

Associations between COVID-19 transmission rates, park use, and landscape structure

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1 **Associations between COVID-19 transmission rates,** 2 **park use, and landscape structure**

3 Thomas F. Johnson¹, Lisbeth A. Hordley¹, Matthew P. Greenwell¹, Luke C. Evans¹

4 1: Ecology and Evolutionary Biology, School of Biological Sciences, University of Reading, Reading, UK

5 Corresponding author: Thomas Frederick Johnson (Thomas.frederick.johnson@outlook.com)

6 **Abstract**

7 The COVID-19 pandemic has had severe impacts on global public health. In England, social
8 distancing measures and a nationwide lockdown were introduced to reduce the spread of the virus.
9 Green space accessibility may have been particularly important during this lockdown, as it could
10 have provided benefits for physical and mental wellbeing. However, the associations between public
11 green space use and the rate of COVID-19 transmission are yet to be quantified, and as the size
12 and accessibility of green spaces vary within England's local authorities, the risks and benefits to
13 the public of using green space may be context-dependent. To evaluate how green space affected
14 COVID-19 transmission across 299 local authorities (small regions) in England, we calculated a
15 daily case rate metric, based upon a seven-day moving average, for each day within the period
16 June 1st - November 30th 2020 and assessed how baseline health and mobility variables influenced
17 these rates. Next, looking at the residual case rates, we investigated how landscape structure (e.g.
18 area and patchiness of green space) and park use influenced transmission. We first show that
19 reducing mobility is associated with a decline in case rates, especially in areas with high population
20 clustering. After accounting for known mechanisms behind transmission rates, we found that park
21 use (showing a preference for park mobility) was associated with decreased residual case rates,
22 especially when green space was low and contiguous (not patchy). Our results support that a
23 reduction in overall mobility may be a good strategy for reducing case rates, endorsing the success
24 of lockdown measures. However, if mobility is necessary, outdoor park use may be safer than other
25 forms of mobility and associated activities (e.g. shopping or office-based working).

26

27 **Keywords**

28 COVID; coronavirus; ecosystem services; fragmentation; green space; health; park use; public
29 health

30 **1. Introduction**

31 The COVID-19 pandemic has had severe impacts on public health (Mahase, 2020) and remains an
32 emergency of international concern. In response to the pandemic, the UK government implemented
33 social distancing measures and nationwide lockdowns to control the spread of the virus (UK
34 Government, 2020a). During these periods, the general public were limited in the distances they
35 could travel and, at certain points, the number of times they could leave their residence each day;
36 with an allowance of one non-essential trip during the peak of transmission (UK Government,
37 2020a). Though social restrictions have fluctuated in response to case rates, social distancing has
38 been constant and there has been a general message of reduced movement and staying local
39 where possible for much of 2020 and throughout 2021. These restrictions have meant that
40 members of the public became more reliant on amenity spaces close to their residences for daily
41 exercise and/or recreation (Geng et al., 2021). Green spaces may provide a comparatively safe
42 place for these activities, though the amount and structure of green space available for public use
43 differs widely across the UK. Here we evaluate if differences in the availability and structure of
44 public green space within local authorities (local government bodies responsible for public services
45 within a specified area) in England, and their usage, influenced the local rate of incidence of
46 COVID-19.

47 Green spaces, which we define as vegetated non-arable areas - see Taylor & Hochuli (2017) for
48 further details - provide important cultural and recreational ecosystem services, benefiting both
49 mental and physical health (Beyer et al., 2014; Cohen-Cline et al., 2015). These benefits are usually
50 considered in terms of reducing the prevalence or severity of conditions such as mental stress
51 (Nutsford et al., 2013) or cardiovascular disease (Seo et al., 2019), and some of these benefits have
52 continued throughout the pandemic (Slater et al., 2020; Soga et al., 2020). However, the influence
53 of green space use on disease transmission rates has received less investigation, but is of great

54 importance as green space use has increased rapidly during the pandemic (Venter et al., 2020).
55 Furthermore, it is unclear how 'safe' green spaces are during periods of higher incidence especially
56 in densely populated areas (Shoari et al., 2020).

57 We anticipate that green space could impact COVID-19 incidence in two ways: general health and
58 wellbeing, and transmission. It is conceivable that general health and well-being is greater in areas
59 with more green space, as higher levels of green space are associated with healthier populations
60 (Maas et al., 2006; Mitchell and Popham, 2007; van den Berg et al., 2015). As COVID-19 has a
61 greater impact on those with underlying health conditions and sedentary lifestyles (Hamer et al.,
62 2020; Jordan et al., 2020), green space may, therefore, indirectly provide some level of resilience to
63 the disease and/or reduce incidence. However, our key focus here is on transmission, as it is likely
64 that the major benefits of outdoor recreation in green space are related to a lower risk of infection.
65 Current evidence suggests that COVID-19 is spread via droplet infections, contact with
66 contaminated individuals or surfaces, and through aerosol transmission (Bahl et al., 2020). These
67 risks are likely minimised in green space areas, as generally, they are less spatially confined, and
68 contain fewer surfaces prone to frequent touching or contact. Consequently, green space use may
69 represent a safe form of recreation by minimising risk of infection.

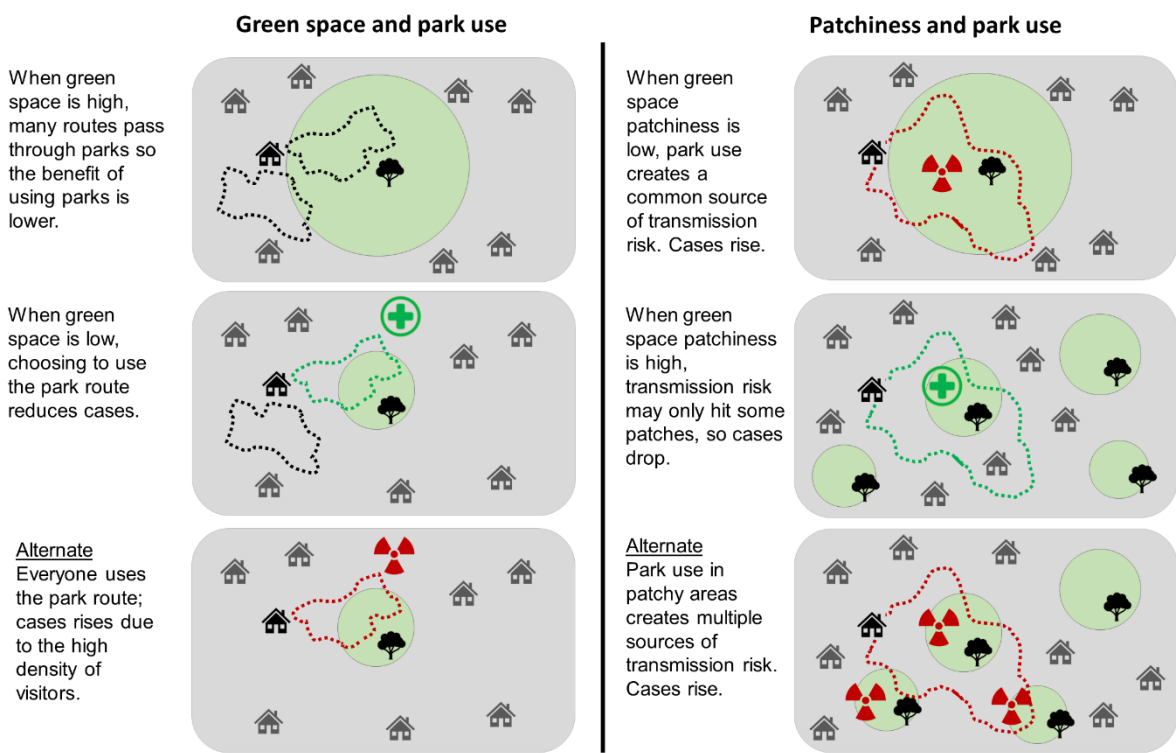
70 In England approximately 87% of the population are within a 10-minute walk of public parks and
71 gardens (Shoari *et al.* 2020). However, both the structure and amount of green space vary between
72 local authorities, and both could influence COVID-19 incidence. Generally, it has been found that
73 greater health benefits are derived from larger areas of green space (Ekkel and de Vries, 2017). In
74 the context of disease transmission, larger areas may offer more space per individual, lowering
75 transmission risk. However, smaller fragmented areas of green space are common in many
76 residential areas and are, therefore, more accessible to much of the population and may be used
77 more frequently. Further, if public use is distributed across fragmented green spaces, the wider
78 effects of a transmission incident could be reduced, as contacts would be isolated to the members
79 of a neighbourhood or community adjacent to a particular green space. This process can be seen in
80 animal diseases where habitat fragmentation reduces transmission due to limiting interactions
81 between groups in different patches (Mccallum and Dobson, 2002). However, fragmentation also

