



# UCL

## **Centrality as A Process in Local Neighbourhoods:**

# **Exploring the Potential Impact of the Urban Multi-Type Centres and Physical Barriers on Centrality and the Socio-economic Condition of Communities**

by

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## **Declaration**

I, Zicheng Fan confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

## **Abstraction**

In the United Kingdom, high streets can be regarded as common centres that attract and gather people in urban space, while physical barriers such as railway tracks may restrict and weaken spatial connections. Both of centres and barriers are tangible spatial elements in urban planning context. On the other hand, the concepts of integration and choice developed in space syntax theory make it possible to measure the intangible centres, the multi-scale centrality structure in urban spatial network. Here arises an important question: what are the possible similarities and differences between the impact of multi-scale morphological centres based on integration measurement on urban community space and the impact of common centres and barriers? Based on the question above, this study attempts to take 457 communities in central and northern London as case studies, and measure the spatial relationship between the community and various adjacent centres and barriers with network analysis methods. On this basis, Multi-scale Geographically Weighted Regression(MGWR) and Binary Logistics Regression methods are employed to explore the possible impact of various centres and barriers on the socio-economic conditions of the local communities. The study found that the small-scale morphological centres based on their spatial integration are more likely to be associated with better socio-economic conditions, while the morphological centres with high integration on multiple scales, and high streets and primary roads, may have a negative impact on such conditions. Also, rail tracks , as a typical physical barrier, are generally found to have a negative impact on the socio-economic condition of the nearby communities. In addition, the study found that the high centrality spaces can be regarded as another type of spatial barrier, whose negative impact on adjacent communities and attraction to residents' daily activities may solidify residents' cognitive boundaries of everyday domains.

**Keyword :** Space syntax; Community; Centrality; Barrier; Network Analysis

## Table of Contents

|  |           |
|--|-----------|
| <b>Abstraction .....</b>   | <b>5</b>  |
| <b>Table of Contents .....</b>   | <b>6</b>  |
| <b>List of Figures.....</b>  | <b>8</b>  |
| <b>List of Tables .....</b>  | <b>10</b> |
| <b>Chapter 1. Introduction.....</b>  | <b>11</b> |
| 1.1 Background .....   | 11        |
| 1.2 Research Questions .....   | 12        |
| 1.3 Dissertation Structure.....  | 13        |
| <b>Chapter 2. Literature Review .....</b>  | <b>14</b> |
| 2.1 Introduction.....  | 14        |
| 2.2 Centres in Different Contexts .....  | 14        |
| 2.3 Relationship Between Centres and Communities .....   | 15        |
| 2.4 Relationship between Physical Barriers and Communities.....                                  | 17        |
| 2.5 Measurable Communities .....   | 19        |
| 2.6 Summary .....  | 20        |
| <b>Chapter 3. Methodology .....</b>  | <b>21</b> |
| 3.1 Introduction.....  | 21        |
| 3.2 Community Detection for M25 London .....   | 22        |
| 3.3 Multi-scale Centre Detection for M25 London.....   | 23        |
| 3.4 Spatial Relationship Measurement between Communities, Centres and Barriers .....             | 28        |
| 3.5 Measurement of Social-Economic Conditions of Communities.....                                | 31        |
| 3.6 Statistical Methods.....   | 32        |
| <b>Chapter 4. Mapping the Spatial and Social Attributes of Communities .....</b>                 | <b>35</b> |
| 4.1 Introduction.....  | 35        |
| 4.2 Deprivation Indices of Communities .....   | 35        |
| 4.3 Distance and Density Attributes of Communities.....  | 37        |
| 4.4 Summary .....  | 40        |
| <b>Chapter 5. General Impact of Different Centres and Barriers on Adjacent Communities .....</b> | <b>41</b> |
| 5.1 Introduction.....  | 41        |
| 5.2 Summary of the MGWR Results .....  | 42        |
| 5.3 Impact of the Multi-scale Morphological Centres .....  | 45        |
| 5.4 Impact of Highstreets and Primary Roads .....  | 51        |
| <b>Chapter 6. Centres and Barriers' Impact on Strengthening Social Differences .....</b>         | <b>57</b> |
| 6.1 Social Differences between Two Sides of the Track .....                                      | 57        |



|  |           |
|--|-----------|
| 6.2 Summary and Comparison of Binary Logistics Regression Models .....                                 | 60        |
| <b>Chapter 7. Discussion .....</b>   | <b>64</b> |
| 7.1 The Scale Difference of Morphological Centres' Impact .....  | 64        |
| 7.2 Integration and Function based Centres .....   | 65        |
| 7.3 Centres and Barriers' Compound Impact on Social Difference.....                                    | 65        |
| 7.4 Centres as Invisible Barriers .....  | 66        |
| <b>Chapter 8. Conclusion .....</b>   | <b>67</b> |
| 8.1 Findings & Innovation .....  | 67        |
| 8.2 Limitation.....  | 68        |
| 8.3 Future Research .....  | 68        |
| <b>References.....</b>   | <b>69</b> |
| <b>Appendix A. Data Source .....</b>   | <b>74</b> |
| <b>Appendix B. Details about MGWR Analysis.....</b>  | <b>76</b> |
| <b>Appendix C. Ranking of the Distance and Density Attributes of Communities .....</b>                 | <b>79</b> |
| <b>Appendix D. Complete Tables of 'Variables in the Equation' in Binary Logistics Regression... 82</b> | <b>82</b> |
| <b>Appendix E. Author's Previous Educational Project Report .....</b>                                  | <b>84</b> |

## List of Figures

Figure 2-1: Hypothesis about the Negative Impact of the Over-integrated Centre Structure

Figure 3-1: Methodology Framework

Figure 3-2: Intersection Points of Road Segments in M25 London

Figure 3-3: Community Detection with Louvain Method in M25 London

Figure 3-4: Normalized Angular Integration Value at Different Analysis Radius

Figure 3-5: Different Combinations of Foreground and Background Network  
of NAIN3200, NAIN1800 and NAIN800

Figure 3-6: Reclassification of London Streets Based on Overlapping Integration Maps at  
Different Scales

Figure 3-7: Centre Type A with High Integration only on R800 Scale

Figure 3-8: Centre Type B with High Integration on R800 and R1800 Scale

Figure 3-9: Centre Type C with High Integration on R800, R1800 and R3200 Scale

Figure 3-10: Distribution of Centre Type C and A in Local Areas

Figure 3-11: 6 Boroughs in Central and Northern London

Figure 3-12: 457 Communities Detected in the Boroughs

Figure 3-13: Centroids of Segments in 457 Communities

Figure 3-14: Centre Type A in the Extended Research Area

Figure 3-15: Centre Type B in the Extended Research Area

Figure 3-16: Centre Type C in the Extended Research Area

Figure 3-17: High Streets in the Extended Research Area

Figure 3-18: Primary Roads in the Extended Research Area

Figure 3-19: On the ground Rail Track in the Extended Research Area

Figure 3-20: Rail Stations in the Extended Research Area

Figure 3-21: A Sample of Distance Measurement in Local Area

Figure 3-22: Data Format Conversion for Deprivation Indices

Figure 3-23: Difference in Bandwidth of GWR and MGWR Analysis

Figure 4-1: Mapping of Deprivation Scores for Communities

Figure 4-2: Mapping of Distance to Integration Based Centres

Figure 4-3: Mapping of Distance to Function Based Centres

Figure 4-4: Mapping of Distance to Rail Tracks and Stations

Figure 4-5: Mapping of Density Attributes

Figure 5-1: Variables included in the MGWR Analysis

Figure 5-2: Regression Coefficients of Centre Type B in Income Deprivation Model

Figure 5-3: Regression Coefficients of Centre Type C in Income Deprivation Model

Figure 5-4: Regression Coefficients of Centre Type A in Crime Deprivation Model

Figure 5-5: Regression Coefficients of Centre Type C in Crime Deprivation Model

Figure 5-6: Regression Coefficients of Centre Type B in Barrier Deprivation Model

Figure 5-7: Regression Coefficients of Centre Type C in Barrier Deprivation Model

Figure 5-8: Regression Coefficients of High Street in Income Deprivation Model

Figure 5-9: Regression Coefficients of Primary Road in Income Deprivation Model

Figure 5-10: Regression Coefficients of High Street in Crime Deprivation Model

Figure 5-11: Regression Coefficients of Primary Road in Crime Deprivation Model

Figure 5-12: Regression Coefficients of High Street in Barrier Deprivation Model

Figure 5-13: Regression Coefficients of Primary Road in Barrier Deprivation Model

Figure 6-1: 106 Communities Selected for Detailed Research

Figure 6-2: 8 Groups Divided for Selected Communities

Figure 6-3: Ranking of Income Deprivation Group 1-4

Figure 6-4: Ranking of Crime Deprivation Group 1-4

Figure 6-5: Ranking of Income Deprivation Group 5-8

Figure 6-6: Ranking of Crime Deprivation Group 5-8

Figure 6-7: Samples of Binarized Variables in Logistics Regression

Figure 6-8: Variables Included in the Logistics Regression Analysis

### **List of Tables**

Table 5-1 Goodness of Fit of MGWR Models Corresponding to Deprivation Indices

Table 5-2 Bandwidth of Independent Variables in Different MGWR Models

Table 5-3 MGWR Mean Estimates of Coefficients

Table 5-4 MGWR Estimates of Coefficients Corresponding to the Morphological Centres

Table 5-5 MGWR Estimates of Coefficients Corresponding to the Function-based Centres

Table 6-1 Variables in the Equations Corresponding to Crime Deprivation

Table 6-2 Variables in the Equations Corresponding to Living Environment Deprivation

Table 6-3 Variables in the Equations Corresponding to Other Deprivation Indices

## **Chapter 1. Introduction**

### ***1.1 Background***

Centres and barriers are a group of common binary concepts in urban study, which may have a complex impact on urban forms and social-economic conditions. Centres often point to the system's most attractive and active structures, while barriers are often associated with exclusion and limitations. In urban space, many physical objects can be classic representation of centres and barriers. For example, in urban planning and design scenarios, high streets can be a division in important local areas based on their commercial functions (Griffiths, Vaughan, Haklay, & Jones, 2008), while common physical barriers in cities can include railway tracks and rivers, which have a noticeable impact on urban traffic and road networks (Roberto & Hwang, 2015) and social conditions (Kramer, 2012; Mitchell, & Lee, 2014).

On the other hand, the concept of integration developed in space syntax theory makes it possible to quantitatively measure urban space's centrality (Hillier & Hanson, 1984), and determine to what extent space is integrated or isolated. Theoretical assumptions in space syntax such as foreground network and background network (Hillier, 1996) and centrality as a process (Hillier, 1999) clarify that the centrality of the urban spatial network is largely a morphological reflection of urban activities and a necessary condition for the formation of functional centres. On this basis, a morphological centre based on network structure is often directly used as an analogy of concrete centre areas in the interpretation of space syntax analysis. However, considering the significant differences between the two in terms of their composition and definition principles, whether there is a clear corresponding relationship between the morphological structure based on integration and the functional centres and physical barrier in urban space remains to be further defined. Besides, the similarities or differences between the integration-based centre's impact and the impact of other traditional centres or barriers on urban space is an area that requires further study and clarification.

Questions above are also observed in a previous educational project by the author, about centrality's impact on communities along railway tracks (Fan, 2021). This study preliminarily found that space with high integration on multiple scales may have a significant negative impact on the income and crime deprivation indices of adjacent communities and the rail track as a physical barrier may exacerbate this negative impact to a certain extent. However, limited by the sample size, the universality of the findings could not be verified, and the highly integrated spaces found in the above-mentioned project commonly coincided with the

functional centres of high streets. Thus, it is unknown whether there are differences in the role of different types of centres and to what extent differences exist.

According to the preliminary findings and questions, this study can be regarded as an extension of previous work. Firstly, based on classical space syntax analysis, this study hopes to develop a method to accurately extract urban multi-scale morphological centres according to the distribution characteristics of centrality in urban networks. On this basis, there is an attempt to measure the spatial relationship between urban communities and morphological centres, functional centres and physical barriers in this study. This study plans to utilise a large sample to study the general impact of various centres and physical barriers on the socio-economic attributes of the community and the differences in the impact of different types of centres. Finally, this study aims to verify the relationship between the centrality structure in urban networks and the concrete centre and barrier areas in urban spaces, so as to reduce ambiguity in the interpretation of space syntax analysis.

## ***1.2 Research Questions***

The main purpose of this study is to explore the general impact of centrality on urban space and to verify the relationship between the centrality structure in urban networks and the concrete centre and barrier areas in urban spaces. The core question of the research is: what is the potential impact of the integration-based centre, the functional centre and the physical barrier on the social-economic conditions of communities? The following sub-questions have been identified to answer the overarching research question at different stages:

1. How can the centre and community areas be defined and detected in urban spaces?
2. How can the spatial relationships between local communities and different nearby centres and barriers be quantitatively measured?
3. What are the possible differences of the impact of centres defined at different spatial scales?
4. What is the possible impact of the centres identified by spatial centrality and by function centres on nearby communities?
5. What is the possible role of urban physical barriers in shaping the impact of different types of centres?

### ***1.3 Dissertation Structure***

The dissertation is structured as follows. Chapter 1 introduces the reasons why this study was undertaken, and its core research questions. In Chapter 2, essential concepts related to the research questions are explained, together with the previous finding of research on centres, barriers and their possible impacts on communities. Chapter 3 introduces the methods to define the spatial relationships between communities, centres and barriers and the statistical tools used to test the correlation between the spatial relationships and communities' socio-economic conditions in this study. Chapter 4 maps and introduces communities' socio-economic conditions and spatial relationships with centre and barrier elements nearby. Chapter 5 outlines the result of the MGWR analysis and the findings of the general impact of centres and barriers on communities. On this basis, Chapter 6 describes the findings from binary logistics regression and further discusses the roles of different centres in areas near railway tracks. Then, Chapter 7 discusses and summarises the significant patterns of centres and barriers' impact and attempts to answer the research questions of this study. Chapter 8 is a conclusion and review of the dissertation and also presents the potential of future research in this area.

## **Chapter 2. Literature Review**

### ***2.1 Introduction***

In this literature review, concepts of centrality and centres in different contexts will be defined, including centrality in network science and space syntax theory, as well as the concepts of function-based central areas or streets. On this basis, the chapter further discusses the impact of centrality, centres and physical barriers on community lives, as well as the interactions between centres and physical barriers found in previous studies. At the end of this chapter, the main hypotheses of this study are put forward for further testing.

### ***2.2 Centres in Different Contexts***

This research focuses on the impact of morphological and functional centres on communities and their possible relationship with physical barriers in a city. On this basis, centrality and the centre structure can be defined in two different contexts: (1) in the network context and (2) in the urban planning context.

#### ***2.2.1 Centrality in Network Analysis and Space Syntax Theory***

Centrality was initially a concept related to a series of structural indicators of network with its origin in social network analysis (Newman, 2010). There are some well-applied centrality indicators, such as degree centrality (Freeman, 1978), closeness centrality (Bavelas, 1950) and betweenness centrality (Freeman, 1977), which indicate the importance or cohesiveness of the local or global structure within a network.

In space syntax theory, centrality as a theoretical concept of space and society has been greatly expanded. Spatially, centrality can be regarded as a property that a street obtains in connecting with other streets. Typical centrality algorithms in social network analysis were absorbed and further developed as the measurement of the street network, namely connectivity, integration and choice (Hillier, 1996). Functionally, spatial concentration of various types of urban activities at different scales can be regarded as the embodiment of centrality. Hillier (ibid.) proposed the concept of the foreground and background network, pointing out that the foreground network formed by the natural coexistence of centres at various scales undertakes the main functions and activities of the city. Besides, the centrality of urban activities is also expressed as a spatially led process based on network centrality. “At all levels of the hierarchy, centres grow and fade, often in response to changing conditions quite remote from the actual



centres” (Hillier, 1999, p.109). The close relationship between centrality and various activities makes centrality pervasive across the urban network (Hillier, 2009). In conclusion, centrality can be regarded as a cumulative structure in the social or spatial network. Especially in a street network, centrality reflects the composite property of street morphology and function.

### *2.2.2 Centres Defined in Function and Planning Context*

In the field of urban planning, there are different perspectives about centrality and centre structure. The centre can be regarded as a concrete area with clear boundary or location, which undertakes specific functions in the urban system, such as the Central Business District (CBD) and traditional markets and commercial areas. In the United Kingdom, the high street is typically a function-defined centre indicating the location of the primary commercial street of towns or cities (Carmona, 2015, p.3). According to Griffiths, Vaughan, Haklay, and Jones (2008, p.1155), the high street can be regarded as a complex socio-spatial entity that carries social stability and local identity, associated with the presence of a wide variety of small local shops, and helps ensure easy accessibility to everyday services for pedestrians. According to these definitions, there is a possibility of spatial coincidence between the high street and high centrality street, and their relationship can be further discussed. Specifically, Griffiths et al. (2008, p.1159) argued that high streets in Britain are often described as "unplanned central places" and are characterised by their roles as local attractors of activities. This is consistent with the attraction and gathering characteristics of high centrality streets to pedestrian movement in the natural movement theory of spatial syntax (Hillier et al., 1993). Considering the similarity, high centrality streets may be regarded as potential high street areas and other types of urban centres or morphological substitutes to a certain extent, although there are still many differences. This hypothesis will be further tested in the following research.

## ***2.3 Relationship Between Centres and Communities***

### *2.3.1 Foreground and Background Network*

In space syntax, the relationship between centre and community can firstly be extended to the relationship between urban foreground and background network. On the one hand, Hillier (2009) summarised the relationship between the foreground network and economic sustainability and the background network and social sustainability. It was argued that the sustainability of cities relies on the positive interaction among environment, economy and society and a balanced constitution of a dual network. On the other hand, Tao Yang explains

the interaction between foreground and background network from the perspective of multi-scale and network structure. A clear boundary between the dual network often depends on the observation scale (or the analysis radius). Due to the mixing of urban activities, foreground and background networks at different scales overlap with each other to have an impact, and form a fuzzy boundary to distinguish the specific network (Yang & Hillier, 2007; Hillier, 2009). To sum up, the foreground and background network corresponding to the centre and community are interdependent in the urban system and may have a diversity of relationships due to their fuzzy boundaries on multiple scales.

### *2.3.2 Centrality and Community Performance*

In social-economic topics, centrality often has a dual impact on the community. On the one hand, the existence of urban centre streets has been found to be correlated with criminal activities. Specifically, many studies provide evidence that mixed land use in communities, especially a higher proportion of commercial use, is associated with a higher crime rate (Kinney, 2008; Browning, 2010). In crime pattern theory, mixed land use is thought to make the community more exposed to the activities of potential offenders (Brantingham & Brantingham, 1995, p.14). In this context, centres like high streets as the locus of commercial facilities are also regarded as a potential cause of crime and fear of crime. From the perspective of urban morphology, research based on centrality measurement also support these findings. For example, Summers and Johnson found (2017) that higher levels of integration and choice were associated with greater odds of a street segment containing at least one crime. Besides, a positive correlation was also found between crime activities and higher global integration (Baran, Smith, & Toker, 2007) and local integration (Nubani & Wineman, 2005), respectively.

However, the centrality and the diversity it provides may also be of positive significance to community safety and obviously plays a role in a flourishing city. Sohn (2016) revealed that not all commercial facilities are negatively related to community safety and grocery stores, restaurants, and offices compared with shopping centres have a positive role in decreasing residential burglary. This supports the advocacy of mixed land use in Eyes on the Street theory (Jacobs, 1961) and Crime Prevention Through Environmental theory (CPTED) (Cozens, Saville, & Hillier, 2005). In addition to the impact on crime, centrality and types of urban centres are closely related to economic sustainability, especially employment opportunities, public service and convenient infrastructures, which contribute to vitality and prosperity of urban space.

## ***2.4 Relationship between Physical Barriers and Communities***

The complexity of urban environment determines that there can be many different forms of spatial relationships between centres and communities. Furthermore, some physical barriers in a city, such as railway tracks, may play a prominent role in shaping their spatial relationships and interactions. Previous studies have revealed that physical barriers may affect community performance and the formation of centres, respectively.

