A spatial exploration of the role of proximate public green space and prevalence of COVID-19 in London, UK.

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Website: https://bookdown.org/isabella_brant98/Reproducible-Methodology/

I. INTRODUCTION

The ongoing outbreak of SARS-CoV-2 (COVID-19) has reinforced the importance of equal accessibility to proximate green space for health and pandemic resilience. Proximity to public green space has become a vital, physical and cultural need for citizens in London following the unprecedented restrictions to movement (Whitten, 2020; London Green Spaces Commission, 2020). However, whilst the national and local lockdowns resulted in a "re-engagement" with outdoor recreation and green spaces throughout the country (Day, 2020 p.1183), stark inequalities of publicly-accessible, proximate green space has been re-exposed both nationwide and in London (Friends of the Earth, 2020; London Sustainable Development Commission, 2020, London Green Spaces Commission, 2020).

The UN Sustainable Development Goals formally recognise the value of green space having dedicated target 11.7 to the provision of creating more equal, inclusive and just green spaces within sustainable city developments (UN, 2015). Recently, Public Health England (PHE) have presented the stark reality of proximate green space inequality in relation to COVID-19 (PHE, 2020). In their assessment of green space proximity they concluded that "living in a greener environment can promote and protect good health, and aid in recovery from illness and help with managing poor health" (PHE, 2020, p.11). These observations link to a wider evidence base of a positive relationship between the physical and mental wellbeing ecosystem services green spaces provide to urban citizens (Bolund and Hunhammar, 1999).

Studies on COVID-19 have flooded the research space since its outbreak however few studies have explored the spatial factors of the virus's prevalence. Most research concerning environmental risk factors of COVID-19 have focused on socio-economic, age and health related variables (City Intelligence, 2020; Mahase, 2020). Since wider research provides evidence that local green space is associated with improved wellbeing and health resilience, this study aims to bridge the research gap and investigate this in relation to COVID-19.

This study will therefore be the first to explore whether an association exists between public green space proximity and the prevalence of COVID-19 in London's Middle Super Output Areas (MSOA). The association is explored spatially, using geographically weighted regression, to identify any spatial variation across London. The study hopes to contribute to understanding COVID-19 and provide recommendations for future pandemic planning and sustainable city development.

Research aims:

1. Explore the association between the proportion of proximate public green space and COVID-19 prevalence in London MSOAs.
2. Investigate the associations using geographically weighted regression.

II. LITERATURE REVIEW

Defining public green space

Various names for green space are used interchangeably (PHE, 2020, p.17). For the purpose of this study, the definition of green space will be that of "any area of vegetated land, urban or rural" that is publicly accessible (ibid.).

Green space inequality in London

The Greenspace Information for Greater London (GiGL) classified 47% of Greater London as green (2019). Yet, designated publicly accessible green space was found to cover only 18% of Greater London (London Sustainable Development Commission, 2020). GiGL's research found that only 50% of homes in London are within the London Plan's recommended distance of 400m to their designated, small public green space (of 2 hectares) (GiGL, 2019). A recent study also uncovered the disparity between London's wealthiest and most deprived wards in relation to their proportions of parkland and private gardens (Duncan et al., 2020).

Proximate green space

Proximity to green space in England has been disputed between official policy and green space actors. The London Plan provides the clearest set of government recommendations for green space proximity in London. The plan determines proximity (in metres) dependent on the size of the green space. For example, all Londoners should have access to a local park (of at least 2 hectares) within 400 metres of their homes (Greater London Authority, 2016). Natural England's Accessible Natural Greenspace Standard (ANGSt) recommends that *everybody* in England should be within 300 metres, or a 5 minute walk, of 2 hectares of green space (Natural England, 2010; Cooling, 2019).

Green space and health

Numerous studies highlight the benefits of urban green space and public health. Association between the amount of green space and mortality has been noted (Coutts et al., 2010: Gascon et al., 2016) whilst income-related health inequality was found to be less pronounced for populations with more exposure to green space (Mitchell and Popham, 2008). Areas with higher proportions of green space have also been associated with lower prevalence of disease rates (Maas et al., 2009).

Physical health benefits have been associated with proximity to local parks due to higher chances of using the spaces for physical activity (Cohen et al., 2007; Bedimo-Rung et al., 2005). Whilst local neighbourhood variations in levels of greenery impact health related behaviours and rates of obesity (Ellaway et al., 2005).

Lack of access to good quality green space is also a determinant of health inequalities. More deprived neighbourhoods have higher exposure to social and environmental risks to health, such as less access to green space and poorer air quality (The Marmot, 2010).