82 typically results from reductions in the total area of green space (Fahrig, 2013), leading to less
83 overall space per individual, possibly increasing transmission rates.

84 Whilst the effects of green space on COVID-19 transmission are currently unclear, other
85 environmental and social factors are known to influence both the spread and severity of the
86 disease. For example, human mobility drives the spread of infectious diseases (Kraemer et al.,
87 2019) and studies have shown that reducing social interactions by restricting mobility can lead to a
88 decrease in transmission rates of COVID-19 (Chinazzi et al., 2020; Gatto et al., 2020). Furthermore,
89 as diseases are often spread along transport links and in offices (Gatto et al., 2020; Zhang et al.,
90 2018), enforcing lockdown situations that curtail movement, such as requiring people to work from
91 home, can have a great effect on reducing transmission rates. In addition to mobility, health and
92 social factors have been associated with increased severity of the disease such as age, underlying
93 health conditions, and deprivation (Richardson et al., 2020; Williamson et al., 2020). Consequently,
94 any possible effects of green space must be considered after attempting to account for factors that
95 could increase recorded incidence.

96 Given the stated benefits of green space, it is important to attempt to evaluate using the available
97 evidence, the impact of green space use on transmission rates. In addition, understanding the
98 influence of green space on COVID-19 incidence could provide an estimate of the value of green
99 space for maintaining public health if subjected to a resurgence of the COVID-19 pandemic. And, in
100 the longer term, indicate the potential benefits of local green space on future pandemics of
101 comparative severity. Here, using time series of COVID-19 cases within local authorities in England,
102 we explore how both green space use and access (i.e. availability of green spaces) influence
103 COVID-19 incidence. Our approach is to first construct a baseline transmission model to attempt to
104 control for factors likely to influence recorded COVID-19 incidence and then to explore how green
105 space influenced case rates above or below this baseline. We predict that green space and the way
106 it is structured will, in itself, have no effect on case rates. However, we expect that an increase in
107 relative park use (i.e. spending time in green space over indoor activities) will make the structure
108 and availability of green space important (Figure 1). Specifically, when green space is low, park use
109 will likely represent a safer form of movement (e.g. compared to shopping), unless the green space

110 becomes a congregation zone that inflates transmission risk. Furthermore, we predict that case
 111 rates will be lower when green space is fragmented, as the disease will be contained in more
 112 localised areas. For example, if the local authority has one large park the presence of an infected
 113 individual puts more people at risk than an infected individual attending one of many parks. Further,
 114 we predict, as others have found (Kraemer et al., 2020), that increased mobility will increase
 115 incidence, but that park use (measured as relative use of parks) is a relatively safe form of mobility
 116 (e.g. preferable over shopping).



117

118 **Figure 1.** Mechanisms by which green space and patchiness could interact with park use to influence
 119 COVID-19 transmission. The upper two rows describe the primary predictions, whilst the bottom row explains
 120 alternate predictions. All variables (e.g. population density) except green space and patchiness, respectively,
 121 are held at a constant in these predictions. Green circles with a tree icon indicate the presence of green
 122 space. Dotted lines indicate walking routes, which becomes park use when the line overlaps a green space.
 123 The green health symbol indicates that the landscape metric and park use is beneficial, whilst the red toxic
 124 symbol indicates a risk.

