COVID-19 Hackathon 3: Ecosystem Services

Background

Due to the severe impacts of COVID-19 on public health, there is much interest in identifying risk factors for virus transmission. Control measures, such as the two metre buffer rule have been implemented nationwide, however, keeping this distance can be challenging and even cautious individuals will cross-paths in public spaces. Consequently, managing and understanding transmission in public spaces is essential for controlling the virus. Here, we evaluate how landscape structure, available green space and recreational areas, and human behaviour influence COVID-19 transmission, looking at three key questions:

Can we understand how a healthy natural environment modulates the spread of COVID-19? One of the only activities available to people during the pandemic has been outdoor recreation e.g. using parks. This makes park use one of the key opportunities for transmission, but parks can vary in size and use, so not every park is likely to be equally risky. We expect the chances of catching COVID-19 will be greater when people have less green-space available (e.g. parks are more densely populated) and when green-spaces occur as one large contiguous area, instead of smaller fragmented patches where total interactions with other individuals is reduced.

Have changed human behaviours impacted on the spread? People coming into contact with one another increases the risk of transmission, therefore understanding mobility patterns may help us understand transmission rate. It is also valuable to assess how green-space use has changed relative to other mobility and how this impacts transmission. Given parks and green-space are now one of the few remaining recreational activities, it's plausible that use of public parks will increase, especially in places where gardens are less available e.g. central London. We expect that parks might facilitate the spread of COVID-19 but likely are safer spaces than other types of indoor mobility (e.g. recreational retail shopping). However, the benefits of park use may be dependent on the local landscape as people with access to plentiful greenspace may not derive the same benefits of park mobility relative to those with limited green-space. Conversely, parks may be particularly safe if green-space is high, where chances of crossing paths with an infected individual are low.

Can we use this insight to improve health outcomes? If we can identify how landscape structure and changing mobility influence transmission (e.g. number of new COVID-19 cases), we expect this information can improve case forecasting, identify particularly risky areas, and propose strategies to control transmission. Further, we hope that it may give the general public insight into the benefits/risks of green-space use during a pandemic.

Methods

COVID-19 data

The number of daily lab-confirmed cases of COVID-19 for the 343 local authorities in England up to 29/06/2020 were sourced and two metrics were derived to explain different aspects of the spread of COVID-19 in each local authority (pre- and post-peak case rates, Figure 1). We defined the observation period as starting when there were six out of seven consecutive days with a new COVID-19 case in the authority and ending when there were less than six new cases in seven consecutive days. The derived COVID-19 metrics were measured through slope coefficients of first-order autoregressive broken-stick models with a log-10 transformation of 'New daily cases' against 'Date' for each authority. We retained only those sites with at least 50 days of consecutive confirmed cases and removed areas where the regressions had a poor fit ($R2 < 0.5$) leaving a total of 84 authorities for the remainder of the analysis.

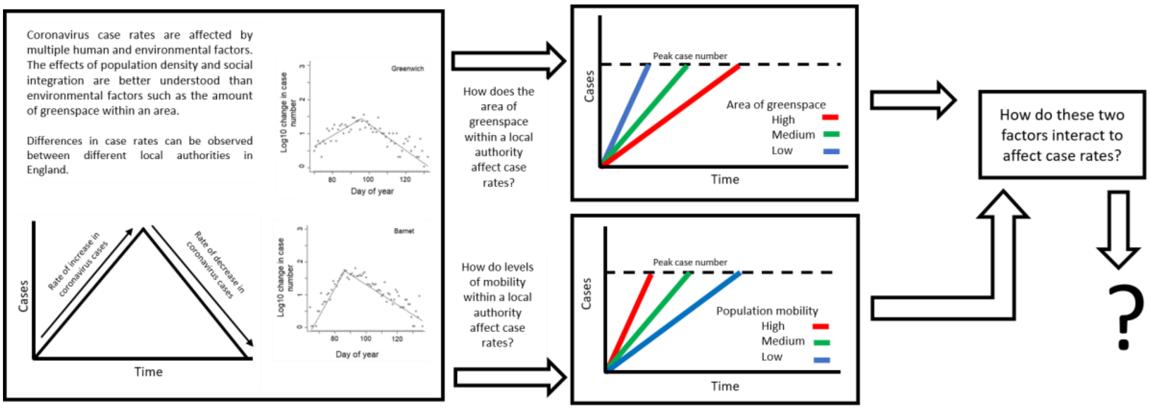

Figure 1. Conceptual model demonstrating method to identify how landscape and behavioural factors influence case rates

