

1 Understanding the use of greenspace before and 2 during the COVID-19 pandemic by using mobile 3 phone app data

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20 — **Abstract** —

21 Engagement with natural areas has increased during the Covid-19 pandemic, and this may well
22 form one of the enduring legacies of this time. A better understanding of human interactions with
23 urban greenspace, and how patterns of use have changed, including inequalities of use, will be crucial
24 for decision makers to adequately manage and direct resources within these natural spaces as we
25 recover from the pandemic. Current evidence on use of natural spaces is limited and does not easily
26 support site-specific analysis or with fine spatio-temporal distinctions. Coupled with difficulties on
27 primary data gathered throughout the pandemic, there is a general knowledge gap on how changing
28 behaviour has reshaped the use of natural areas and what inequalities have arisen in this dynamic.
29 Through the case study of Glasgow's open spaces, with a specific focus on one urban park, we apply
30 new forms of urban big data from mobile devices to show how the use of greenspace has changed
31 through the restrictions imposed during Covid-19 pandemic. The research findings will help park
32 managers, urban planners, and policymakers better design the recovery and renewal of our cities
33 after the pandemic.

37 **1** Introduction

38 Natural ecosystems, including urban green and blue spaces, are valued for diverse reasons.
39 On the one hand, they are important for natural environment conservation and biodiversity
40 (Haines-Young and Potschin-Young, 2018). On the other hand, they provide an array of
41 valuable cultural ecosystem services by offering spaces for leisure and recreation which can
42 promote mental and physical health and well-being (Nath, Zhe Han and Lechner, 2018). In
43 a time of pandemic, the perceived benefits of natural spaces are amplified (Kleinschroth and
44 Kowarik, 2020; Poortinga et al., 2021). Nature has been a source of physical and mental

45 respite for many during the pandemic, with lockdown rules heightening the appreciation
46 for local parks and greenspaces (Kleinschroth and Kowarik, 2020). While restrictions on
47 movement may initially have reduced access to greenspace (Ugolini et al., 2020), appreciation
48 for these natural spaces has grown (Ugolini et al., 2020; Poortinga et al., 2021), and the use of
49 parks and public greenspaces has increased overall in comparison to previous years (Natural
50 England, 2020; Office for National Statistics, 2021). Understanding public interactions
51 with urban natural areas, and the factors that influence behaviours in these areas, can
52 improve decision making on how to best preserve or enhance the benefits they provide to
53 the communities who engage with them (Kabisch, Qureshi and Haase, 2015). Despite the
54 rising importance of greenspace in public policy, the understanding of human–environment
55 interaction in urban greenspace is incomplete (Kabisch, Qureshi and Haase, 2015) with
56 shortfalls in traditional research methods. Traditionally, the survey questionnaire is the
57 most common tool used to understand interaction with urban greenspace, conducted in
58 person on-site or off-site through a telephone/internet survey (Kabisch, Qureshi and Haase,
59 2015). While fundamental to understand the wide-scale changes in preferences and social
60 norms towards nature spaces, especially in critical times like these (Natural England, 2020;
61 Office for National Statistics, 2021), the technique has several disadvantages for analysis at
62 high resolution. Although providing a wide socio-demographic coverage, surveys often lack
63 spatial-temporal details, can be highly aggregated, suffer from low response rate, and may not
64 cover individual observations over a prolonged period of time. The broad focus and sampling
65 strategy of survey-based techniques cannot provide the near real-time insights needed at a
66 local level to inform management strategies. To better understand how patterns of greenspace
67 use have shifted during the pandemic, and whether these represent a temporary phenomenon
68 or a more durable shift or structural change, we can look towards new forms of urban big
69 data. The global penetration of smartphones and the integration of Global Positioning
70 System (GPS) technology in various portable devices generate large volumes of opportunistic
71 behavioural data, which open a window into how people use natural spaces (Ilieva and
72 McPhearson, 2018; Cui et al., 2021). In the context of urban greenspace, the last decade has
73 seen rapid growth in the application of GPS data from mobile phones for the exploration of
74 human-nature interactions in the city (Cui et al., 2021). Throughout the Covid-19 pandemic,
75 researchers have sought to understand changes in the use of greenspace (Ugolini et al., 2020;
76 Poortinga et al., 2021), however, response using mobile phone data has been limited to
77 more general mobility patterns (Khataee et al., 2021). In terms of urban greenspace, urban
78 big data from Strava and Google have been applied to explore human-nature interactions
79 through the pandemic (Venter et al., 2020; Rice and Pan, 2021), however, at the time of
80 writing, a clear gap exists in in the literature to utilise new forms of mobile phone data
81 to shed light on the situation before and during pandemic. Through the case study of the
82 City of Glasgow’s open spaces, with a specific focus on the Alexandra Park, this research
83 explores how new forms of urban big data can be used to better understand human-nature
84 interactions through the changing restrictions caused by the Covid-19 pandemic.