125 **2. Methods**

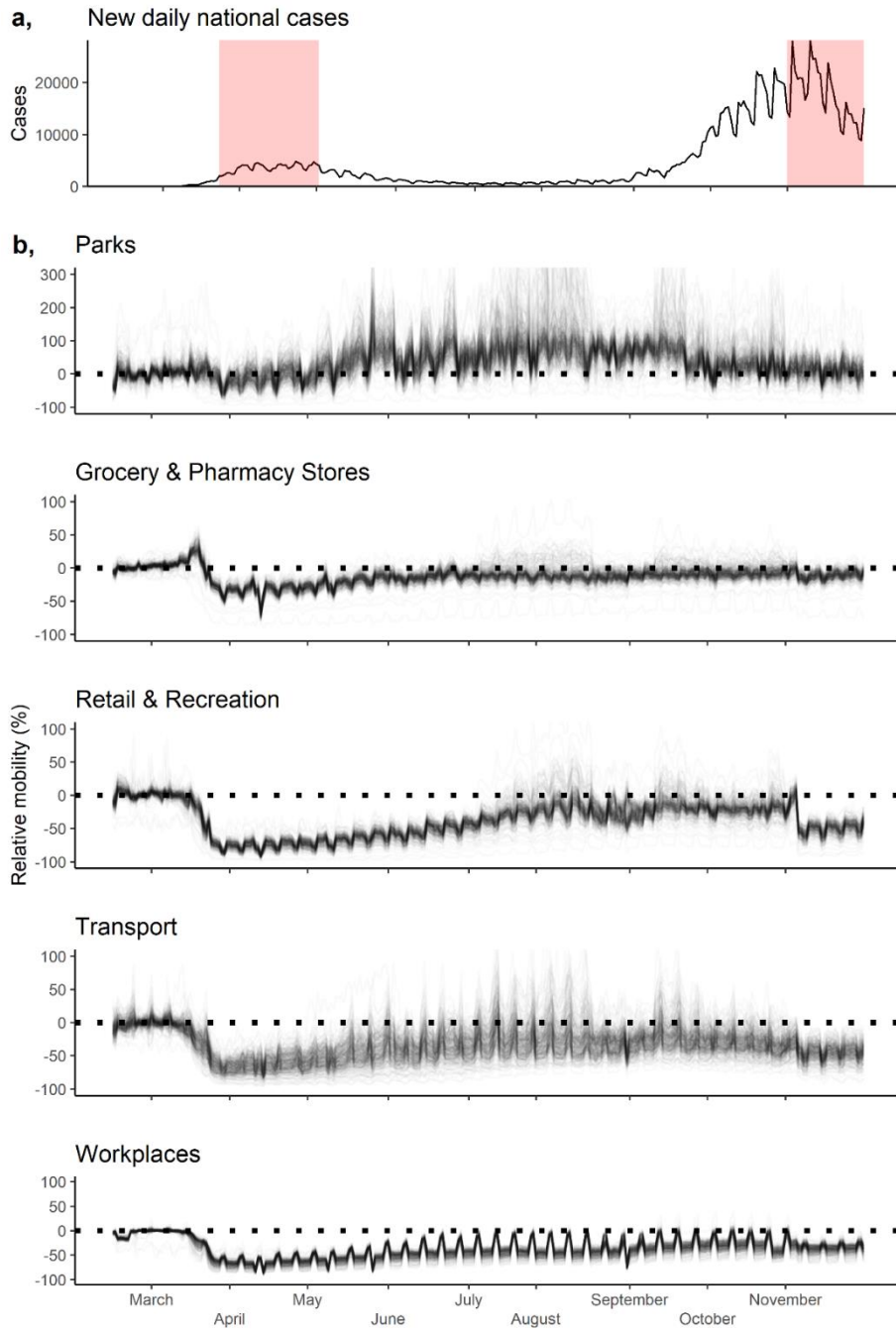
126 2.1 Data compilation

127 2.1.1 COVID-19 case rates

128 We compiled daily lab-confirmed cases (incidence) of COVID-19 in England from February 15th
129 2020 up to November 30th 2020 (available from <https://coronavirus.data.gov.uk/>). We only included
130 cases until November, as in December England began an aggressive vaccination campaign and the
131 more infectious COVID B1.1.7 variant began to spread widely (Horby et al., 2021) – factors that
132 could confound our models (see below). Cases were recorded at the lower tier local authority
133 (administrative areas for local government) level (N = 299). These local authorities vary in size (3 –
134 26,000km²), demographics, cultures, and in socio-economic circumstances. Incidence over this time
135 was highly variable with periods of rapid increases, which were then relatively controlled by periods
136 of national lockdown (Figure 2). To determine factors influencing COVID-19 transmission, we
137 estimated case rates for each day in each local authority. Case rates were derived by fitting log-
138 linear models, regressing the natural log of daily cases against date (days). To reduce the effect of
139 daily variation in reported cases and instead capture the general trend, we fit these regressions over
140 7-day moving windows (Figure S1) e.g. to estimate the case rate on August 4th, a regression was fit
141 between cases from August 1st – 7th, for August 5th a regression was fit between August 2nd – 8th.
142 The coefficients of these models provided a daily case rate. We converted these coefficients into a
143 daily percentage change in cases. We opted to calculate case rates instead of using raw daily case
144 numbers, as case rates more adequately capture transmissibility i.e. regardless of whether cases
145 jumped from 5 to 10, or 50 to 100, the case rates would capture the doubling effect. Furthermore,
146 case rates are more robust to variation in the population size of a local authority.

147

148



149

150 **Figure 2.** a) Daily lab-confirmed cases across England, with lockdown periods (with restricted mobility)
 151 indicated with red shading. b) Google mobility trends (Google, 2020), describing change in mobility over time
 152 for five different categories, relative to a baseline period (January 3rd to February 6th 2020). We excluded the
 153 sixth category 'residential mobility' as it is measured differently to all other categories (Google, 2020). Each
 154 line within the mobility trends represents a local authority. All plots extend from February 15th to November
 155 30th 2020. For the 'parks' plot, we limited the y-axis at 300% to exclude a small number of extreme
 156 observations with high park use.

157

158 *2.1.2 Baseline transmission variables*

159 We compiled variables which describe the mechanisms considered to influence case rates (Table
160 1). Firstly, we derived two variables which describe the structure of the local authority population:
161 population density – residential population density (controls for green space in the green
162 transmission model below); and population clustering – Moran’s I spatial autocorrelation of
163 residential population density (controls for patchiness in the green transmission model below).
164 Secondly, we compiled three variables which characterise the human population in each local-
165 authority prior to COVID-19: health – risk of premature death or a reduction in quality of life due to
166 poor mental or physical health (Ministry of Housing Communities & Local Government, 2019);
167 demography - the percentage of the population over 70 (Office for National Statistics, 2021a);
168 economy – the percentage of unemployed-individuals in the non-retired local authority population
169 (UK Government, 2018). A high baseline health, whereby few individuals have pre-existing
170 underlying health conditions, may decrease the chances of an individual presenting with severe
171 symptoms of COVID-19 and further passing the virus to others (Clark et al., 2020). Accounting for
172 this baseline health may also assist in controlling for the presence of asymptomatic undetected
173 infections in case rates.

174

175 **Table 1.** Description of variables within the baseline and green transmission models, including the
 176 scale at which the variable is measured, where ‘Static’ indicates only one value is derived per local
 177 authority, whilst there are unique values for each case rate in ‘Timeseries’ variables.

Variable	Description	Scale
<i>Baseline transmission model</i>		
Population density	Local authority population size in mid-year 2019 divided by local authority area [in sq.km]. Source: Office for National Statistics (2021c)	Static
Population clustering	Moran’s I spatial autocorrelation of residential population density in 2011, extracted from the UK’s gridded 1km resolution population raster. Source: UK Government (2020b)	Static
Health	The health aspect of the multiple deprivation index, describing the risk of premature death or a reduction in quality of life due to poor mental or physical health. Low values indicate greater health deprivation. Source: Ministry of Housing Communities & Local Government (2019)	Static
Demography	Percentage of local authority population aged over 70 in June 2019. Source: Office for National Statistics (2021b)	Static
Economy	Percentage of local authority population (adult non-retired) unemployed in December 2019. Source: UK Government (2020c)	Static
Mobility change	Daily mean overall mobility in each local authority across five of the Google mobility metrics: transport, workplaces, parks, grocery & pharmacy stores, and retail & recreation. Overall mobility averaged over the previous 2 to 12 days before each case rate. Source: Google (2020)	Timeseries
Community cases	Seven-day rolling average in cases within each local authority. Variable also included within the green transmission model. Source: https://coronavirus.data.gov.uk/	Timeseries
<i>Green transmission model</i>		
Green space	Green space per person (m ²). Derived by dividing total green space area in each local authority by the local authority’s population size. We consider green spaces as any area meeting the following land cover types: broadleaved woodland, coniferous woodland, improved grassland, neutral grassland, calcareous grassland, acid grassland, fen, marsh and swamp, heather, heather grassland, and bog. We excluded agricultural land cover types as these were deemed a largely inaccessible/private land cover area. Source: Rowland et al. (2017)	Static
Patchiness	Median frequency of parks within a 1km buffer around local authority houses. Source: Office for National Statistics (2021a)	Static
Park use	Contribution of park use to the overall mobility metric, derived by extracting the residuals of a linear model between park mobility (response) and overall mobility (predictor) within each local authority. A positive residual value indicates park use exceeds what we would expect given park and overall mobility trends within the local authority. As with the mobility change variable, park use is averaged over the 2 to 12 days before each case rate. Source: Google (2020)	Timeseries

178

179

180 National lockdowns, and the resulting reduction in people's mobility, were an important tool for
181 reducing transmission within England during the COVID-19 pandemic. We used Google Community
182 Mobility Reports to track human mobility and its effect on case rates (Google, 2020). These reports
183 chart movement trends over time across six categories: retail and recreation, groceries and
184 pharmacies, transit stations, workplaces, residential, and parks. These trends describe how visitors
185 to, or time spent in, each of the six categories changed compared to a pre-pandemic 5-week period
186 (the median value from January 3rd to February 6th 2020). As the mobility data contained missing
187 values (c.12%) for some local authorities and dates (Figure S2), we were conscious that these
188 missing values may lead to statistical inference errors within the models below. As a result, we filled
189 missing mobility values using *mice: multiple imputation chained equations* R package and '2l.pan'
190 imputation approach, which is a hierarchical normal model within homogenous within group
191 variances (Van Buuren and Groothuis-Oudshoorn, 2011). This hierarchical structure allowed us to
192 model mobility trends accounting for differences in local authorities. We included the following terms
193 within our imputation model: five Google mobility timeseries (all except residential), as well as a 1-
194 day lag period for each timeseries, the number of days along the timeseries since February 15th with
195 a cubic polynomial term, an indicator variable to describe whether each day was a weekend or not,
196 and the timeseries of daily COVID-19 cases within the local authority. We also included terms that
197 didn't vary through time, including: the latitude and longitude of the local authority, and all local
198 authority covairates within the baseline and green transmission models below (population density,
199 population clustering, health, demography, economy, green space, and patchiness). Finally, we also
200 included some national metrics that could influence local mobility, including: a timeseries of daily
201 COVID-19 cases measured at the national scale, as well as the mean daily temperature and
202 precipitation within Central England. We ran this model through 10 chains, each with 20 iterations,
203 and 20 pan iterations. The imputation model converged.

