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

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HIGHLIGHTS
• Effect of park use and green spaces on COVID transmission is currently unclear.
• Modelled transmission against mobility and landscape variables in England.
• Reducing mobility and shifting mobility outdoors may reduce transmission.
• Parks may have provided a relatively safe space for outdoor recreation.
• Park benefits are likely greatest in urban areas.

GRAPHICAL ABSTRACT

ABSTRACT

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

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1. Introduction

The COVID-19 pandemic has had severe impacts on public health (Mahase, 2020) and remains an emergency of international concern.

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

Green spaces, which we define as vegetated non-arable areas – see
Taylor and Hochuli (2017) for further details – provide important cul-
tural and recreational ecosystem services, benefitting both mental and
physical health (Beyer et al., 2014; Cohen-Cline et al., 2015). These
benefits are usually considered in terms of reducing the prevalence or se-
verity of conditions such as mental stress (Nutsford et al., 2013) or
cardiovascular disease (Seo et al., 2019), and some of these benefits
have continued throughout the pandemic (Slater et al., 2020; Soga
et al., 2020). However, the influence of green space use on disease trans-
mission rates has received less investigation, but is of great importance
as green space use has increased rapidly during the pandemic (Venter
et al., 2020). Furthermore, it is unclear how ‘safe’ green spaces are dur-
ing periods of higher incidence especially in densely populated areas
(Shoari et al., 2020).

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

In England approximately 87% of the population are within a 10-min
walk of public parks and gardens (Shoari et al., 2020). However, both
the structure and amount of green space vary between local authori-
ties, and both could influence COVID-19 incidence. Generally, it has been
found that greater health benefits are derived from larger areas of
green space (Ekkel and de Vries, 2017). In the context of disease trans-
mission, larger areas may offer more space per individual, lowering
transmission risk. However, smaller fragmented areas of green space
are common in many residential areas and are, therefore, more accessi-
bile to much of the population and may be used more frequently. Fur-
ther, if public use is distributed across fragmented green spaces, the
wider effects of a transmission incidence could be reduced, as contacts
would be isolated to the members of a neighbourhood or community
adjacent to a particular green space. This process can be seen in animal
diseases where habitat fragmentation reduces transmission due to lim-
iting interactions between groups in different patches (Mccallum
and Dobson, 2002). However, fragmentation also typically results from re-
ductions in the total area of green space (Fahrig, 2013), leading to less
overall space per individual, possibly increasing transmission rates.

Whilst the effects of green space on COVID-19 transmission are cur-
cently unclear, other environmental and social factors are known to in-
fluence both the spread and severity of the disease. For example, human
mobility drives the spread of infectious diseases (Kraemer et al., 2019)
and studies have shown that reducing social interactions by restricting
mobility can lead to a decrease in transmission rates of COVID-19
(Chinaazzi et al., 2020; Gatto et al., 2020). Furthermore, as diseases are
often spread along transport links and in offices (Gatto et al., 2020;
Zhang et al., 2018), enforcing lockdown situations that curtail move-
ment, such as requiring people to work from home, can have a great ef-
fect on reducing transmission rates. In addition to mobility, health and
social factors have been associated with increased severity of the dis-
case such as age, underlying health conditions, and deprivation
(Richardson et al., 2020; Williamson et al., 2020). Consequently, any
possible effects of green space must be considered after attempting to
account for factors that could increase recorded incidence.

Given the stated benefits of green space, it is important to attempt to
evaluate the impact of green space use on transmission rates using the
available evidence. In addition, understanding the influence of green
space on COVID-19 incidence could provide an estimate of the value
of green space for maintaining public health if subjected to a resurgence
of the COVID-19 pandemic. And, in the longer term, indicate the poten-
tial benefits of local green space on future pandemics of comparative se-
virity. Here, using time series of COVID-19 cases within local authorities
in England, we explore how both green space use and access (i.e. avail-
ability of green spaces) influence COVID-19 incidence. Our approach is
to first construct a baseline transmission model to attempt to control
for factors likely to influence recorded COVID-19 incidence and then
to explore how green space influenced case rates above or below this
baseline. We predict that green space and the way it is structured will,
in itself, have no effect on case rates. However, we expect that an in-
crease in relative park use (i.e. spending time in green space over indoor
activities) will make the structure and availability of green space impor-
tant (Fig. 1). Specifically, when green space is low, park use will likely
represent a safer form of movement (e.g. compared to shopping), unless
the green space becomes a congregation zone that inflicts transmission
risk. Furthermore, we predict that case rates will be lower when green
space is fragmented, as the disease will be contained in more localised
areas. For example, if the local authority has one large park the presence
of an infected individual puts more people at risk than an infected indi-
vidual attending one of many parks. Further, we predict, as others have
found (Kraemer et al., 2020), that increased mobility will increase inci-
dence, but that park use (measured as relative use of parks) is a rela-
tively safe form of mobility (e.g. preferable over shopping).

