Assessment Cover Sheet

Student Registration Number*:	**220228651**
Module Code/Title:	**TRP627 GIS for Built Environment Professionals**
Word Count:	**1908**
Date of Submission:	**19/5/2023**
Module Lead:	**Ruth Hamilton, Jingxia Wang**
Registered with DDSS and entitled to the Yellow Sticker Scheme:**	

* For group submissions, please put the student registration number for all group members

** If this is group submission, individual students are not required to disclose their Yellow Sticker eligibility. If you wish to remain anonymous to your group, please submit your submission receipt to USP@sheffield.ac.uk, with your group name, and we will notify the marker that someone in this group has YS eligibility.

PLEASE do not put your name on this cover sheet or on your submitted work. Your work is marked anonymously and therefore should not include your name. The use of your registration number on the form is to help admin staff identify your work should the need arise, but cannot be cross-referenced by marking staff.

===

Student Declaration:

I hereby declare that this submission is entirely my own work, in my own words, and that all sources used in researching it are fully acknowledged and all quotations properly identified.

By submitting your work via the online portals you agree that the work you are submitting is entirely your own work. Submission of work that is not your own, is against the university's unfair means policy and further investigation and action will be taken, which may result in you failing your module.

Geographical visualization report

I. Evaluation of the Service Levels of Different Types of Urban Green Spaces

Dataset:

Sheffield City Green data

Sheffield LSOA Boundaries

2021 England Census population density data

1. Data preprocessing

1.1 Population Density data preprocessing

(1) **Data connection:** Merge the population density data of each area within the LSOA obtained from ONS into the LSOA shp file using the 'join' method by the same index (LSOA CODE), making it accessible in the attribute table.

(2) **Data Cleaning:** By inspecting the attribute table, it was found that some areas had null values, manifesting as a population density value of 0 in the polygon area attribute table of the shp file.

(3) **Analyze the causes of null values:**

a) There are indeed no residents.

b) The number of residents is minimal, so the value tends towards zero when calculating density, leading to it being ignored.

c) Errors in data processing or transmission due to the natural randomness in complex systems during the statistical process, data reporting process, or data acquisition process.

d) These areas are within the range of urban green spaces, so no one lives there.

(4) **Data supplementation:**

a) Supplement the data insufficiency by spatial interpolation.

b) Before interpolation, there is an assumption: the population density of a city area is approximate to that of its adjacent, similar city areas. (Wu & Murray, 2005)

c) The optimal way for such a situation should be Population-Based

Interpolation. However, this technique cannot be used when the data have no association with specific populations or the resolution of available population data is not higher than that of the data to be interpolated. Therefore, another more intuitive interpolation method based on distance-weighted assignment, IDW (Marcelli et al., 2022), is adopted.

d) By converting the LSOA area to centroids, a raster image of population density distribution is obtained using IDW interpolation.

e) Continuously adjust the size of the generated raster so that each LSOA corresponds to one or several raster units. In this way, the population density of each raster unit will be roughly equal to the population density of its corresponding LSOA. But there is a problem with this approach. That is, it assumes that the population density is uniformly distributed within each LSOA area.

f) The data obtained from ONS are not detailed to levels below LSOA. Each LSOA area corresponds to a density value. This makes the distribution of population density within each LSOA unit can be considered uniform, which conforms to the assumption of uniform distribution in the previous item. Therefore, the selected grid size is appropriate.

g) After generating the raster image of population density, the corresponding raster is cut out with the missing data range as the mask layer.

h) Use the Zonal statistic analysis tool to calculate the average of the raster image in the corresponding areas.

i) Obtain the interpolation of the value-missing area by cutting the mask layer in the extract.

j) Assign these values to the cells with missing population density data in the entire Sheffield population density layer according to the same index.

(5) **Add a new field:**

By editing the attribute table, add the completed population data to the population density attribute of the LSOA layer. Add a field to calculate the area of each LSOA unit and convert it to km^2, add a population field, and get the population quantity through the expression area×population density.

1.2 Greenspace data preprocessing

Clipping the range of urban green spaces and excluding non-public green spaces in the filter based on the expression. This leaves six types of urban green space.