204 Conventionally, as part of a multiple imputation framework, these 10 chains should then be
205 modelled separately and coefficient standard errors should be inflated with Rubin's rules (Little and
206 Rubin, 2002). However, given the small percentage of missing values, and that there are currently
207 no well defined steps for using Rubin's rules in generalized additive models (see our models below),

208 we instead averaged mobility values across the 10 chains to produce mean estimates of mobility for
209 each category, day, and local authority i.e. conducting single imputation. We ensured the
210 imputations produced plausible values (Figure S3). From this mobility dataset, we derived a variable
211 which described overall mobility change for each date in each local authority, which is the average
212 mobility change across five of the six categories (excluding residential) for each day in each local
213 authority. We excluded the residential mobility category as it is inversely correlated with all other
214 categories and is measured differently (Google, 2020). However, as there is likely a delay between
215 a mobility reduction and a case rate reduction (Lauer et al., 2020), we lagged the overall mobility
216 change metric by linking each case rate with the mean mobility change from 2 – 12 days prior. As a
217 result of this lag, we trimmed the temporal extent of dataset to cover March 1st – November 30th
218 2020 (instead of February 15th – November 30th 2020).

219 *2.1.3 Green variables*

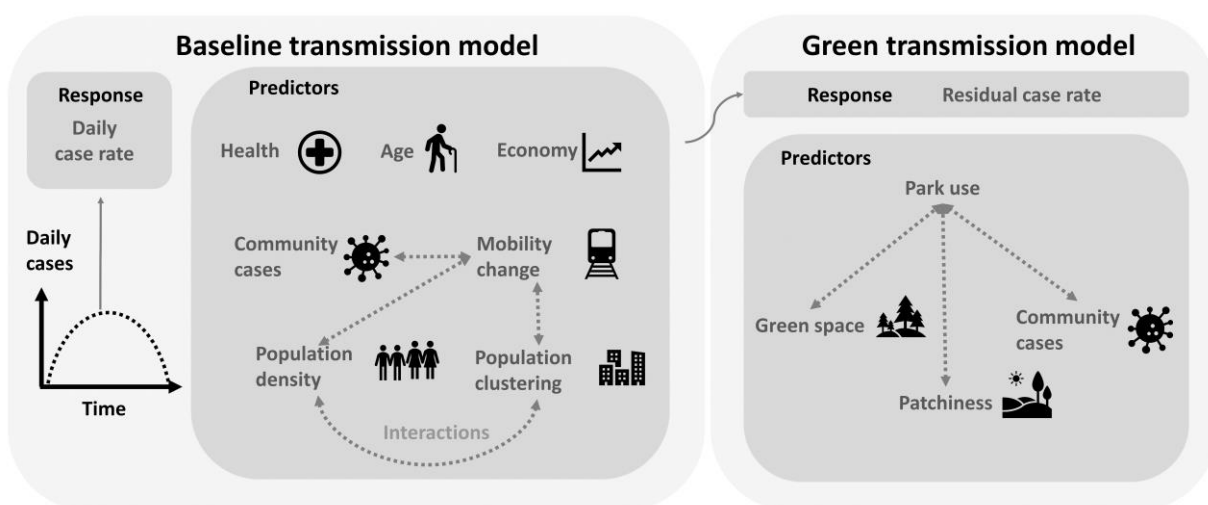
220 We compiled two variables which describe the structure of green spaces in each local authority:
221 patchiness – median frequency of parks within a 1km² radius around households in the local
222 authority (Office for National Statistics, 2021c); green space – available green space per person
223 (m²) within the local authority, derived by dividing the green-cover area by the local authority
224 population size. Green-cover area was calculated from the UKCEH 2015 25 metre land cover raster
225 (Rowland et al., 2017) and covered a variety of landscape categories (Table 1). For this green-cover
226 area calculation, we set a 1km buffer around the local authority, to represent green space access of
227 households on the local authority border.

228 Using the mobility dataset, we also produced a park use variable, which represents how parks are
229 used relative to overall mobility. This park use metric is derived by fitting a linear model between
230 park use and overall mobility within each local authority, and extracting the residual park use, where
231 positive values represent a preference for using parks over other forms of mobility for a given date
232 (in the original percentage units). Parks include public gardens, castles, national forests, campsites,
233 observation points, and national parks, but exclude surrounding countryside in rural areas. As a
234 result, the Google (2020) definition of parks differs slightly to the landscape categories used in our

235 green space metric but was our best available representation of how green space was used during
 236 the pandemic. As in the overall mobility change metric, park use represents the mean use of parks
 237 in the prior 2 to 12 days.

238 2.2 Modelling

239 We developed two core models (Figure 3): baseline transmission – aimed at controlling for the
 240 major mechanisms influencing case rates; and green transmission – impact of landscape structure
 241 and park use on case rates. The baseline and green transmission models are both focussed on
 242 case rates, but we anticipated that any effects of green space on COVID-19 case rates were likely
 243 to be much smaller than variables known to influence disease transmission (e.g. population
 244 density). As a result, we structured our analyses to first account for the presence of these more
 245 influential variables in a baseline transmission model, and then in the green transmission model, we
 246 explored how green areas (the focus of this study) can alter the residuals of these case rates.
 247 Conventionally, it is advised to include all variables within one regression instead of analysing the
 248 residuals separately (Freckleton, 2002). However, variables were highly correlated (e.g. population
 249 density and green space are derived in similar ways), and resulted in multicollinearity issues.
 250 Dealing with the major mechanisms first (e.g. population density) mitigated these multicollinearity
 251 issues.



252

253 **Figure 3.** Model structure for baseline transmission and green transmission difference models, depicting the
 254 process for developing the response variables, as well as the predictors used in each model.

255 To control for the baseline health and transmission mechanisms influencing COVID-19 case rates,
256 we developed a generalized additive model within the *mgcv* R package (Wood, 2021), with case
257 rate as the response – inverse hyperbolic sine transformed to address heavy tailed residuals. We
258 included the following parameters as linear predictors: health, demography, economy, population
259 density (\log_{10} transformed), population clustering, and mobility change. We also included
260 interactions between population density and clustering, population density and mobility change, and
261 population clustering and mobility change. In model development, it was clear that the residuals
262 were experiencing extreme positive temporal autocorrelation, where case rate values were very
263 similar to values from the previous day. As a result, we also included the previous days case rate
264 (one day lag) as a linear predictor in the model. We included random intercept smoothing over the
265 local authorities to account for the non-independence of multiple case rates within the same local
266 authorities. Due to working hour restrictions in England, case counts on Saturdays and Sundays
267 were largely underestimated, and then over-estimated on Mondays and Tuesdays. As a result, we
268 also included a cyclic smoothing term (with up to 7 knots) over day of the week to capture reporting
269 biases and control for daily variation (days within a week) in case reporting. We extracted the
270 residuals from this model for the green transmission model.

271 To assess how landscape structure and park use influenced residual case rates, we again
272 developed a generalized additive model, with residual case rates from the baseline transmission
273 models as the response, as well as the following linear predictor parameters: park use, green space
274 (\log_{10} transformed), patchiness, as well as interactions between park use and green space, and
275 park use and patchiness. These models also included random intercept smoothing over local
276 authorities, but we did not control for the smoothing over days of the week, which was addressed in
277 the earlier baseline transmission model.