85 **2 Data and Methods**

86 **2.1 Data and study area**

87 The mobile phone app data used in the analysis is location-based service data from Huq
88 (<https://huq.io/>). This data is generated when a mobile phone application updates the
89 location of a mobile device using a combination of available location sensors, such as
90 Bluetooth, cellular tower, Wi-Fi, or GPS (Wang and Chen, 2018). The data features high

91 resolution (typically 10s of metres), timestamped location information (geospatial coordinates)
 92 for individual mobile users captured periodically to reflect mobility and behaviour events
 93 covering the period 2019 to 2020 for activities within Glasgow, UK. The case study area
 94 consists of a large sample of over 300 major open spaces located in the City of Glasgow, UK.
 95 The spatial extent of the natural areas was made available by Glasgow City Council for use
 96 in this research and encompasses all major opens spaces, amenity spaces and parkland in
 97 the city. Geomni UKBuildings land use data was utilised to enrich the mobile data for the
 98 process of home location detection. The dataset represents the structure, characteristics, and
 99 use of commercial, public and residential buildings across the study area, available through
 100 the digimap services in the UK (<https://digimap.edina.ac.uk/>).

101 2.2 Data analysis

102 Using 2019 and 2020 mobile phone app data from the provider Huq, we extracted all GPS
 103 points (impressions) within Glasgow’s open spaces. Since we had the unique user ID for each
 104 of the mobile phone app users, we were able to understand different users’ movement patterns
 105 within the city. For one site of specific importance to local policy makers, the Alexandra
 106 Park, we also extracted the number of visits for the 2020 period and assessed the 7-day
 107 rolling average. For visitors to this site, we estimated a home region at the Scottish datazone
 108 level. We expanded the state of the art in home detection algorithms by first enriching the
 109 mobile phone app data with high resolution land use data from Geomni’s UKBuildings layer.
 110 For each visitor to Alexandra Park, we enriched their mobile phone app data and analysed
 111 only impressions within residential space. Based on common activity heuristics techniques
 112 (Alexander et al., 2015), a user’s home region was assumed as the region where they recorded
 113 the maximum number of active evenings in residential space during the study period; where
 114 an evening is assumed to be 8pm to 7am. Only users who returned a definitive home region
 115 were retained for further analysis. Finally, we assessed the number of impression/visits
 116 throughout the pandemic to Alexandra Park and explored where these visitors were coming
 117 from.

118 3 Results and Discussion

119 3.1 Mobile phone app data in Glasgow’s open spaces

120 We extracted over 769,000 impressions across two years in Glasgow’s open spaces (Figure
 121 1). The sites with the most impressions were Kelvingrove Park, Glasgow Green and Pollock
 122 Country Park (Table 1). George Square and the Botanic Gardens are also present in the list.
 123 Parklands represent a much larger surface area than amenity and open space, and it is not
 124 surprising they dominate the list of top sites in terms of the number of impressions. The
 125 relatively smaller open and amenity spaces have less impressions overall but have a higher
 126 density of impressions which is also to be expected.

