Exploring the relationship between greenspaces and social vulnerability in Manchester, UK.

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Abstract:

Greenspace is a powerful tool for reducing urban inequality. Access to greenspace has been linked to improved community health and reduced social divisions (Jabbar, Yusoff and Shafie, 2021; Jennings and Bamkole, 2019).

The aim of this paper is to provide policy makers with a better understanding of how urban greenery shifts with levels of deprivation in Manchester City Council.

The study findings show no significant relationship between urban greenery (including coverage and accessibility metrics) and IMD scores in Manchester City Council. Policy makers are therefore advised to focus on enhancing greenspace quality as opposed to quantity, and are encouraged to consider local contexts such as greenspace use and quality when planning greenspace developments.

Keywords: Manchester, Deprivation, Urban Greenary, Inequality, IMD

GitHub Repository

- **GitHub Link:** https://github.com/maria25cc/IRP220022200

Declaration

> In submitting this assignment, I hereby confirm that I have read the University's statement on Good Academic Practice. The following work is my own. Significant academic debts and borrowings have been properly acknowledged and referenced.

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Introduction

Quality urban greenery is a necessity for wellbeing. It is associated with higher levels of physical and mental wellbeing, stress reduction, and improved air quality (Jabbar, Yusoff and Shafie, 2021). Additionally, green spaces may help foster a sense of community by providing accessible spaces for different social groups, reducing social divisions (Jennings and Bamkole, 2019). At a moment where major western cities are experiencing record highs of mental health concerns, loneliness, and pollution (Ventriglio et al., 2021), access to urban greenery offers an antidote. Yet urban greenery remains inaccessible to marginalised communities (Nesbitt and Meitner, 2016; Mears et al., 2019; and Spencer et al., 2020). In this context, promoting equal access to green spaces for all community members is a critical step to reducing urban inequality.

Understanding where and how to focus urban greenspace developments to maximise social benefits is critical for efficient resource management.

Greenspace accessibility is a key factor in encouraging community use and extrapolating its wellbeing benefits. According to a review of greenspace accessibility metrics published in 2017 by Ekkel and Vries, both quantitative and qualitative studies show proximity to greenspace to be an important determinant in greenspace accessibility. Beyond proximity, access to public transit stops has also been identified as important for promoting greenspace accessibility (Xiao, Shi and Gu, 2021), especially for marginalised communities, who in urban areas are less likely to have access to private vehicles (Curl, Clark and Kearns, 2018). In addition to accessibility, the size and coverage of greenspace areas are important indicators of greenspace quality. A systematic review of greenspace quality found that green patch size was linked to improved "BMI, cardiovascular mortality, chronic morbidities, depression, general health status, and quality of life" (Nguyen et al., 2021). Seeing the importance of accessibility and coverage in establishing greenspace use for community wellbeing, this study will use spatial data to create a composite index that highlights both elements.

Despite much literature exploiting the link between income and access to greenspace (Nesbitt and Meitner, 2016; Mears et al., 2019; and Spencer et al., 2020), relatively few studies, and primarily in the USA, have analysed the effect of urban greenery on established composite indicators of inequality (Liu et al., 2024). Tackling urban inequality requires a more holistic understanding of that move beyond income. One such study was conducted in 2024 by Yingjie Liu and Xinyue Gu, who found that areas with low urban greening in Seattle, USA, had higher levels of poverty, unemployment, and social segregation. In a similar way, this study will use a composite indicator of social inequality, the Index of Multiple Deprivation (IMD), to contribute to the emerging understanding of the relationship between social inequality (beyond income metrics) and urban greenspace.

As England's official measure of deprivation, the IMD offers valuable insight into patterns of inequality at a detailed scale; the statistical output is divided into 33,755 areas, called the Lower-layer Super Output Areas (LSOAs) (Gov.UK, 2025). Scores range from 1 to 10, with 1 representing the 10% most deprived LSOAs in England. It is important to note that the IMD scores are relative: they show that one area is more deprived than another but not by how much (Noble et al., 2025). For the purpose of this research, a comparison in levels of deprivation is sufficient, as previous studies have already pointed to high levels of inequality within Manchester (Folkman, 2017).

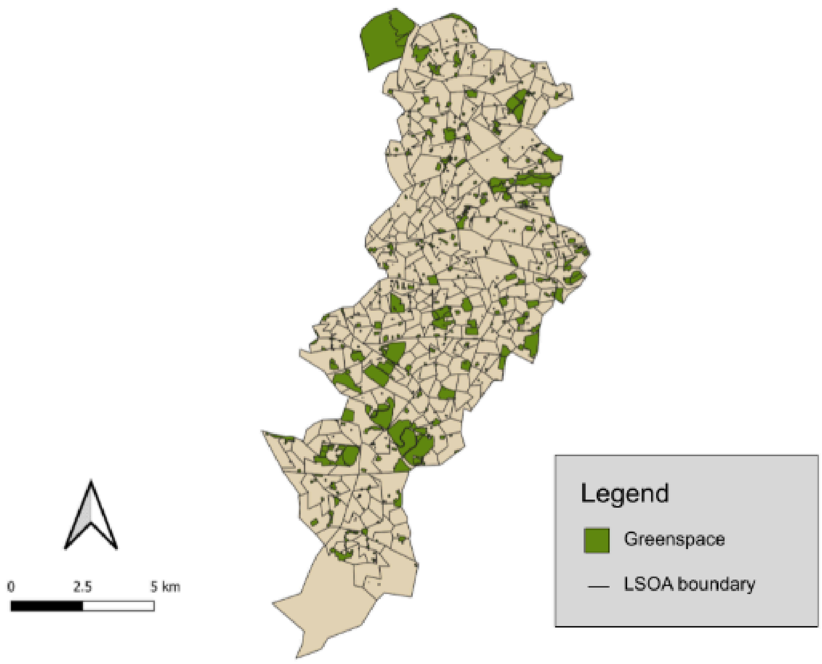
This study addresses the following research question: is there a correlation between urban greenspace coverage and accessibility and IMD scores in Manchester? To address this, the paper will use spatial data and QGIS software to create a multi-criteria evaluation (MCE) score of greenspace accessibility (including proximity to greenspace and proximity to public transit stops), and greenspace coverage. The MCE score will then be aggregated to fit LSOA dimensions in order to enable a comparison with the IMD data. The processed data will be analysed using python to explore graphical relationships between variables and determine statistical correlations.

Methodology

Study Area

This research will focus on the local authority of Manchester city council, mapped in figure 1, which covers 282 LSOA. Manchester is the largest city in the North of the UK with the highest levels of income inequality (Folkman, 2017). The study areas' high population density (Manchester City Council, 2021), as well as the high levels of inequality offer a good framework for understanding how variations in greenspace accessibility correlate with the index of multiple deprivation.

Figure 1 - Map showing the distribution of greenspace and LSOA in the local authority Manchester city council.