2. Visualization

2.1 Reasons for making

Urban green spaces are vital to the health of urban residents. Research shows that viewing or visiting green spaces can have positive health effects, such as accelerating surgical recovery, improving cardiovascular health, improving mental health, and reducing all-cause mortality (Lee & Maheswaran, 2010).
The composition and structural properties of urban green spaces are related to the health benefits that green spaces can bring, such as usability, accessibility, configuration, and vegetation composition (Lee & Maheswaran, 2010). Therefore, a better understanding of the service capacity of urban green spaces will help guide new planning.

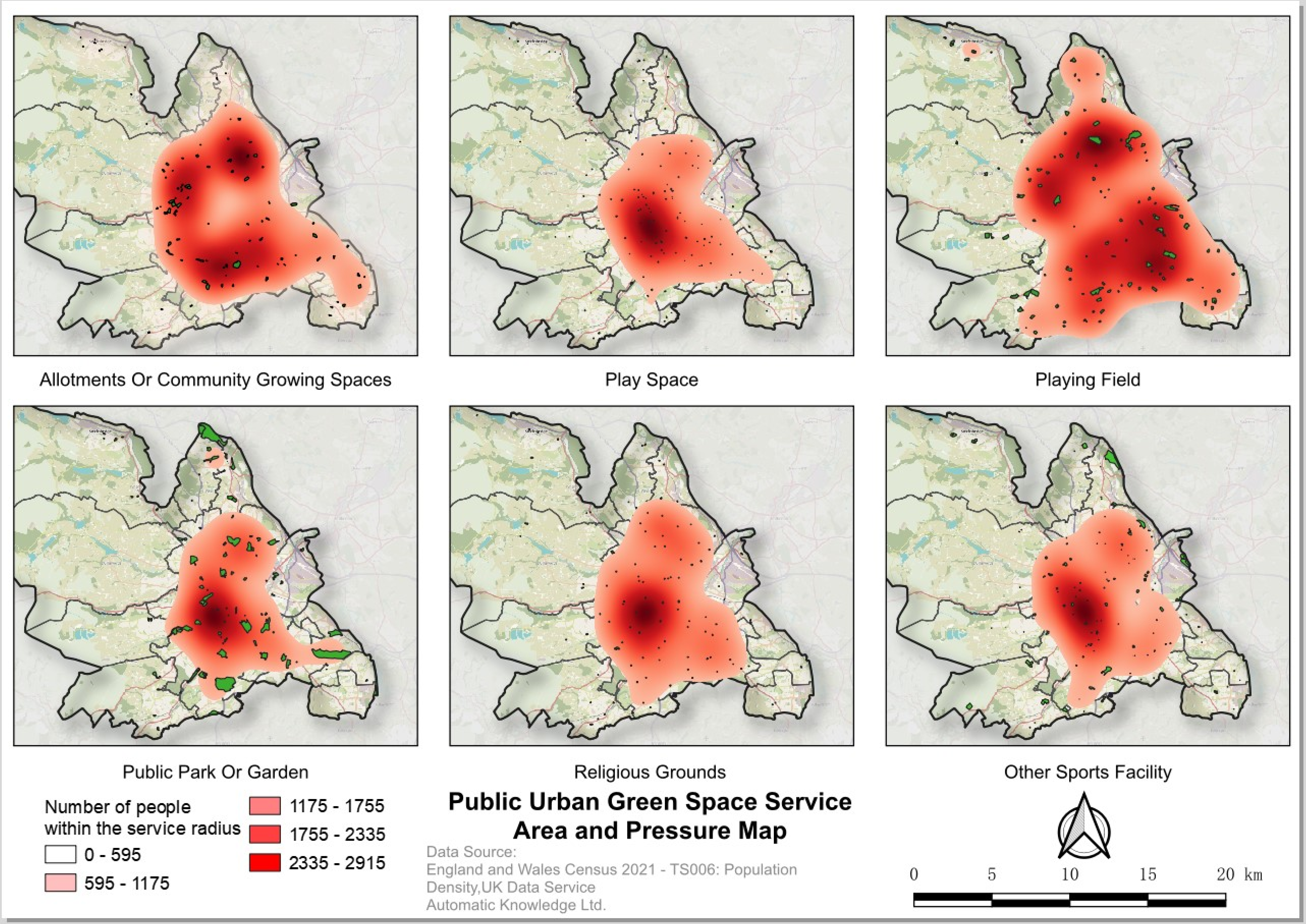
Related research aims to develop and test an urban green space public health indicator to support health and environmental policy. A method for calculating an accessibility proxy indicator value was proposed, using the number of residents accessible to urban green spaces (NACC); the total number of residents within the city (NTOTAL); and the score of residents living within the chosen distance in urban green space areas (UGSI): UGSI = (NACC / NTOTAL) * 100 (proxy indicator). Based on the currently limited data, this report adopts a simplified algorithm derived from this concept. The number of people on a unit area of urban green space is measured as a simplified urban accessibility proxy indicator to evaluate the service level of urban green spaces. (Annerstedt van den Bosch et al., 2015)