Social and environmental covariates

To measure green-space access, 10 random locations were sampled within a 5km2 area of each authority. Landscape metrics were extracted from sample locations using the UK 2015 25m land cover map and were summarised into variables that described the abundance of urban space, the abundance of green space, and greenspace fragmentation (see ecosystem variables in supplementary Table S1). We also compiled data on social covariates that may influence COVID-19 case rate such as population density, composition of ethnicities, and unemployment rates, collected from ONS censuses (see core variables Table S1)

Mobility data, representing the relative change in movement since the baseline period (Jan 3rd - Feb 6th), was only available for 60 of the 343 local authorities in England, but was available in 6 of England's 9 regions. To avoid the risk of biasing the data by only using local authorities with observations, we imputed the missing local mobility data. Multiple imputation chained equations, which provide robust inference (Little & Rubin, 2002), were applied, producing a series of imputed datasets. The imputation model included all variables that could account for missingness and explain local authority mobility, including: local authority COVID-19 cases, national COVID-19 cases, regional mobility, and date,as well as variables in Table S1 and a hierarchical term structuring the observations per local authority (See Figure S1). We derived two main metrics from the mobility data, total relative mobility which is the change in overall mobility since baseline and relative park preference which is the difference between mobility in public parks and all mobility not in parks. Thus it measures the preference for park use when people are already mobile, e.g. a 10 minute walk in a retail area vs a 10 min walk in a park. A full overview of the environmental and social variables are provided in Table S1.

Modelling Data

We modelled both COVID-19 metrics against the variables in TableS1 with a linear model. Each variable was included as a main effect but we also included 3 interactions within each model: 1, green space vs with patchiness; 2, green space vs park-use (mobility); 3, Addresses with gardens vs park-use. To meet the model assumption of gaussian distributed residuals we had to transform the COVID-19 metrics - we used an inverse-hyberbolic sine transformation on the pre- and post-peak case rates. In each of these four models we used bi-directional stepwise selection via Akaike's information criterion (AIC). We report the back-transformed model-coefficients and marginal effects.

Results

In these results we only describe the effects of landscape structure and changed human behaviour (mobility), not already well-established effects such as population density. We also only show plots for the pre-peak period; plots for the post-peak period can be viewed in the supplementary material.

Before the peak there was a 9.4% (SD: ± 22%) daily increase in cases across the local authorities, and a slow decrease in cases after the peak (mean: -2%; SD: 0.8%). In both the pre- and post peak case rate models, 10 variables were identified as important (Figure 2), with both pre- and post-peak cases affected by mobility and landscape structure variables