(map created by author using open greenspace data from OS and LSOA data from ONS, 2025)

Data Collection & Processing

The data used for this study, as well as its source and publication data is shown in table 2, links to data sources can be found in appendix 1. This study used the most recent available data for all categories in order to maximise relevance for policy makers. Data was collected from recognised sources such as government websites to ensure reputability.

Table 1 - Data used for the project, including name, purpose, publisher, date published, and file type.

Name of datafile	Purpose	Publisher	Date Published	File type
IMD scores	Chosen measure of deprivation	Gov.UK	Oct 2025	csv
Local Authority Boundaries	Used for clipping data to Manchester city council	Office for National Statistics (ONS)	May 2024	csv
National Public Transport Access Nodes	Measure of green space accessibility	Gov.UK	Nov 2025	csv
OS Open Greenspace	Measure of green space accessibility and coverage	Gov.UK	Apr 2025	GeoPackage

As an initial processing step, all csv files were converted to vector files in QGIS. During this process, the coordinate reference system (CRS) was set to ESPG:27700 for all layers. All data files were also cropped to only include data within the Manchester city council local authority boundary.

Multi-criteria evaluation of greenspace accessibility

To begin, the study conducted a multi-criteria evaluation (MCE) of greenspace accessibility in QGIS. MCE is a valuable tool for evaluating the suitability of a space based on a variety of attributes (Dujaval, 2022), and will therefore be helpful in understanding the accessibility of greenspaces in Manchester's LSOA based on access to public transit and distance to greenspace. Key processing steps and calculations are described below.

To begin, the vector layer for public transit stops was clipped to only include bus stops within 10 meters of green space by using the extract within distance tool in QGIS (results in appendix 2). Then, vector layers for public transit stops and greenspace were converted into raster form in QGIS. This was done to enable distance calculations. Then, the proximity(rasterdistance) tool was used to generate distance rasters for each variable. Each distance raster was then clipped to the outline of the Manchester city local authority area using the extract by location tool (results in appendix 3). A cell size of 10m was applied across all outputs to match the resolution of the selected CRS.

Then, to combine the two variables into a single indicator, each distance raster was normalised to a 0-1 scale using the formula y=f(x), such that f(min value)=1 and f(max value)=0 (results and full formulas in appendix 4). For the purpose of this analysis, lower distances to all variables are preferred, as, according to literature they represent greater accessibility to parks. According to a metanalysis by Xiao et al. published in 2021, shorter distances to greenspace are a critical indicator of greenspace accessibility. Ease of access to public transport stops are also related to greenspace accessibility, though less frequently, and were therefore given a lower weight (Xiao, Shi and Gu, 2021). Using the above formula ensures that values closer to 1 represent more favorable greenspace accessibility conditions.

Finally, the normalised criterion rasters were combined based on their relative importance in determining greenspace accessibility, see table 2 (results in appendix 5).

Table 2 - Weight given to each criterion for the greenspace accessibility MCE calculation.

Distance to green space	70%
Distance to bus stops	30%

Aggregating data to LSOA

The next step for the analysis was to calculate the greenspace coverage for each LSOA, and combine this with the greenspace accessibility data calculated above, which would then enable a comparison of greenspace coverage and accessibility in Manchester with IMD data.

To start, in QGIS, the IMD layer, which had been downloaded as a csv file, was converted to a vector layer, and the data was cropped to fit the extent of the Manchester local authority boundary. Then, the mean of the MCE greenspace accessibility raster was calculated for each LOCA in the IMD layer by using the zonal statistics tool (results in appendix 6).

To calculate the coverage of greenspace in each LSOA, the zonal statistics tool was used to find the sum of greenspace pixels in each LSOA. As each pixel was set to represent 10*10m, these values were then multiplied by 100 to obtain the value for the coverage of greenspace in each LSOA in metres squared. Then, the area of greenspace in m2 was divided by the total area of each LSOA to find the percentage of greenspace coverage for each LSOA on a scale of 0-1 (results in appendix 7).

Finally, a weighted index of overall greenspace accessibility was produced by combining greenspace accessibility and greenspace coverage. The variables were integrated using equal weights, as they are both critical elements to greenspace use as highlighted above. This final score of this calculation ranges from 0-1, where higher numbers indicate better greenspace coverage and accessibility (results in appendix 8).

Statistical analysis

Finally, spatial and statistical analysis was conducted using python to examine the relationship between greenspace quality and IMD in Manchester. First, spatial data was processed and visualised using GeoPandas. Two maps were produced, one which visualised the IMD score of each LSOA, and another to visualise the combined greenspace coverage and accessibility indicator created in the step above. Then, the relationship between the two variables was plotted using a heatmap. Finally, following the example of Xiao et al. who in 2021 analysed the spatial distribution of urban greenery with measures of socioeconomic status, the relationship between variables was quantified using both Pearson and Spearman correlation tests.

Figure 1 shows an LSOA in the North West corner of Manchester City Council covered almost entirely by greenspace. This LSOA, named Manchester 004b, includes Heaton park, which covers the majority of its land area (Manchester City Council, n.d.). Its greenspace coverage is 52% higher than any other LSOA, making it an outlier. For this reason, it was excluded from the analysis.

Statistical Analysis

```
# Import necessary libraries
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt
import mapclassify
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
pip install notebook
```

Show hidden output

```
gdf=gpd.read_file("/content/drive/MyDrive/University/Year 4/GG3209/day2.gpkg")
gdf.head()
```

	LSOA21CD	LSOA21NM	LSOA21NMW	BNG_E	BNG_N	LAT	LONG	GlobalID	area	coverage
0	E01005061	Manchester 018A	None	386335	397111	53.4706	-2.20733	622526b1-80a7-452a-9a44-354c35ed240f	856063	0.0
1	E01005063	Manchester 018C	None	385853	396436	53.4645	-2.21456	419dd552-58d5-4e69-bc98-f18d02511512	321729	1.0
2	E01005065	Manchester 018D	None	385314	397132	53.4707	-2.22271	c7aa7157-4672-4c1f-b1e8-e173c0b7b8fe	727378	0.0
3	E01005066	Manchester 018E	None	384428	397188	53.4712	-2.23606	7800a62a-b951-4b79-b6ff-7d7d3b94baaf	134208	0.0
4	E01005067	Manchester 020A	None	387120	396879	53.4685	-2.19549	ba82e55c-5cde-49ef-aa20-535026085700	461813	3.0

5 rows × 33 columns

```
!pip install pingouin
```

Show hidden output

```
#remove outlier
gdf = gdf[gdf["LSOA21NM"] != "Manchester 004B"]
```