After the data processing above, the two designed independent variables for this proxy indicator (population, distance to green spaces) are visualized.

2.2 Making process

By setting the buffer radius to 500 meters for a 5-minute walk distance for residents (Cetin, 2015), overlapping buffers are merged, and the number of people within the impact range of urban green spaces in different LSOA areas is cut out using this as a mask layer. The obtained density multiplied by the buffer area can give the number of people served by urban green spaces within each LSOA range.

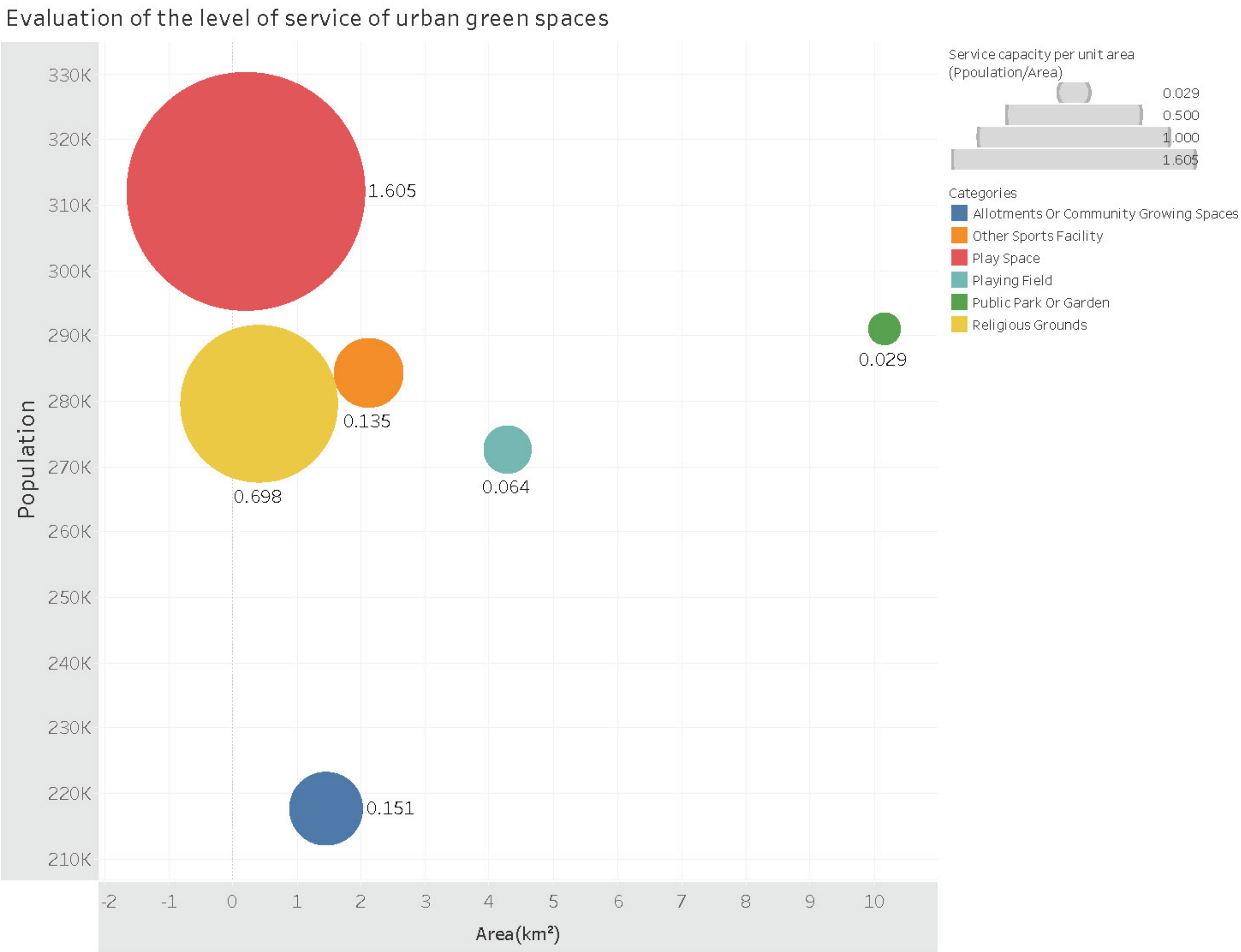
Points are generated inside the buffer polygon based on the calculated population quantity within the LSOA range. Heat maps are created based on this point data, which describes urban green spaces' service range and service pressure.