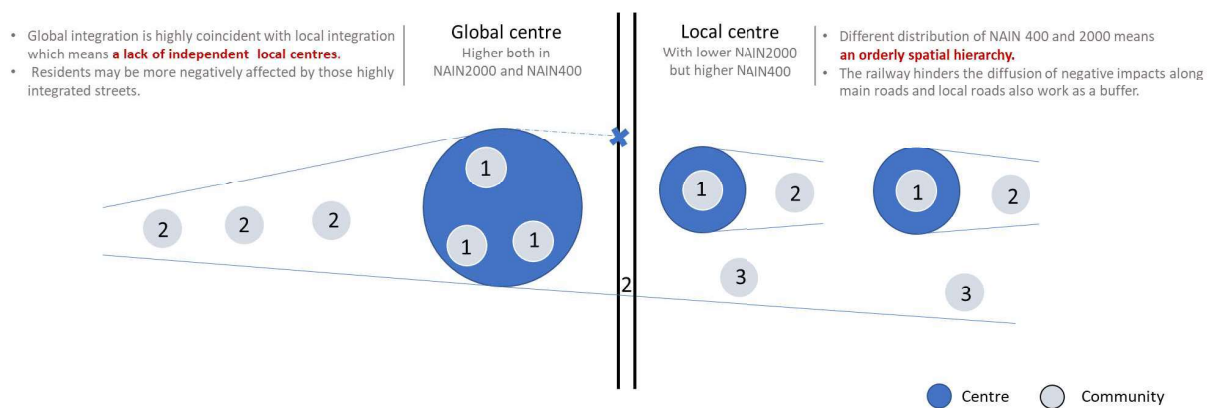
### *2.4.1 Physical Barriers' Impact on Local Difference*

The existence of physical barriers has been found relevant to local differences in social or economic conditions of communities. For example, Kramer (2012) compared the proportion of black people in different areas of Philadelphia and found a correlation between physical barriers and the local distribution of different ethnic groups. Another piece of research examined the correlation between physical barriers that coincide with a community boundary, such as rivers, parks, railways and highways and socio-economic difference using the Scottish Index of Multiple Deprivation (SIMD) in Glasgow (Mitchell & Lee, 2014). In this study, it was found that there was a significant association between deprivation differences and rivers, and physical barriers join to constitute the dividing line of different socio-economic conditions. In general, the physical barrier that creates spatial separation may also lead to social differences.

### *2.4.2 Interaction between Physical Barriers and Centres*

As centrality measurements in space syntax theory, integration and choice are commonly used to detect possible isolated structures in urban spaces and physical barriers have been found correlated with isolation and adverse socio-economic conditions. For example, in *Space is the Machine*, Hillier (1996, p.132.) picked out three housing estates around King's Cross in London with segregated lines in a global integration map. These estates become problematic due to their complex inner structure and their lack of connection with the global network. Moreover, the physical barriers surrounding King's cross play an essential role in reducing connections. In addition, Bolton (2018) applied space syntax measurement to identify the long-term segregation impact of London railway terminals in urban space. A decrease in integration and choice value was observed in neighbourhoods with the development of most terminals (Bolton, 2018, p354).

From the previous educational project (as listed in Appendix E) (Fan, 2021), there is an interesting phenomenon that the overlapping of global and local integration centres near a railway track are more likely to correlate with the adverse conditions of the surrounding communities, while single local centres play a positive role. This phenomenon can be more significant in communities with a higher built-up density. Thus, it is assumed that there is a compound impact of integration centres and barriers on urban space. Specifically, the narrow area along a railway track makes communities overly exposed to high centrality across different scales, which may result in a negative impact. However, there were only limited objects included in the research and the possible spatial coincidence between high street and integration centres in the research area makes it unclear as to which spatial elements play a more significant role. The limitation of this previous study provides inspiration for this study to further explore different centres' roles in community life and their interaction with physical barriers.



**Figure 2-1:** Hypothesis about the Negative Impact of Over-integrated Centre Structures

(Source: Fan, Z. (2021). *The Life along the Tracks - A Study of the Railways' Impact on Spatial and Socio-Economic Conditions of Communities Along the Lines*, BARC0026: Analytical Design Research Project (ADRP). University College London. Unpublished essay.)

## ***2.5 Measurable Communities***

The literature review above has mainly discussed the impact of centres and barriers on general community space. However, in research practice, it is often necessary to define the community as a continuous area to accurately analyse the social and spatial conditions. A series of attempts have been made to identify the continuous local area corresponding to social significance and the community boundary.

Early studies on space syntax revealed that integration is highly correlated with pedestrians' movement patterns and this correlation may vary according to the analysis boundary (Hillier *et al*, 1992). It is assumed that a boundary with consistent configurational features and maximise the correlation can be relevant to the local area of community. Dalton developed the hypothesis and argued that community spaces can be measured directly based on global continuity (homogeneity) and local identifiability (heterogeneity), without reference to social records (Dalton, 2011, p.44). Based on the axial analysis in space syntax, Dalton developed a community measurement using point intelligibility and point synergy (Dalton, 2007). Yang and Hillier (2007) proposed the Embeddedness (EMD) measurement using node count density differences between different radius in segment analysis. Both of these studies provide a descriptive method (Law, 2018, p.72), which were effective in testing the association between the spatial network and a named area in London but failed to find and extract continuous and flexible communities with specific sizes.

In contrast, the community detection algorithm in network analysis provides a different view. Girvan and Newman (2002) introduced the modularity method to identify communities with internal continuity. As a grouping method, it deletes the edges with the highest betweenness (choice) in a graph step-by-step to pick out well-connected communities with the highest modularity. Blondel *et al.* developed the principle and introduced Louvain method to realise the rapid identification of large-scale networks (Blondel *et al.*, 2008). Law (2018) applied Louvain method to the segment-based community detection of urban streets and proved its accuracy and reliability in reflecting community relations. Although Dalton believes that modularity-based methods tend to exclude roads with high choice from the community, resulting in incompleteness of the identified boundary (Dalton, 2011, p.115), this feature allows the free discovery of new communities of flexible size based on the network structure, beyond the restriction of traditional descriptive methods. In general, the community detection algorithm can be an ideal method in exploring and defining communities in urban road network.

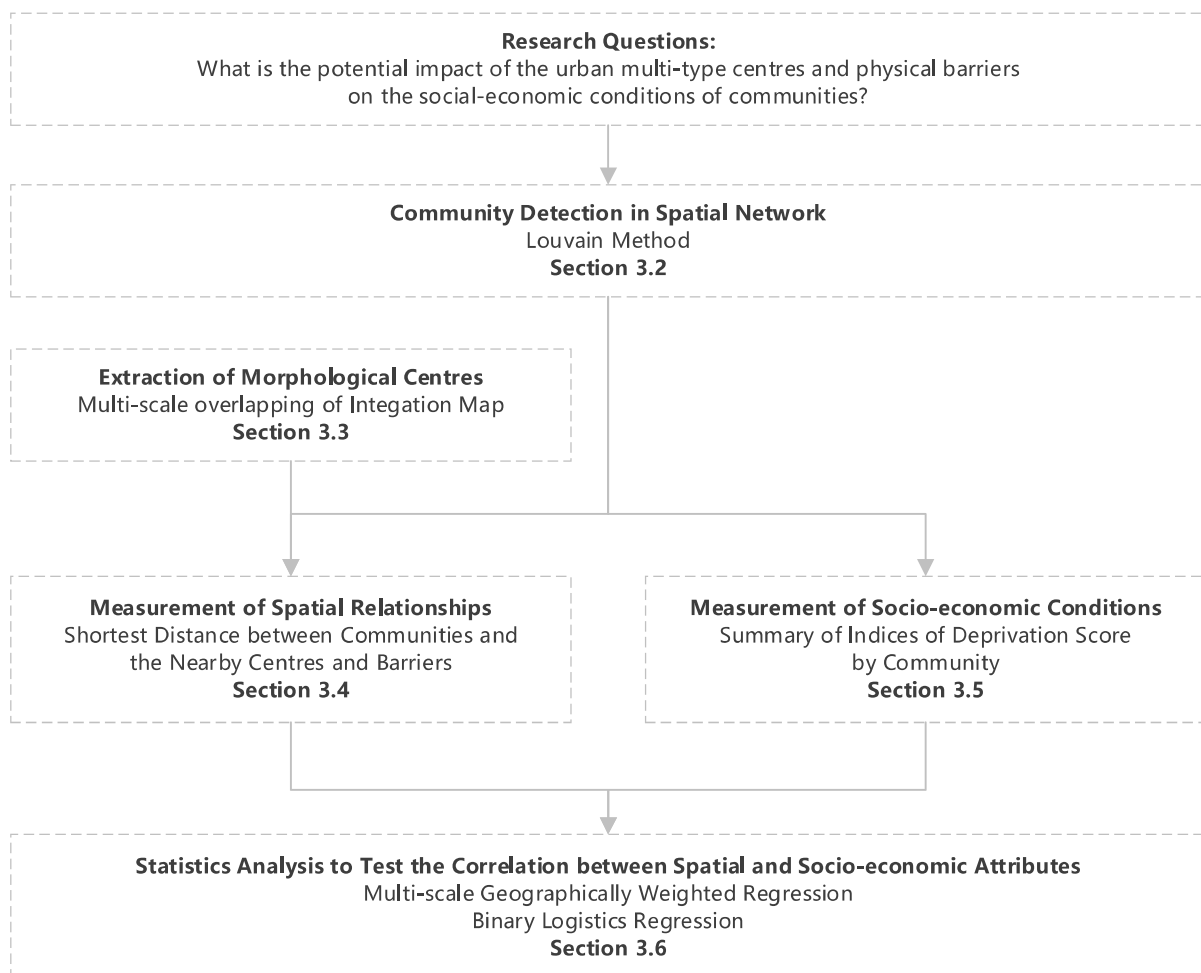
## ***2.6 Summary***

This literature review has introduced the concepts of centrality in network analysis and space syntax contexts and the function-based centre of high streets. Also, it has summarised previous findings on the possible impact of the above-mentioned centres and urban physical barriers on the community, as well as the interactions between them. Despite research of the respective effects of different centres and barriers, there is a lack of systematic comparative study on the roles of these spatial elements. In addition, the potential compound effect of centres and barriers on communities requires further verification. Thus, this study will analyse and compare the impact of integration-based centres, function-based centres and urban physical barriers on communities in the same framework and further discuss the internal relationship between the centrality of urban spatial networks and the concrete centres and barrier areas in a city.

## Chapter 3. Methodology

### 3.1 Introduction

As in Figure 3-1, in order to explore the potential impact of centres and barrier on communities, this research starts from detection of segment-based communities in the M25 London road network, which is used as the basic unit for following analysis. On this basis, there is an attempt to distinguish the cumulative intensity of spatial centrality on multiple scales, based on the overlapping of integration map. Spatial data of other centre and barrier elements are also collected. Then, shortest distance from communities to the nearest centres and barriers can be calculated to quantitatively define their spatial relationships. With the social deprivation index corresponding to the communities and a variety of statistical tools, the research further explores the potential impact of centres and barriers on communities' socio-economic condition.

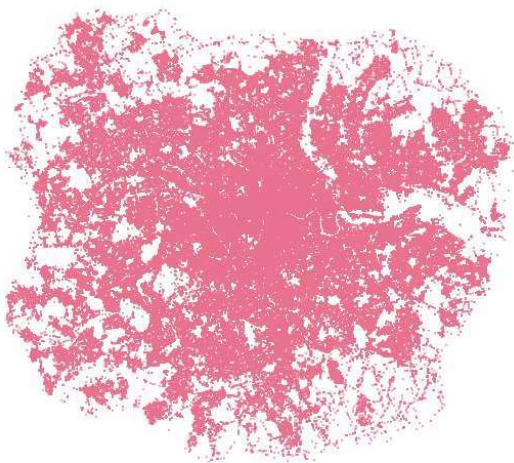


**Figure 3-1:** Methodology Framework

### 3.2 Community Detection for M25 London

#### 3.2.1 Convert the Spatial Network into Graph

To detect the community structure in the urban road network, the first is to convert the spatial network into an analysable graph, composed of nodes and links. Considering that various types of socio-economic data in follow-up analysis rely on the road segments to summarise. The road segments are regarded as nodes while the road intersections are links. On this basis, the ‘line intersection’ tool in QGIS can be used to calculate the intersection relationship of any two segments in two groups of spatial networks and generate corresponding intersection points, as in Figure 3-2(a). A corresponding graph can be generated by using the intersection relation recorded in the points’ attribute table, as shown in Figure 3-2(b).



(a). Mapping of Intersection Points

|   | Ref | Ref 2 |
|---|-----|-------|
| 1 | 0   | 1     |
| 2 | 0   | 3508  |
| 3 | 1   | 0     |
| 4 | 1   | 2     |
| 5 | 10  | 9     |
| 6 | 10  | 11    |
| 7 | 10  | 3014  |
| 8 | 100 | 99    |

(b). A Sample of Reference Pairs of Intersected Segments

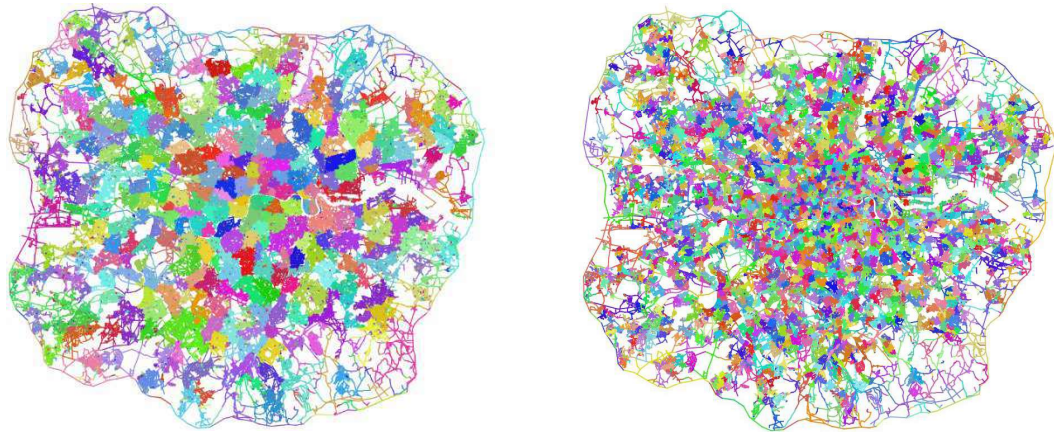
**Figure 3-2:** Intersection Points of Road Segments on the M25 London

#### 3.2.2 Louvain Method for Community Detection

The identification of community structures in large-scale urban spatial networks is based on the Louvain algorithm (Blondel et al., 2008). This algorithm is especially suitable for fast processing large-scale networks. The selection of this method refers to Stephen Law's research on street based local area (ST-LAs) (Law, 2018). As an improved modularity method, the Louvain algorithm searches communities from a single node at the bottom of the graph and gradually discovers larger communities in an upper layer. In this process, smaller communities are gradually merged into a larger one. The results of community detection with resolution = 1 and resolution = 0.04 as samples are shown in Figure 3-2. The resolution parameter constrains



the running time of the model and the number of communities merged, which further affects the size of the community. The larger the resolution parameter, the larger the size of the identified community.



(a). Result with Resolution = 1

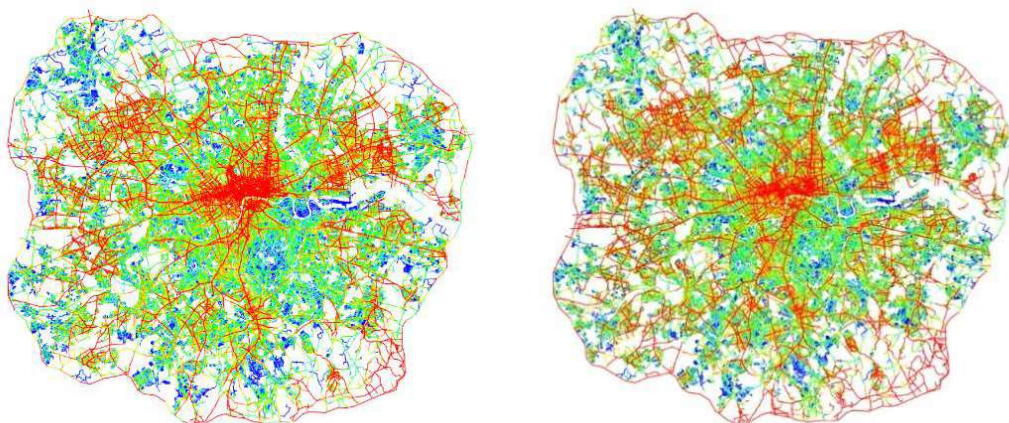
(b). Result with Resolution = 0.04

**Figure 3-3:** Community Detection with the Louvain Method in the M25 London

### ***3.3 Multi-scale Centre Detection for M25 London***

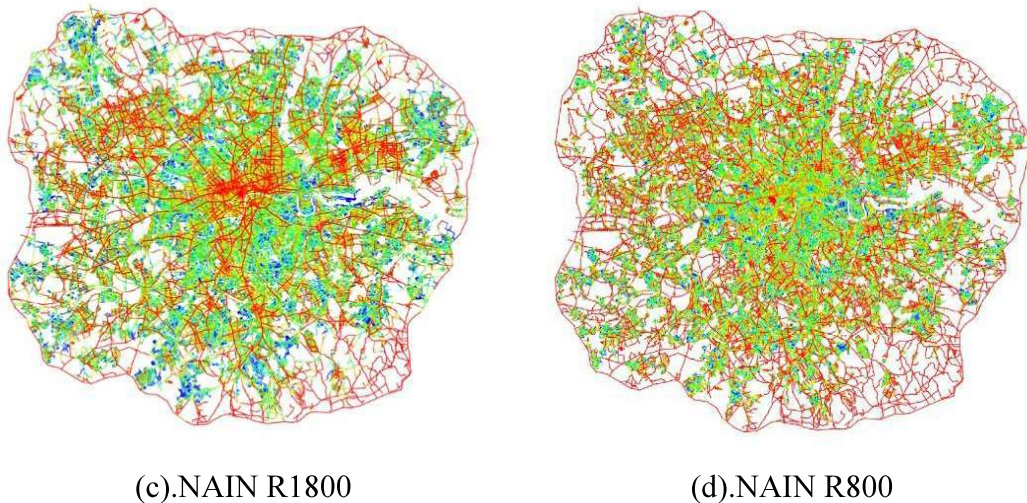
#### ***3.3.1 Integration Analysis***

Normalised Angular Integration (NAIN) (Hillier, Yang, & Turner, 2012), an improved integration calculation to balance density difference across different areas, was calculated first at different scales to identify the pervasive morphological centres from the local community to the busiest commercial area (Figure 3-4).



