching labels that did not have meaningful OSM counterparts. For example, abstract labels describing certain phenomena like “*cloud*”, “*rain*”, and “*sunset*” were not matched.

A detailed review of the matched pairs revealed that, as anticipated, most pairings were logical based on the text similarity between labels and tags with definitions. However, some minor adjustments were still needed, as some matches were not entirely consistent with the theme of health-promoting activities in parks. For example, the term “*outdoor*” was initially linked to `swimming_pool=outdoor`. But as there cannot be a suitable equivalent for “*outdoor*” on OSM, we removed this pairing and equivalent ones, such as “*park*,” as all photos were taken in parks. Another instance was the pairing of “*water*”, which did not capture the specific role of water features in parks in promoting health. We manually adjusted this to `water=river`, which better reflects bodies of water commonly found in parks. Through this review step, we improved the quality of the matched pairs, ensuring they more closely align with the theme of health-promoting park activities. The need for this manual step should not diminish the effectiveness of the semantic search within sentence embeddings. It was merely to eliminate labels that could not meaningfully correspond with an OSM tag and to match a few labels with more domain-relevant tags. This matching process yielded 2,171 label-tag pairs in total. Of these, 1,432 pairs corresponded to an OSM tag with health-promoting benefits, such as “*steeplechase*” being matched to `athletics=steeplechase` involving physical health benefits, while 739 pairs, such as “*Lamp Post*” being matched to `man_made=lamp_post` did not imply health benefits.

We evaluated the accuracy of the resulting label-tag matchings by asking three domain experts to independently assess whether the 20 most frequent matchings from Flickr tags to activity categories were plausible and correct. We aggregated their responses using majority voting. Given the multiple languages present in the dataset, we used only the tags from London in this evaluation step, as they were in English. The experts agreed with 82% of the matchings, which is highly accurate considering they are based solely on individual tags.

Having assured that the matchings are accurate, we proceeded to profile the parks based on the activities associated with the matched OSM tags, following the same scoring approach as what we used for the OSM *park elements* and *spaces* (cf. Equation 2). In our validation, we chose a minimum of 250 images from each park and at least 15 parks in each city. This criterion was established to secure a robust number of images for each park, enhancing the accuracy of our analysis. This approach helped us avoid any potential bias that could have been introduced by individual photographers if a park had only a few images.

Figure 12 depicts the computation of the Flickr activity scores. The method is the same as for the OSM tags; however, on the y-axis, we use the count of the matched Flickr labels instead of the OSM tags. The method for scoring is described in Section 4.5; the mapping of Flickr Labels to OSM tags and activities is explained in Section 4.7.

⇒ You are an expert in urban planning and public health, with a specialization in urban parks. You have studied how parks promote health and have an understanding of the various activities that people engage in within them. Proficient in the OpenStreetMap project and skilled in tagging urban elements, particularly those within parks, your responsibility involves assigning activities to specific park elements based on OpenStreetMap tags.

⇒ Consider these 6 categories of activities people do in urban parks:

Physical activities This category is about leisure pursuits that involve physical movement and sports. Example activities are: Walking, hiking, trail running, biking, swimming, rock climbing, canoeing, kayaking, horseback riding, outdoor sports, and group fitness classes.

Mind-body activities This category is about physical practices that combine movement, breathing techniques, and meditation to promote relaxation, stress reduction, and overall well-being. Example activities are: Yoga, meditation, and tai chi.

Nature appreciation activities This category is about leisure pursuits that involve enjoying and exploring the natural world. Example activities are: Bird watching, camping, picnicking, fishing, painting, drawing, photography, and nature journaling.

Environmental activities This category is about gardening and conservation of parks. Example activities are: Gardening, planting trees and flowers, and participating in conservation efforts and volunteering.

Social activities This category is about coming together and communal experiences that involve engaging with others. Example activities are: Attending outdoor festivals and concerts, playing sports, and volunteering.

Cultural activities This category is about activities that celebrate and showcase the cultural diversity and heritage of the community. Example activities may include cultural festivals, art exhibits, music performances, storytelling, and cultural workshops.

Given the categories of "Physical activities", "Mind-body activities", "Nature appreciation activities", "Environmental activities", "Social activities", "Cultural activities", and "none of the above"; How would you classify the following OpenStreetMap Tags found in a park and which [0,100] reliability scores (even multiple scores) would you give to your assessment? You can assign up to two categories, but you don't have to!