278 *2.2.1 Sensitivity analysis*

279 In both the baseline and green transmission models, we were conscious that some parameter
280 effects may have varied through time. For example, some covariates may have been particularly
281 influential prior to mandatory mask wearing in shops on July 24th 2020. As a result, we extracted the

282 first four weeks of data from our case rate dataset and ran the models on this subset. We then
283 shifted the data forwards one week and re-ran the models, repeating this procedure (moving
284 window), creating 40 replicates of the coefficients each representing a different-overlapping period
285 of time between March 1st and November 30th 2020. From this, we established that the majority of
286 coefficients were very stable over time (Figure S4), but mobility change, health, case rate lag, and
287 park-use were somewhat variable. Looking at how these coefficients change through time, it was
288 clear that mobility change had a temporal trend, where mobility effects were greatest when cases
289 were at their highest. As a result, we amended the baseline transmission model to include an
290 interaction between the mobility variables and the number of cases (averaged over the nearest 7
291 days) in the local authority at a given moment in time (see Equation S1-2 for the final model
292 structures). There was no clear temporal trend in the health, case rate lag, and park-use variables
293 so these remained untouched within the models. We also noted that the magnitude of the mobility
294 change effect was far greater in the first lockdown period (March – May 2020). We suspect the large
295 effect is genuine, but given there were spatial biases in case-testing availability during the first
296 lockdown, we opted to re-model the data with a trimmed temporal extent (June 1st to November 30th
297 2020). From this, it was apparent that coefficients were generally far more conservative using the
298 trimmed dataset, albeit still in the same direction (Figure S5). Given this discrepancy in results
299 (depending on the temporal extent), we opted to restrict our analyses throughout the rest of this
300 manuscript to solely focus on the more conservative trimmed temporal extent, which is likely to be
301 far less effected by spatial variability in case-testing availability – so more robust. As a result, all
302 model outputs and projections (see below) are derived from the data covering June 1st to November
303 30th 2020.

304 In the analyses, we opted to fill missing mobility values with imputation instead of using complete-
305 case analyses, where any observations with missing mobility data are removed. However, given the
306 small percentage of missing values, and that the mobility data is averaged across five categories,
307 and then again through time, we wanted to ensure model coefficients did not change drastically
308 under imputation, which could be a sign of a statistical inference error (Johnson et al., 2021). As a
309 result, we repeated the analyses using only complete-case observations and compared model

310 coefficients between the missing value approaches. Given the similarity in the complete-case and
311 imputation coefficients (Figure S5), we continued using the coefficients from the imputation model
312 which covered a greater array of local authorities.

313

314 *2.2.2 Model checking*

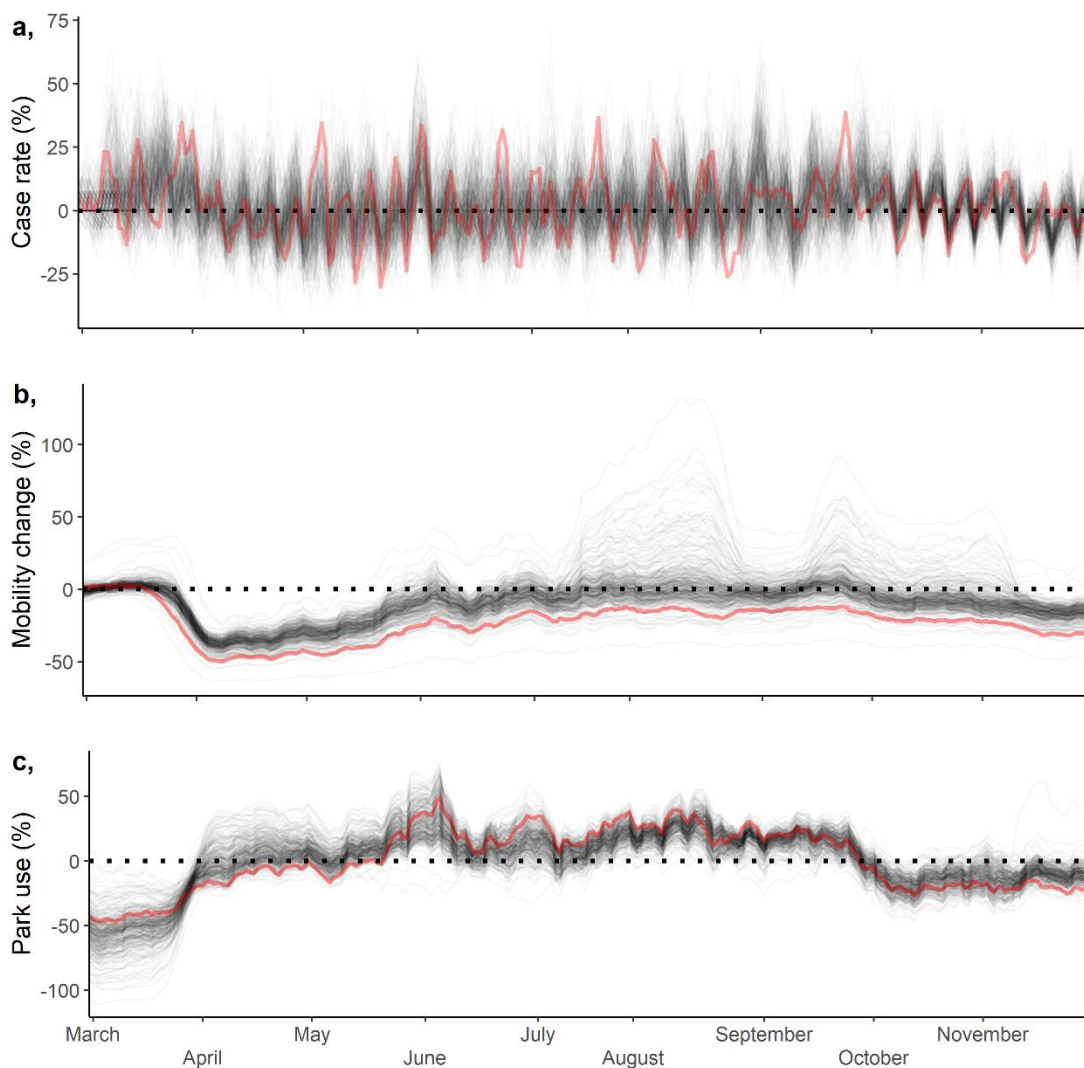
315 We standardised (subtracting values from their mean and dividing by their standard deviation) all
316 predictor variables in the models to determine effect sizes and reduce multicollinearity where
317 interactions are present. All model assumptions passed e.g. multicollinearity (variance inflation
318 factors less than 3 within both the baseline and green transmission model), concurvity (observed
319 and estimated concurvity less than 0.1), absence of spatial (Moran's I = 0.1) and temporal
320 autocorrelation (Figure S6), homogeneity of variance, and normality of residuals. When
321 summarising results, we report the mean \pm standard deviation, and when describing model outputs
322 we report the standardised slope coefficient and 95% confidence intervals. We also report the R^2 for
323 each model. All analyses were conducted in R 4.0.3 (R Development Core Team, 2020).

324 *2.2.3 Projecting cases*

325 To understand how mobility patterns have influenced cases, we projected cases using the baseline
326 and green transmission models under three scenarios: 1) cases under observed mobility patterns;
327 2) cases after a 20% reduction in each day's overall mobility; 3) cases after a 20% increase in each
328 day's park use. We ran the baseline and green transmission models through each of the scenarios
329 for every local authority between March 1st and November 30th 2020. We standardised all authorities
330 so they had the same starting number of cases (10), community cases (10), and lagged case rate
331 (0.58%; the mean case rate across local authorities on February 28th). These cases, community
332 cases, and lagged case rate were updated and iteratively informed by the new model predictions,
333 instead of the observed data. As a result, the projected case rates are solely influenced by the
334 landscape structure and mobility patterns in the local authority. We constrained the case rates so
335 they could not exceed the range of the observed case rates (-40% to 70%). We converted the
336 projected case rates into projected cases, against the starting case value of 10.