(a).NAIN R5000

(b).NAIN R3200



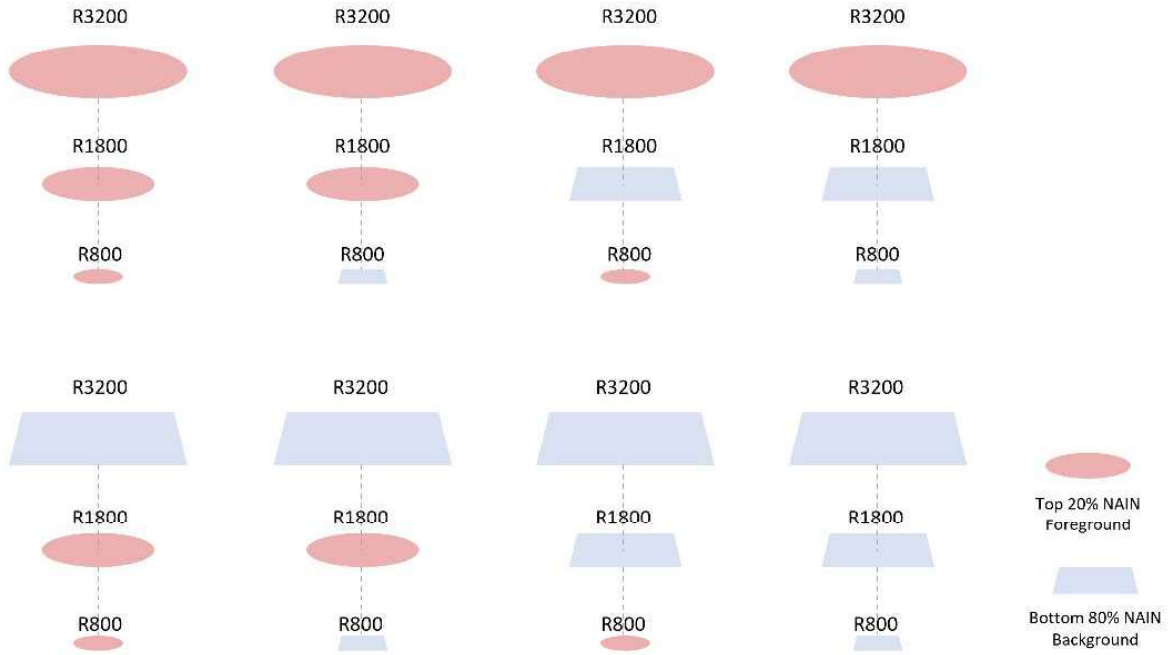
**Figure 3-4:** Normalized Angular Integration Value at Different Analysis Radius

### 3.3.2 *Overlapping of the Multi-scale Integration Map*

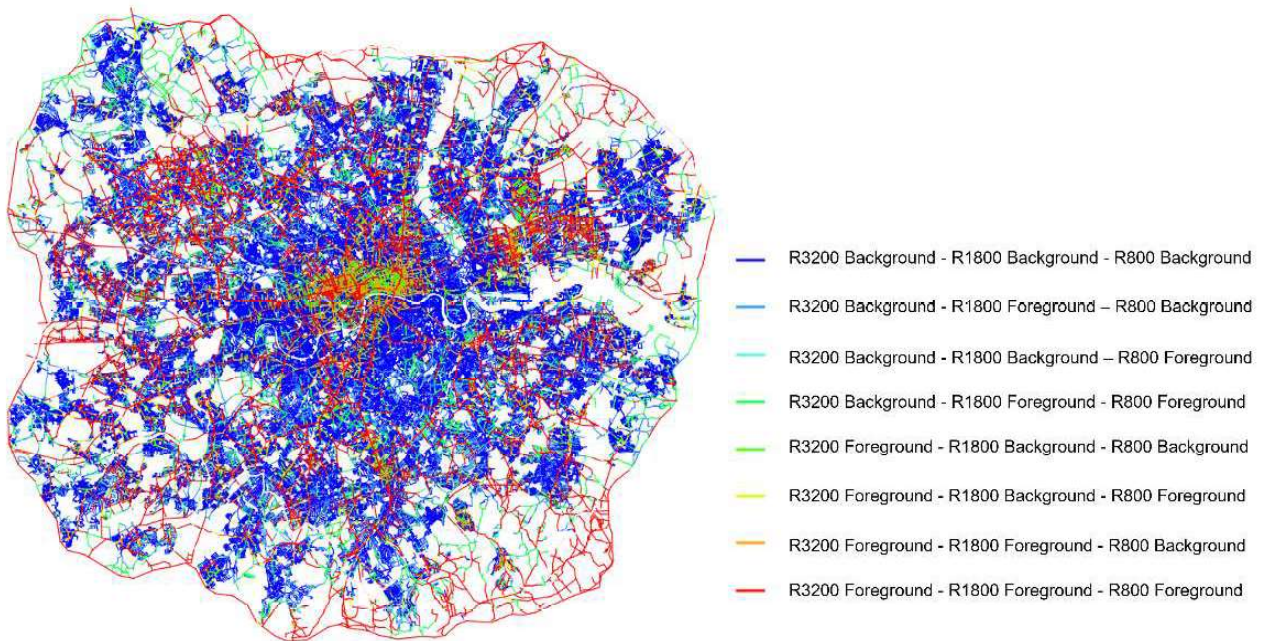
Considering that the integration centres at different scales are changeable in location and size and are likely to overlap with each other, it is necessary to define the multi-scale centrality characteristic of the specific area first. For example, some high streets in residential areas show high integration at a local scale, but not be involved in a global centre because of its location in the urban fringe. In contrast, some streets keep a stable higher integration across the different scales, which indicates their very different properties from other streets.

With a proper scale difference, NAIN 3200, NAIN1800 and NAIN800 values were selected as three typical centrality indicators of global, medium and local scales to reclassify the streets in M25 London. Traditionally, the top 10% of integration values are used for the integration core (Hillier & Hanson, 1984), but in this research a looser limit of 20% was applied to find and group the relative continuous core area. On this basis, the integration maps of three different scales overlapped with each other for the reclassification of the streets. As shown in Figure 3-5, there are 8 types of combinations. The results of the street reclassification are shown in Figure 3-6.





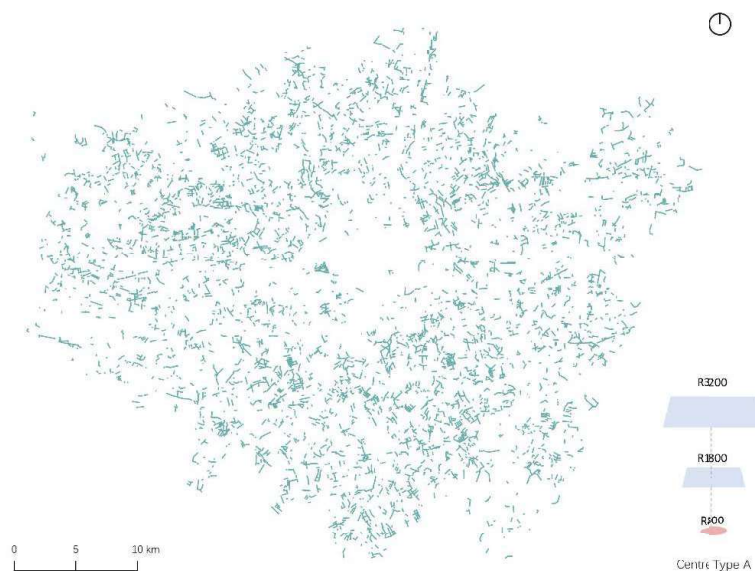
**Figure 3-5:** Different Combinations of Foreground and Background Network of NAIN3200, NAIN1800 and NAIN800



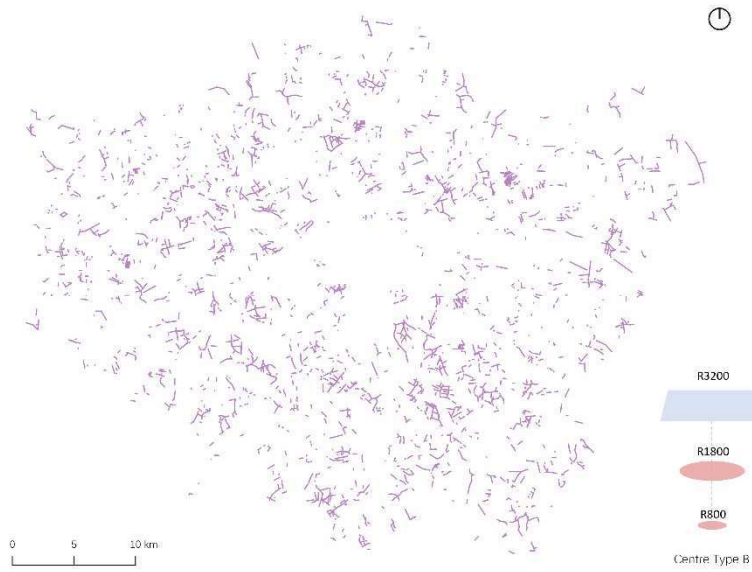
**Figure 3-6:** Reclassification of London Streets Based on Overlapping Integration Maps at Different Scales

### 3.3.3 Extraction of the Multi-scale Integration Centre

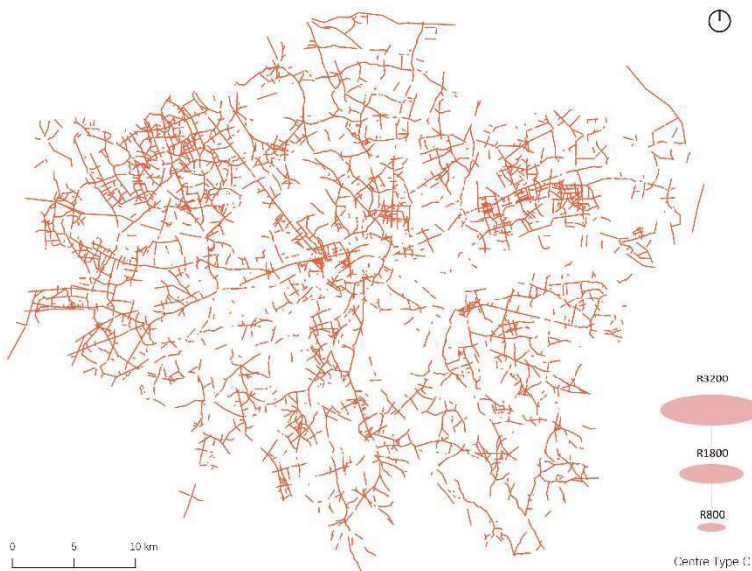
From the re-classified map, streets with higher integration only on the local scale (R800) can be extracted as Centre Type A (Figure 3-7). Similarly, streets with higher integration on both the local and medium scale are defined as Centre Type B, and Centre Type C for full-scale higher integration streets (Figure 3-8 & 3-9). The three types of centres can be regarded as typical morphological centres representing the scale difference and with location defined. Figure 3-10 shows an example of the distribution difference of Centre Type C and A in local areas. Further comparison can be carried out between the functional centres and the morphological centres.



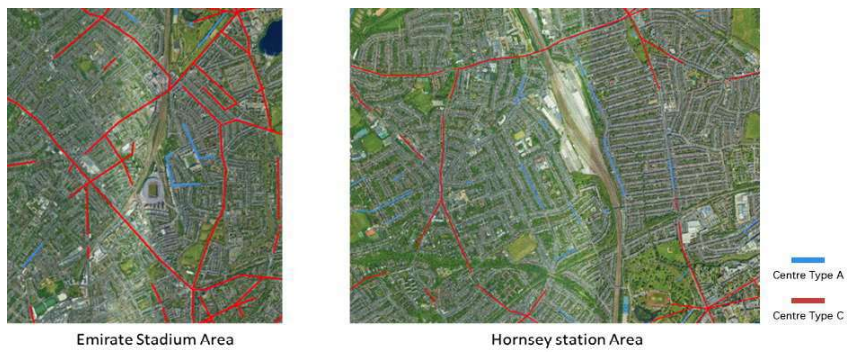
**Figure 3-7:** Centre Type B with High Integration on R800 and R1800 Scale



**Figure 3-8:** Centre Type B with High Integration on R800 and R1800 Scale



**Figure 3-9:** Centre Type C with High Integration on R800, R1800 and R3200 Scale

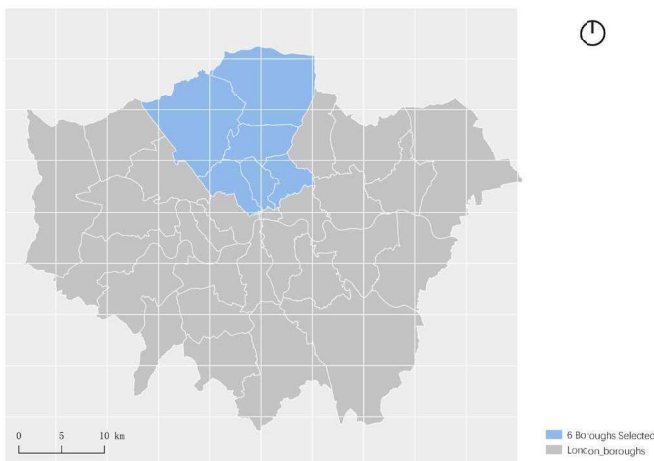


**Figure 3-10:** Distribution of Centre Type C and A in Local Areas

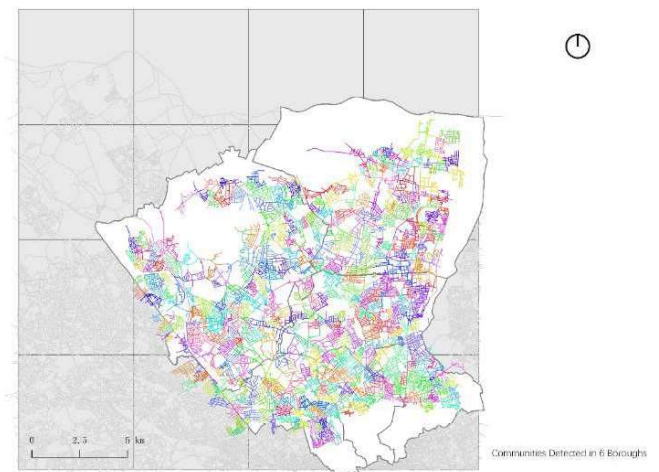
### ***3.4 Spatial Relationship Measurement between Communities, Centres and Barriers***

#### ***3.4.1 Research Areas and Selected Communities***

As in figure 3-11 & 3-12, 457 communities of 6 boroughs in central and northern London were selected as the research objects and an expanded area around the boroughs was applied to collect spatial data of centres and barriers closely related to the communities. Try to quantitatively define the spatial relationship between the 457 communities and their nearest spatial elements and calculate the household and road density characteristics of each community. The spatial elements in this study mainly include three morphological centres of different scales, the high street as functional centre, and rail tracks as a physical barrier. In addition, primary roads and rail stations are added as control variables, corresponding to high streets and rail tracks, respectively.



**Figure 3-11:** 6 Boroughs in Central and Northern London



**Figure 3-12:** 457 Communities Detected in the Boroughs

#### ***3.4.2 Measurement of Distance from Communities to Centres and Barriers***

With the network analysis module of ArcGIS, the spatial relationship is defined by calculating the shortest distance between edges of communities and their nearest spatial elements. Specifically, it is divided into four steps,

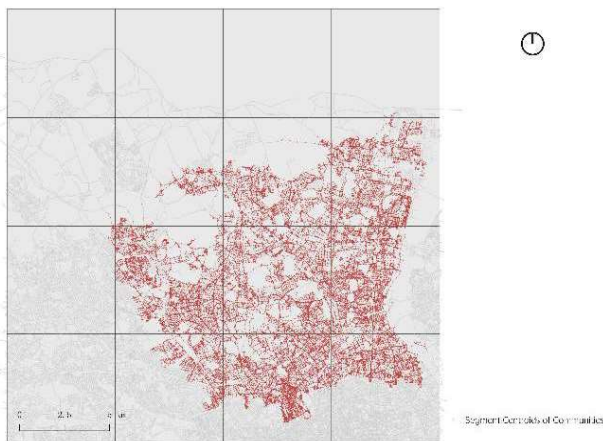
- (a) Extract the centroid of each street segment in communities as the source points,
- (b) Extract the sample points of various spatial elements as the target points,



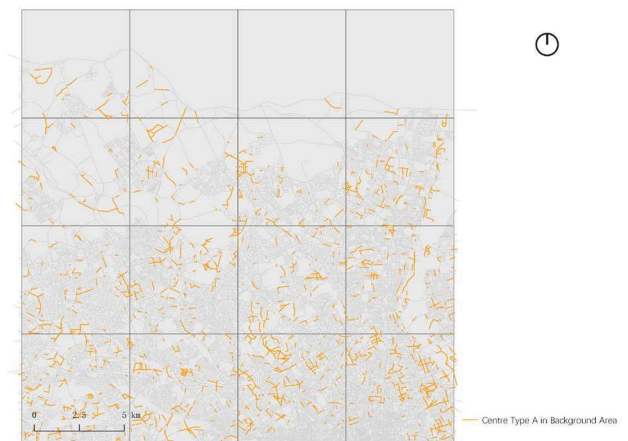
(c) Calculate the Dijkstra shortest<sup>1</sup> distances, from every source point to the closest target based on the ‘closest facility’ function (Algorithms used by the ArcGIS Network Analyst extension—ArcMap | Documentation, 2021)

(d) Summarize the mean value of the shortest distances by community.

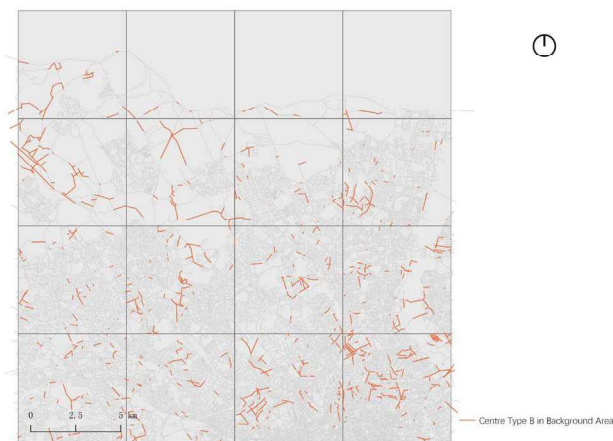
The distributions of origin and various destination elements are displayed as in figure 3-13 to Figure 3-20. The figure 3-21(a) & (b) show an example of the calculation results of the shortest path between each segment and the nearest rail station in the Emirates Stadium area.



**Figure 3-13:** Centroids of Segments in 457 Communities



**Figure 3-14:** Centre Type A in the Extended Research Area

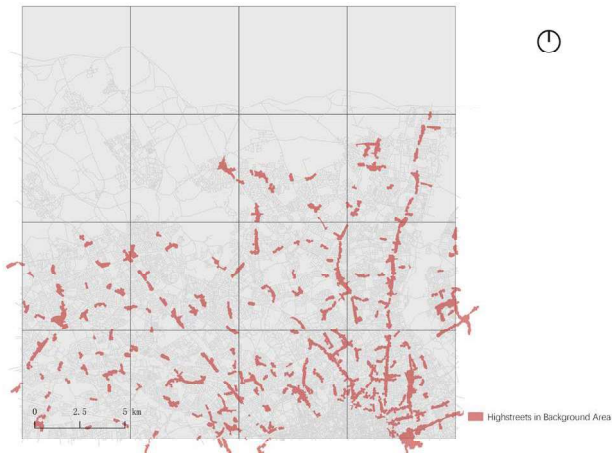


**Figure 3-15:** Centre Type B in the Extended Research Area



**Figure 3-16:** Centre Type C in the Extended Research Area

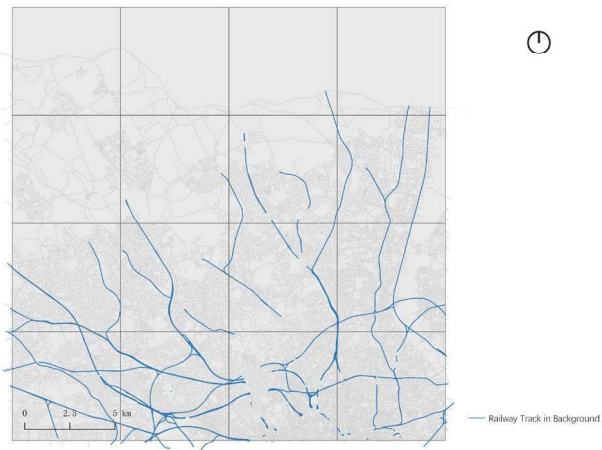
<sup>1</sup> Dijkstra's algorithm is a graph algorithm conceived by Edsger W. Dijkstra in 1956, for finding the shortest paths between nodes. Commonly the algorithm is applied in road networks graph to find shortest paths from the source to a given destination or to all other potential destinations. The algorithm is also applied in space syntax measurement of mean depth, thus included in other related measurements such as integration and choice (Hillier & Hanson, 1984).