2. Methods

2.1. Data compilation

2.1.1. COVID-19 case rates

We compiled daily lab-confirmed cases (incidence) of COVID-19 in
England from February 15th 2020 up to November 30th 2020 (available
from https://coronavirus.data.gov.uk/). We only included cases until
November, as in December England began an aggressive vaccination
campaign and the more infectious COVID B1.1.7 variant began to spread
widely (Horby et al., 2021) – factors that could confound our models
(see below). Cases were recorded at the lower tier local authority
level (administrative areas for local government; N = 299). These
local authorities vary in size (3–26,000km²), demographics, cultures,
and in socio-economic circumstances. Incidence over this time was
often spread along transport links and in of

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During the COVID-19 pandemic, we used Google Community Mobility, an important tool for reducing transmission within England. Case rates in controlling for the presence of asymptomatic undetected infections in 19 (Clark et al., 2020). Accounting for this baseline health may also assist chances of an individual presenting with severe symptoms of COVID-19 if they have pre-existing underlying health conditions, may decrease the risk of premature death or a reduction in quality of life due to poor mental or physical health (Ministry of Housing Communities and Local Government, 2011). This hierarchical structure allowed us to model mobility trends accounting for differences in local authorities. We included the following terms within our imputation model: five Google mobility timeseries (all except residential), as well as a 1-day lag period for each timeseries, the number of days along the timeseries since February 15th with a cubic polynomial term, an indicator variable to describe whether each day was a weekend or not, and the timeseries of daily COVID-19 cases into a daily percentage change in cases. We opted to calculate case rates instead of using raw daily case numbers, as case rates more adequately capture transmissibility i.e. regardless of whether cases jumped from 5 to 10, or 50 to 100, the case rates would capture the doubling effect. Furthermore, case rates are more robust to variation in the population size of a local authority.

2.1.2. Baseline transmission variables

We compiled variables which describe the mechanisms considered to influence case rates (Table 1). Firstly, we derived two variables which describe the structure of the local authority population: population density – residential population density (controls for green space – the percentage of the population over 70 (Office for National Statistics, 2021a); economy – the percentage of unemployed-individuals in the non-retired local authority population (UK Government, 2018); A high baseline health, whereby few individuals have pre-existing underlying health conditions, may decrease the chances of an individual presenting with severe symptoms of COVID-19 (Clark et al., 2020). Accounting for this baseline health may also assist in controlling for the presence of asymptomatic undetected infections in case rates.

National lockdowns, and the resulting reduction in people’s mobility, were an important tool for reducing transmission within England during the COVID-19 pandemic. We used Google Community Mobility Reports to track human mobility and its effect on case rates (Google, 2020). These reports chart movement trends over time across six categories: retail and recreation, groceries and pharmacies, transit stations, workplaces, residential, and parks. These trends describe how visitors to, or time spent in, each of the six categories changed compared to a pre-pandemic 5-week period (the median value from January 3rd to February 6th 2020). As the mobility data contained missing values (c.12%) for some local authorities and dates (Fig. S2), we were conscious that these missing values may lead to statistical inference errors within the models below. As a result, we filled missing mobility values using mice: multiple imputation chained equations R package and ‘l2lpan’ imputation approach, which is a hierarchical normal model within homogeneous within group variances (Van Buuren and Groothuis-Oudshoorn, 2011). This hierarchical structure allowed us to model mobility trends accounting for differences in local authorities. We included the following terms within our imputation model: five Google mobility timeseries (all except residential), as well as a 1-day lag period for each timeseries, the number of days along the timeseries since February 15th with a cubic polynomial term, an indicator variable to describe whether each day was a weekend or not, and the timeseries of daily COVID-19 cases into a daily percentage change in cases. We opted to calculate case rates instead of using raw daily case numbers, as case rates more adequately capture transmissibility i.e. regardless of whether cases jumped from 5 to 10, or 50 to 100, the case rates would capture the doubling effect. Furthermore, case rates are more robust to variation in the population size of a local authority.

5th a regression was fit between August 2nd – 8th. The coefficients of these models provided a daily case rate. We converted these coefficients into a daily percentage change in cases. We opted to calculate case rates instead of using raw daily case numbers, as case rates more adequately capture transmissibility i.e. regardless of whether cases jumped from 5 to 10, or 50 to 100, the case rates would capture the doubling effect. Furthermore, case rates are more robust to variation in the population size of a local authority.