127 Table 1. Huq impressions in the top 4 open spaces (2019/2020).

Name	Location	Impressions	Per ha
Kelvingrove Park	West End	55497	S1614
Glasgow Green	Parkhead	46508	875
Pollock Country Park	Cardonald	42299	300
Small community park	Parkhead	27499	53195

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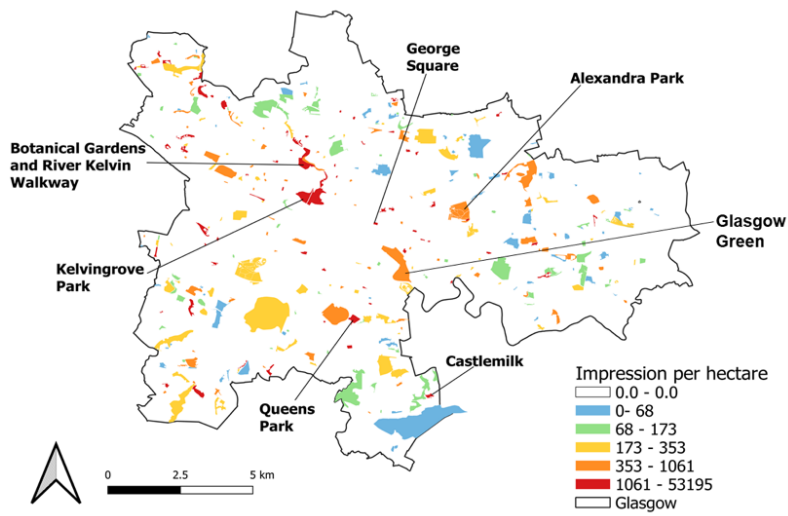
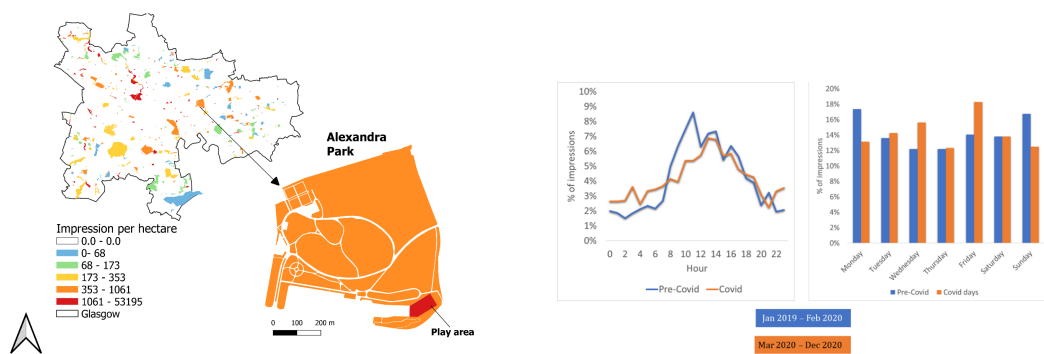


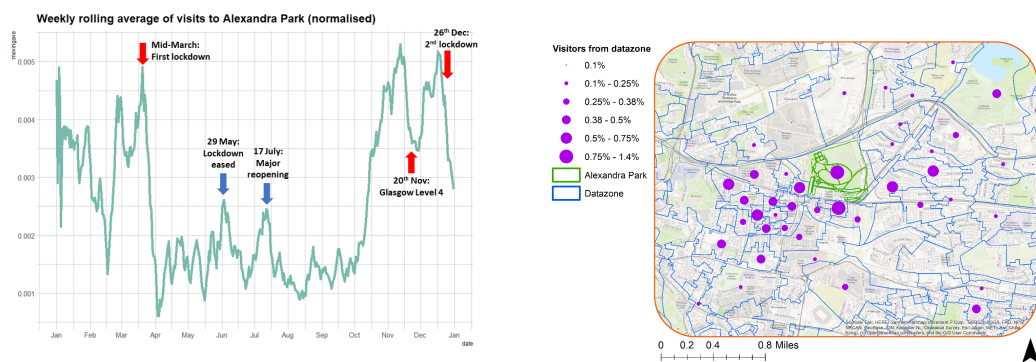
Figure 1 Huq impressions in Glasgow's open spaces (2019/20)