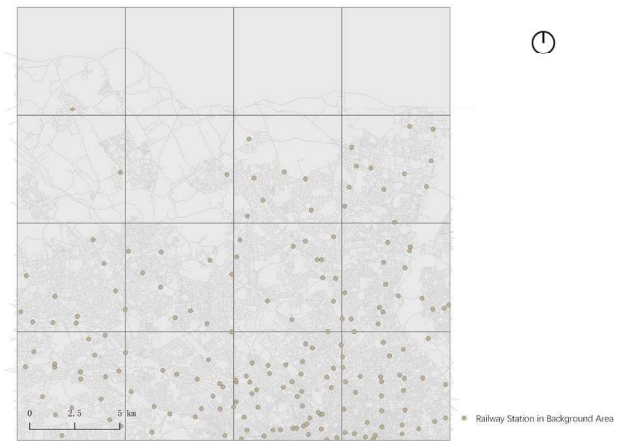
**Figure 3-17: High Streets in the Extended Research Area**



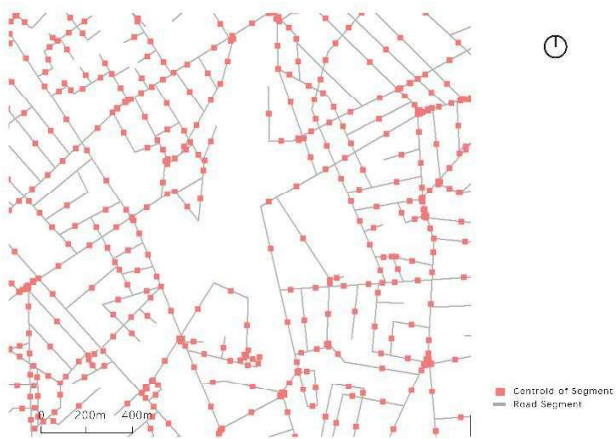
**Figure 3-18: Primary Roads in the Extended Research Area**



**Figure 3-19: On the ground Rail Tracks in the Extended Research Area**



**Figure 3-20: Rail Stations in the Extended Research Area**



(a). Centroids of the Road Segment as Origins



(b). Shortest Path to the Nearest Rail Station

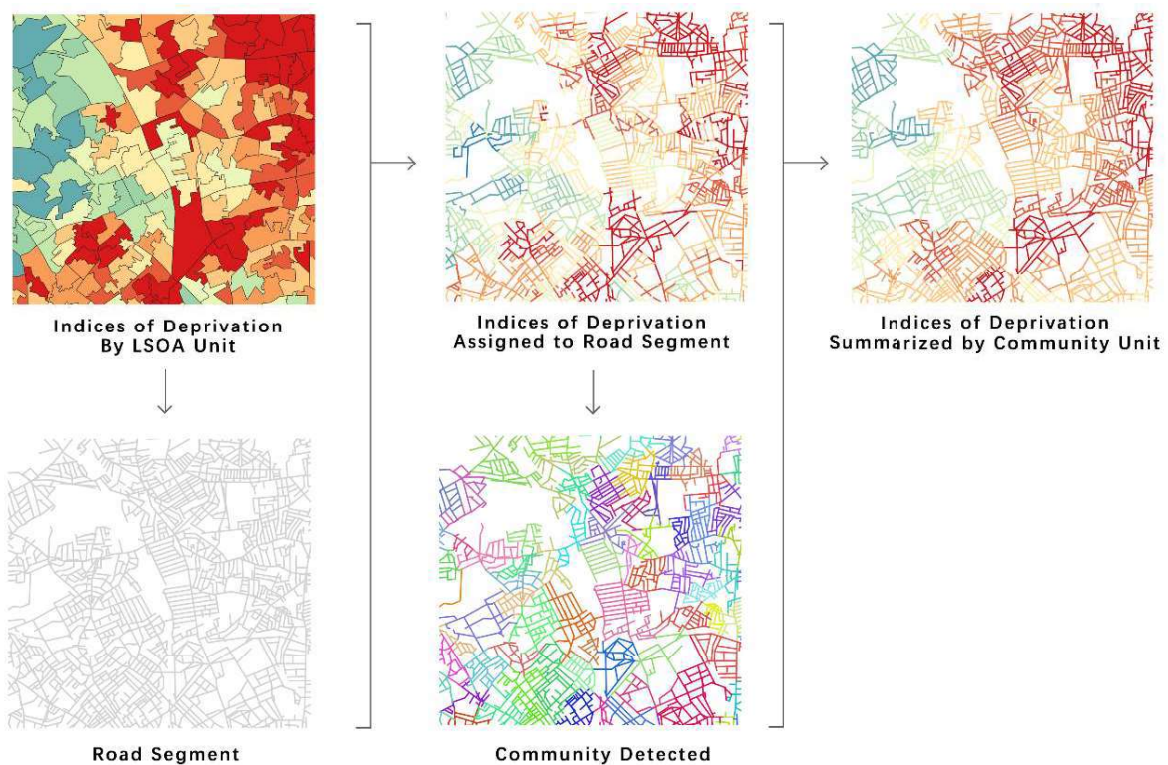
**Figure 3-21: A Sample of Distance Measurement in Local Area**



### 3.5 Measurement of Social-Economic Conditions of Communities

This study mainly used data from the English Indices of Deprivation 2019 (IoD2019) to characterise the socio-economic attributes of the communities (Ministry of Housing, 2019). The IoD2019 takes the Lower Super Output Area (LSOA) as the data statistical unit, calculates the regional attributes from eight deprivation indicators including income, employment and crime, and converts them into the global ranking and ranking score. Details of the IoD2019 are listed in Appendix A.

Considering that the communities detected above are the real objects of this study, it was necessary to change the summary carrier of IoD2019 data. The score of IoD2019 data was first assigned to the segments corresponding to LSOA units. On this basis, the mean value of the relevant score was further summarised by community. The lower the score, the better the relevant socio-economic conditions corresponding to the community.



**Figure 3-22:** Data Format Conversion for Deprivation Indices

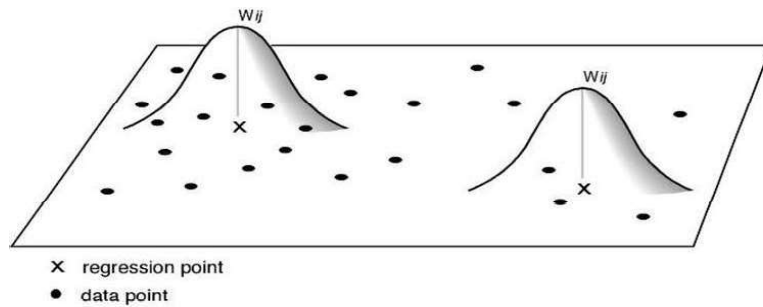
### **3.6 Statistical Methods**

The study adopted two statistical analysis methods to study the potential impact of various centres and barriers on the communities, and the mutual relationship between them.

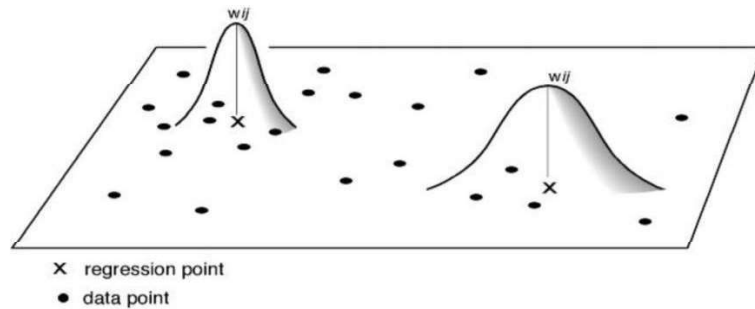
#### *3.5.1 Multi-scale Geographically Weighted Regression*

The first task in statistical analysis is to explore to what extent various centre and barrier elements may be related to the socio-economic conditions of communities in the study area, and what their general roles could be. Considering that local differences and spatial autocorrelation (Tobler, 1970) can be universal in geographical phenomena in complex urban areas, which are usually ignored by traditional regression models such as Ordinary Least Squares (OLS) (Fotheringham, Charlton, & Brunson, 1996), Multi-scale Geographically Weighted Regression (MGWR) was used to analyse the general impact of various spatial elements on the economic and social attributes of communities.

MGWR is an improved Geographically Weighted Regression (GWR) model developed by Arizona State University (Fotheringham, Yang, & Kang, 2017). Compared with the OLS model where independent variables are applied to explain the dependent variable in all samples by default, the GWR and MGWR models predict bandwidth for each independent variable to explain the geographical phenomena at a limited local scale (Fotheringham, Charlton, & Brunson, 1996; Fotheringham, Yang, & Kang, 2017). On this basis, the MGWR model further reveals the scale difference between different independent variables' impact, by predicting and fitting their different bandwidths, as in Figure 3-20. Analysis was carried out based on the MGWR 2.2 software (Oshan *et al.*, 2019). Taking the scores of various deprivation indices as dependent variables, respectively, the independent variable included the distance between the community and various centres and barriers as well as the road density and household number of the community.



(a). Same bandwidth for each independent variable in GWR analysis



(b). Unique Bandwidth each independent variable in MGWR analysis

**Figure 3-23:** Difference in Bandwidth of GWR and MGWR Analysis

(Source : Oshan, T. M. et al. (2019) *MGWR: A Python Implementation of Multiscale Geographically Weighted Regression for Investigating Process Spatial Heterogeneity and Scale*, *ISPRS International Journal of Geo-Information*, 8(6), p. 269. doi: [10.3390/ijgi8060269](https://doi.org/10.3390/ijgi8060269).)

### 3.5.2 Binary Logistics Regression

The second task in statistical analysis is to explore the possible interaction between communities and various spatial elements and attributes in specific spatial scenarios and phenomena. Based on the hypothesis in the literature review, the existence of railways may have a negative impact on the socio-economic attributes of the community. In addition, the coexistence of multi-scale integration centres and railway tracks may further amplify this impact and bring significant local social differences on both sides of the track. To test this hypothesis, multiple groups of communities close to the railway track were taken as case studies in this research. Binary logic regression was used to explore whether the existence of specific spatial attributes will enhance the possibility that the community has higher or lower deprivation level than other communities in the same group, so as to measure the correlation between spatial attributes and local social differences in the community. The analysis is carried out with SPSS 20.

Logistics regression is often used to model the probability of a category or event existing ('Logistic regression', 2021). On this basis, binary logistics regression is a simple model whose dependent variable only has two levels. Relative odds or odds ratio is the main parameter used to interpret the binary logistics regression model. Specifically, the odds ratios of independent variable 1 in event A means compared to the situation where variable 1 is not meet, the ratio of event A occurrence to non-occurrence, when independent variable A is meet (Tranmer & Elliot, 2008).

## **Chapter 4. Mapping the Spatial and Social Attributes of Communities**

### ***4.1 Introduction***

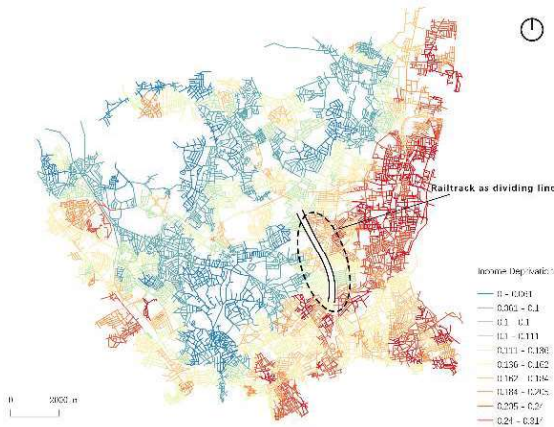
This chapter maps and introduces the socio-economic conditions of 457 communities, the spatial relationships between communities and various centres and barriers, and households and road density of communities. Among them, socio-economic conditions correspond to the distribution characteristics of 8 deprivation scores and the relationship between communities and adjacent centres and barriers is represented by the average of the shortest distance between them.

### ***4.2 Deprivation Indices of Communities***

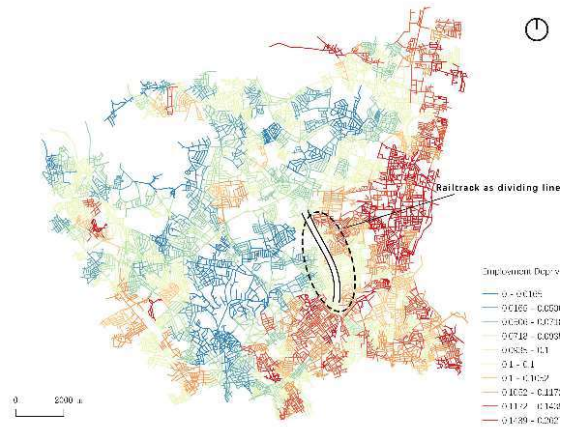
As shown in Figure 4-1 (a-h), different deprivation scores may show a similar pattern of spatial distribution in the research area. Deprivation scores are commonly higher in the southeast and the marginal west of the research area, especially in most communities of Haringey, Hackney and Islington areas, while they are not that high in Barnet and the north of Camden. This consistency indicates that there could be a significant spatial dependence in the global distribution of deprivation, and the existence of specific spatial or social reasons may play a vital role.

In addition to the similarity in the global distribution, there are also differences in local deprivation distributions. For example, communities near the Great Northern line in Haringey have obvious east-west differences of deprivation related to income, employment and crime, as shown in Figure 4-1(a-c). For barrier and education deprivation, the difference extends to nearly all communities along the Great Northern line in the research area, as shown in Figure 4-1(d-e). As a typical physical barrier, the Great Northern line can be found a clear relation with most deprivation scores.

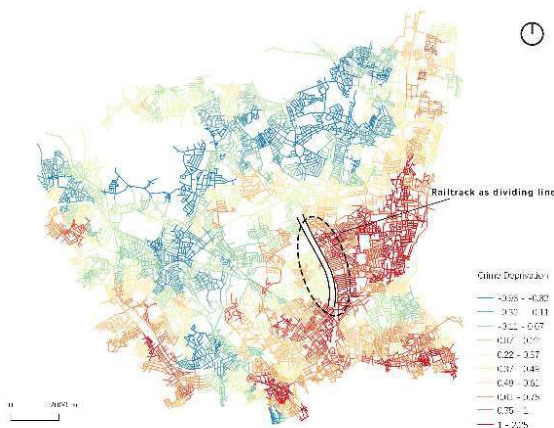




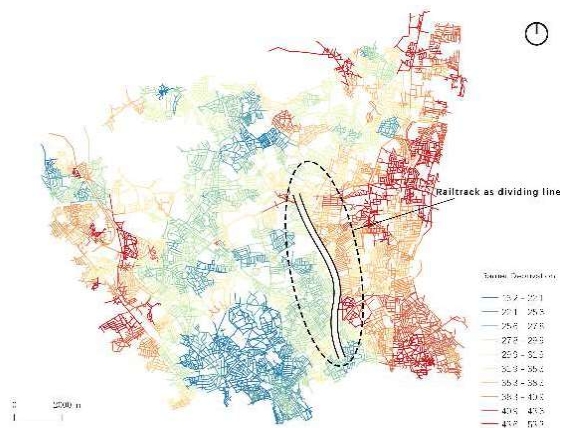
(a).Income Deprivation



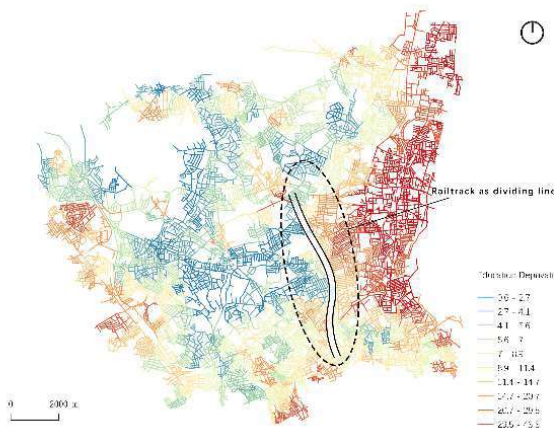
(b).Employment Deprivation



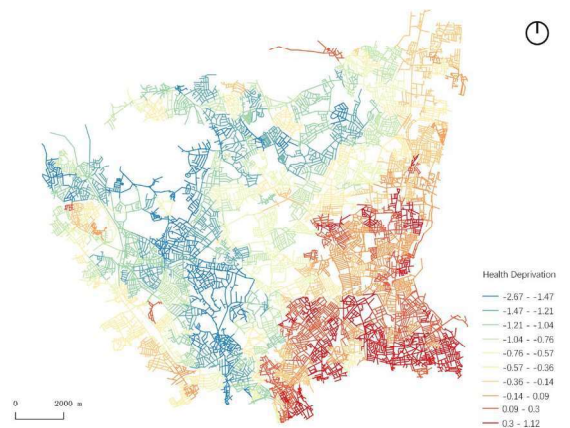
(c).Crime Deprivation



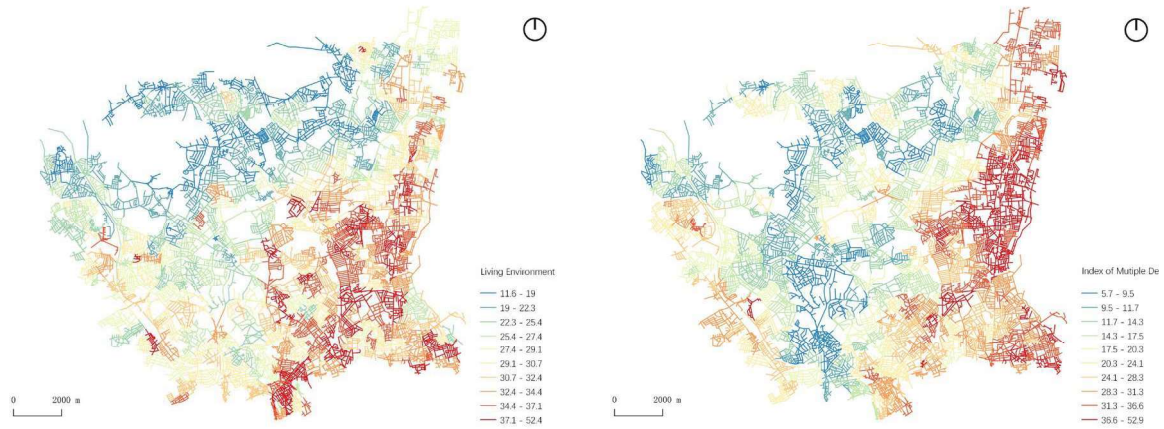
(d).Barrier Deprivation



(e).Education Deprivation



(f).Health Deprivation



(g).Living Environment Deprivation

(h).Multiple Deprivation

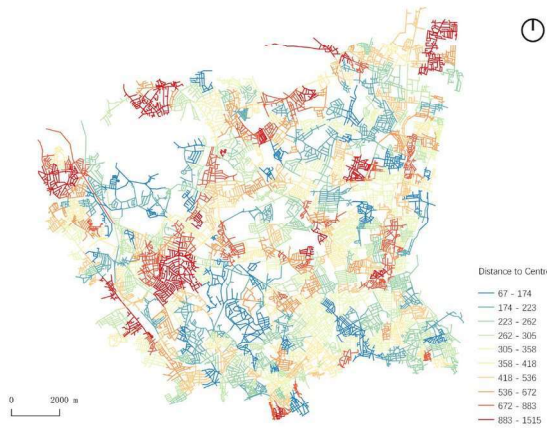
**Figure 4-1:** Mapping of Deprivation Scores for Communities

### ***4.3 Distance and Density Attributes of Communities***

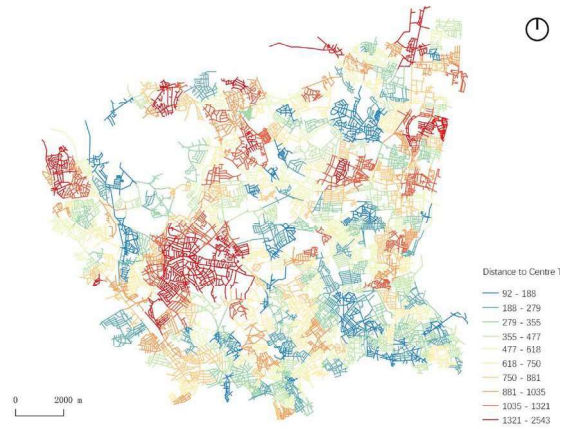
In terms of distance and density distribution, the distance distribution between the community and Centre Type A and B shows a similarly even pattern as a whole, and communities in the northern area can be slightly farther away from Centre Type A and B, as shown in Figure 4-2 (a-b). In contrast, the distance between the communities and Centre Type C shows the characteristics of East-West distribution, with communities in the west relatively farther away from Centre Type C, as shown in Figure 4-2 (c). For the high street and primary road, the dotted high street is more discrete in space (as shown in Figure 3-17 in the methodology section), which makes the distance distribution more uniform. In contrast, the distance to primary road is subject to the trend of primary road, forming an obvious corridor composed of communities adjacent to primary road. Similarly, the distance distribution between communities and rail track and rail station is subject to the location and trend of main railway tracks.

The distribution characteristics of road density and household are similar to the deprivation score as a whole, which are higher in the southeast and lower in the west and north. However, households are more evenly distributed in most communities in the study area and the high value of road density is more concentrated in the area near central London. Besides, the distance distribution between the community and the high street also shares similarities with the distance distribution corresponding to the morphological centres.