2.1.2. Baseline transmission variables

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

National lockdowns, and the resulting reduction in people’s mobility, were an important tool for reducing transmission within England during the COVID-19 pandemic. We used Google Community Mobility Reports to track human mobility and its effect on case rates (Google, 2020). These reports chart movement trends over time across six categories: retail and recreation, groceries and pharmacies, transit stations, workplaces, residential, and parks. These trends describe how visitors to, or time spent in, each of the six categories changed compared to a pre-pandemic 5-week period (the median value from January 3rd to February 6th 2020). As the mobility data contained missing values (c.12%) for some local authorities and dates (Fig. S2), we were conscious that these missing values may lead to statistical inference errors within the models below. As a result, we filled missing mobility values using mice: multiple imputation chained equations R package and ‘l2lpan’ imputation approach, which is a hierarchical normal model within homogeneous within group variances (Van Buuren and Groothuis-Oudshoorn, 2011). This hierarchical structure allowed us to model mobility trends accounting for differences in local authorities. We included the following terms within our imputation model: five Google mobility timeseries (all except residential), as well as a 1-day lag period for each timeseries, the number of days along the timeseries since February 15th with a cubic polynomial term, an indicator variable to describe whether each day was a weekend or not, and the timeseries of daily COVID-19 cases within the local authority. We also included terms that didn’t vary through time, including: the latitude and longitude of the local authority, and all local authority covariates within the baseline and green transmission models below (population density, population clustering, health, demography, economy, green space, and patchiness). Finally, we also included some national metrics that could influence local mobility, including: a timeseries of daily COVID-19 cases measured at the national scale, as well as the mean daily temperature and precipitation within Central England. We ran this model through 10 chains, each with 20 iterations, and 20 pan iterations. The imputation model converged.

Conventionally, as part of a multiple imputation framework, these 10 chains should then be modelled separately and coefficient
standard errors should be inflated with Rubin’s rules (Little and Rubin, 2002). However, given the small percentage of missing values, and that there are currently no well-defined steps for using Rubin’s rules in generalized additive models (see our models below), we instead averaged mobility values across the 10 chains to produce mean estimates of mobility for each category, day, and local authority i.e. conducting single imputation. We ensured the imputations produced plausible values (Fig. S3). From this mobility dataset, we derived a variable which described overall mobility change for each date in each local authority, which is the average mobility change across five of the six categories (excluding residential) for each day in each local authority. We excluded the residential mobility category as it is inversely correlated with all other categories (Google, 2020). However, as there is likely a delay between a mobility reduction and a case rate reduction (Lauer et al., 2020), we lagged the overall mobility change metric by linking each case rate with the mean mobility change from 2 to 12 days prior. As a result of this lag, we trimmed the temporal extent of the dataset to cover March 1st – November 30th 2020 (instead of February 15th – November 30th 2020).

2.1.3. Green variables
We compiled two variables which describe the structure of green spaces in each local authority: patchiness – median frequency of parks within a 1km² radius around households in the local authority (Office for National Statistics, 2021b); green space – available green space per person (m²) within the local authority, derived by dividing the green-cover area by the local authority population size. Green-cover area
In both the baseline and green transmission models, we were conscious that some parameter effects may have varied through time. For example, some covariates may have been particularly influential prior to mandatory mask wearing in shops on July 24th 2020. As a result, we extracted the first four weeks of data from our case rate dataset and ran the models on this subset. We then shifted the data forwards.
one week and re-ran the models, repeating this procedure (moving window), creating 40 replicates of the coefficients each representing a different-overlapping period of time between March 1st and November 30th 2020. From this, we established that the majority of coefficients were very stable over time (Fig. S4), but mobility change, health, case rate lag, and park-use were somewhat variable. Looking at how these coefficients change through time, it was clear that mobility change had a temporal trend, where mobility effects were greatest when cases were at their highest. As a result, we amended the baseline transmission model to include an interaction between the mobility variables and the number of cases (averaged over the nearest 7 days) in the local authority at a given moment in time (see Eq. S1–2 for the final model structures). There was no clear temporal trend in the health, case rate lag, and park-use variables so these remained untouched within the models. We also noted that the magnitude of the mobility change effect was far greater in the first lockdown period (March – May 2020). We suspect the large effect is genuine, but given there were spatial biases in case-testing availability during the first lockdown, we opted to re-model the data with a trimmed temporal extent (June 1st to November 30th 2020). From this, it was apparent that coefficients were generally far more conservative using the trimmed dataset, albeit still in the same direction (Fig. S5). Given this discrepancy in results (depending on the temporal extent), we opted to restrict our analyses throughout the rest of this manuscript to solely focus on the more conservative trimmed temporal extent, which is likely to be far less affected by spatial variability in case-testing availability – so more robust. As a result, all model outputs and projections (see below) are derived from the data covering June 1st to November 30th 2020.