337 **3. Results**

338 Across the 299 local authorities, case rates fluctuated substantially through time (Figure 4a).
339 Mobility declined substantially during the first national lockdown in March to May, and in the run up
340 to winter (Figure 4b). During the summer months, mobility and the variance in mobility increased,
341 and in some local authorities these increases were close to 100% (doubling mobility). In contrast,
342 park use increased during the first lockdown and remained high (approximately 25% above
343 baseline) until winter approached in October (Figure 4c). There was less variation in park use trends
344 between local authorities than in the mobility change metric.



345
346 **Figure 4.** a) Temporal patterns in case rates (a), mobility change (b) and park use (c) between March 1st and
347 November 30th 2020, with each line representing a different local authority. The red line represents the Oxford
348 local authority and acts purely as an example. Case rates are defined as the daily percentage change in
349 cases calculated over a seven day moving average. Mobility change is the mean daily percentage change

350 over five mobility types (Park, Grocery and Pharmacy stores, Retail and recreation, Transport, and
351 Workplaces) extracted from Google community mobility reports (Google, 2020). Park use is the relative
352 contribution of park mobility to overall mobility change, derived by extracting the residuals of a linear model
353 with park mobility regressed against overall mobility within each local authority i.e. are people visiting parks
354 more than we would expect on a given date.

355 3.1 Baseline transmission models

356 Using the dataset with a trimmed temporal extent of June 1st to November 30th 2020 (see sensitivity
357 analysis above), we observed an association between a reduction in mobility and a decline in case
358 rates, and changes in mobility had a larger impact when there was a higher number of average
359 cases and when the population was more clustered (Table 2; Figure 5c, d). Population density and
360 population clustering had no significant impact on case rates. Increases in the health index and
361 proportion of the population over the age of 70 were both associated with significant decreases in
362 case rates (Table 2; Figure 5a, b). This baseline transmission model had an R^2 of 0.45.

363

364 **Table 2.** Estimated regression parameters from the baseline and green transmission models with 95%
 365 confidence intervals. Values rounded to two significant figures, those with confidence intervals not overlapping
 366 zero (i.e. significant at the $p = 0.05$ threshold) are shown in bold. These coefficients were derived from models
 367 utilising the trimmed temporal extent dataset covering June 1st to November 30th 2020 – see sensitivity
 368 analysis above.

Coefficient [95% confidence intervals]

Baseline transmission model

Intercept	0.38 [0.36, 0.39]
Lag case rate	1.55 [1.53, 1.57]
Population density	0.020 [-0.006, 0.050]
Population clustering	0.011 [-0.006, 0.028]
Mobility	0.17 [0.15, 0.19]
Case average	0.061 [0.042, 0.080]
Baseline health	-0.031 [-0.054, -0.007]
Percentage over 70	-0.051 [-0.079, -0.023]
Percentage unemployed	0.0027 [-0.024, 0.029]
Mobility:Case average	0.11 [0.092, 0.13]
Population density:Population clustering	0.0060 [-0.011, 0.023]
Population density:Mobility	-0.011 [-0.025, 0.004]
Population clustering:Mobility	0.029 [0.012, 0.047]

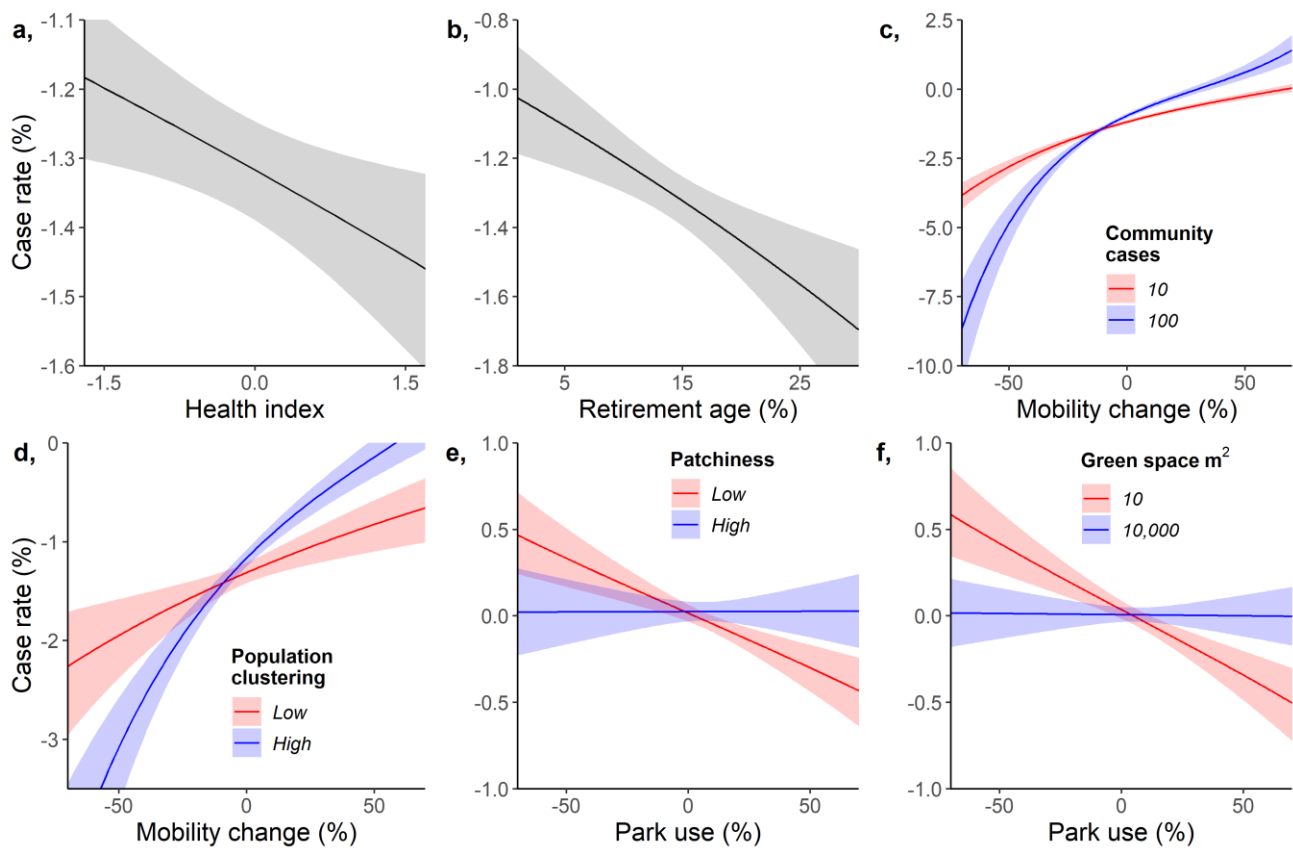
Green transmission model

Intercept	0.0001 [-0.016, 0.016]
Park use	-0.057 [-0.074, -0.041]
Green space	0.0035 [-0.018, 0.025]
Patchiness	0.010 [-0.011, 0.032]
Park use:Green space	0.032 [0.010, 0.053]
Park use:Patchiness	0.024 [0.0026, 0.045]

369

370

371



372

373 **Figure 5.** Marginal effects of important interaction parameters in the baseline transmission and in the green
 374 transmission models. Marginal effects are held at zero for all other parameters as variables were z-
 375 transformed. Panels depict the effect of: a) health, with low values indicating health deprivation; b) the
 376 percentage of the population over 70; c) an interaction between mobility and community cases (the 7-day
 377 average number of cases in the local authority); d) an interaction between mobility and human population
 378 clustering set at 0.2 (Low) and 0.7 (High), where 0 indicates a random distribution of clustering, and 1
 379 indicates a complete separation in clustering; e) an interaction between park use and patchiness (the median
 380 frequency of parks within 1km of each house in a local authority); and f) an interaction between park use and
 381 green space area per local authority capita. Error bars represent the 95% confidence intervals. These
 382 marginal effect plots were derived from models utilising the trimmed temporal extent dataset covering June 1st
 383 to November 30th 2020 – see sensitivity analysis above