Spatial approaches for measuring proximity and accessibility to green space

Physical distance from an administrative boundary or residential post-codes are used in proximity analysis and includes: Euclidean or Network measures (Mora-Garcia et al., 2018). Euclidean distance buffers are commonly used in measuring proximity and accessibility to greenspace by calculating the intersected green spaces within various buffers (Houlden et al., 2019; van den Berg et al., 2010). However, using Euclidean buffers has been disputed for its real-life accuracy of road distance and travel time (Shahid et al., 2009). Network analysis such as isochrone catchment buffers, are considered a more precise method of measuring proximity (Kolcsár et al., 2021).

Spatial analysis for health

Spatial autocorrelation found in spatial data can bias results of a global regression model and cause inaccurate inferences about the data if dealt with inappropriately. Local spatial models such as Geographically Weighted Regression (GWR) compensate for the non-stationarity and enable model parameters to vary over space (Brunsdon et al., 1996). GWR is commonly used for spatial epidemiology (Liu et al., 2011; Chen and Truong, 2012) and has been used to explore associations between green space and health (Houlden et al., 2019).

III. HYPOTHESIS

Based on the literature, I will be hypothesising that there is a negative association between COVID-19 prevalence and higher proportions of proximate, public green space.

III. METHODOLOGY

R was used for the data cleaning, processing and analysis. A full, reproducible breakdown of the methodology and data can be found on the GitHub repository and Bookdown website linked on the covering page.

i. Study Area

The analysis uses the 983 Middle Super Output Area (MSOA) boundaries in London as the area of study (Figure 1).[1] This spatial scale was used due to the smallest scale the COVID-19 case data was aggregated to at the time of collecting the data.