(a) Location of Alexandra Park

(b) Difference in impressions in Alexandra Park before and during Covid-19

Figure 2 Location and impressions in study area



(a) visits to Alexandra Park (2020)

(b) Home location for Alexandra Park visitors

Figure 3 Visits and home location of visitors to Alexandra Park

129 3.2 Changes in use of Alexandra Park during the pandemic

130 For one site of specific interest to policy makers, Alexandra Park (Figure 2), we tested some
131 more detailed analysis in terms of the changes in use caused by the COVID-19 pandemic.
132 Analysis shows some changes in the morning peak (shift from 10am to 12pm) at the park
133 before and during the pandemic (Figure 2), with some differences in the daily number of
134 impressions between the periods (Sunday and Monday peak rather than Friday peak). The
135 introduction and lifting of various lockdown rules are reflected in the visitation patterns
136 throughout 2020 (Figure 3). After the first lockdown was imposed in March 2020 there is a
137 large drop in visits to the park which did not recover until the end of 2020, and a second
138 national lockdown appears to reduce numbers again. The small reductions in visits following
139 two lockdown easings in the Summer of 2020 could be caused by a substitution effect where
140 the potential to engage in other activities replaces recreation in open space. In terms of who
141 visits the park, Figure 3 shows the distribution of visitors based on their home region. We
142 can clearly see that the surrounding residential neighbourhoods makes up a large portion of
143 those visiting Alexandra Park which is to be expected given the various stay at home/stay
144 local measures imposed throughout 2020.

145 3.3 Limitations and future directions

146 The research presented here should garner support for urban big data for human-nature
147 interaction, but some limitations should be noted on the findings presented. While this type
148 of mobile phone app data represents the near exact location of the device, with a higher
149 spatial precision and higher granularity than other types of mobile phone app data such as
150 call detail records (Wang, He and Leung, 2018), there remains some level of error in the
151 GPS data. The analysis does not account for GPS points that may fall inside or outside
152 of the open space boundary in error due to the limited accuracy attributed to the GPS
153 point. Future research will overcome this by relying on stop detection techniques which
154 looks at a user's impression in time sequence to ensure those passing by the open space are
155 not mistakenly included as part of the analysis. In terms of representativeness of the data,
156 these new forms of data carry the risk of bias through uneven population and demography
157 coverage (elderly and vulnerable groups have lower mobile phone usage rate) while the details
158 of dataset construction lie largely hidden, dependent on private providers. This may lead
159 us to mis-diagnose problems and misdirect efforts to reduce inequalities, for example, or to
160 produce results which are dataset-dependent rather than generalisable. In future work we
161 will explore the inherent biases of mobile phone app data and develop correction techniques
162 which achieve more representative population coverage for mobility research.

163 4 Conclusion

164 While the health and well-being benefits of greenspace access have been increasingly recognised,
165 they have taken on even greater significance over the last 16 months due to the Covid-19
166 restrictions, which may form one of the enduring legacies of this time. This research sheds
167 light on the changes in use of greenspace through the case study of Glasgow's open spaces
168 and one urban park in particular, Alexandra Park, throughout the various Covid-19 related
169 restrictions. Our findings show that the park was most visited by those in the surrounding
170 area and that visitation patterns was impacted by the various lockdowns and stay at home
171 orders throughout 2020.

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