⇒ Provide the answer in the format: Main Activity|Reliability Score (of the main activity)|Secondary Activity (if it exists)|Reliability Score (of the secondary activity)|Explanation (not more than 20 words)

⇒ leisure=playground

⇒ Social|80|Physical|70|Children utilize playgrounds for both physical activity and exercise, as well as for social interactions through cooperative play.

⇒ leisure=pitch

⇒ Physical|90|Social|75|People engage in team sports on sports pitches, encompassing both physical activity and a social aspect due to the collaborative nature of team-based sports.

⇒ leisure=garden

⇒ Nature-appreciation|80|Environmental|60|People utilize gardens to cultivate an appreciation for nature, while gardens also serve as spaces for environmental activities, such as planting flowers and engaging in gardening practices.

⇒ amenity=bench

⇒ Social|80|Nature-appreciation|40|People utilize benches for relaxation and social interaction, fostering a sense of community. Moreover, benches offer the opportunity to immerse oneself in the surrounding nature, encouraging moments of contemplation and introspection.

⇒ natural=wood

⇒ Nature-appreciation|100|None|100|Forested areas, such as woods, primarily serve the purpose of appreciating and connecting with nature.

⇒ amenity=parking_space

⇒ None|90|None|100|A parking space does not inherently cater to a specific activity.

Figure 11. Preparatory prompt provided to the LLM classifiers via the OpenAI API. The tag and the definition were subsequently prompted. Regular text refers to 'user' messages, gray text refers to 'system' messages, and underlined text refers to 'assistant' messages. ⇒ denotes the beginning of a new message. Bold markup was added for improved readability.

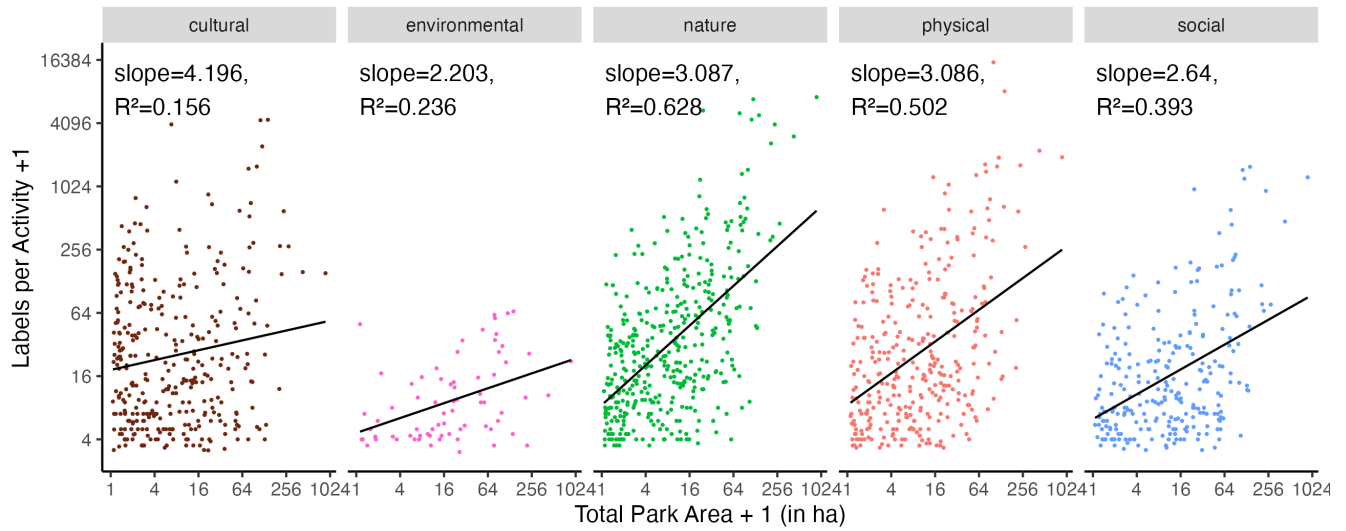


Figure 12. Visualizing the fit of the linear model for determining the park scores using matched Flickr labels for London, UK. The horizontal axis denotes the park's area (\log_2), and the vertical axis is the number of categorized labels of images from these parks (\log_2).

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