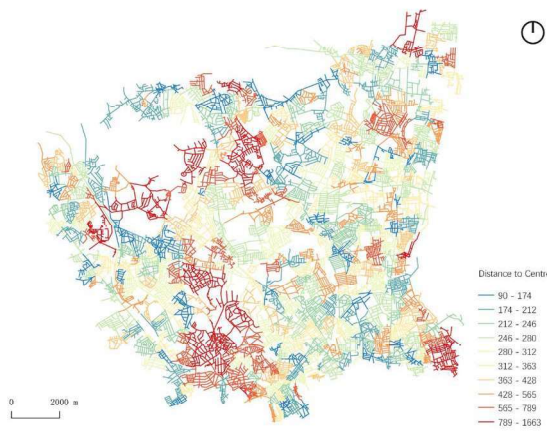




(a). Distance to Centre Type A

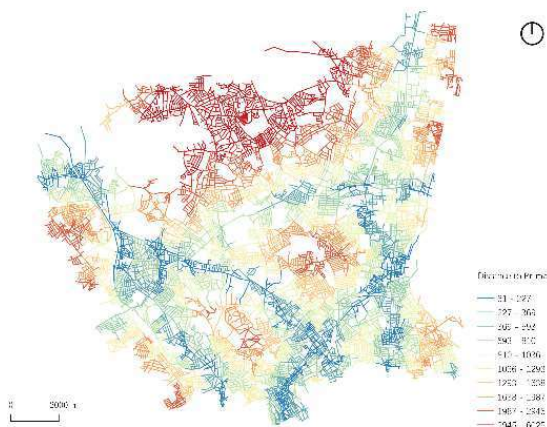


(b). Distance to Centre Type B

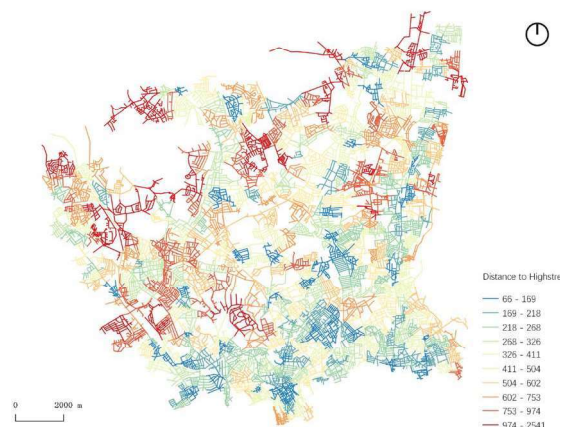


(c). Distance to Centre Type C

**Figure 4-2: Mapping of Distance to Integration Based Centres**



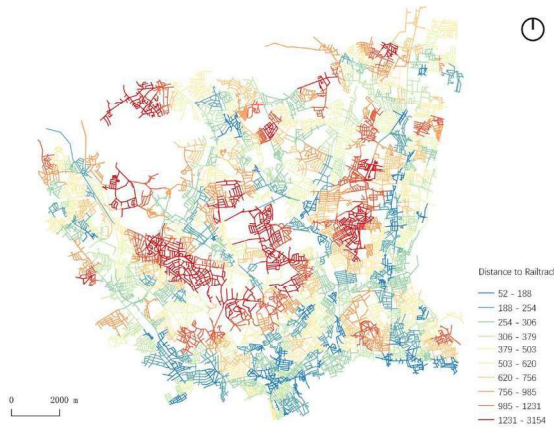
(a). Distance to Primary Road



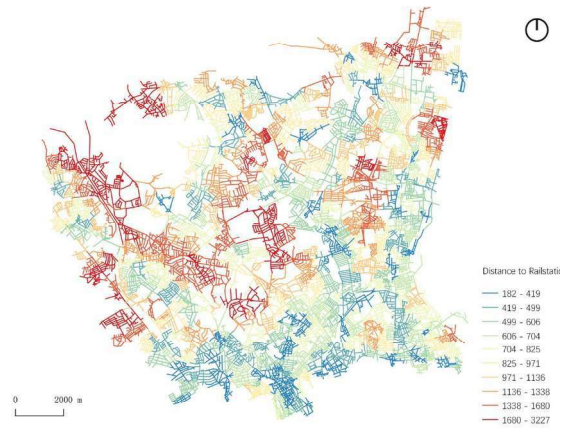
(b). Distance to Highstreet

**Figure 4-3: Mapping of Distance to Function Based Centres**



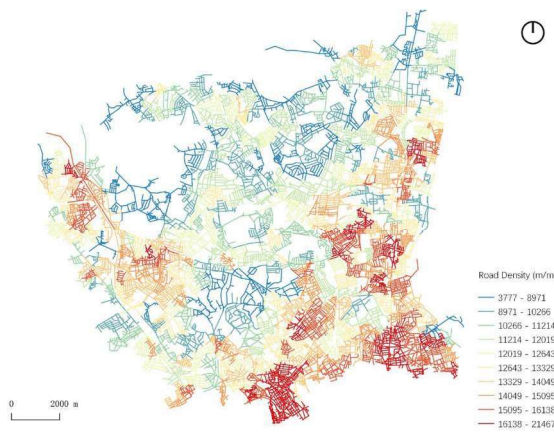


(a). Distance to Rail Track

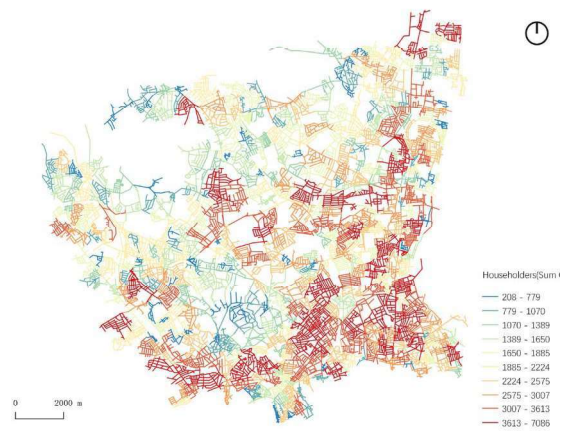


(b). Distance to Rail Station

**Figure 4-4:** Mapping of Distance to Rail Tracks and Stations



(c). Road Density



(d). Household Density

**Figure 4-5:** Mapping of Density Attributes

#### ***4.4 Summary***

The mapping of the social and spatial characteristics above reveals that, firstly, there is a significant spatial dependence on the socio-economic conditions of communities globally. In particular, communities in the east generally have higher deprivation scores. In addition, noticeable local differences can be observed on both sides of the Great Northern line, which indicates a unique role of railway track. In terms of the spatial relationship, the original shape and spatial distribution of different centres and barriers may significantly affect their spatial relationship with adjacent communities. In addition, the distance between high streets and adjacent communities shares similar distribution with the distance of various morphological centres and communities. Finally, it can be difficult to find the intuitive relationship between spatial elements and communities' socio-economic conditions only by comparing the mappings. An in-depth exploration relies on further analysis of statistical models, which will be outlined in the next chapter.

# Chapter 5. General Impact of Different Centres and Barriers on Adjacent Communities

## 5.1 Introduction

As shown in Figure 5-1, taking the deprivation scores of income, employment, crime, barriers, health, education and the living environment as dependent variables separately, this chapter explores the possible roles of different centre and barrier elements and density attributes in affecting the deprivation score, using MGWR analysis. The chapter first summarises the analysis results of all 7 models. On this basis, taking the models corresponding to income, crime and barrier deprivation as examples, this chapter further discusses the possible impact of morphological centres and functional centres on communities and their differences.

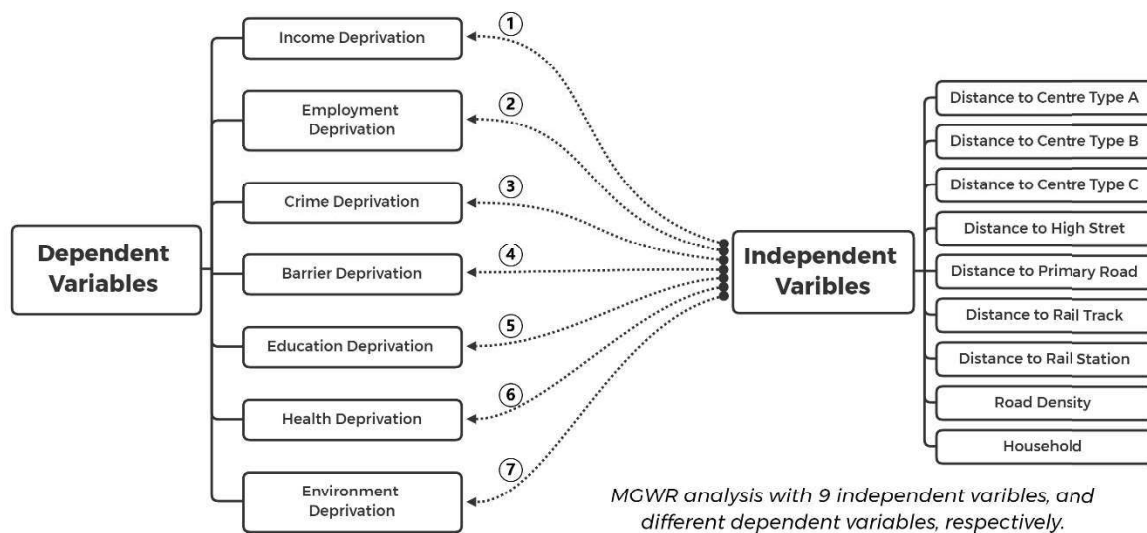


Figure 5-1: Variables included in the MGWR Analysis

## 5.2 Summary of the MGWR Results

For different MGWR models, the section summarises the goodness of fit, the bandwidth of independent variables in each model, and mean regression coefficients of independent variables in model equations.

### 5.2.1 Goodness of Fit Comparison

Table 5-1 lists the goodness of fit of the MGWR models corresponding to different dependent variables respectively, and all the distance and density attributes are included as independent variables for each model. The goodness of fit of MGWR models is generally higher than those of the OLS model based on the same model parameters. Due to the inclusion of scale difference of variables' impact, MGWR models reduce the noise in the regression coefficient compared with general regression analysis, resulting in a more robust regression coefficient.

| Dependent Variables<br>(Deprivation Type) | Adj. R <sup>2</sup> |       |
|---|---------------------|-------|
|   | OLS                 | MGWR  |
| Income                                    | 0.241               | 0.781 |
| Employment                                | 0.214               | 0.703 |
| Crime                                     | 0.224               | 0.758 |
| Barriers                                  | 0.136               | 0.822 |
| Health                                    | 0.363               | 0.874 |
| Education                                 | 0.098               | 0.854 |
| Living Environment                        | 0.46                | 0.702 |

**Table 5-1:** Goodness of Fit of MGWR Models Corresponding to Deprivation Indices

### 5.2.2 Bandwidth Characteristics

Table 5-2 lists the bandwidths corresponding to each independent variable in different models, fluctuating between 43-456. The larger the bandwidth, the larger the effective scale of the variable, and the stronger the consistency of the variable's impact. The smaller the bandwidth, the smaller effective scale of the variable, and there may be more local differences of the variables' impact. Among the independent variables, the distance between the community and railway track can be regarded as a full-scale variable, whose bandwidth in six models were greater than 450. This means that the impact of the railway on adjacent communities can be largely consistent, independent of its location and other spatial factors. In addition, community households and the distance to Centre Type A also have larger bandwidth in most models. In contrast, Centre Type B and primary roads show generally smaller bandwidth characteristics. The bandwidths of other independent variables vary greatly in each model.

| Dependent Variables<br>(Deprivation Type) | Income | Employment | Crime | Barriers | Health | Education | Living<br>Environment |
|---|--------|------------|-------|----------|--------|-----------|-----------------------|
| Interface                                 | 43     | 49         | 43    | 43       | 46     | 43        | 79                    |
| Centre Type A                             | 418    | 300        | 103   | 456      | 72     | 165       | 373                   |
| Centre Type B                             | 49     | 43         | 450   | 51       | 43     | 43        | 46                    |
| Centre Type C                             | 144    | 56         | 149   | 150      | 146    | 56        | 456                   |
| High Street                               | 456    | 63         | 58    | 96       | 49     | 456       | 455                   |
| Primary road                              | 56     | 391        | 47    | 45       | 51     | 79        | 65                    |
| Rail Track                                | 456    | 456        | 456   | 450      | 99     | 454       | 455                   |
| Rail Station                              | 63     | 119        | 186   | 43       | 60     | 70        | 355                   |
| Road Density                              | 56     | 256        | 142   | 61       | 257    | 456       | 65                    |
| Household                                 | 387    | 456        | 427   | 456      | 84     | 54        | 352                   |

Frequently Larger Bandwidth
  Frequently Smaller Bandwidth

**Table 5-2:** Bandwidth of Independent Variables in Different MGWR Models

### 5.2.3 Coefficients Characteristics

Table 5-3 lists the mean regression coefficients corresponding to each independent variable in the different models. Generally, the regression coefficient represents the strength of the independent variable's impact on the dependent variable. In MGWR models, considering the local differences of geographical phenomena, objects at different locations are assigned different regression coefficient for the same independent variable (Fotheringham, Yang, & Kang, 2017). The mean coefficients corresponding to railway track are negative in most models, and the absolute value is also higher. This indicates that the closer to the railway track, the higher the various deprivation indices. Combined with the characteristics of larger bandwidth, the existence of the railway may have a negative impact on the socio-economic attributes of the community on the global scale. Similarly, mean coefficients corresponding to Centre Type C show a negative pattern as those of the railway track, while the absolute values are not that significant. In addition, the absolute value of mean estimates of Centre Type A and household is smaller than 0.01, which has weak influence in each model. The mean coefficients of other independent variables vary widely and need to be further compared with the coefficient distribution.

|               | Income | Employment | Crime  | Barriers | Health | Education | Living Environment |
|---------------|--------|------------|--------|----------|--------|-----------|--------------------|
| Interface     | 0.013  | 0.033      | -0.072 | -0.138   | 0.01   | -0.034    | 0.019              |
| Centre Type A | 0.028  | 0.08       | -0.052 | 0.02     | 0.042  | 0.001     | -0.009             |
| Centre Type B | -0.007 | 0.042      | -0.01  | -0.113   | -0.003 | 0.035     | 0.009              |
| Centre Type C | -0.105 | -0.077     | -0.027 | -0.079   | -0.07  | -0.107    | -0.009             |
| High Street   | 0.08   | 0.091      | -0.19  | 0.126    | -0.036 | 0.114     | -0.177             |
| Primary Road  | -0.041 | 0.131      | -0.114 | -0.14    | 0.117  | 0.058     | -0.293             |
| Rail Track    | -0.171 | -0.194     | -0.08  | -0.148   | -0.135 | -0.14     | 0.039              |
| Rail Station  | 0.038  | -0.009     | 0.029  | 0.068    | 0.056  | 0.002     | -0.044             |
| Road Density  | 0.1    | 0.034      | -0.005 | -0.066   | 0.016  | 0.024     | 0.127              |
| Household     | -0.016 | 0.066      | -0.094 | -0.005   | -0.015 | -0.037    | -0.028             |

■ Mean coefficients with consistent negative pattern

**Table 5-3:** MGWR Mean Estimates of Coefficients

### 5.3 Impact of the Multi-scale Morphological Centres

Regarding income, crime and barrier deprivation models, this chapter further analyses the spatial distribution of coefficients corresponding to different morphological centres (Centre type A, B, c) and the possible scale difference of centres' impact. Table 5-4 shows the data distribution of mean estimates in these models and the detailed analysis is outlined in the following sections.

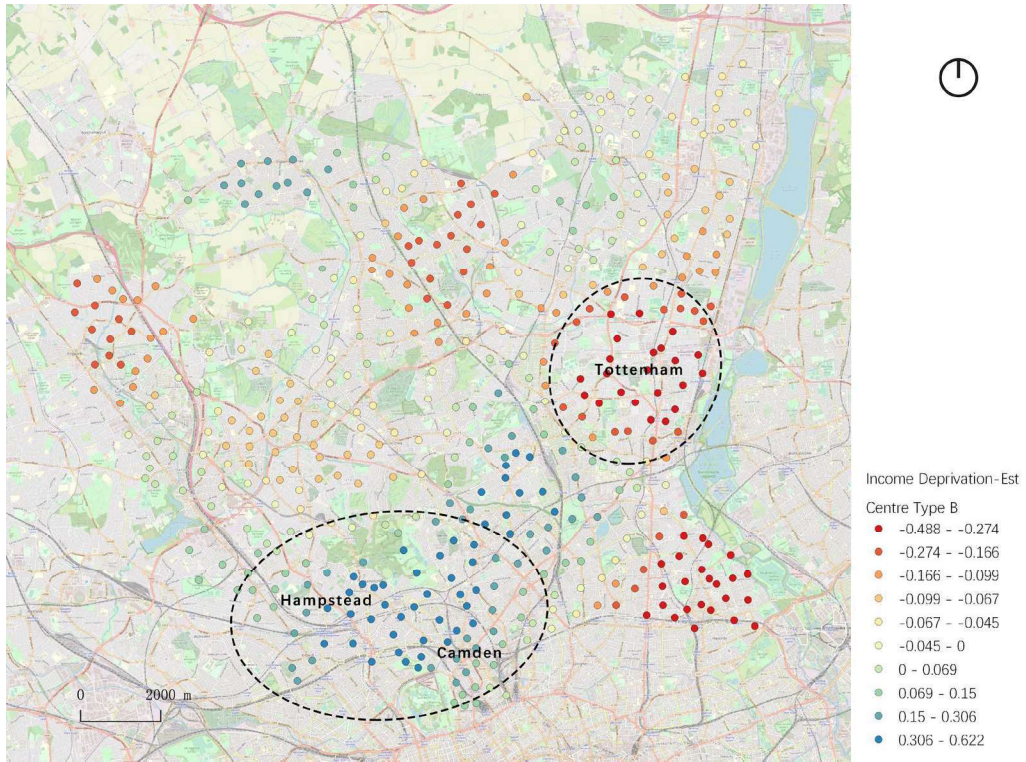
| Dependent Variable             | Independent Variable | Min    | Median | Max   |
|--------------------------------|----------------------|--------|--------|-------|
| Income Deprivation             | Centre Type A        | -0.015 | 0.021  | 0.089 |
|                                | Centre Type B        | -0.488 | -0.045 | 0.622 |
|                                | Centre Type C        | -0.307 | -0.077 | 0.141 |
| Crime Deprivation              | Centre Type A        | -0.446 | -0.023 | 0.156 |
|                                | Centre Type B        | -0.022 | -0.018 | 0.026 |
|                                | Centre Type C        | -0.2   | -0.034 | 0.16  |
| Living Environment Deprivation | Centre Type A        | 0.008  | 0.021  | 0.031 |
|                                | Centre Type B        | -0.633 | -0.125 | 0.33  |
|                                | Centre Type C        | -0.23  | -0.082 | 0.064 |

**Table 5-4:** MGWR Estimates of Coefficients Corresponding to the Morphological Centres

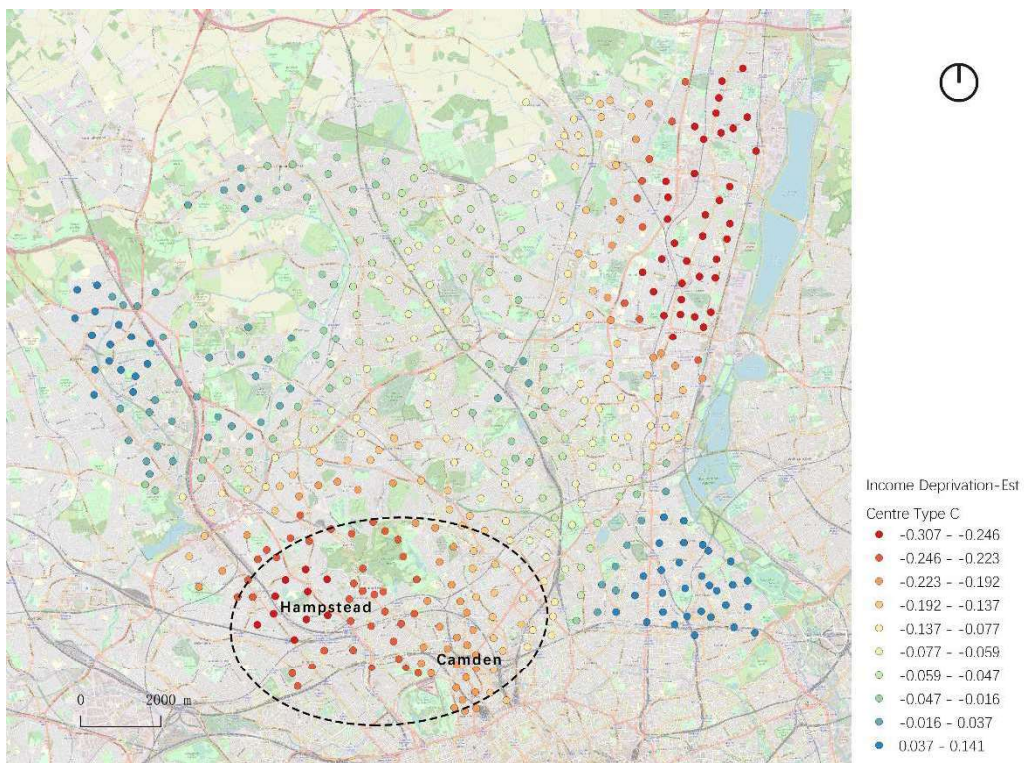
#### 5.3.1 The relationship between Morphological Centres and Income Deprivation

Here maps the regression coefficients of different spatial elements. Regarding the income deprivation of the community, the regression coefficients of Centre Type A is limited, while Centre type B and C, as two different-scale centre structures, may have significantly opposite impacts on adjacent communities in a specific area. As shown in Figure 5-2, the coefficient corresponding to Centre Type B is negative and significant in the south of the study area. However, in the same area, communities' distance to Centre Type C has a positive coefficient (Figure 5-3). This indicates that communities close to a single local centre may have a relatively lower level of income deprivation in the southern area, while residents closer to multi-scale integrated centres may suffer more from income problems. This difference supports a possible hypothesis, that is, centrality at a moderate level may help improve the community's socio-economic status while it may have a negative effect after excessive accumulation.