Figure 1 – London MSOA study area

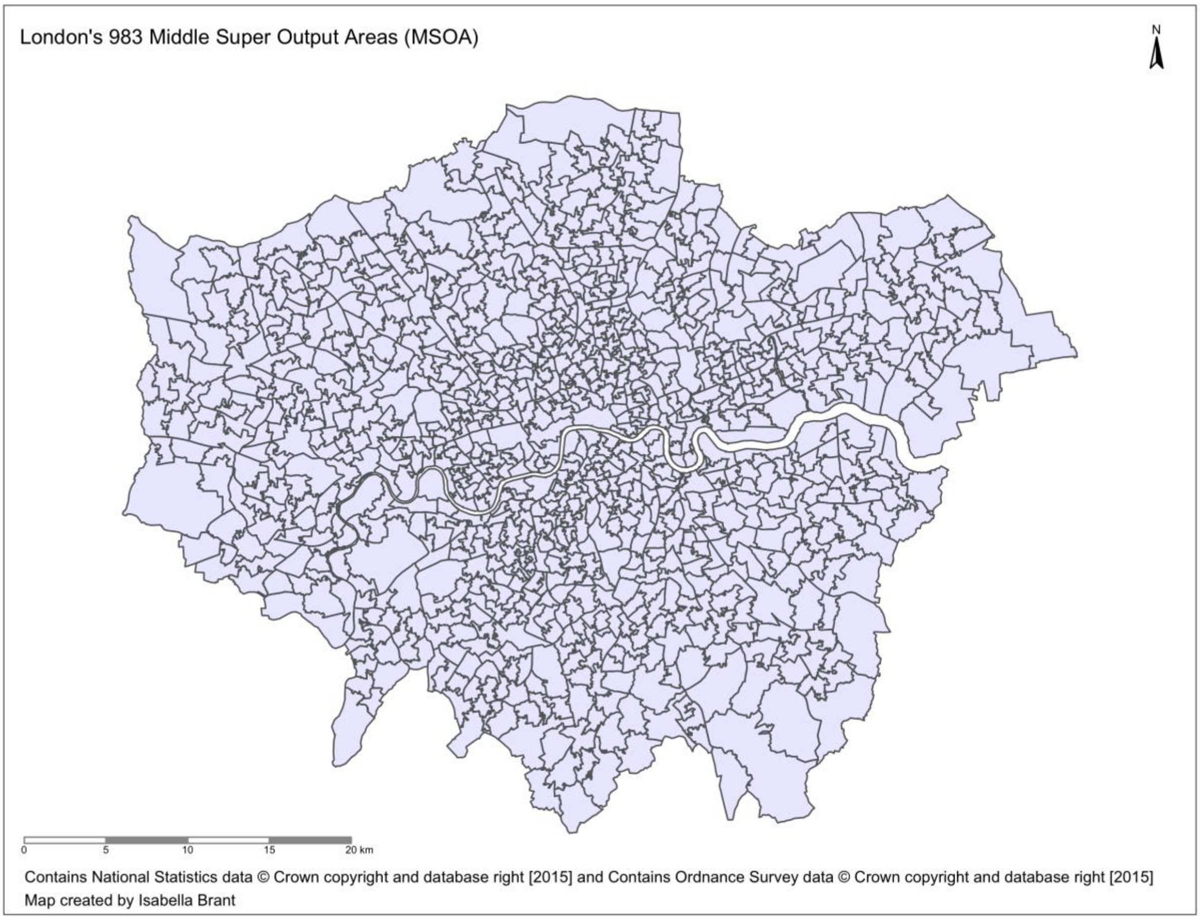


Table 1 – London MSOA land, green space and population statistics

	Number of MSOAs	Average MSOA land area (ha)	Average MSOA population	Average area of proximate public green space (ha) in each MSOA
Greater London	983	160.07	8315	75.80

[1] The statistical MSOA boundary data is provided as a shapefile from the London Datastore. Several population and household related statistics accompany this shapefile.

ii. Data Sources

The COVID-19 case data was sourced from the UK government's COVID-19 data dashboard. This dataset contains the recordings of confirmed positive cases of the virus beginning from the first week of testing on 20th March 2020 to 8th December 2020. The green space data was sourced from the Ordnance Survey's (OS) Open Greenspace dataset which provides geographic information for "likely" publicly accessible green spaces and their access points (Ordnance Survey, 2020, p.1). Additional data for the MSOAs, such as socio-economic, demographic and wellbeing information was sourced from the MSOA Atlas on the London Datastore. This data was collected in Spring 2014 with most referenced to the 2011 census.

iii. Data Cleaning and Processing

An abbreviated breakdown of the data cleaning and processing workflow can be found in Figure 2 and the tutorial on Bookdown. Creating the prevalence of COVID-19 and proportion of proximate public green space variables required several decisions to be made that are disclosed below.

Prevalence of COVID-19 in each MSOA variable

To represent the prevalence of COVID-19 in each MSOA a percentage of the total number of COVID-19 cases to the population size of each MSOA was required. The COVID-19 variable was created from total cases in each MSOA from the official announcement of the "second wave" on September 18th 2020 to the data available at the time of collection (8th December 2020) (BBC, 2020). Deciding to include only the recorded confirmed cases of COVID-19 from the second wave was based on the data's more accurate representation of the virus' prevalence. Mass testing to the wider public was well established by this time with over 200,000 tests processed each day by Mid-September (Briggs et al., 2020). The final variable is a percentage of confirmed positive cases to the population size of each MSOA. This represents the prevalence of COVID-19 in each MSOA.

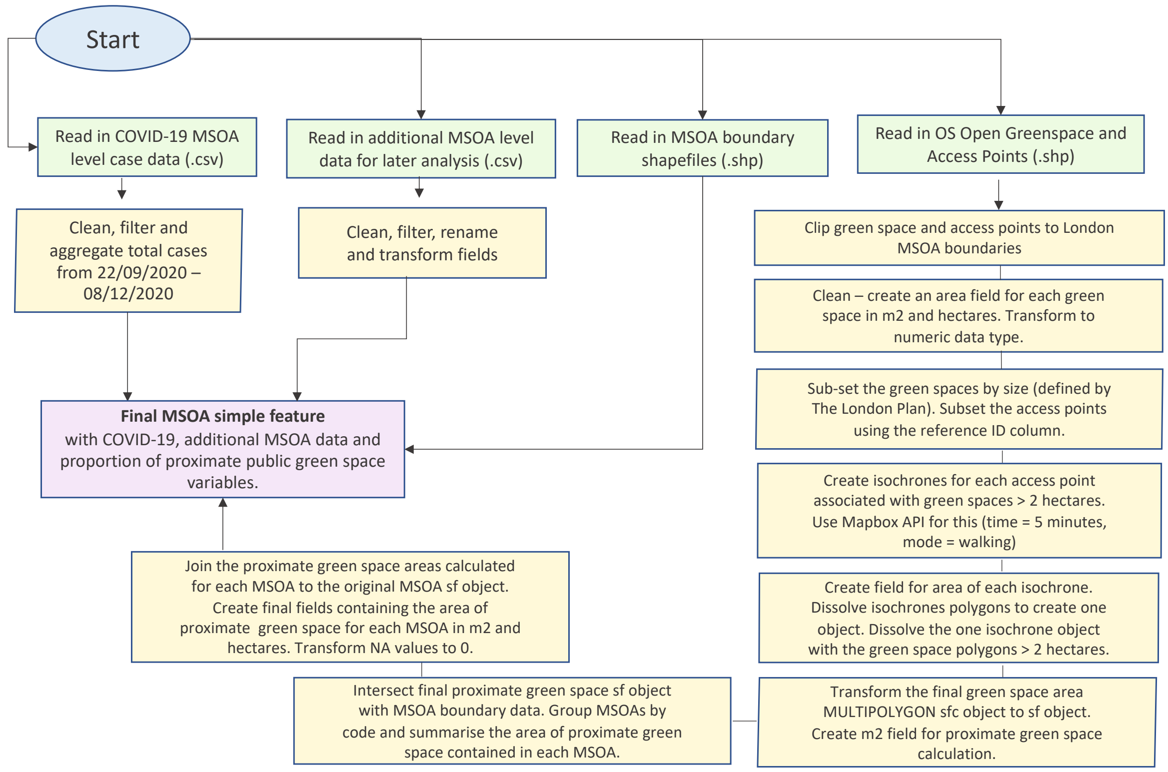
Proportion of the total land area in each MSOA that falls within the proximate public green space buffer.