Allotments Or Community Growing Spaces
Play Space
Playing Field
Public Park Or Garden
Religious Grounds
Other Sports Facility
Number of people within the service radius
0 - 595
595 - 1175
1175 - 1755
1755 - 2335
2335 - 2915
Public Urban Green Space Service Area and Pressure Map
Data Source:
England and Wales Census 2021 - TS006: Population Density,UK Data Service
Automatic Knowledge Ltd.
0
5
10
15
20 km

From this map, we can see the spatial distribution of the service pressure of different types of urban green spaces and understand the accessibility proxy indicator values in different areas.

However, if we want to clearly compare the accessibility proxy indicators, we still need to calculate for each category.

Given the huge number of results that would be obtained if the proxy indicators of each green space were outputted, merging and outputting the indicator values of the same type of green space would be a more suitable choice.



Looking at the influence range of urban green spaces, the distribution of urban green spaces across Sheffield is relatively uniform. There is not a particularly noticeable regional concentration in terms of spatial distribution. However, small urban green spaces, which are smaller in area, make up the majority, while there are fewer large urban green spaces.

From the table above, apart from public parks or gardens, which occupy a larger area, the total area of other types is very similar. Therefore, with relatively close areas, the heat map reflects the population distribution characteristics in Sheffield. The city center and surrounding areas have a higher population concentration, increasing service pressure on urban green spaces.

The accessibility proxy indicator values in the table reflect the supply and demand relationship of various green spaces. The larger the indicator value, the greater the demand, and vice versa.

In summary, this reflects the issue of spatial fairness of urban green spaces in Sheffield. Although many places in Sheffield have access to green spaces, there is a shortage of large and high-quality green spaces. On the other hand, smaller, lower quality green spaces are more readily available, but these green spaces may not provide the greatest potential health benefits. And these areas are more concentrated in the city center, where increasing green space supply faces challenges. In already developed urban environments, creating or expanding green spaces may be difficult (Mears et al., 2019).

II. Are there similar spatial characteristics between commuting and economic activity patterns in England?

Dataset:

UK Census 2011: Location of usual residence and place of work by method of travel to work

Google night satellite image

3. Data preprocessing

This dataset contains the coordinates of the start and end points and the count of flows. The data is complete, with no missing values, and can be used directly.

4. Visualization

4.1 Reasons for making

The brightness of nighttime lights is often used as an indicator to measure the level of economic activity in an area. This is because light is usually highly correlated with human activities, especially commercial and industrial activities. Generally speaking, the brighter the light, the more active the economic activities in the area, and thus the higher the economic level may be (Elvidge et al., 2012).

Nighttime light data (also known as nighttime light images) is frequently used by researchers to study economic development, population distribution, and urbanization. Since all economic activities involve human participation, this report attempts to explore the relationship between the spatial characteristics of these two factors.