384

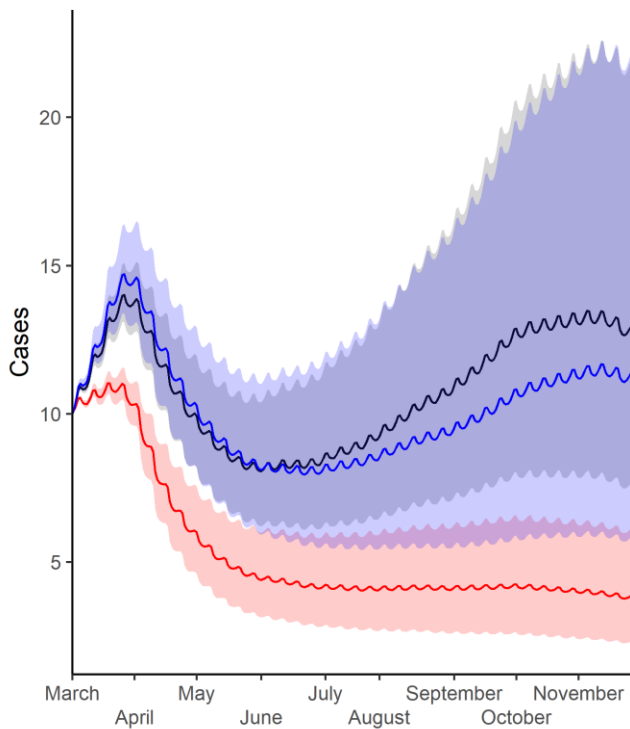
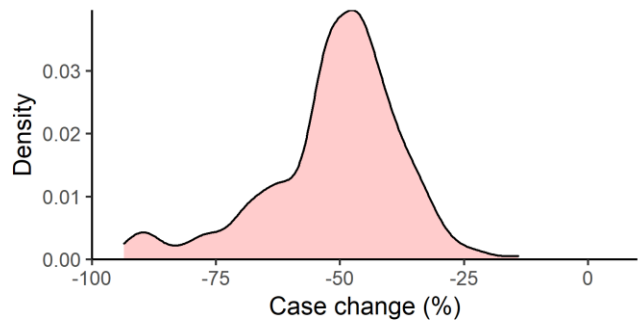
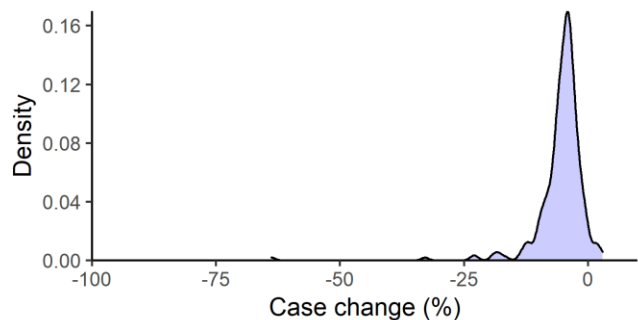
385 3.2 Green transmission models

386 Park use was associated with decreased residual case rates (Table 2; Figure 5e) but the size of the
 387 effect depended on the availability of green space and how patchy it was. When patchiness was
 388 high and when there was a large amount of greenspace, park use had less of an impact on case
 389 rates, though was still associated with a significant reduction in cases. The green transmission
 390 model had a small R^2 of 0.01, despite the significant effects.

391 3.3 Projected cases

392 Reducing mobility is a far more effective measure of limiting COVID-19 transmission than increasing
393 park use (Figure 6). Across local authorities between March 1st and November 30th 2020, a 20%
394 reduction in mobility is projected to have led to 51% fewer cases on average (Figure 6b; 95%
395 quantiles: -88.7% to -29.7%). In contrast, a 20% increase in park use is estimated to have only
396 reduced cases by 5.4% (Figure 6c; 95% quantiles: -17.3% to 0.6%). So whilst park use is
397 associated with reducing COVID-19 transmission, the benefits would only be relatively small.
398 However, there is spatial variation in these findings, with some areas potentially benefitting more
399 than others from a reduction in mobility or increase in park use (Figure 7).

400

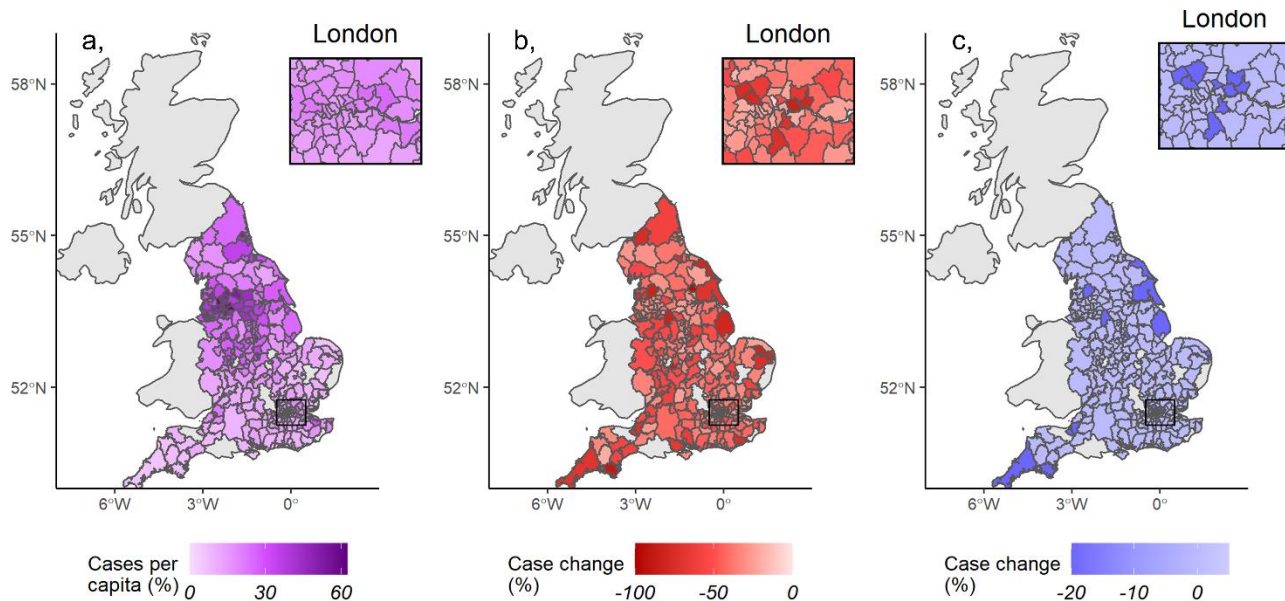
a, Projected cases in Oxford**b, Mobility change: -20%
Case change (%): -51.0 [-88.7, -29.7]****c, Park use: +20%
Case change (%): -5.4 [-17.3, 0.6]**

402

403 **Figure 6.** a) Projected daily cases between March 1st and November 30th 2020 within Oxford under three
 404 scenarios: 1) observed mobility patterns (black); 2) a further 20% reduction in observed mobility (red); and 3)
 405 20% increase in observed park use (blue). In these projections, we set the initial cases (on March 1st) at 10,
 406 and with lagged case rate of 0.58% - the mean value across local authorities on February 28th. All other
 407 covariates were held at their observed values. Error ribbons represent 95% confidence intervals. Panels b and
 408 c represent the distribution of projected change in cases across local authorities under the 20% mobility
 409 reduction (b) and 20% park use increase (c) scenarios i.e. how much could cases have been reduced under
 410 these scenarios. Case change was derived by dividing the total cases between the March and November
 411 periods under each scenario by the cases in the observed mobility scenario (black), multiplying this value by
 412 100, and then subtracting 100. Whilst these projections cover the period March 1st – November 30th 2020, the
 413 coefficients used to derive the projections were taken from the trimmed temporal extent dataset of June 1st –
 414 November 30th 2020, where coefficients were more conservative and less prone to bias (see *sensitivity*
 415 *analyses* above).