Higgs et al. observed that measuring proximity largely depends on the spatial data representations available for the research (2012, p.329). Taking this into account, this study will be pursuing an inverse method to measuring proximity to public green space by creating isochrones buffers from the green space access points in the OS Open Greenspaces dataset. It was decided that the most appropriate data to use for this study were the access points since they represent the location where the public can enter and exit a green space. Walking mode isochrones were decided as the most appropriate proximity measure since network analyses provide a more accurate measure of proximity than standard Euclidean distance (Kolcsár et al., 2021).

The proximity analysis also only focused on proximity to green spaces of 2 hectares or more. This decision was based on both The London Plan's proximity recommendation that all citizens should have access to a green space of *at least* 2 hectares within 400m of their homes and the ANGSt green space standard of 2 hectares of green space within 300m or a 5 minute walk (Greater London Authority, 2016; Natural England, 2010).

The final variable represents the proportion of a MSOA's total land area that falls within the proximate public green space, 5-minute walk isochrone buffer.

Figure 2 - An abbreviated flowchart of the data cleaning and processing workflow conducted in R:



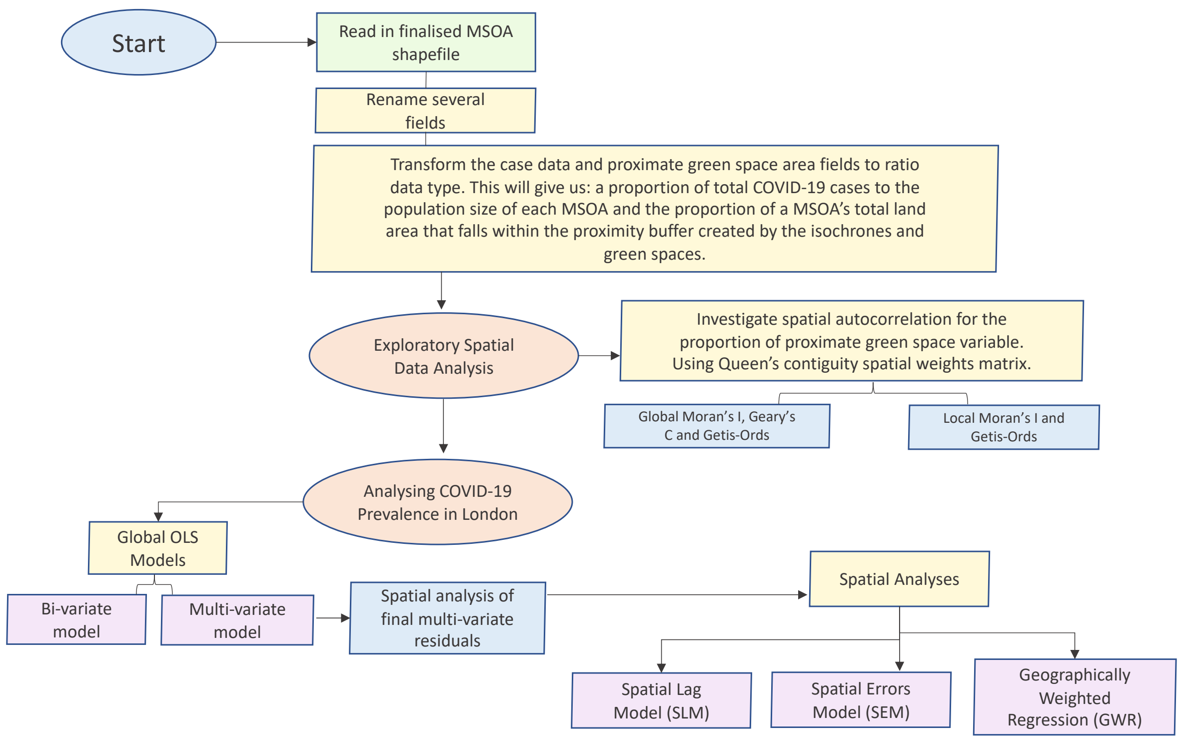
iv. Measuring the associations

The methods used for measuring the association between the proportion of proximate public green space and the prevalence of COVID-19 within London MSOAs are:

1. Bi-variate and multi-variate Ordinary Least Square (OLS) models
2. Quantifying spatial autocorrelation using spatial statistics for the final model residuals from the multi-variate OLS model

3. Geographically Weighted Regression (GWR) to adjust for non-stationarity and investigate the spatial variation of the coefficients

Figure 3 - An abbreviated overview of the analytical workflow conducted in R



OLS regression model equations:

A bi-variate OLS regression where $ln\text{C}19_i$ is the normal-logged predicted value of MSOA ι's COVID-19 prevalence, where β_0 is the calculated constant and β_1 is the proximate public green space coefficient and GS_{1i} is the amount of proximate public green space within each MSOA.

$$ln\text{C}19_i = \beta_0 + \beta_1\text{GS}_{1i}$$

Multi-variate OLS regression models are run to include additional independent variables. The equation is identical to the bi-variate model but β_n is the coefficient of explanatory variable n and X_{ni} is the value of the explanatory variable n.

$$ln\text{C}19_i = \beta_0 + \beta_1\text{GS}_{1i} + \cdots \beta_n\text{X}_{ni}$$

A multi-variate OLS regression model is also run without the proximate public green space variable to observe its contribution to the model.

GWR model equation:

A GWR model is run to adjust for non-stationarity. The coefficients β_{ni} can vary spatially and a separate model can be run at each MSOA location. For example β_{1i} represents the proximate public green space coefficient at MSOA ι's location and $\mathbf{GS}_{1i}$ is the amount of proximate public green space within MSOA ι.

$$lnC19_i = \beta_{0i} + \beta_{1i}GS_{1i} + \cdots \beta_{ni}X_{ni}$$

The kernel bandwidth for the GWR was determined by using a Queen's contiguity spatial weights matrix.

IV. RESULTS

The distribution of the COVID-19 prevalence variable appeared to be positively skewed (Figure 4). It was decided that the variable would be logged for the analysis. The distribution of the proximate public green space variable appeared to have a normal distribution (Figure 5).

Figure 4 - Distribution of the proportion of COVID-19 variable.