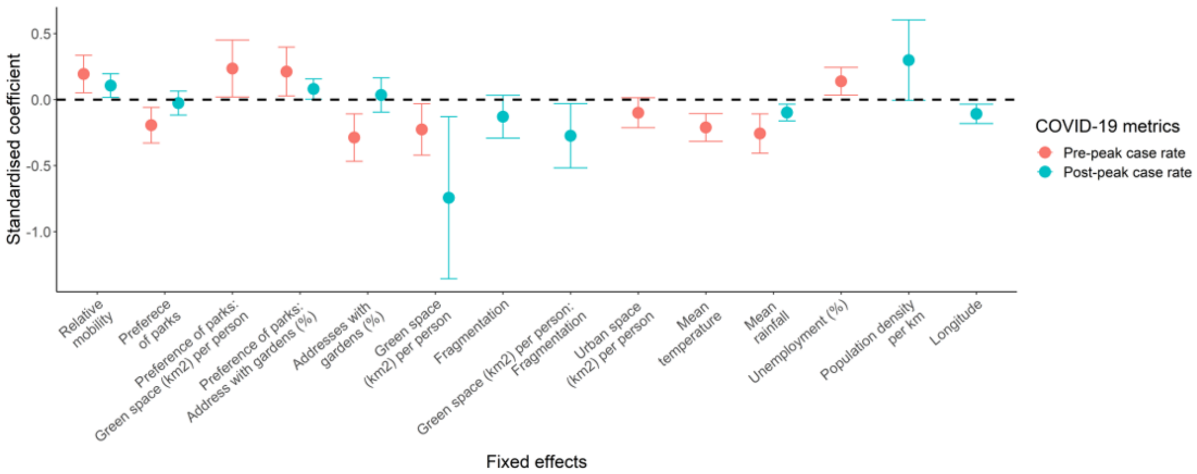

Figure 2. Effect size for parameters included in best fitting pre- and post-peak case rate models. Parameters with intervals not overlapping zero (dashed line) have an effect at the 95% confidence level. Parameters above zero indicate an increase in the parmeter results in a faster pre-peak rise (blue) and slower post-peak dip (red), whilst parameters below zero have a slower pre-peak rise (blue) and a faster post-peak dip (red). All parameters were z-transformed to standardise effect size.

Human behaviour - mobility

The pre- and post-peak case rates decrease when total relative mobility decreases, demonstrating that reducing mobility slows COVID-19 transmission (Figure 3) . A further reduction in transmission also occurs during the pre-peak period if people use parks over other other mobility categories (Figure 4).

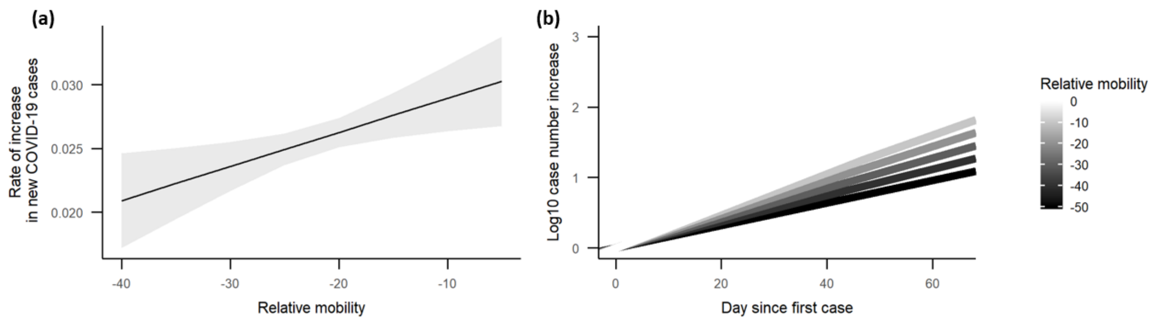

Figure 3. Impact of relative mobility on COVID-19 pre-peak case rate (a). Shaded area around the line represents the 95% confidence intervals. (b) Change in slopes of relative mobility over time for pre-peak increase in cases.

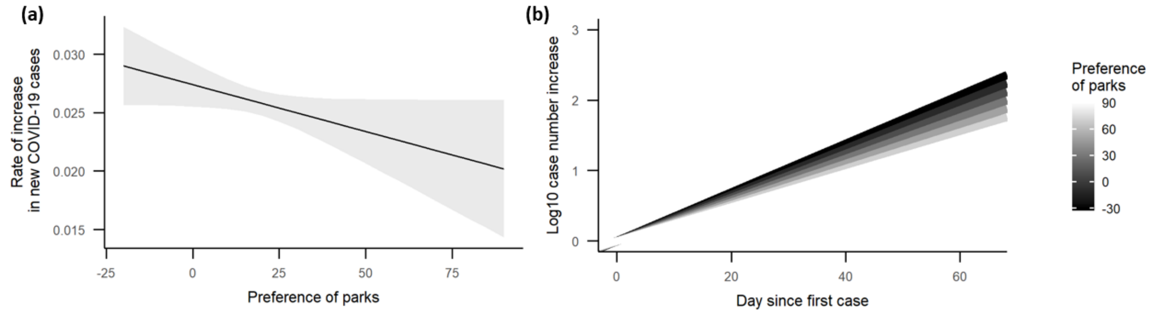

Figure 4. Impact of using parks (relative to other mobility categories) on COVID-19 pre-peak case rate (a). Shaded area around the line represents the 95% confidence intervals. (b) Change in slopes of park preference over time for pre-peak increase in cases.