Results

Figure 1 shows no clear pattern between greenspace across Manchester's LSOA. One central area, as well as a smaller area in the north eastern edge appear to have a slightly higher greenspace accessibility and coverage scores. On a scale of 0 to 1 where 1 represents highest greenspace coverage and access, figure 1 shows little overall variation in greenspace accessibility and coverage scores across Manchester, with the vast majority of LSOA ranging from 0.55 to 0.59.

```
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
plt.suptitle("Figure 1 - Greenspace acessibility and coverage score by LSOA", fontsize=16)
plt.title("Values closer to 1 indicate better greenspace coverage and accessibility", fontsize=11)
gdf.plot(
    column="testing",
    cmap="YlGn",
    scheme="NaturalBreaks",
    k=5,
    legend=True,
    edgecolor="black",
    ax=ax,
    legend_kwds={
        "loc": "lower right",
        "title": "MCE Score"
    }
)

ax.axis("off")
plt.show()
```

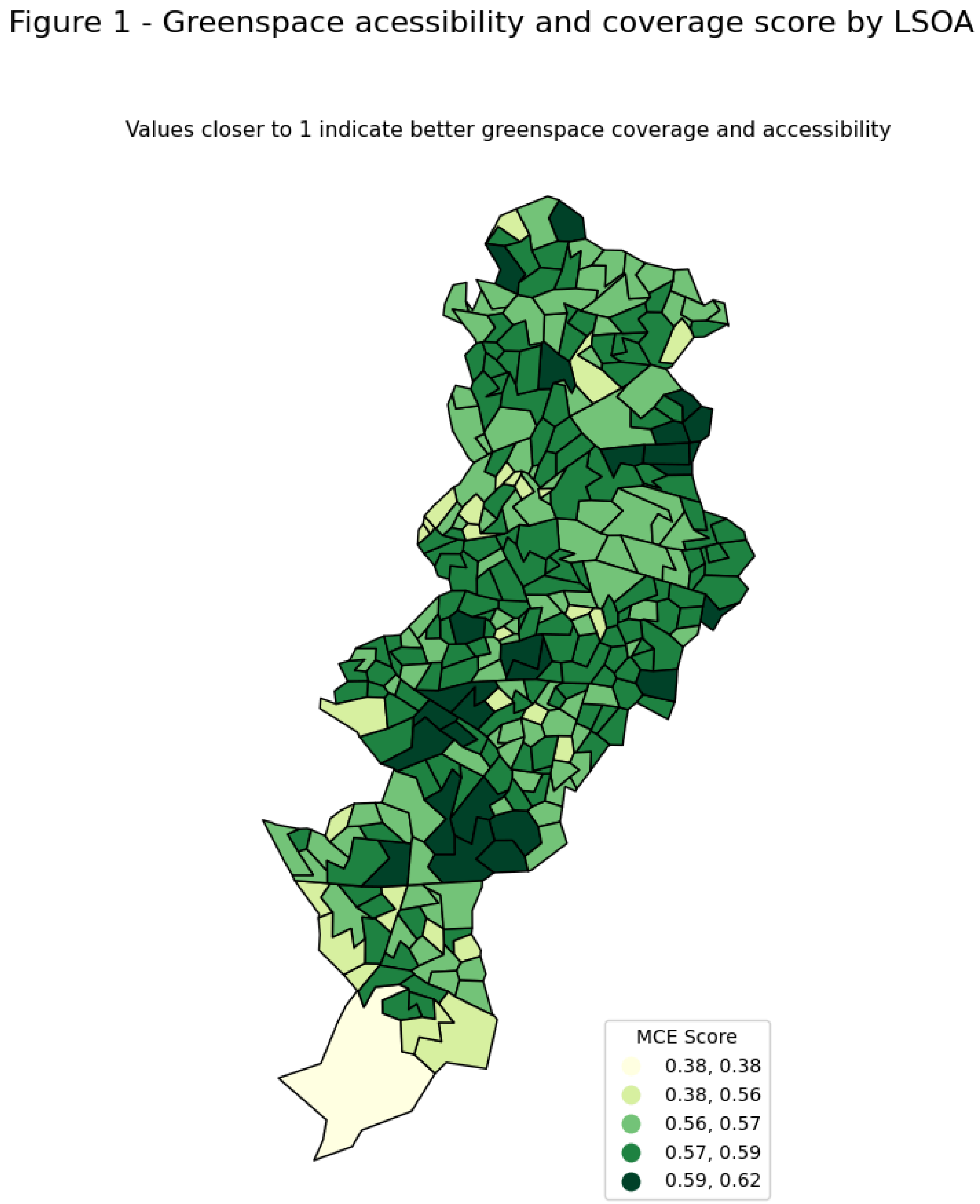


Figure 2 shows more variation. Lower IMD scores are present across Manchester's north east edge, and its southern section. The central portion has higher IMD scores, which matches with the slightly higher greenspace accessibility and coverage scores seen in the central regions of figure 1.

```
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
plt.suptitle("Figure 2 - IMD score by LSOA", fontsize=16)
plt.title("Where 1 indicates the most deprived 10% of LSOAs)", fontsize=11)
gdf.plot(
    column="1Index of Multiple Deprivation (IMD) Decile (where 1 is most deprived 10% of LSOAs)",
    cmap="OrRd_r",
    scheme="NaturalBreaks",
    k=10,
    legend=True,
    edgecolor="black",
    ax=ax,
    legend_kwds={
        "loc": "lower right",
        "title": "IMD Score"
    }
```

```
    }
)

ax.axis("off")
plt.show()
```

Figure 2 - IMD score by LSOA

Where 1 indicates the most deprived 10% of LSOAs)