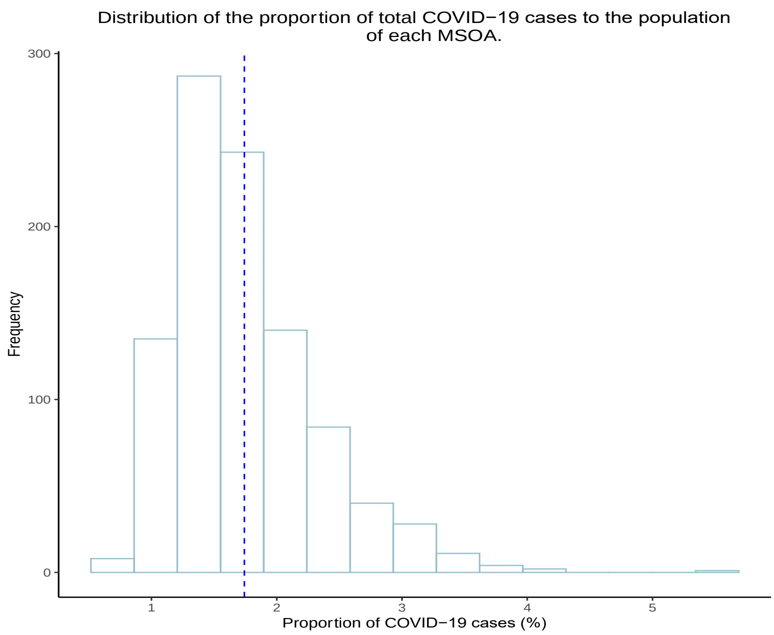
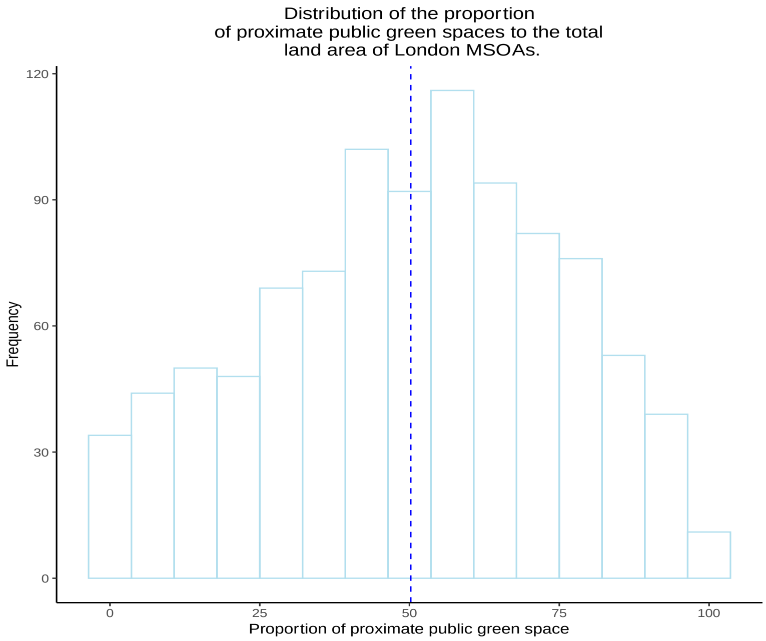
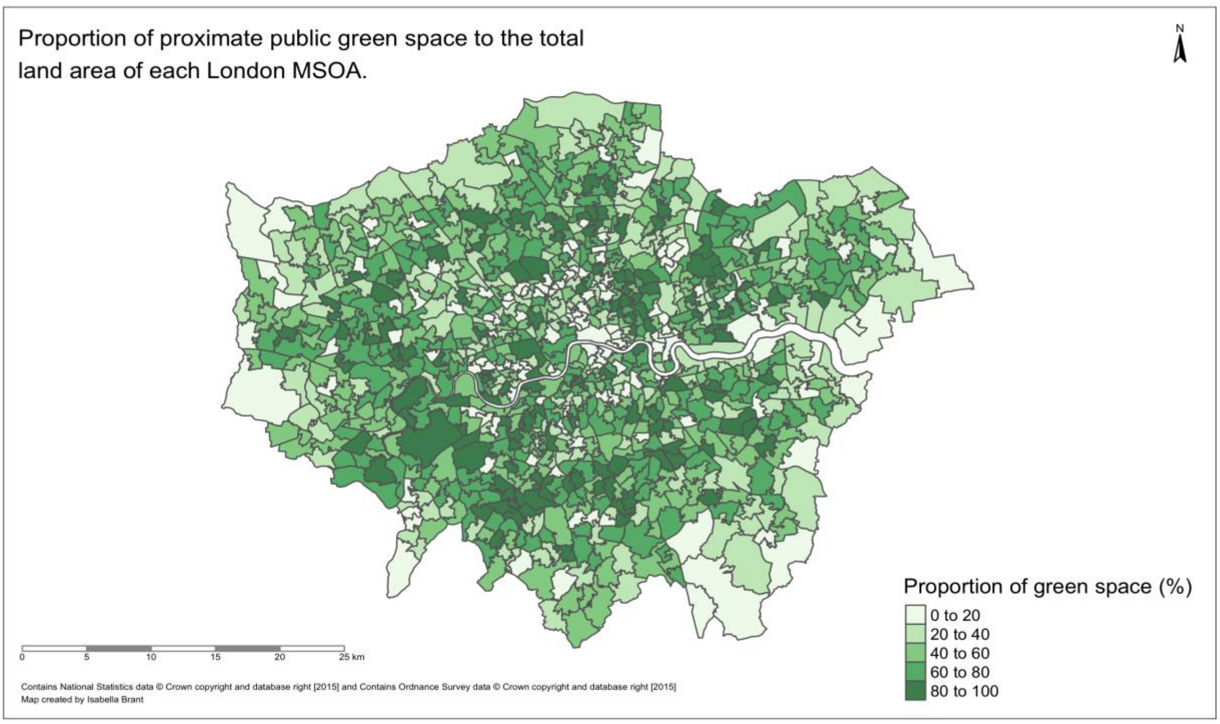


Figure 5 - Distribution of proportion of proximate public green space variable



Mapping the proportion of proximate green space in London visually indicates that there is spatial autocorrelation within the proximate public green space variable (Figure 6). This is unsurprising when large green spaces in London, such as Richmond Park, spread over several MSOAs. The following results verify the observation of spatial autocorrelation.

Figure 6 - Map of the proportion of proximate public green space in London MSOAs.