Landscape structure and its interaction with human behaviour

Areas with more green space per person had a slower pre-peak case rate and faster decrease in post-peak cases (Figure 5a). and when the area of green space per person is low, a high preference of parks (using parks over other mobilities) can compensate for this and slow an increase in cases (Figure 5b,c). Pre-peak case rate was also slower in areas where addresses had a higher proportion of gardens (Figure 6a). When there are few gardens, the pre-peak case rate is lower if people have a high preference for parks (Figure 6b,c). Urban space per person and green space fragmentation had no effect on either pre- or post-peak case rate, but when people have access to a greater amount of green-space per person, post-peak case rates are lower in more patchy-fragmented areas than in contiguous areas i.e. fragmented green spaces have a faster post-peak case drop (Figure S5).

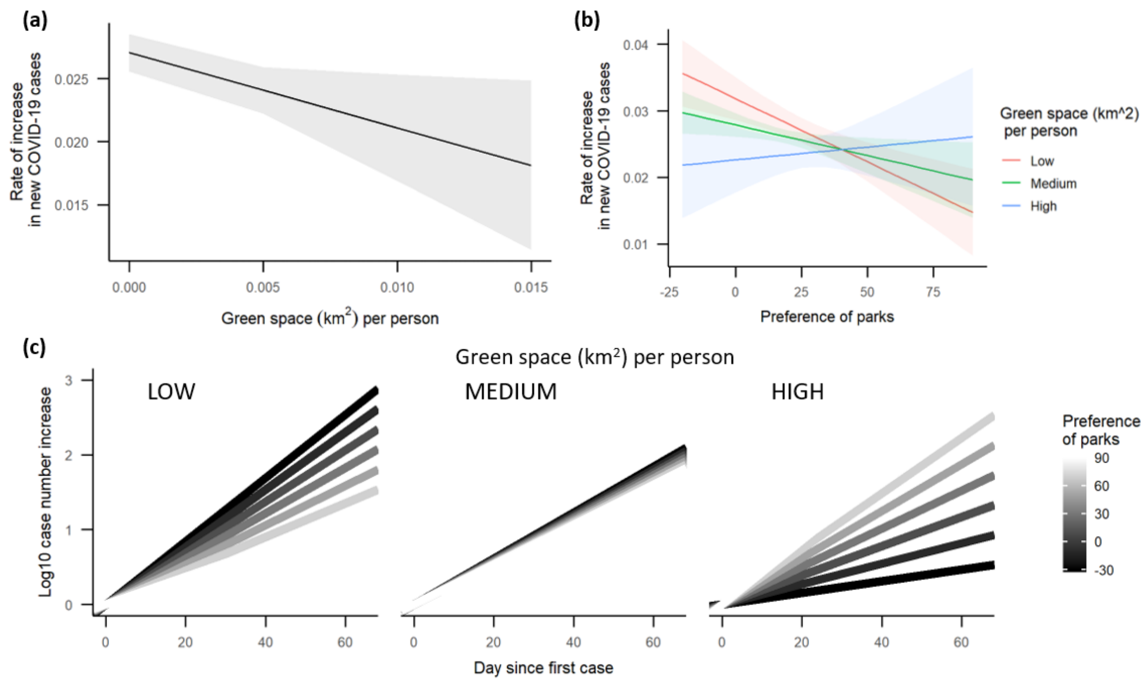

Figure 5. Relationship between Green space (km2) per person and the rate of increase in new COVID-19 cases (a) and the interaction with preference of parks (b). Shaded area around the line(s) represents the 95% confidence intervals. (c) Change in slopes of park preference over time for 3 categories of green space area (km2) per person (low, medium and high) for pre-peak increase in cases.