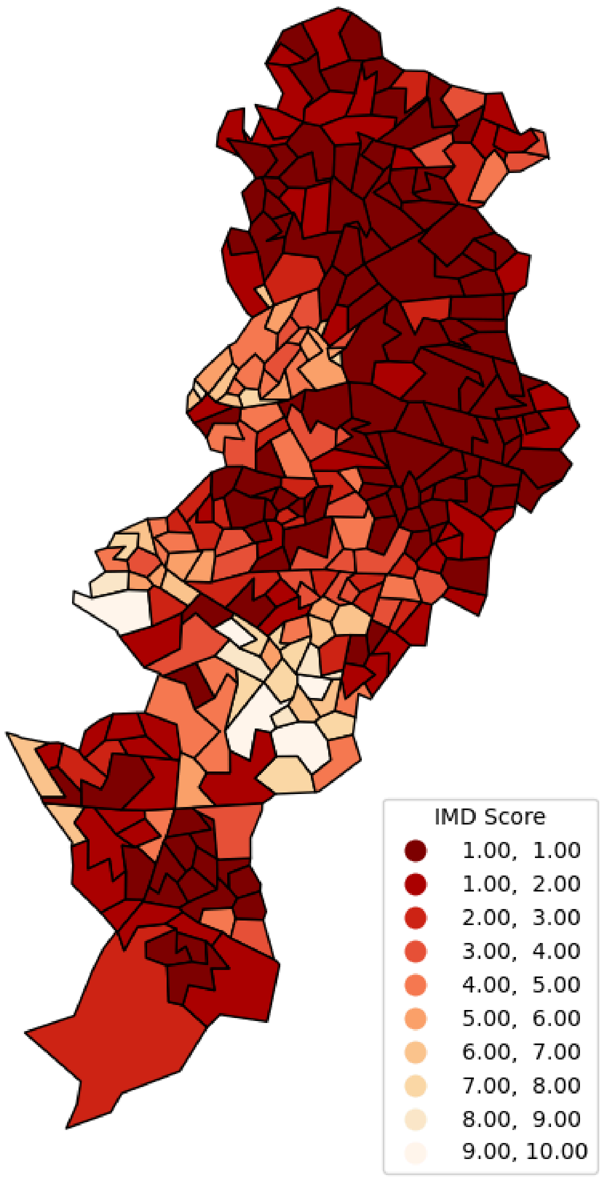
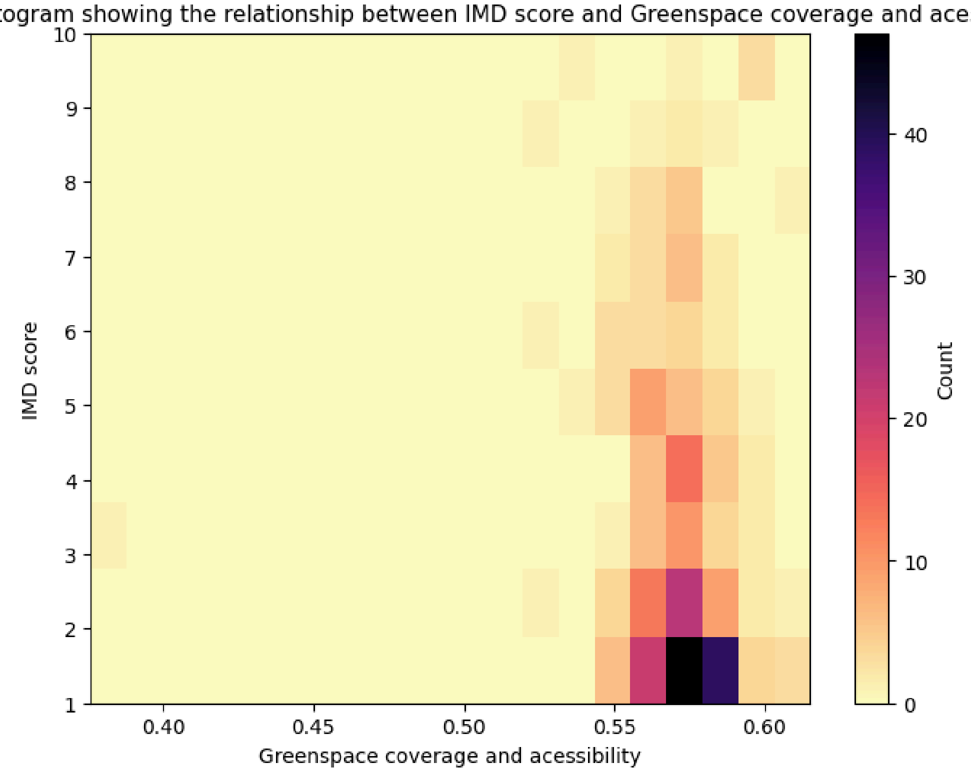


Figure 3 shows no evident correlation between IMD score and greenspace quality. The majority of LSOA are concentrated at a greenspace quality score of 0.57, and an IMD score of 1. These findings are supported by both the pearson and spearman correlation analysis, which were calculated to be -0.12 and -0.18 respectively. Both values indicate a weak negative correlation between IMD scores and Greenspace coverage and accessibility. The p-value was found to be less than 0.01, which indicates a rejection of the hypothesis (Barcelona Field Studies Centre, 2019).

```
plt.figure(figsize=(8,6))
plt.title("Figure 3 - Histogram showing the relationship between IMD score and Greenspace coverage ar
plt.hist2d(gdf["testing"],
           gdf["1Index of Multiple Deprivation (IMD) Decile (where 1 is most deprived 10% of LSOAs)"]
           bins=[20, 10],
```

```
              cmap='magma_r')
plt.xlabel("Greenspace coverage and acessibility")
plt.ylabel("IMD score")
plt.colorbar(label="Count")
plt.show()
```

Figure 3 - Histogram showing the relationship between IMD score and Greenspace coverage and acessibility




```
#Pearsons correlation testing

corr = gdf["testing"].corr(gdf["1Index of Multiple Deprivation (IMD) Decile (where 1 is most depriv
print(corr)
```

-0.12386084908662286

```
#spearman correlation testing

import pingouin as pg

pg.corr(gdf["testing"],
        gdf["1Index of Multiple Deprivation (IMD) Decile (where 1 is most deprived 10% of LSOAs)"],
        method="spearman")
```

	n	r	CI95%	p-val	power
spearman	294	-0.183205	[-0.29, -0.07]	0.001607	0.886059

Discussion

Greenspace coverage and accessibility is not, according to the results of this study, correlated with higher IMD scores in Manchester. The lack of correlation may in part be due to spatial planning history of Manchester. Greenspace distribution in Greater Manchester has stayed relatively stable since the 2000s, and declines in urban greenery have been most noticeable in densely populated residential areas (Zhao et al., 2021). While global patterns of urban greenspace have been linked to lower population density (Bille, Jensen and Buitenwerf, 2023), the relationship becomes less evident at a smaller scale (Wellmann et al., 2020). There is no specific correlation between population density and IMD scores in Manchester (Gov.UK, 2025). If greenspace coverage in Manchester is more strongly linked to urban population density than IMD scores, this may explain the lack of correlation in figure 3. Further research is needed to explore the links between urban greenspace and population density in Manchester.

Incorporating field data into the methodology of this study may produce different results. In 2010, for a study on the accessibility of urban accessibility greenspaces in Greater Manchester, Kazmierczak, Armitage, and James found that while the distribution of greenspace in Manchester was "very good", the area of accessible greenspaces was unsatisfactory. Findings revealed that only 36% of entrances met "minimum quality requirements". Out of 74 sampled sites, only 58 were available for general use, and the quality of paths was "low" for 38% of sites (Müller et al., 2010). Field data offers valuable insights that are not accessible through spatial data, and may have revealed a stronger correlation between greenspace and IMD scores.

Similarly, further research may consider incorporating qualitative data on the primary use of green-spaces in LSOA with different IMD scores. A qualitative study on perceptions of greenspace among marginalised groups in Leeds, published in 2023 by Ward et al. found that participants reported litter and lack of cleanliness as a barrier to green space access. Safety concerns in greenspaces due to drug taking, vandalism, and drinking were also frequently reported as barriers to access, especially among women and elderly participants (Ward et al., 2023). Qualitative barriers to greenspace access cannot be understood through this study's methodology, which focused on a spatial analysis, and may be silently contributing to greenspace inequality in Manchester. Future research should consider incorporating qualitative elements to better understand use of greenspace across deprivation levels.

Finally, this study focused on analysing three key spatial factors for urban greenspace accessibility. While the relationship is less evident, other spatial variables such as environment types, vegetation types, and population demographics data, have also been linked to better greenspace accessibility (Nguyen et al., 2021), and may therefore have produced different results .