The analysis led to several interesting results. The proportion of proximate public green space showed to be insignificant in the bi-variate OLS model (Table 2) however when added to a multi-variate OLS regression it was flagged as statistically significant (Table 3b). The original hypothesis that there is a negative association between COVID-19 prevalence and proportion of proximate green space can be accepted when observing the negative coefficient. Although small, the negative coefficient in the global model tells us that a 1% increase in the proportion of proximate public green space leads to a -0.09165% decrease in COVID-19 prevalence. Comparing the goodness of fit of the final multi-variate OLS model with *and* without the proportion of proximate green space variable, it demonstrated that although small, the proximate green space variable *did* contribute positively to the final model (Table 3a & 4).

Table 2 - Bi-variate OLS model results

	coefficient	p-value	R^2	Adjusted R^2
pr_gsha	-0.0007236	0.0655	0.003454	0.002438

Table 3a - Final multi-variate OLS model results:

	p-value	R^2	Adjusted R^2
Final model results	< 2.2e-16	0.2913	0.284

Table 3b - Proximate public green space variable results in the model:

	coefficient	p-value
pr_gsha	-0.0009165	0.006994

Table 4 - Multi-variate model results without green space variable:

	p-value	R^2	Adjusted R^2
Final model results without green space variable	< 2.2e-16	0.2859	0.2793

Despite these results, when the global Moran's I was run on the final multi-variate OLS residuals the result of 0.460 demonstrated that moderate spatial autocorrelation existed in the global model (Table 5). This, although unsurprising, violates the OLS assumption of independence of errors and suggests that the global model is inappropriate for making accurate inferences about the associations between the dependent and independent variables.

A geographically weighted regression (GWR) was run and the coefficient results of the proportion of proximate public green space variable demonstrated a spectrum of negative and positive coefficients across London (Table 6, Figure 7). The GWR map visualises this spatial variation. The most significant negative coefficients for proximate public green space were highlighted in South West London (south of Richmond Park) and South East London (around Welling and Bexleyheath). This was unsurprising considering the MSOAs in these areas benefit from high proportions of proximate public green space because of Richmond Park and various, large public green spaces just South East from the Thames. The GWR results also highlighted interesting spatial patterns where a positive relationship between the proportion of proximate public green space and prevalence of COVID-19 existed. Areas which experience this relationship, such as the City of London, were to be expected when considering their low proportion of proximate public green space. However, the stark contrast between South West London's cluster of negative coefficients and the positive coefficients both East and West of the cluster could indicate other, underlying factors that explain the variation.

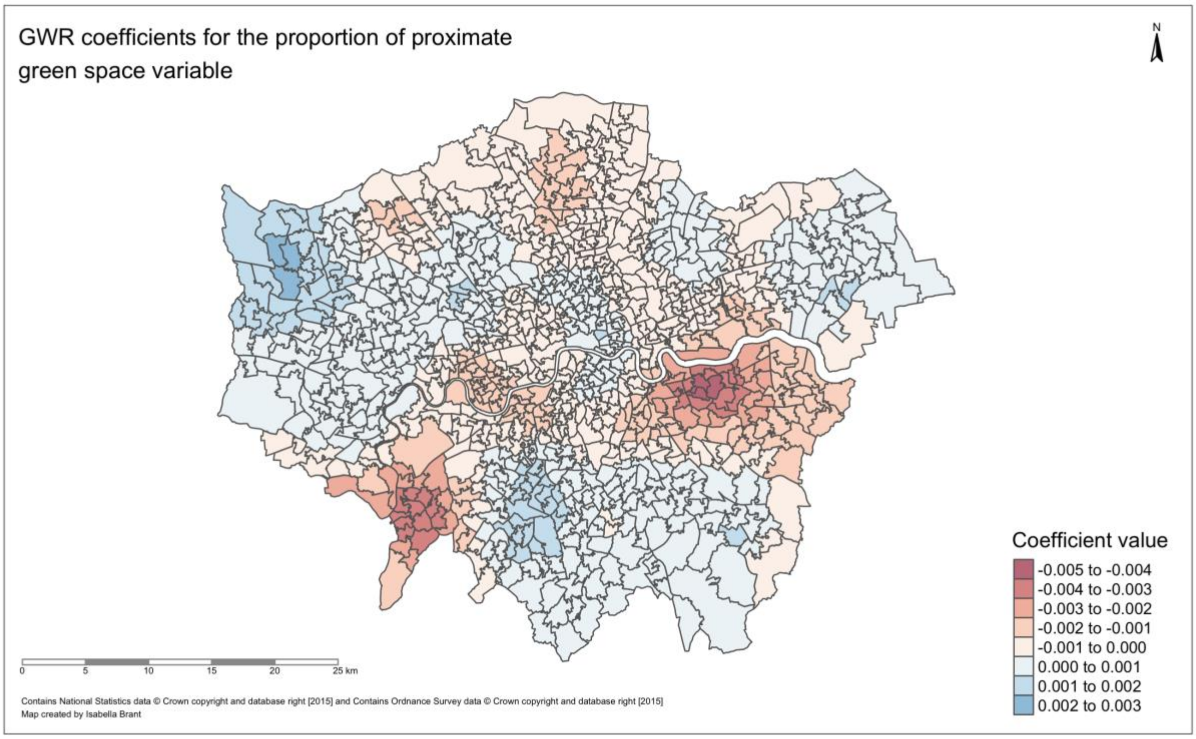
Table 5 - Spatial statistic results of multi-variate OLS residuals