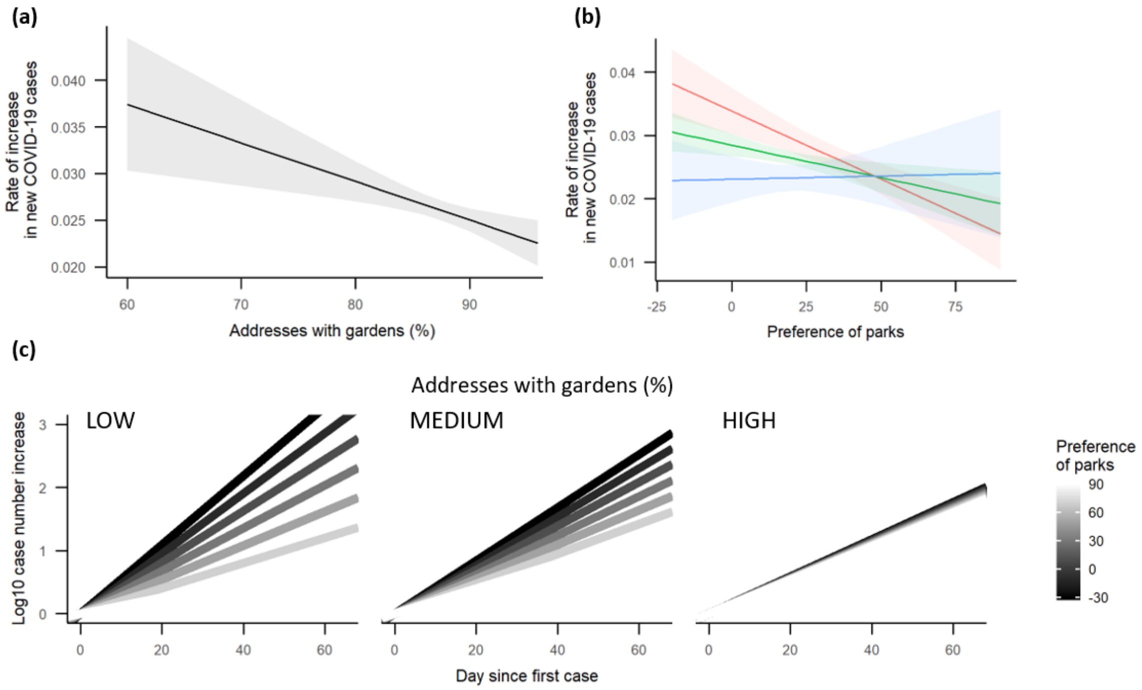

**Figure 6. Relationship between % of addresses with gardens and the rate of increase in new COVID-19 cases (a) and the interaction with preference of parks (b). Shaded area around the line(s) represents the 95% confidence intervals. (c) Change in slopes of park preference over time for 3 categories of % addresses with gardens (low, medium and high) for pre-peak increase in cases.

Key messages

1. Landscape structure is an important driver of case rates, with reduced transmission when green space is high, especially if these areas with high green space are fragmented. Access to gardens also reduces transmission rates, with garden owners likely feeling less confined in their home, so have a reduced need to access local parks and other mobility categories.
2. More mobility increases coronavirus transmission rates, but these rates are less severe if mobility is in a park compared to indoor locations (e.g. shopping).
3. Use of parks was more beneficial in areas with less green space. These areas are likely more urbanised with a greater population density, so the safest form of mobility in these locations is to explore parks.
4. Despite park use being generally beneficial, it can become detrimental in areas with many gardens and high green space. Mobility (leaving home) carries a risk, but is still an essential activity. This risk is exacerbated if a garden is available (i.e where the need to leave home is reduced), and when access to large green spaces are an option (which would be less risky than a congested local park).

Can we use this insight to improve health outcomes? As landscape and mobility are important drivers of case rates, these should be accounted for in forecasting. We can also recommend park-use over other forms of mobility, especially when green space is low. However, if a garden is available the risk of infection increases with park use. In the longer-term these results could have implications for landscape planning and disease ecology.

References

Little, R.J. and Rubin, D.B., 2002. Statistical analysis with missing data. John Wiley & Sons. New York.
Public Health England, 2020. Disparities in the risk and outcomes of COVID-19.. Accessed: 29th June 2020.