Conclusion

Urban greenspace is essential to personal and community wellbeing. In Manchester, greenspace accessibility and coverage, measured through spatial analysis, shows little variation across deprivation levels. Future research may focus on supplementing the spatial methodology of this study with field and qualitative data. Policy makers may focus on enhancing greenspace quality, as opposed to quantity. Future greenspace developments should take into consideration local contexts such as greenspace use and safety to ensure that marginalised communities can reap the maximum benefits.

Appendix

Appendix 1

Link to datasources: OS open greenspace layer - https://www.data.gov.uk/dataset/4c1fe120-a920-4f6d-bc41-8fd4586bd662/os-open-greenspace1

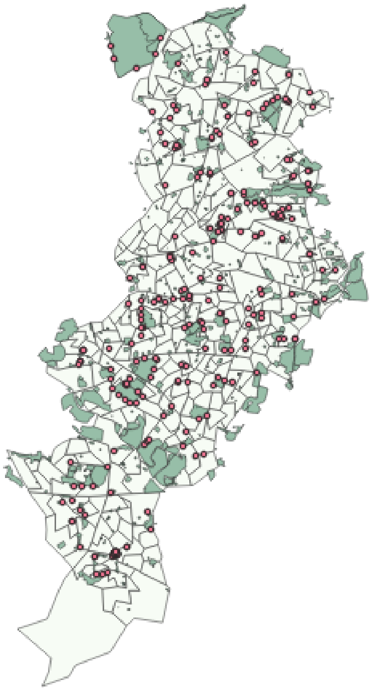
Local Authority Boundaries - https://geoportal.statistics.gov.uk/datasets/ons::local-authority-districts-may-2024-boundaries-uk-bfe-2/about

IMD scores - https://deprivation.communities.gov.uk/

National Public Transport Access Nodes - https://beta-naptan.dft.gov.uk/download

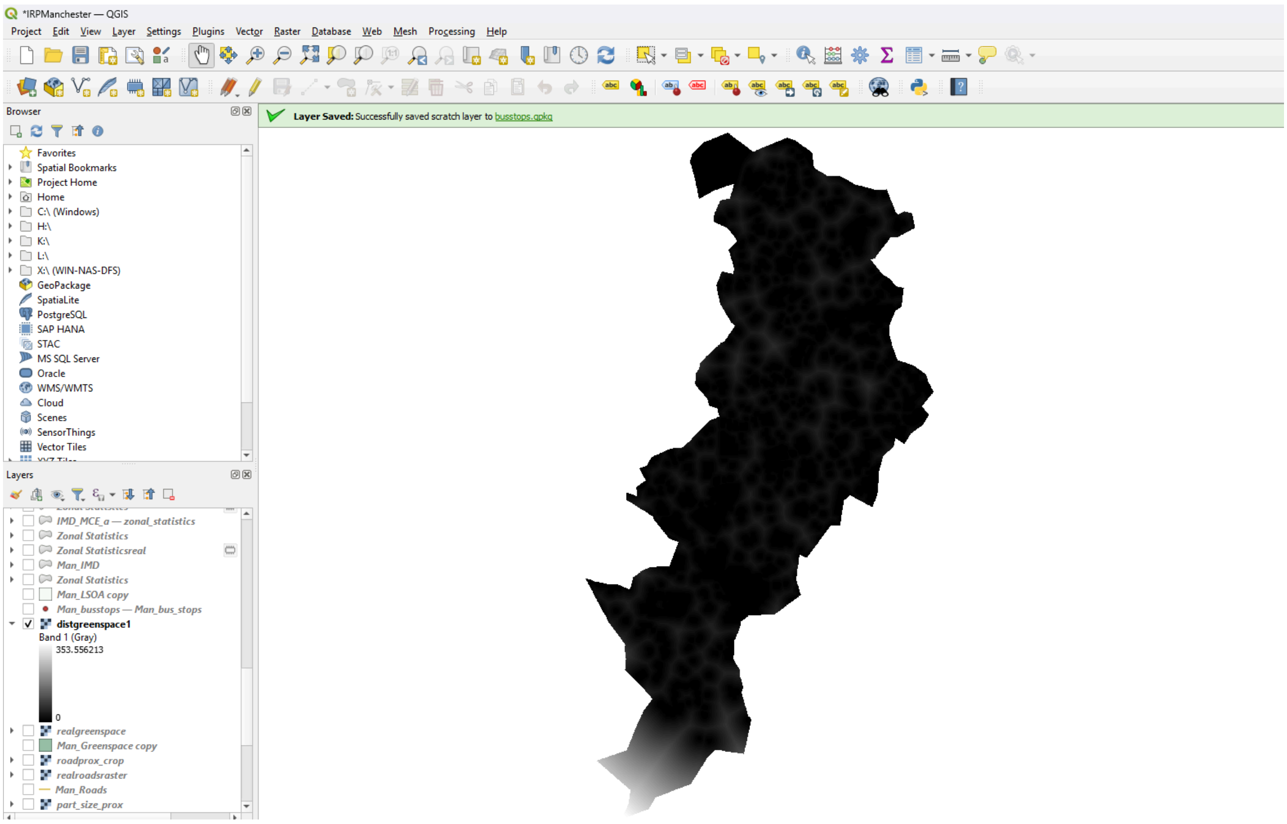
Appendix 2

Results from clipping the bus stop data to only include stops within 10 meters of green areas.