In the analyses, we opted to fill missing mobility values with imputation instead of using complete-case analyses, where any observations with missing mobility data are removed. However, given the small percentage of missing values, and that the mobility data is averaged across five categories, and then again through time, we wanted to ensure model coefficients did not change drastically under imputation, which could be a sign of a statistical inference error (Johnson et al., 2021). As a result, we repeated the analyses using only complete-case observations and compared model coefficients between the missing value approaches. Given the similarity in the complete-case and imputation coefficients (Fig. S5), we continued using the coefficients from the imputation model which covered a greater array of local authorities.

2.2.2. Model checking

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

2.2.3. Projecting cases

To understand how mobility patterns have influenced cases, we projected cases using the baseline and green transmission models through each of the scenarios for every local authority between March 1st and November 30th 2020. We standardised all authorities so they had the same starting number of cases (10), community cases (10), and lagged case rate (0.58%; the mean case rate across local authorities on February 28th). These cases, community cases, and lagged case rate were updated and iteratively informed by the new model predictions, instead of the observed data. As a result, the projected case rates are solely influenced by the landscape structure and mobility patterns in the local authority. We constrained the case rates so they could not exceed the range of the observed case rates (−40% to 70%). We converted the projected case rates into projected cases, against the starting case value of 10.

3. Results

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

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

3.2. Green transmission models

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

3.3. Projected cases

Reducing mobility is a far more effective measure of limiting COVID-19 transmission than increasing park use (Fig. 6). Across local authorities between March 1st and November 30th 2020, a 20% reduction in mobility is projected to have led to 51% fewer cases on average (Fig. 6b; 95% quantiles: $-88.7\%$ to $-29.7\%$). In contrast, a 20% increase in park use is estimated to have only reduced cases by 5.4% (Fig. 6c; 95% quantiles: $-17.3\%$ to $0.6\%$). So whilst

| 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                  | 0.012 [0.010, 0.053] |
| Park use:patchiness                   | 0.024 [0.0026, 0.045] |
park use is associated with reducing COVID-19 transmission, the benefits would only be relatively small. However, there is spatial variation in these findings, with some areas potentially benefiting more than others from a reduction in mobility or increase in park use (Fig. 7).

4. Discussion

In this study, we attempted to quantify the effects of local green space on COVID-19 case rates after accounting for mechanisms known to influence pandemics in our baseline transmission model. We found that high overall mobility was associated with increased case rates, especially when population clustering was high. After accounting for these variables, we found that higher park use, compared to other amenity areas, was associated with a reduction in case rates, especially in local authorities with low green space and with contiguous green space. These results suggest that utilising green spaces rather than car-recreation areas, was associated with a reduction in case rates, especially in local authorities with low green space and with contiguous green space. These results suggest that utilising green spaces rather than car-

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

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

Whilst park use, overall, had a relatively small effect, we did note stronger effects of park use when the context of the local area was considered as using parks was beneficial in authorities with low green space and authorities with contiguous green space (Figs. 5e–f and 6). That park use has a minor beneficial effect overall seems to support our hypothesis that recreation in green space and parks may be safer than in other amenity areas. This is probably because it is easier to maintain distance and green spaces have fewer surfaces which could result in transmission if contaminated. However, the limiting impact of this when green space is high and accessible seems to suggest diminishing returns in how park use can impact COVID-19 transmission. This is perhaps not
surprising if the main value of parks in this context is as an alternative to other relatively more hazardous amenity areas. Consequently, if there are other safe options outside of public parks then parks will likely have little impact. However, our findings do suggest that the use of public parks in a highly urbanised area may be advantageous, though as noted above the strongest effect was from the reduction of all forms of mobility. Therefore, cautiously, and given that it corresponds with common sense, we suggest that reducing mobility is a successful strategy for reducing case rates but given a need for some non-essential time outside of a home, using green spaces such as local parks may be the next best thing, particularly in highly urbanised areas.

A major limitation of the work is the difficulty in comparing across local authorities that vary simultaneously in many different variables likely important to case rates. This makes inference about the importance of their individual effects very difficult and so effect sizes should be interpreted cautiously and with caveat. Another challenge is that pandemics are rare events, consequently, our analysis covers only a

![Projected cases in Oxford](image)

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

![Spatial variation](image)

**Fig. 7.** Spatial variation in observed cases per capita (a), and projected case changes under a 20% mobility reduction (b) and 20% increase in park use (c). Case change was derived by dividing the total cases between March and November 2020 under each scenario by the cases in the observed mobility projection, multiplying this value by 100, and then subtracting 100 (see Fig. 6). The coefficients used to derive the projections in b and c were sourced from models utilising the trimmed temporal extent dataset covering June 1st to November 30th 2020 – see sensitivity analysis above.
in addition to the known bene-
the use of parks for recreational activity in these contexts could be ad-
2020; Soga et al., 2020), and consequently, understanding the relative
shown to have bene-
areas. Although further research is needed, these
19 case rates may be reduced with individuals spending time in parks,
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