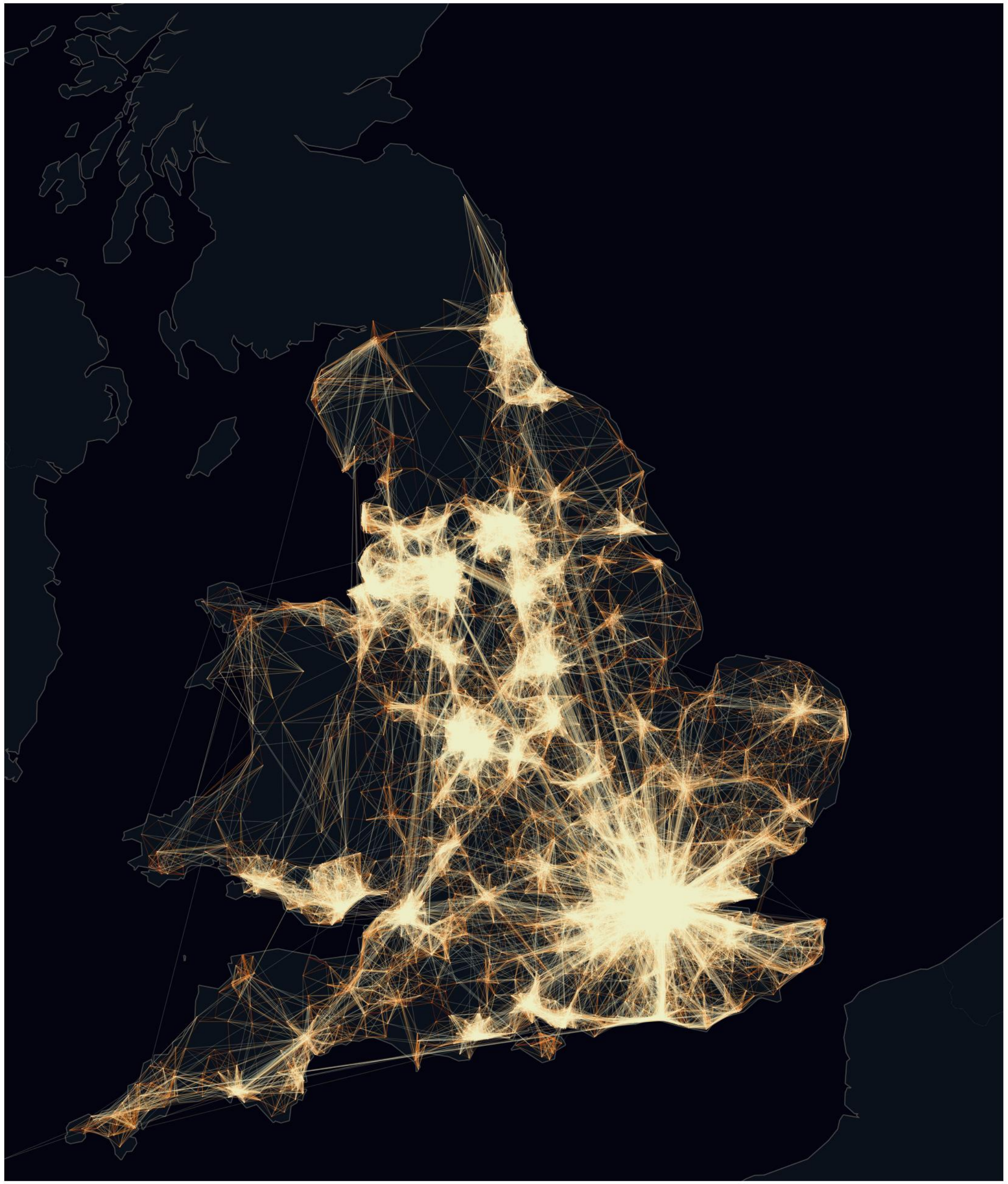
4.2 Making process

Import the CSV file and create point files for residences and workplaces respectively based on coordinates. Since they have the same index, line segments can be generated directly by using x, y to line based on coordinate points, and then the line colors can be graded according to flow data.

The reason for choosing to generate straight lines instead of arcs or Bézier curves is because the collected data does not describe the commuting method of the research object, so there is no basis to simulate possible actual commuting paths. In addition, this connection is just to reflect the relationship between the two places, so a more intuitive and simpler form like a straight line is used.

In order to achieve better visual effects to observe spatial features, two world maps are created, and the differentiation of land and sea is achieved in one layer with inverse polygons. Add glow effect to the flow line created earlier.

Import the night light satellite map in the geo-reference tool, and adjust the control points to achieve the correspondence of their spatial positions.