416

417



418

419 **Figure 7.** Spatial variation in observed cases per capita (a), and projected case changes under a 20%
 420 mobility reduction (b) and 20% increase in park use (c). Case change was derived by dividing the total cases
 421 between March and November 2020 under each scenario by the cases in the observed mobility projection,
 422 multiplying this value by 100, and then subtracting 100 (see Figure 6). The coefficients used to derive the
 423 projections in b and c were sourced from models utilising the trimmed temporal extent dataset covering June
 424 1st to November 30th 2020 – see sensitivity analysis above

425

426 4. Discussion

427 In this study, we attempted to quantify the effects of local green space on COVID-19 case rates
 428 after accounting for mechanisms known to influence pandemics in our baseline transmission model.
 429 We found that high overall mobility was associated with increased case rates, especially when
 430 population clustering was high. After accounting for these variables, we found that higher park use,
 431 compared to other amenity areas, was associated with a reduction in case rates, especially in local
 432 authorities with low green space and with contiguous green space. These results suggest that
 433 utilising green spaces rather than carrying out other activities (e.g. visiting shops and workplaces)
 434 may reduce the transmission rate of COVID-19, but these benefits are limited compared to reducing
 435 mobility more generally.

436 From our baseline transmission model results, case rates were lower in local authorities with
 437 healthier populations and older populations (Figure 5a-b). These results are logical, firstly as

438 previous evidence has shown COVID-19 has a greater impact on those with underlying health
439 conditions (Hamer et al., 2020; Jordan et al., 2020) and more severe cases may be more likely to
440 be tested and reported. Secondly, whilst the elderly are more at risk of mortality from COVID-19
441 (Williamson et al., 2020), this fact was widely reported in public health guidance and older people
442 may have reduced contact with other individuals (Canning et al., 2020). Our baseline transmission
443 model also shows that reducing mobility is most valuable when community cases are high and in
444 areas with high population clustering (Figure 5c-d). This is consistent with person-person contact as
445 the major mechanism of transmission and appears to demonstrate the general effectiveness of
446 lockdown measures in reducing case rates, as others have demonstrated previously (Davies et al.,
447 2020; Lau et al., 2020). Mobility had less impact in low clustered areas, which again may be
448 expected, as people are more likely to be able to maintain distance and the potential number of
449 interactions is reduced.

450 Once we had accounted for known drivers of case rates, we investigated how landscape structure
451 and park use (i.e. mobility in green spaces) affected residual case rates using the green
452 transmission model. Here we found that using parks, relative to other types of mobility, was
453 associated with a reduction in case rates (Figure 5-6). However, reducing overall mobility (i.e.
454 mobility to all amenity areas) led to a far more substantial decline in case rates. For example, a 20%
455 reduction was projected to reduce cases by c.35%, whilst a 20% increase in park use was projected
456 to reduce cases by 5% to 10% (Figure 6). This suggests that the use of parks may have modestly
457 helped in reducing transmission rates in some areas during the pandemic, but reducing overall
458 mobility is substantially more beneficial than maintaining mobility at pre-pandemic levels and
459 spending that mobility in parks.

460 Whilst park use, overall, had a relatively small effect, we did note stronger effects of park use when
461 the context of the local area was considered as using parks was beneficial in authorities with low
462 green space and authorities with contiguous green space (Figure 5e-f and Figure 6). That park use
463 has a minor beneficial effect overall seems to support our hypothesis that recreation in green space
464 and parks may be safer than in other amenity areas. This is probably because it is easier to
465 maintain distance and green spaces have fewer surfaces which could result in transmission if

466 contaminated. However, the limiting impact of this when green space is high and accessible seems
467 to suggest diminishing returns in how park use can impact COVID-19 transmission. This is perhaps
468 not surprising if the main value of parks in this context is as an alternative to other relatively more
469 hazardous amenity areas. Consequently, if there are other safe options outside of public parks then
470 parks will likely have little impact. However, our findings do suggest that the use of public parks in a
471 highly urbanised area may be advantageous, though as noted above the strongest effect was from
472 the reduction of all forms of mobility. Therefore, cautiously, and given that it corresponds with
473 common sense, we suggest that reducing mobility is a successful strategy for reducing case rates
474 but given a need for some non-essential time outside of a home, using green spaces such as local
475 parks may be the next best thing, particularly in highly urbanised areas.

476 A major limitation of the work is the difficulty in comparing across local authorities that vary
477 simultaneously in many different variables likely important to case rates. This makes inference
478 about the importance of their individual effects very difficult and so effect sizes should be interpreted
479 cautiously and with caveat. Another challenge is that pandemics are rare events, consequently, our
480 analysis covers only a snapshot of time for each local authority. During this period, many different
481 factors not included in the analysis (e.g. chance super spreading events) may have explained much
482 of the variation between local authorities. Despite this, the model fits are reasonably high. An
483 additional limitation in our analyses is the absence of complete Google mobility data in some local
484 authorities. We handled these missing values with imputation and attempted to ensure models were
485 robust by comparing imputed models with complete-case models. Encouragingly, our complete-
486 case and imputed results are very similar, which suggests the imputation has not introduced any
487 missing data bias (Johnson et al., 2021) – although both the imputation and complete-case analysis
488 could just be equally wrong. Given this uncertainty, and the further limitations we have identified
489 above, our mobility findings should be interpreted cautiously.

490 One potential influence we failed to capture within our case rate modelling was the influence of
491 environmental features like air pollution and weather. Air pollution has already been linked to an
492 increase in COVID-19 related deaths, and potentially even transmission (Travaglio et al., 2021).
493 Similarly, there are plausible hypotheses that suggest weather effects like temperature, ultraviolet

494 light, and wind speed may influence the virus's persistence and in-turn transmission (Carlson et al.,
495 2020). Importantly, both of these environmental features may also interact with the findings in our
496 study. Firstly, park use may become a more inherently risky activity if air pollution at the green
497 space is high. Secondly, as park use is likely very correlated with weather, the effects of park use
498 may be confounded by weather. Both of these points warrant investigation, perhaps at a far finer
499 scale than the local authority level.

500 Understanding the risks of different amenity areas could be important for longer-term management
501 of COVID-19 and the landscape-dependency of this advice could be important for developing 'local-
502 lockdown' guidance. In particular, access to green spaces has been shown to have benefits for
503 mental and physical well-being (Slater et al., 2020; Soga et al., 2020), and consequently,
504 understanding the relative risks of using these areas is important. Our results show that COVID-19
505 case rates may be reduced with individuals spending time in parks, relative to other amenity areas,
506 especially in urbanised, high-density areas. Although further research is needed, these findings
507 suggest that the use of parks for recreational activity in these contexts could be advisable,
508 demonstrating a possible additional utility of these green spaces in addition to the known benefits to
509 health and wellbeing (de Vries et al., 2003; Mitchell and Popham, 2007; Nutsford et al., 2013) in
510 normal non-pandemic conditions.

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515 **Data accessibility**

516 Code and data to repeat analysis are presented in
517 https://github.com/GitTFJ/COVID19_parks_landscape

518

519 **Author contributions**

520 All authors contributed to project design. Analysis was led by TFJ and LCE, but all authors
521 contributed. TFJ and LCE co-wrote the first draft and co-authors contributed to revisions.

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