**Figure 5-2:** Regression Coefficients of Centre Type B in Income Deprivation Model



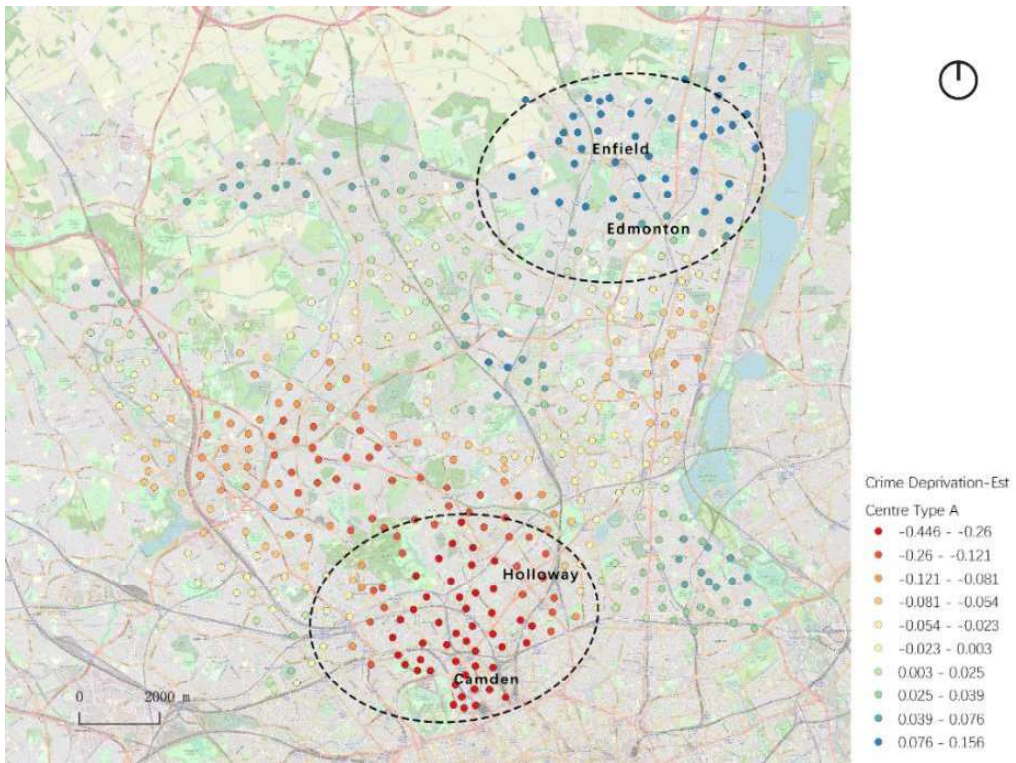
**Figure 5-3:** Regression Coefficients of Centre Type C in Income Deprivation Model



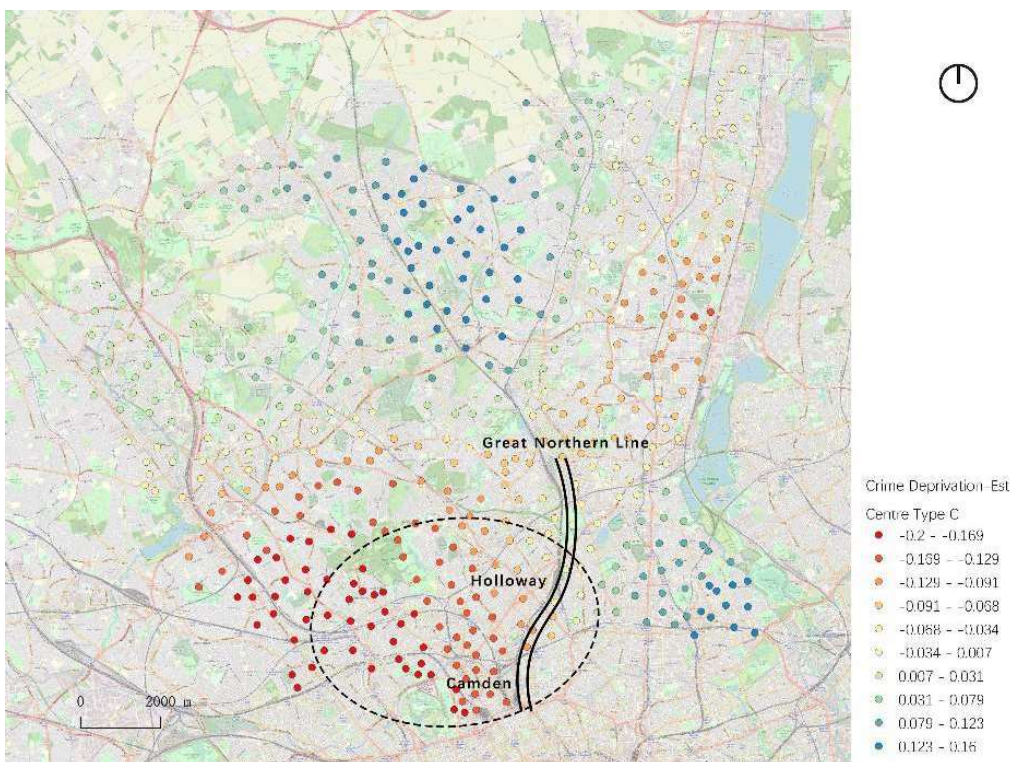
For the above hypothesis, there is one point to further discuss. In space syntax theory, multi-scale centres are usually associated with more employment and opportunities (Hillier, 1996), which seems to contradict the negative effect of Centre Type C. A explanation is that the possible negative impact of the multi-scale centre is a relative description regarding to communities slightly further from the centres. In the complex urban system, the employment and income opportunities created by multi-scale centres usually have a large radiation range rather than directly benefit the adjacent communities. Furthermore, most of the people gathering in centre areas are usually not local residents, which may bring greater uncertainty to communities adjacent to centres.

### *5.3.2 The Relationship between Morphological Centres and Crime Deprivation*

In terms of crime deprivation, Centre Type B has a limited impact. In contrast, Centre types A and C play a more significant role and the two variables' coefficients share similar distribution characteristics. As shown in Figures 5-4 & 5-5, in the south of the study area, the distance between the two centres and nearby communities are negatively correlated with the criminal deprivation score. This indicates that residents living near both types of centres may suffer more from criminal activities. Communities with higher coefficients gather around the town centre of Camden, which is famous for its market and cultural activities near central London. In other areas away from central London, the correlation between crime deprivation and the existence of the morphologic centres is weak.



**Figure 5-4:** Regression Coefficients of Centre Type A in Crime Deprivation Model

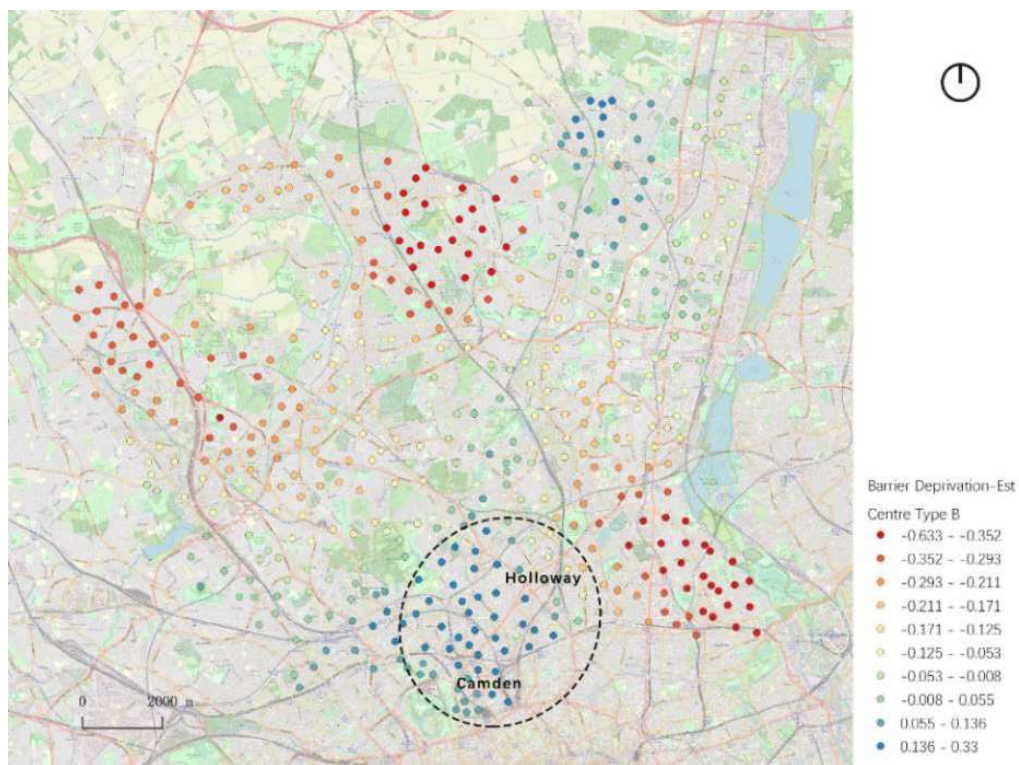


**Figure 5-5:** Regression Coefficients of Centre Type C in Crime Deprivation Model

In addition to the above findings, in both the income and criminal deprivation models, the coefficient distribution corresponding to the morphological centre of different scales can be quite different on both sides of the railway track. Taking the Great Northern Line as an example(Figure 5-5), on the same side of the track, the impact of the morphological centre on the community is usually more similar, and the propagation of the effect is generally interrupted by the railway track. Thus, the limiting effect of rail on shaping centres' impact is worthy of further attention.

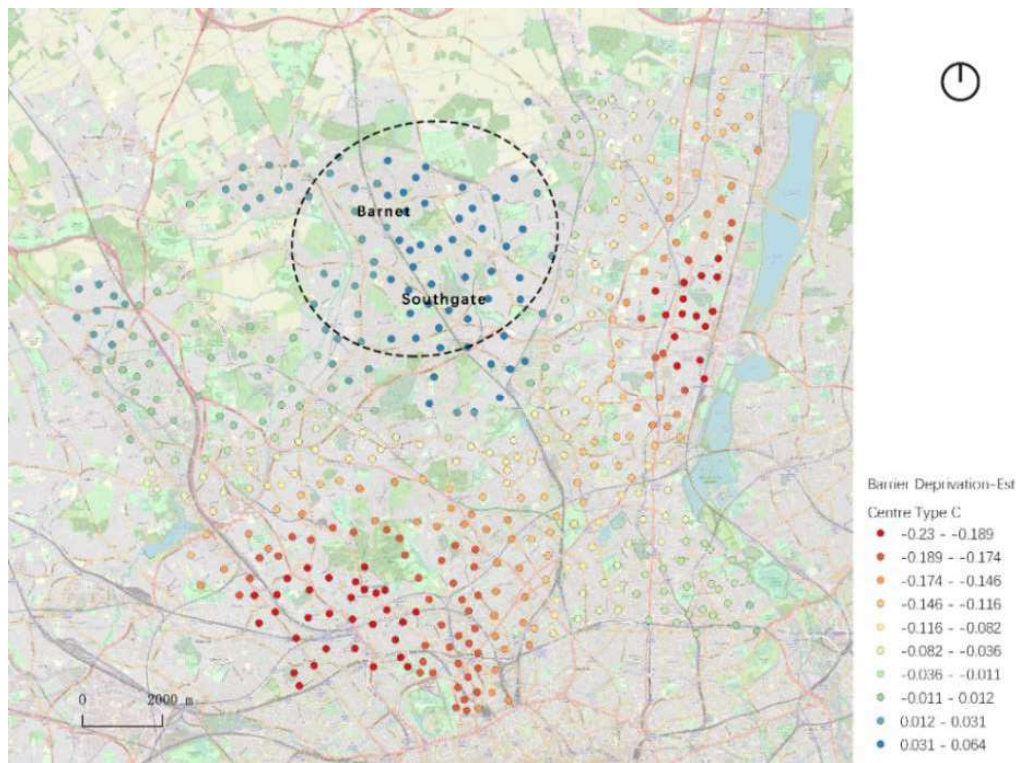
### 5.3.3 The Relationship between Morphological Centres and Barriers Deprivation

For barrier deprivation, the coefficients of Centre Type B and Centre Type C show opposite distribution characteristics in the income model. For Camden and Holloway near central London, the coefficients corresponding to the local centres are positive(Figure 5-6), while the global centres' are negative(Figure 5-7). This preliminarily show that the existence of small-scale morphological centres may help balance the accessibility of public service to nearby communities. In contrast, a large-scale morphological centre may act as a barrier, strengthening the distribution boundary of service facilities among communities.



**Figure 5-6:** Regression Coefficients of Centre Type B in Barrier Deprivation Model





**Figure 5-7:** Regression Coefficients of Centre Type C in Barrier Deprivation Model

In urban fringe areas of northern London, such as Barnet and Southgate, communities closer to the large-scale morphological centres but far away from the small-scale centres may have a lower deprivation level due to the change of service density. Considering that these areas are adjacent to important traffic corridors such as railways and highways, the dependence of the suburban regions on large public transport facilities and public services may lead to this change.

In conclusion, there may be significant differences in the impact of multi-scale morphological centres on communities' deprivation indices, and small-scale centres often play a positive role. Moreover, local differences related to railway tracks are commonly observed in centres' impacts. Since the morphological centres are extracted based on the road network, the process of centres' impact may be related to the physical properties of the road network, where the existence of physical barriers may play a blocking role.

### 5.4 Impact of Highstreets and Primary Roads

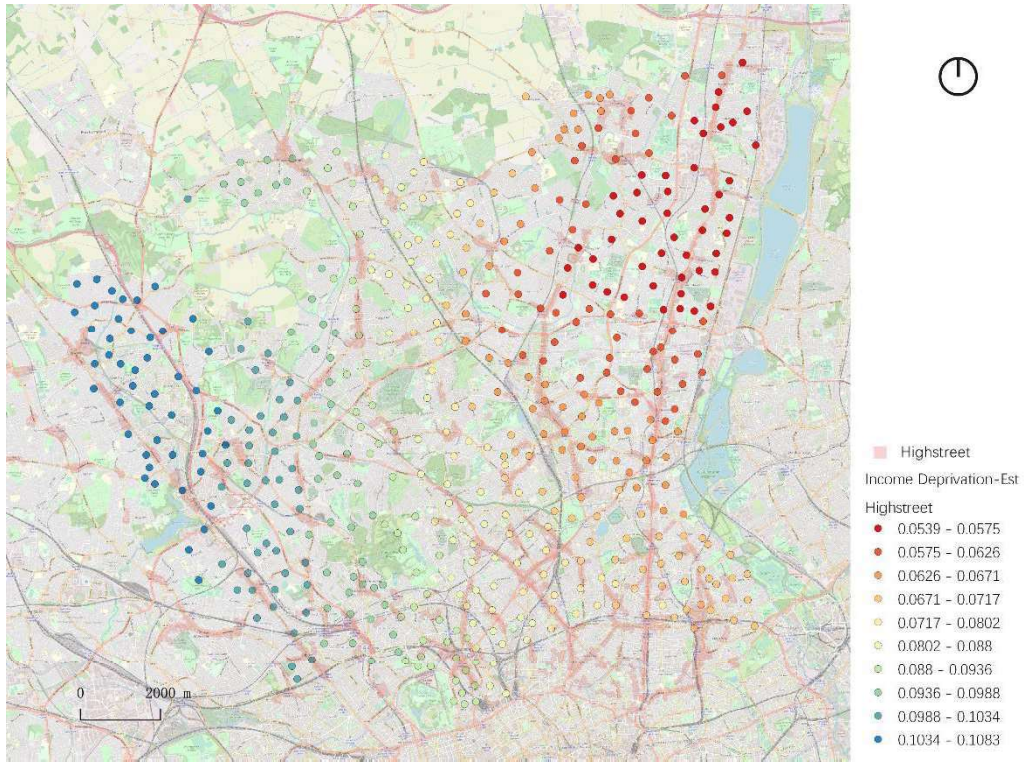
Similarly, taking the MGWR models of income, crime and barrier deprivation as examples, we can further compare the possible impact of high streets and primary roads on nearby communities. The coefficient distribution of the two variables in the corresponding model is shown in Table 5-5 below.

| Dependent Variable | Independent Variable | Min    | Median | Max   |
|--------------------|----------------------|--------|--------|-------|
| Income             | Highstreet           | 0.054  | 0.08   | 0.108 |
| Deprivation        | Primary Road         | -0.565 | -0.074 | 0.785 |
| Crime              | Highstreet           | -0.506 | -0.183 | 0.175 |
| Deprivation        | Primary Road         | -0.988 | -0.143 | 0.674 |
| Barrier            | Highstreet           | -0.118 | 0.12   | 0.342 |
| Deprivation        | Primary Road         | -0.894 | -0.111 | 0.573 |

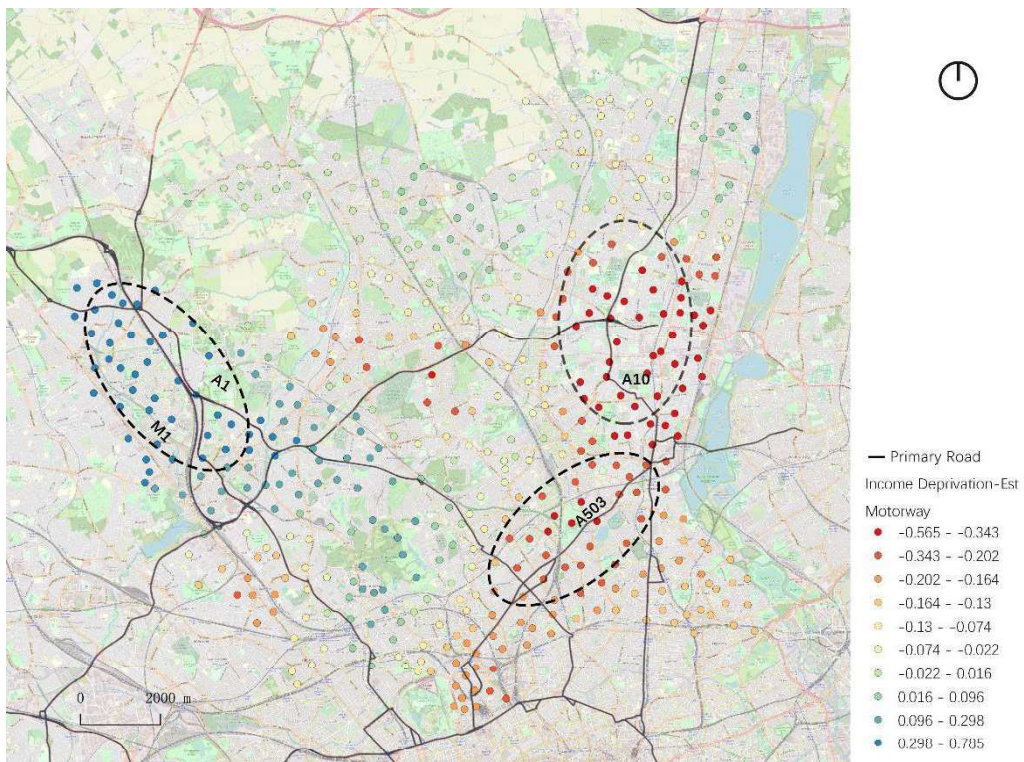
**Table 5-5:** MGWR Estimates of Coefficients Corresponding to the Function-based Centres

#### 5.4.1 The Relationship between Functional Centres and Income Deprivation

For income deprivation, the high street as a full-scale variable is found to have a weak positive impact on nearby communities, as shown in Figure 5-8. In contrast, primary roads' effect may vary according to the location. In this study, primary roads have a significant negative impact on eastern communities, while in the west, there could be a more positive impact, as shown in Figure 5-9.