	statistic
Global Moran's I	0.460

Table 6 - GWR results: proportion of proximate green space coefficients

	min	median	max
pr_gsha	-4.1502e-03	-1.3693e-04	2.1984e-03

Figure 7 - Map of GWR green space coefficients



V. DISCUSSION

Reflecting on the research findings

Association between proportion of proximate public green space and the prevalence of COVID-19 in each MSOA was explored. A Geographically Weighted Regression was run and included 10 variables in the model (Appendix 1). The coefficient results for the proportion of proximate public green space captures the geographic variation of the association between proximate green space and COVID-19 prevalence. The results fit the initial hypothesis that there is a negative association between areas with high proportions of proximate public green space and COVID-19 prevalence. This hypothesis was backed by existing literature that highlight the benefits of proximate green space for individual and public health (Mitchell and Popham, 2008; Maas et al., 2009; Brown et al., 2010; Hartig et al., 2014).

Role of proximate, public green space

The global and local regressions both highlight the role of proximate, public green space in understanding the dynamics of COVID-19 prevalence in London. The GWR highlighted that the role of proximate, public green space is not fixed over space and moves between positive and negative associations with prevalence of COVID-19. These findings therefore show some evidence of the associated health benefits of proximate public green space when observing COVID-19, however, also expose the unsettling reality of health inequalities that exist across London. Localised interventions are therefore needed to tackle the health inequalities that have been exposed by modelling the role of proximate green space to COVID-19 prevalence. Bolund and Hunhammar (1999) observed that ecosystem services have different spatial covers, this could explain the local variations of the green space coefficients and their health-related ecosystem services.

Challenges and limitations

The results pose some limitations to the inferences made. The analysis does not account for use of the local green spaces meaning that regardless of how much green space is in a MSOA (and the associated health benefits of just having local green space) this may not provide the full picture of the role of proximate green space. Although there have been studies that demonstrate unequal use of green space, where those who reside in areas with more green space tend to use them more (Irvine et al., 2013), further research is needed to understand why areas with lower proportions of greenspace have a positive association with COVID-19.

Recommendations

The spatial heterogeneity of the GWR coefficients demonstrate the need for localised recommendations. Although calls have been made to include green space in national pandemic-recovery planning, localised intervention and recommendations are needed to close the health inequality gap. This could be seen in long-term, localised spatial planning for protecting and promoting green spaces for health.

VI. CONCLUSION

This study sought to analyse the role of proximate, public green space and the prevalence of COVID-19. Negative and positive associations between the proportion of proximate, public green space and COVID-19 prevalence varied over space and highlighted the areas of disproportionate health-outcomes across London. This study hopes to have shed light on the spatial heterogeneity of the associated health benefits that proximate, public green space provide. The study suggests that localised planning, promotion and protection of green space is needed to maximise or initiate the health benefits of proximate green space. Modelling COVID-19 and exploring the role of proximate, public green space has further emphasised the importance of proximate green space for equal health outcomes.

Declaration of Authorship

I, Isabella Brant, confirm that the work presented in this assessment is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

IBrant

Date of signature: 08/01/2021

Assessment due date: 11/01/2021

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VII. APPENDIX

Appendix 1 - Variables used in final multi-variate OLS regression model

Variable	Abbreviated name
Average household size	av_hhsz
Percentage of population 65+	pct_65
Percentage of population with a dependent child	p_hhwdc
Percentage of BAME population (Black, Asian, Minority Ethnic)	pct_bam
Percentage of Social Rent Tenure	pct_srn
Percentage of population with level 4 qualifications or above	pct_ql4
Percentage of population economically inactive	pct_eco_i
Percentage of population with bad health	pct_h_b
Life expectancy of males	le_m
Proportion of proximate public green space to the total land area of a MSOA	pr_gsha