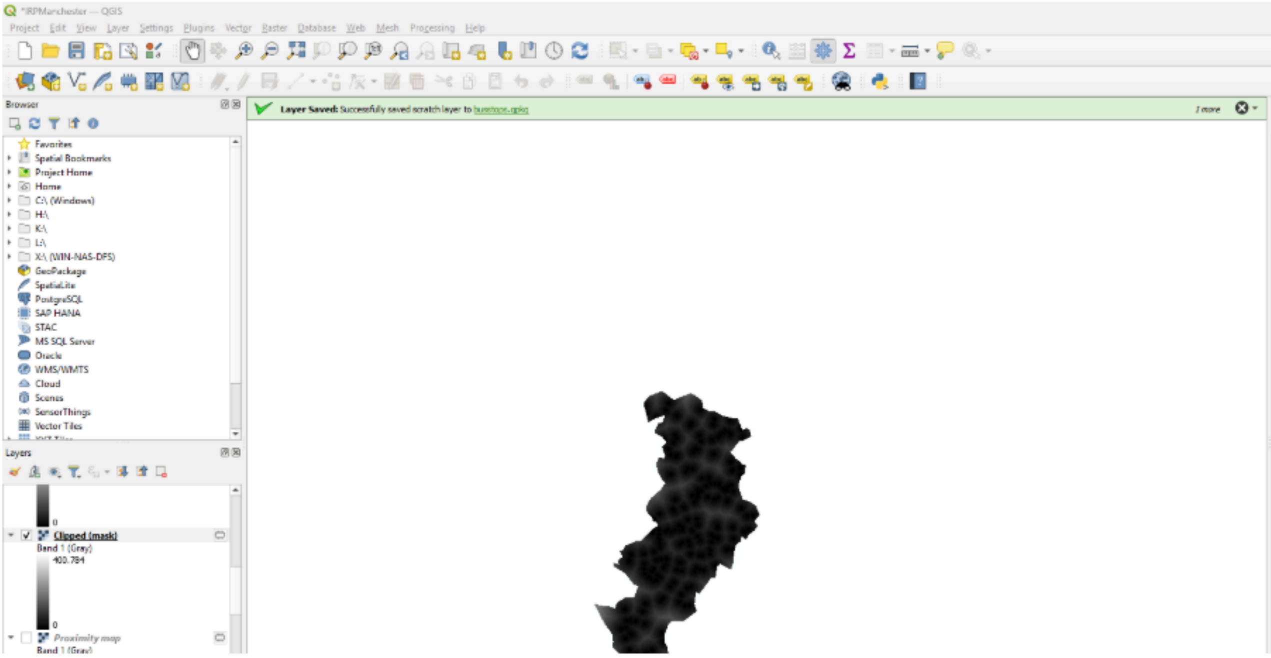


Appendix 3

Appendix 3 Results showing distance rasters for greenspace:

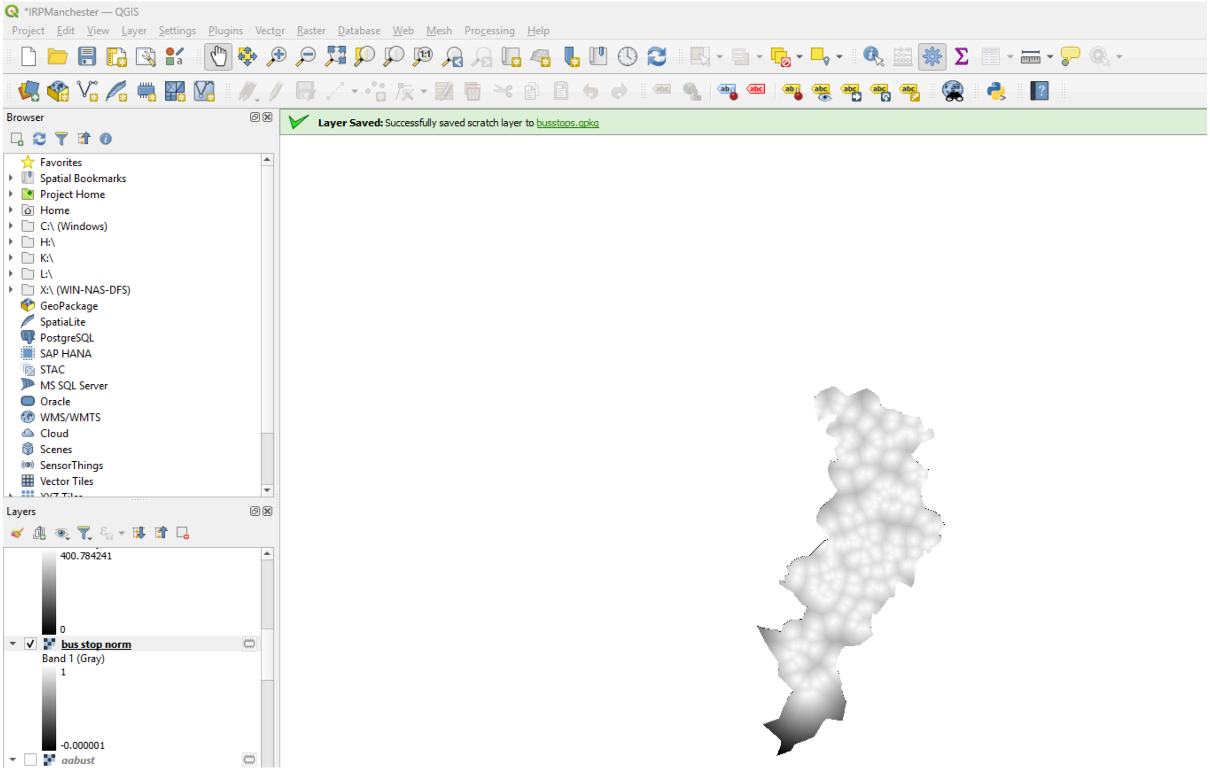


Results showing distance rasters for bustops:


*IRPManchester — QGIS
Project Edit View Layer Settings Plugins Vector Raster Database Web Mesh Processing Help
Browser
Layer Saved: Successfully saved scratch layer to
Favorites
Spatial Bookmarks
Project Home
Home
C:\ (Windows)
H:\
K:\
L:\
X:\ (WIN-NAS-DFS)
GeoPackage
SpatiaLite
PostgreSQL
SAP HANA
STAC
MS SQL Server
Oracle
WMS/WMTS
Cloud
Scenes
SensorThings
Vector Tiles
Layers
Clipped (mask)
Band 1 (Gray)
400.784
0
Proximity map
Band 1 (Gray)