**Figure 5-8:** Regression Coefficients of High Streets in Income Deprivation Model

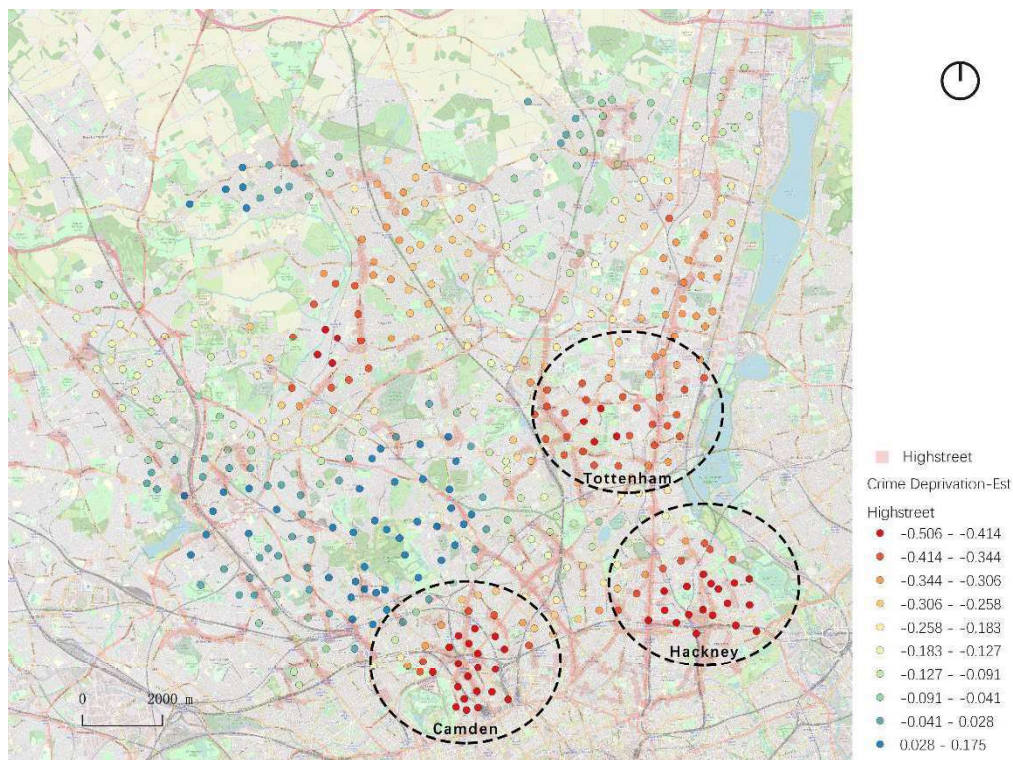


**Figure 5-9:** Regression Coefficients of Primary Roads in Income Deprivation Model

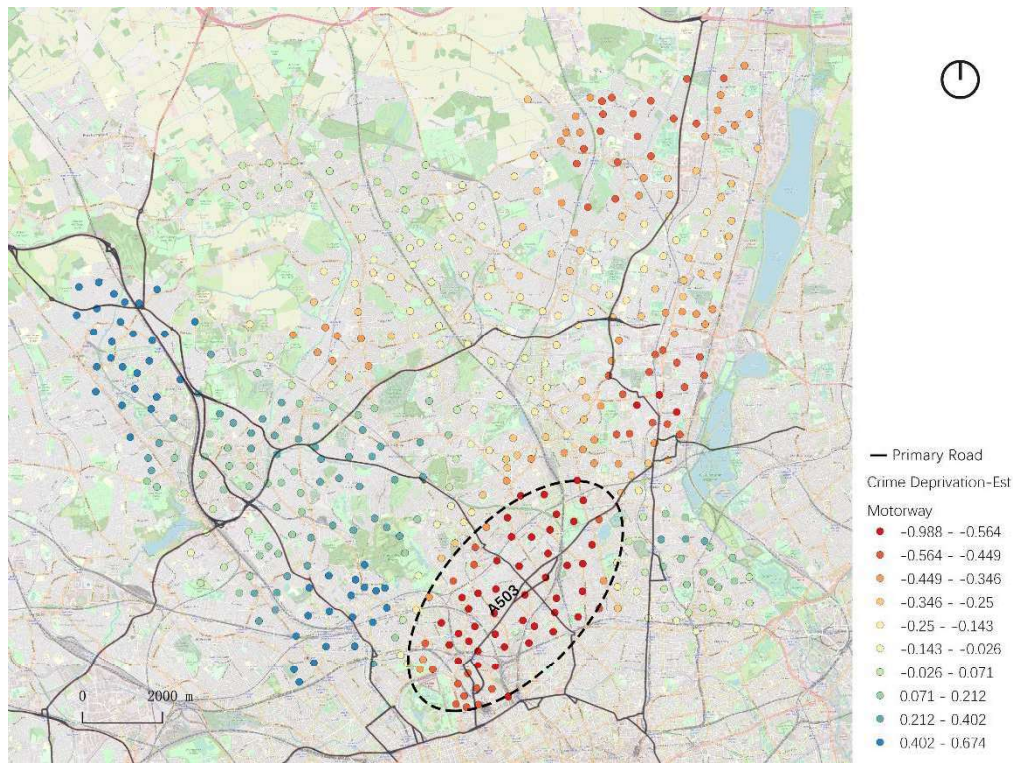


#### 5.4.2 The Relationship between Functional Centres and Crime Deprivation

In terms of crime deprivation, the distance between community and high street can be regarded as a local variable, as shown in Figure 5-10. High streets generally may have a negative impact on adjacent communities, especially in Camden and, Tottenham and Hackney. The spatial distribution of primary roads' coefficients in the crime model may overlap with that in the income model: having a significant negative impact on eastern communities and a positive impact in the west (Figure 5-11). The difference is that the corresponding coefficient along the A503 road in Camden and Holloway is up to -0.988, showing a strong negative correlation and indicating that the existence of primary roads may seriously affect the safety of adjacent communities.



**Figure 5-10:** Regression Coefficients of High Streets in Crime Deprivation Model

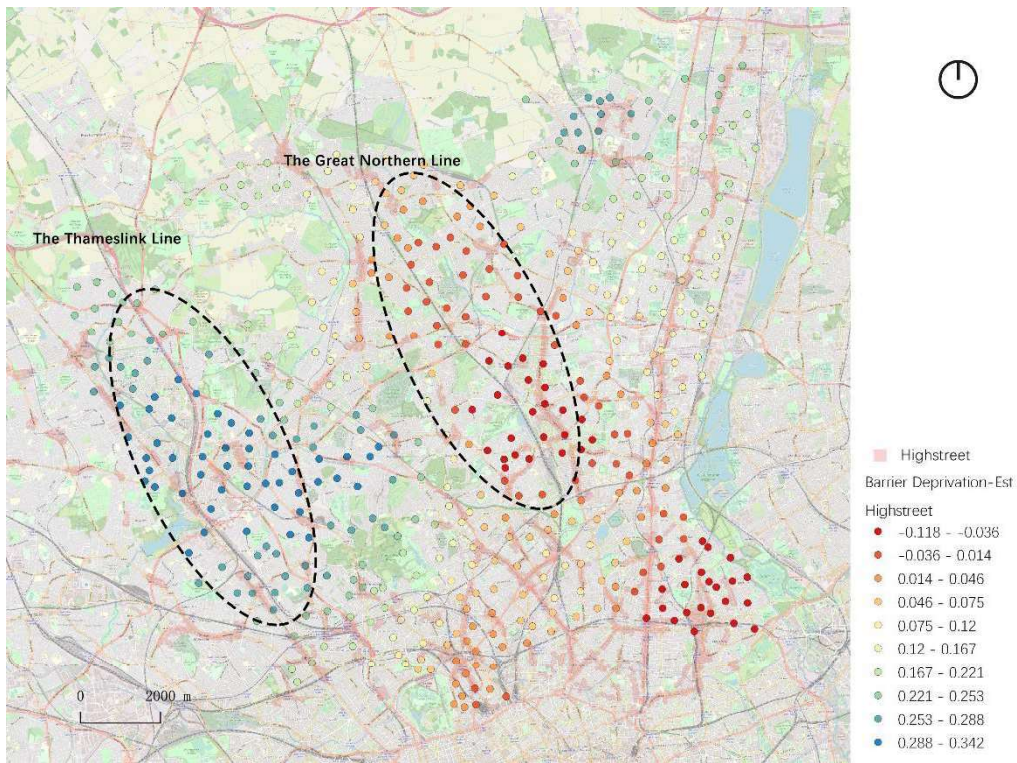


**Figure 5-11:** Regression Coefficients of Primary Roads in Crime Deprivation Model

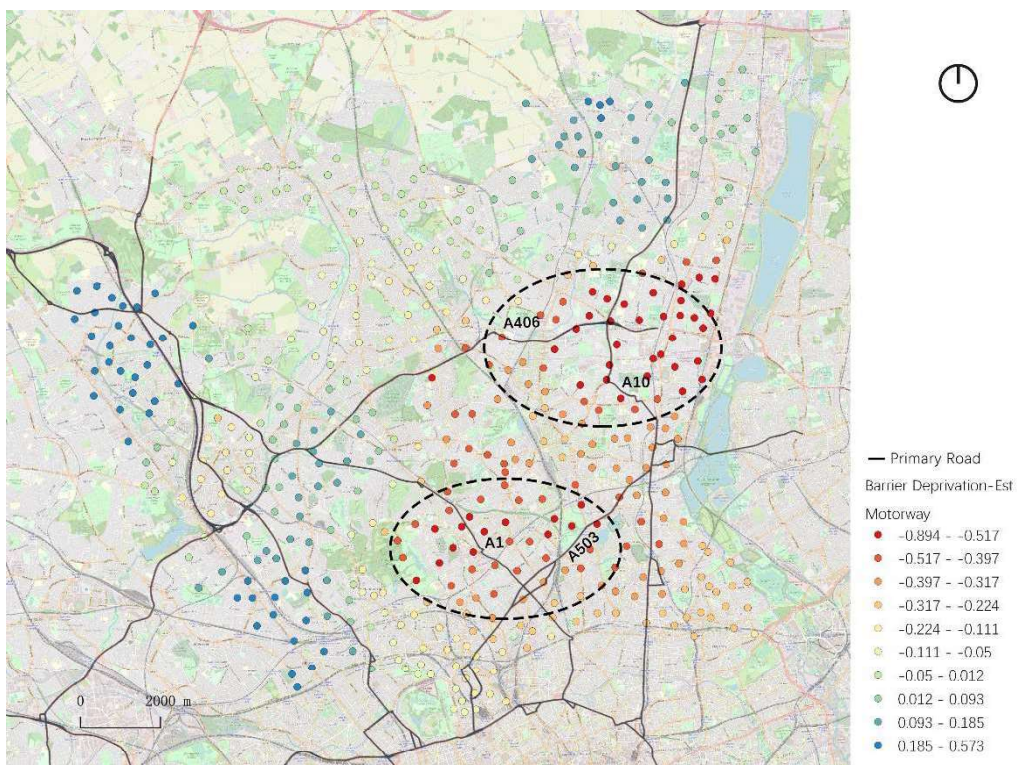
#### 5.4.3 *The Relationship between Functional Centres and Barrier Deprivation*

In terms of barrier deprivation, the role of high streets may be related to the location of the railway track. In this study, it was found that communities along the Great Northern line share a weak negative coefficient, while communities along the Thameslink line show a positive coefficient (as shown in Figure 5-12). The existence of high streets along the Great Northern line may intensify the barrier deprivation faced by the community. The overall impact of primary roads on communities' barrier deprivation is similar to that of high streets, but the absolute value of relevant parameters increases significantly (as in Figure 5-13). The existence of primary roads may have a more significant negative impact on communities' capability to access adjacent service facilities in the east. In addition, this impact may not be limited by railway tracks.





**Figure 5-12: Regression Coefficients of High Streets in Barrier Deprivation Model**



**Figure 5-13: Regression Coefficients of Primary Roads in Barrier Deprivation Model**

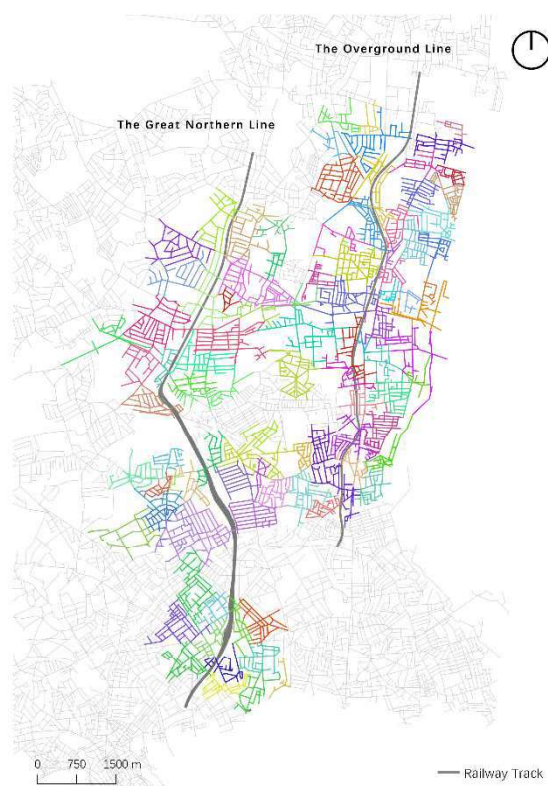
In general, the impact of primary roads and high streets share many similarities in spatial distribution, but there are differences in the characteristics of corresponding coefficients. Distance to the high street is a full-scale variable in income and crime deprivation and this impact is relatively homogeneous and weak, while the impact of primary roads varies greatly according to communities' location, and the estimated coefficients could be much higher than those of other variables. Primary roads' impact on communities reflects a stronger spatial autocorrelation.

## Chapter 6. Centres and Barriers' Impact on Strengthening Social Differences

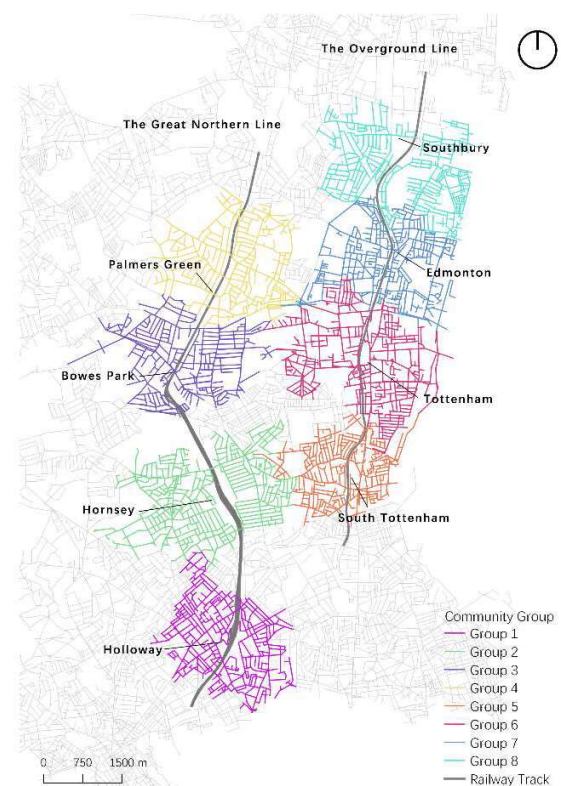
Based on MGWR analysis, we understand the effective scale of each independent variable and the relationship between different independent variables and various community deprivation indices. However, it is difficult for MGWR to explain the interaction between independent variables in certain spatial phenomena and in a specific area. In view of the prominent local differences in socio-economic characteristics of communities along a railway track, binary logistics was applied in this study for further exploration.

### 6.1 Social Differences between Two Sides of the Track

As shown in Figure 6-1, a total of 106 communities on both sides of the Great Northern Line and Overground line were included in this study. According to the spatial connection between the communities and segments of the track, communities were divided into eight groups (Figure 6-2). On this basis, each group was divided into east and west parts, where the number and scale of communities were similar.



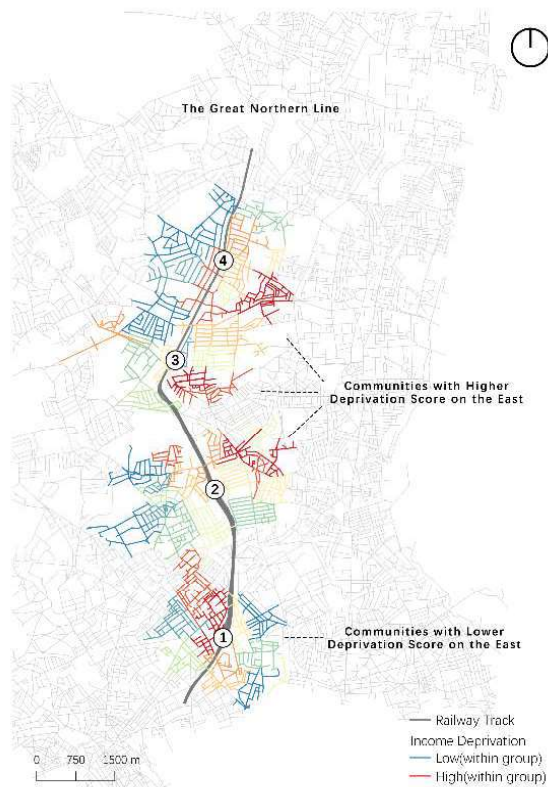
**Figure 6-1:** 106 Communities Selected for Detailed Research



**Figure 6-2:** 8 Groups Divided for Selected Communities



By ranking communities' income and crime deprivation scores in each group as shown in Figures 6-3 & 6-4, we can understand to what extent social differences exist on the two sides of the railway. It is preliminarily found that the deprivation scores on both sides are not evenly distributed in most groups, but communities with higher scores often gather around on one side. Specifically, along the Great Northern Line, the income and crime scores of communities within group 1 (around the Emirates Stadium) in the west were significantly higher than those in the east and communities of the remaining groups 2, 3 and 4 shared a reversed pattern (Figures 6-3 & 6-4). While along the Overground line, there is a consistent pattern in groups 5, 6, 7 and 8 that communities on the east side show relatively higher scores than those on the west side (Figure 6-5 & 6-6).