England Commuter Flow Map

England Night-time Satellite Map

Number of commuting flows

- 10 - 13
- 13 - 19
- 19 - 30
- 30 - 58
- 58 - 1906

0 50 100 150 200 250 km

England: A dual perspective of the daily commute and the night lights

Data Source:
Official Census and Labour Market Statistics.
Kepler.gl.and Google Earth.

4.3 Conclusion

Lighter colors and fewer traffic flows mean that people are working nearby, and these flows gradually outline the contours of each major city on the map. Darker colors and more traffic flows outside the city represent the economic activity connections between the cities.

The map shows that the range of commuting within some cities (light color range) has even exceeded the range of the city's nighttime light. This phenomenon indicates that job opportunities in the city outskirts are increasing, or the number of people commuting from the outskirts to the city is increasing. As this group grows, the city's outward expansion is inevitable. Therefore, this can reflect the city's future expansion trend to a certain extent (Song et al., 2017).

By comparing the commuting map with the nighttime light satellite map, a pronounced central city effect (Nelson et al., 2004) and clustering effect (Porter, 2000) can be found. Large cities, such as London, may have more job opportunities and more economic activities, thus attracting more people. London has active commuting within the city and attracts many people from surrounding cities, even as far away as Durham.

The clustering effect, such as Manchester, Birmingham, and Leeds, also has significant economic activity. This pattern is mainly due to the concentration of resources, infrastructure, and opportunities in these urban areas. Businesses usually position themselves where they can access a large pool of workers, robust transportation networks, and other businesses and services with which they can interact. Such a pattern is not unique to the UK, all developed countries exhibit this characteristic (Delgado et al., 2012).

Reference List:

Annerstedt van den Bosch, M. et al. (2015) ‘Development of an urban green space indicator and the Public Health Rationale’, Scandinavian Journal of Public Health, 44(2), pp. 159–167. doi:10.1177/1403494815615444.

Cetin, M. (2015) ‘Using GIS analysis to assess urban green space in terms of accessibility: Case study in kutahya’, International Journal of Sustainable Development & World Ecology, pp. 1–5. doi:10.1080/13504509.2015.1061066.

Delgado, M., Porter, M. and Stern, S. (2012) Clusters, convergence, and Economic Performance [Preprint]. doi:10.3386/w18250.

lvidge, C.D. et al. (2012) ‘The Night Light Development Index (NLDI): A spatially explicit measure of human development from Satellite Data’, Social Geography, 7(1), pp. 23–35. doi:10.5194/sg-7-23-2012.

Lee, A.C. and Maheswaran, R. (2010) ‘The health benefits of Urban Green Spaces: A review of the evidence’, Journal of Public Health, 33(2), pp. 212–222. doi:10.1093/pubmed/fdq068.

Marcelli, A., Fattorini, L. and Franceschi, S. (2022) ‘Harmonization of Design-based mapping for spatial populations’, Stochastic Environmental Research and Risk Assessment, 36(10), pp. 3171–3182. doi:10.1007/s00477-022-02186-2.

Mears, M. et al. (2019) ‘Understanding the socioeconomic equity of publicly accessible greenspace distribution: The example of Sheffield, UK’, Geoforum, 103, pp. 126–137. doi:10.1016/j.geoforum.2019.04.016.

Nelson, A.C. et al. (2004) ‘Urban containment and central-city revitalization’, Journal of the American Planning Association, 70(4), pp. 411–425. doi:10.1080/01944360408976391.

Porter, M.E. (2000) ‘Location, competition, and economic development: Local clusters in a global economy’, Economic Development Quarterly, 14(1), pp. 15–34. doi:10.1177/089124240001400105.

Páez, A., Farber, S. and Wheeler, D. (2011) ‘A simulation-based study of geographically weighted regression as a method for investigating spatially varying relationships’, Environment and Planning A: Economy and Space, 43(12), pp. 2992–3010. doi:10.1068/a44111.

Song, Y. et al. (2017) ‘The relationships between urban form and urban commuting: An empirical study in China’, Sustainability, 9(7), p. 1150. doi:10.3390/su9071150.

Wu, C. and Murray, A.T. (2005) 'A Cokriging method for estimating population density in urban areas', Computers, Environment and Urban Systems, 29(5), pp. 558–579. doi:10.1016/j.compenvurbsys.2005.01.006.