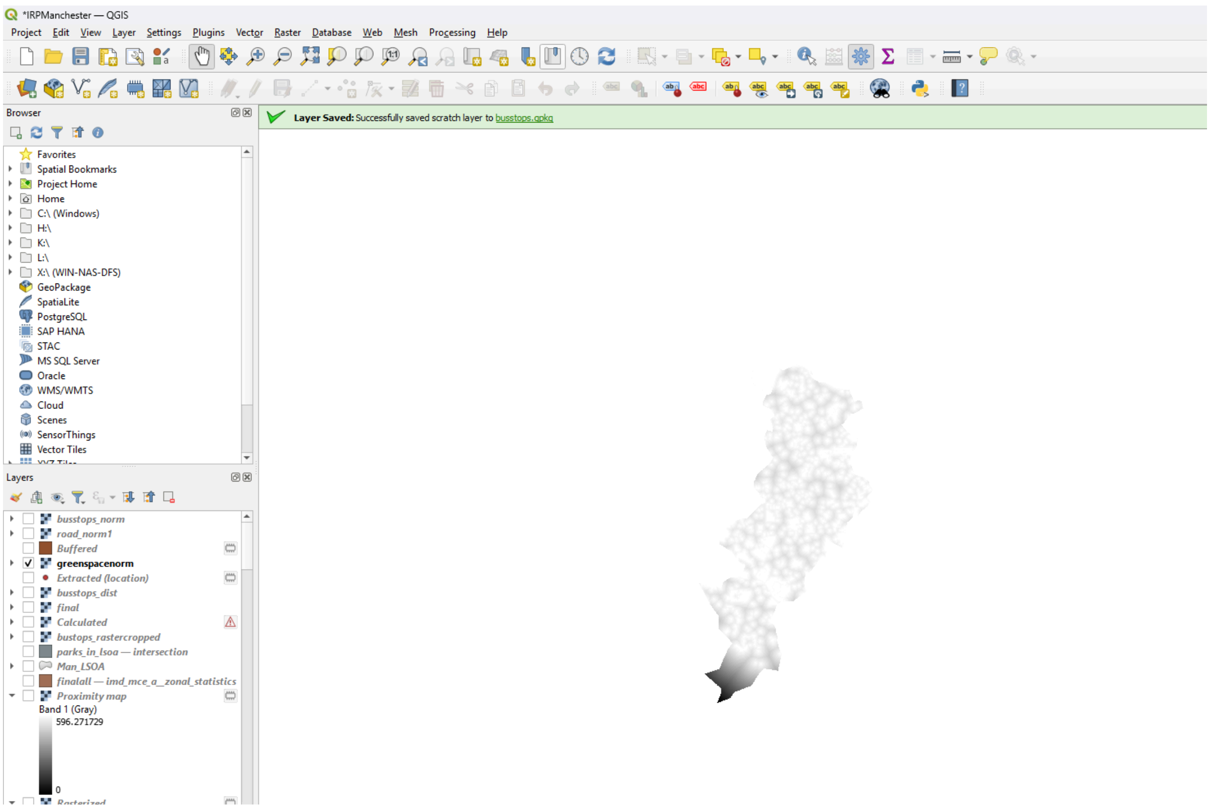
Appendix 4

Results for the bus stop normalised raster:



Input for distance calculator: -(“name of bus stop distance raster”/400)+1

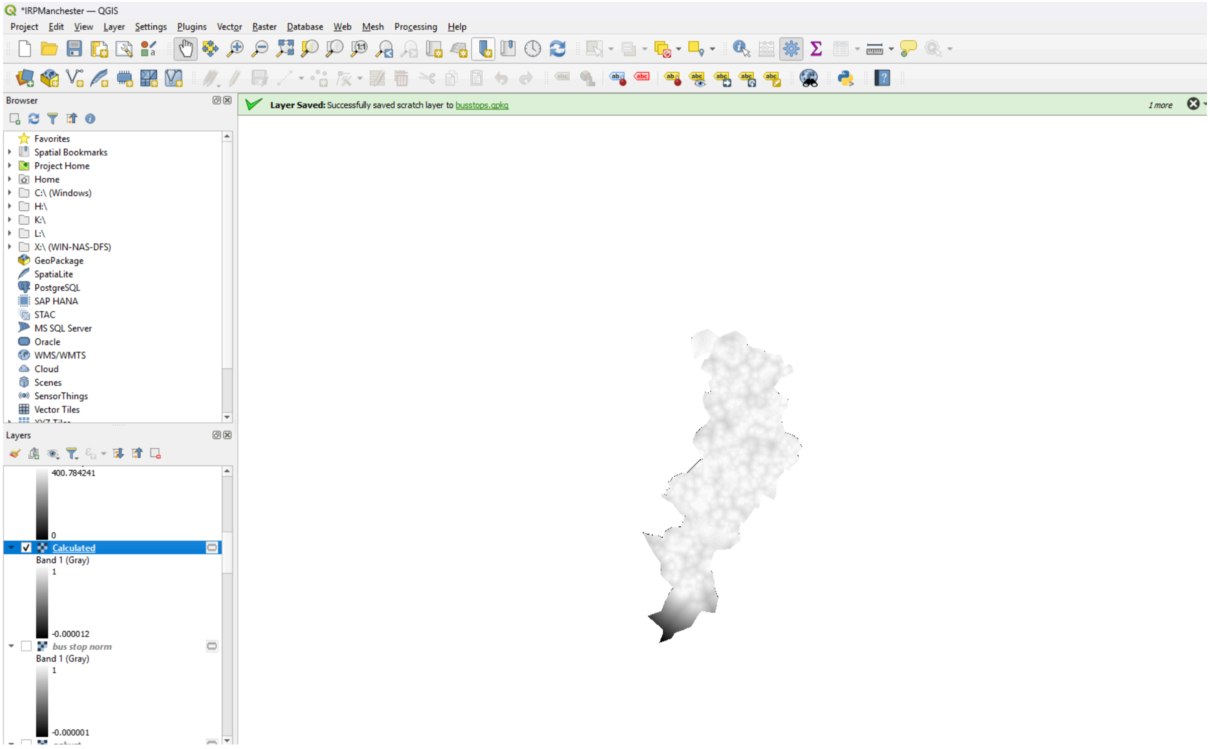
Results for the greenspace normalised raster:



Input for distance calculator: -(“name of greenspace distance raster”/333)+1

Appendix 5

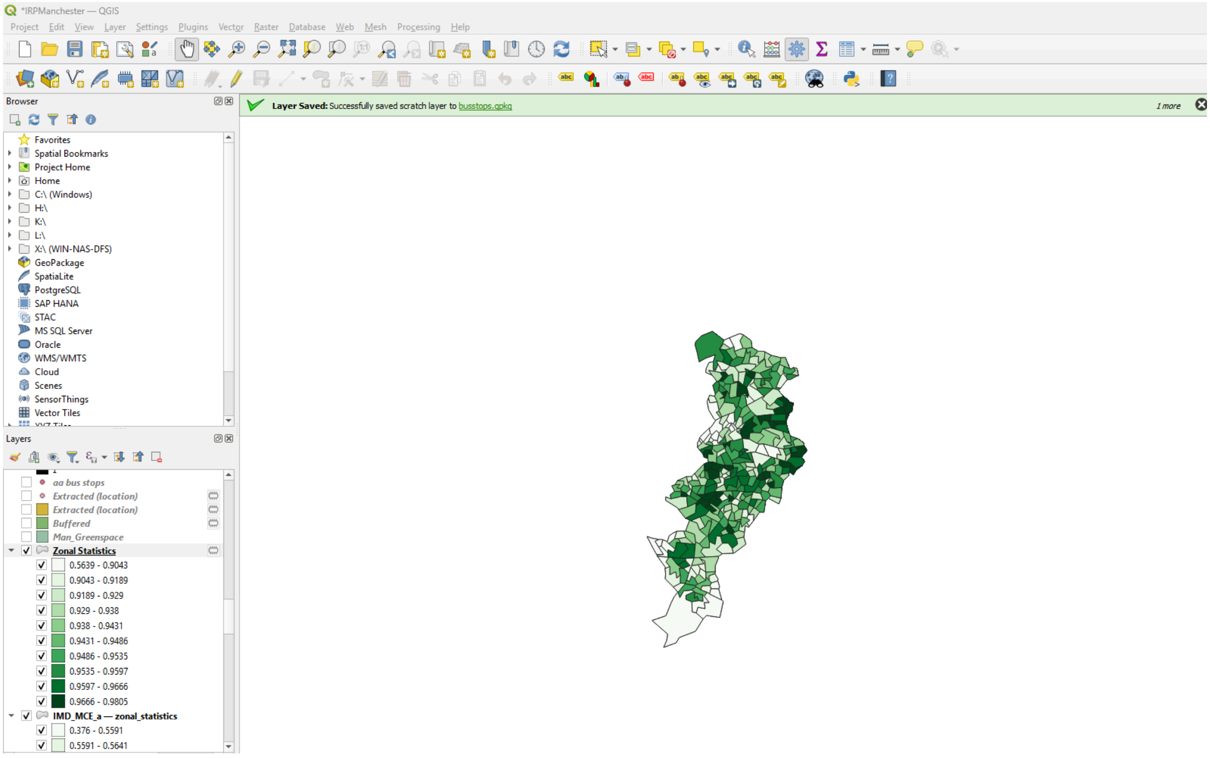
Results for the combined bus stop and greenspace normalised raster:



Input for distance calculator: (“name of greenspace raster” * 0.7) + (“name of bus stop raster” * 0.3)

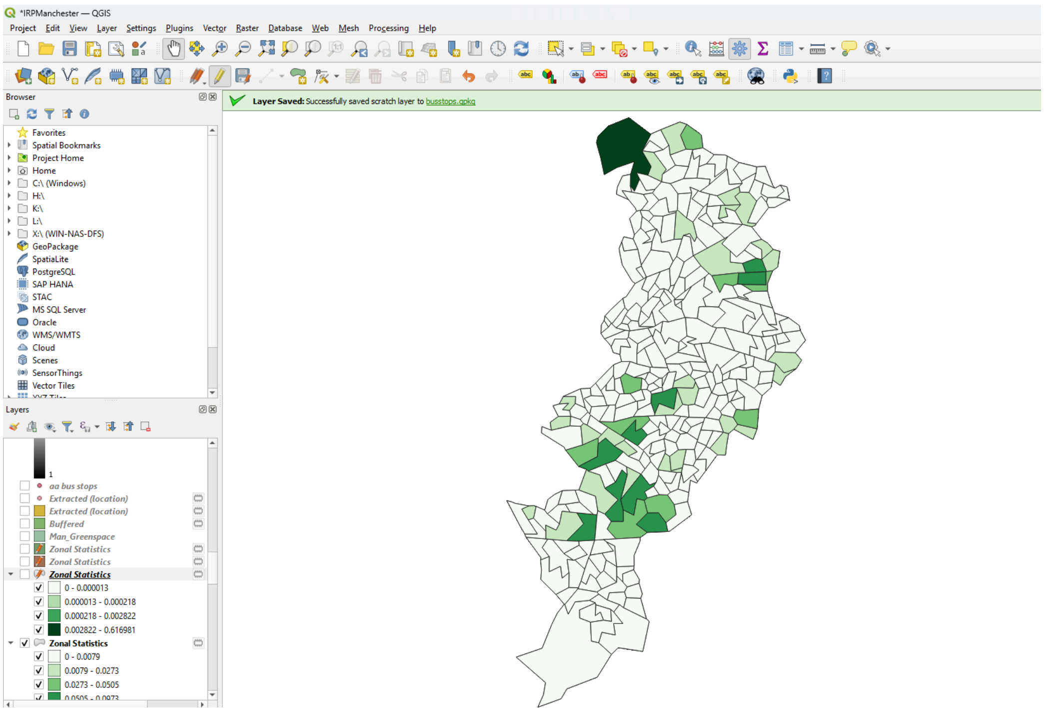
Appendix 6

Results from using the zonal statistics tool on the raster in appendix 5 to calculate mean greenspace accessibility for each LSOA.



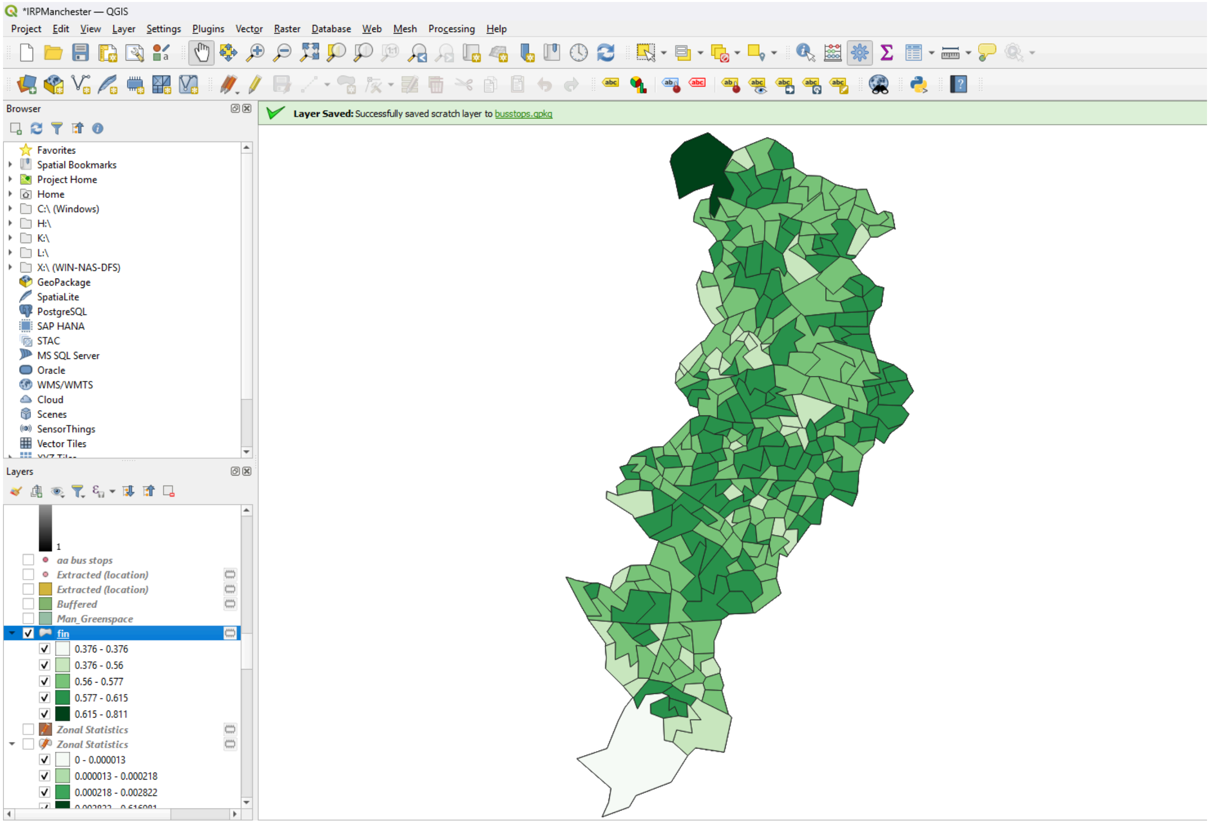
Appendix 7

Results from using the zonal statistics tool on the raster in appendix 5 to calculate mean greenspace accessibility for each LSOA.



Appendix 8

Results from combing the indicators for greenspace coverage and greenspace accessibility to LSOA.



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