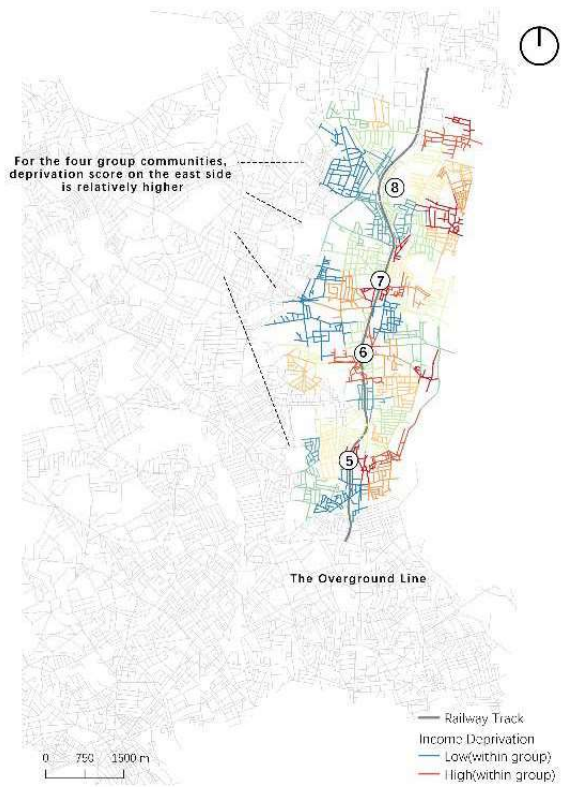


**Figure 6-3:** Ranking of Income Deprivation  
Group 1-4

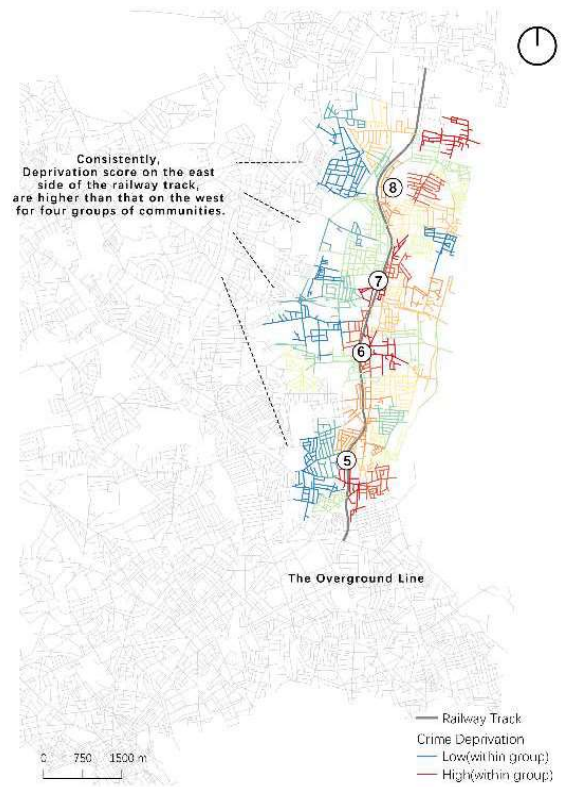


**Figure 6-4:** Ranking of Crime Deprivation  
Group 1-4





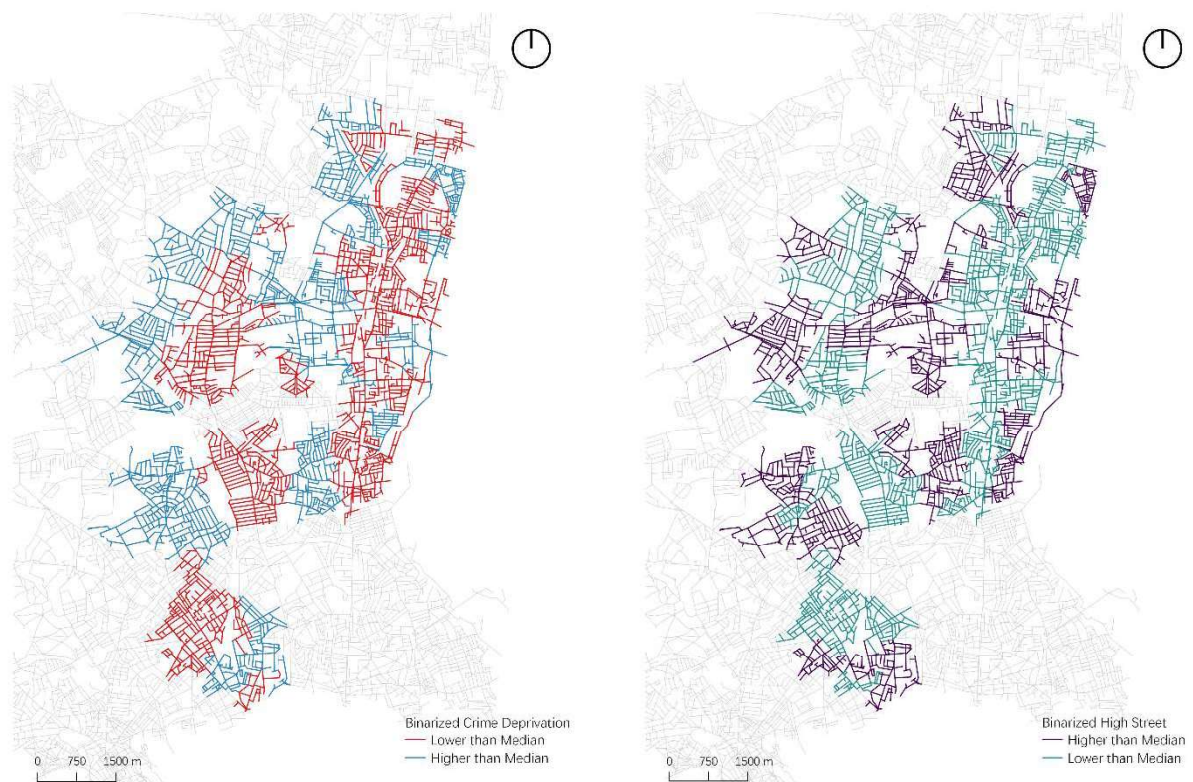
**Figure 6-5:** Ranking of Income Deprivation  
Group 5-8



**Figure 6-6:** Ranking of Crime Deprivation  
Group 5-8

## 6.2 Summary and Comparison of Binary Logistics Regression Models

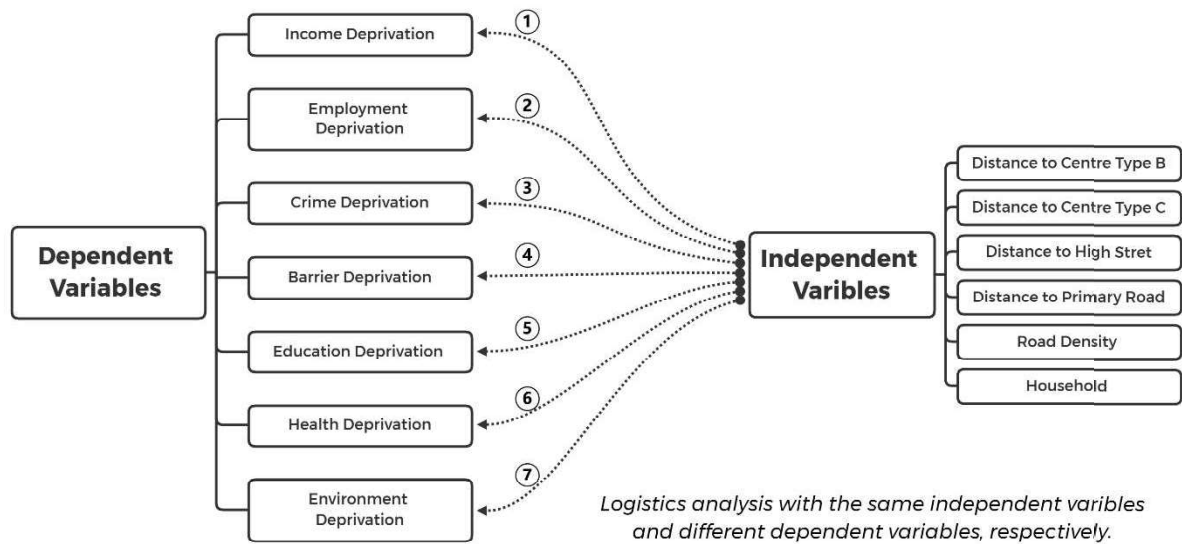
Based on the finding above, binary logistics regression analysis is applied to explore the possible corresponding relationship between the local social difference and the distribution of centres and other elements on both sides of the rail track. After calculating the median values of the deprivation scores, the distance and density attributes in each group, the original variables in each community were binarised and divided into two categories: (1) greater than or equal to the median value, or (2) lower than the median value, as in Figure 6-7 and in the Appendix C. Taking the binarised deprivation scores as dependent variables and the corresponding distance and density variables as covariates, binary logistics regression was used to analyse which type of independent variables may lead to a social deprivation score more likely to exceed the general level (Figure 6-8). The forward stepwise (conditional) method based on maximum likelihood estimation was used to generate the regression equation and select dependent variables with paramount significance.



(a) Binarized Score of Crime Deprivation

(b) Binarized Distance to High Street

**Figure 6-7:** Samples of Binarized Variables in Logistics Regression



**Figure 6-8:** Variables included in the Logistics Regression Analysis

### 6.2.1 Crime Deprivation

The binary logistics model corresponding to crime deprivation has statistical significance. In the Hosmer and Lemeshow test,  $P = 0.600 > 0.05$ , indicating a good fit. In addition, the model correctly classified 72.6% of the research objects. Among the nine independent variables included in the model, the distances from Centre Type B, Centre Type C and high streets were statistically significant, as shown in Table 6-1. The odd ratios (Exp(B)) of communities closer to high streets and Centre Type C were 4.799 and 2.142, respectively. In contrast, the odds ratio of the communities closer to Centre Type C was only 0.475. This difference indicates again that communities close to high streets and Centre Type C are more vulnerable to crime risks and the negative impact of high streets is more prominent. On the contrary, Centre Type C plays a protective role in the same area.

| Deprivation Type | Independent Variables | B     | S.E. | Wald   | df | Sig. | Exp(B) | Step |
|------------------|-----------------------|-------|------|--------|----|------|--------|------|
| Crime            | Centre Type B         | -.743 | .445 | 2.796  | 1  | .094 | .475   |      |
|                  | Centre Type C         | .762  | .437 | 3.037  | 1  | .081 | 2.142  | 3    |
|                  | Highstreet            | 1.568 | .447 | 12.329 | 1  | .000 | 4.799  |      |

a. Full tables are listed as in Appendix D

**Table 6-1:** Variables in the Equations Corresponding to Crime Deprivation

### 6.2.2 Living Environment Deprivation

The model corresponding to living environment development is also statistically significant, with  $P = 0.658 > 0.05$  in the Hosmer and Lemeshow test, and the model correctly classified 72.6% of the research objects. The distance from Centre Type B, the distance from primary roads and high streets, and the road density were statistically significant, as shown in Table 6-2. Among them, the odd ratios corresponding to high streets and primary roads were 3.645 and 3.035 respectively, while the odds ratio of Centre Type C was only 0.262. Similar to crime deprivation, this indicates that communities close to high streets and primary roads may suffer more from the poor living environment, while communities closer to Centre Type C have a better situation relatively. In addition, road density also plays a protective role.

| Deprivation Type   | Independent Variables | B      | S.E. | Wald  | df | Sig. | Exp(B) | Step |
|--------------------|-----------------------|--------|------|-------|----|------|--------|------|
| Living Environment | Centre Type B         | -1.338 | .472 | 8.050 | 1  | .005 | .262   | 4    |
|                    | Primary Road          | 1.110  | .487 | 5.195 | 1  | .023 | 3.035  |      |
|                    | Highstreet            | 1.293  | .503 | 6.622 | 1  | .010 | 3.645  |      |
|                    | Road Density          | -1.174 | .457 | 6.591 | 1  | .010 | .309   |      |

a. Full tables are listed as in Appendix D

**Table 6-2:** Variables in the Equations Corresponding to Living Environment Deprivation

### 6.2.3 Other Deprivation Indices

For income, employment, education and barriers, statistically significant models were also generated, but their goodness of fit was relatively weak (Table 6-3). Among them, the odds ratios corresponding to high streets were all over 2. This shows that communities near high streets are more likely to have a higher deprivation score than those far away from high streets. In addition, there is no statistically significant model for health deprivation indices.

| Dependent Variables<br>(Deprivation Type) | Independent Variables | B     | S.E. | Wald  | df | Sig. | Exp(B) | Step |
|---|-----------------------|-------|------|-------|----|------|--------|------|
| Education                                 | Centre Type C         | .949  | .417 | 5.188 | 1  | .023 | 2.584  | 2    |
|   | Highstreet            | .822  | .416 | 3.904 | 1  | .048 | 2.274  |      |
| Barriers                                  | Primary Road          | 1.044 | .423 | 6.079 | 1  | .014 | 2.841  | 2    |
|   | Highstreet            | .854  | .424 | 4.061 | 1  | .044 | 2.350  |      |
| Income                                    | Highstreet            | .911  | .400 | 5.186 | 1  | .023 | 2.486  | 1    |
| Employment                                | Highstreet            | .829  | .399 | 4.323 | 1  | .038 | 2.291  | 1    |

a. Full tables are listed as in Appendix D

**Table 6-3** : Variables in the Equations Corresponding to Other Deprivation Indices

## **Chapter 7. Discussion**

The chapter summarizes the findings in previous analysis and responses to the sub-questions raised in the introduction, about the possible difference between morphological centres at different scales, the difference between morphological and functional centres, and the relationship between centres and barriers. Analysis of the impact of these spatial objects helps to understand the centrality from different perspectives and helps to form a complete picture.

### ***7.1 The Scale Difference of Morphological Centres' Impact***

Through two types of regression analysis, it was found that morphological centres of different scales may have opposite effects on adjacent communities in many scenarios, with small-scale morphological centres often playing more positive roles. For example, in section 5.3 MGWR analysis reveals that the existence of Centre Type B may have a significant mitigation effect on the income and barrier deprivation of adjacent communities. Similarly, in section 6.2 the binary logistics regression shows that, communities closer to Centre Type B can be more vulnerable to crime and living environment deprivation. In contrast, Centre type C generally aggravates the relative deprivation and difference in the scenarios above.

The morphological centres defined in this study essentially reflect how often the integration centres at different scales coincided in the same area, measuring the scale continuity of high centrality. Meanwhile, according to space syntax theory, the foreground and background networks distinguished by integration analysis reveal the function differences of urban spaces, and the various analysis scales reflect the difference in activity levels and radiation capabilities (Hillier, 1996).

Based on the division above, Centre Type B can be regarded as a typical transition structure between foreground and background networks. On a smaller scale, Centre Type B shows high centrality and may play a role in improving social interaction and enhancing the community domain. While on a larger scale, Centre Type B still can be classified as part of the background network, buffering the impact of overly intensive activities of the foreground network on residents' daily life. The existence of Centre Type B around the community implies that the region has a relatively balanced network structure at multiple scales. In contrast, communities adjacent to Centre Type C can be closely related to the foreground network on various urban scales, which probably means a continuous exposure to negative street activities as in the crime pattern theory (Brantingham & Brantingham, 1995), and possible higher crime risks or other



deprivation problems.

### ***7.2 Integration and Function based Centres***

In previous analysis, Centre Type the impact of Centre Type C rather than Centre Type A or B show a significant similarity with the impact of high street and primary road. Try to further distinguish the similarities and differences of these three types of centre elements:

In terms of effect, the three centers are related to a higher deprivation score of adjacent communities in most models. The difference is that primary roads, as a road division based on traffic function, showed a more prominent correlation with crime and barrier deprivation in the MGWR analysis and had a weak impact in logistics regression. As an area demarcated based on the density of business activities, the high street showed a mitigating effect on income exploitation in the MGWR analysis and had a significant aggravating effect on all kinds of exploitation indexes along the railway in the binary logistic regression. Centre type C showed a relatively more common negative impact in the MGWR but its impact in various models was weaker than that of primary roads and high streets.

In general, there are similarities between the impact of global integration centres and function-based centres, but the correlation between function-based centres and community deprivation could be more significant. On the one hand, through the overlap of multi-scale integration space, we extracted the spatial structure with similar meaning to the traditional function-based centres, but on the other hand, these morphological centres do not seem to constitute a complete interpretation of complex socio-economic phenomena. Perhaps a composite centre measurement method integrating form and function will bring more possibilities

### ***7.3 Centres and Barriers' Compound Impact on Social Difference***

In terms of communities along the track, MGWR analysis revealed that the spread of the impact of morphology centres could be more obviously blocked by physical barriers such as railways, as in the section 5.3. Binary logistics regression found that the existence of high streets on one side of the railway generally significantly exacerbated the various deprivation indices of the community on that side, while there was no significant role of centre Type B or C observed in this study. If Centre Type C and high streets can be regarded as different centrality carriers in morphology and function, the relationship between centrality and physical barriers may be deduced as follows. On the one hand, physical barriers may weaken the morphological

connection of road networks on both sides of the railway so as to significantly weaken the propagation and diffusion of centrality's impact. On the other hand, the active urban commercial and traffic activities attracted by centrality functionally may also enhance the mobility of the region and trigger side effects such as a rise of crime. As a result, enhancing centrality on one side of a railway track may significantly enhance the local social differences of communities on both sides.

#### ***7.4 Centres as Invisible Barriers***

In this study's methodology, the default hypothesis was that high streets and primary roads are divided as centres, while railway tracks are the barrier element. However, according to the results of the analysis, in most cases, the rail track, highly integrated area, high streets and primary roads, have similar adverse effects on adjacent communities. This blurs the boundary between the centre and barriers. Furthermore, from the perspective of community development, regions with high centrality can also be regarded as invisible barriers to residents' lives and play an essential role in shaping and limiting the community form and residents' activity boundary. On one hand, previous analysis has revealed the potential risks of the high centrality (Kinney, 2008; Browning, 2010). These characteristics of the centre may work as a repulsion to keep some residents' housing choices away from high centrality areas. On the other hand, the daily activities of residents such as shopping and recreation rely on nearby high streets, parks and other local centres around the community. Combining residents' mobility and living expenses, the existence of centres outlines an affordable scope for residents to enjoy and recognise the surrounding environment, which may in turn contribute to the cognitive boundary of other urban regions.

## **Chapter 8. Conclusion**

### ***8.1 Findings & Innovation***

The research has put forward new angles to study the centrality of urban space. On the one hand, based on integration analysis and map superposition, the morphological centre with precise location and scope was extracted and put together with the function-defined high street to compare their possible differences on socio-economic impact. This research method can be regarded as an attempt to interpret space syntax from the perspective of traditional urban planning. Since its founding, space syntax has constructed a highly self-consistent but relatively independent urban cognition and spatial analysis system. Axial or segment analysis focuses on the relationship between a single street and the corresponding global or local system (Hillier, 1996). However, people are inclined to form a cognition of space from concrete objects and activities in daily life. This contradiction and mismatch may lead to the vague interpretation of space syntax analysis in a large-scale and complex urban environment. For this reason, this research attempted to promote communication between the classical perspectives of space syntax and urban planning and explored the differences in spatial roles between urban functional centres and their possible morphological alternatives. This study has revealed that high streets are more significantly related to the socio-economic conditions of the community and can be more sensitive to possible local differences between communities near a rail track. On the contrary, although the morphological centre defined based on integration shares properties with high streets in most analyses, its reliance on the long-term spatial structure may weaken its sensitivity to more active urban phenomena in social and economic fields. This difference further supports Hillier's view of centrality as a process, that the existence of multi-scale centre structures in urban networks work as necessary conditions for the development of specific functional centres in a spatial-led process (Hillier, 1999).

On the other hand, the continuity of centrality on multiple scales was further investigated in this research. From the perspectives of traditional planning and land use, different functional centres may have clear and relatively fixed grade differences, subject to their area size and composition of land use, such as the classic theory of the multiple nuclei model (Harris & Ullman, 1945) . However, from the morphological point of view, the degree of centrality may follow the scale of observation and analysis and is flowable in multiple scales (Yang & Hillier, 2007). In this study, compared with multi-scale continuous centres, centres that exist only on a small scale may be more related to positive spatial effects. The latter are often hidden from

the traditional planning perspective as they do not significantly overlap with commercial facilities but only represent a secondary structure of the road network. Similarly, the relationship between negative spatial connection and community decline (Hillier *et al.*, 1993) in the literature review also reflects the possible relationship between secondary spatial structures and social attributes and can be included in Hillier's argument about the background network and social sustainability (Hillier, 2009). This brings a possibility for future research that, for spatial areas with clear boundaries such as communities, we can systematically test and evaluate its possible security and development potential by identifying the proportion of positive or negative secondary structures within the area and their relationship with housing space.

## **8.2 Limitation**

The limitation of this research is mainly reflected in the data aspect. Specifically, data reflecting communities' socio-economic condition come from the Indices of Deprivation score, a ranking score that only expresses a relative feature and may blur the actual socio-economic situation of the community. In addition, according to the needs of this research, data were converted from the original LSOA unit to the community unit. The converting process may have resulted in additional errors.

## **8.3 Future Research**

The findings of this study about the possible impact of multi-scale continuity of centrality and the centre and barrier elements have inspired questions for future research. For example, it is meaningful to explore which types of activities and behaviours are typically related to ignored local centre structures such as Centre Type B in this study. An exploration from the perspective of individual behaviour may deepen our understanding of the interaction mechanism between spatial structure and socio-economic conditions, and feedback the information omitted from the statistical data.

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## Appendix A. Data Source

### *English Indices of Deprivation 2019 (IoD2019)*

A set of relative measures of deprivation for Lower-layer Super Output Area (LSOA) based on seven domains. According to the official document from the National Statistics, the seven domains of deprivation are explained as follows:

- The **Income Deprivation** Domain measures the proportion of the population experiencing deprivation relating to low income. The definition of low income used includes both those people that are out-of-work, and those that are in work but who have low earnings (and who satisfy the respective means tests).
- The **Employment Deprivation** Domain measures the proportion of the working-age population in an area involuntarily excluded from the labour market. This includes people who would like to work but are unable to do so due to unemployment, sickness or disability, or caring responsibilities.
- The **Education, Skills and Training Deprivation** Domain measures the lack of attainment and skills in the local population. The indicators fall into two sub-domains: one relating to children and young people and one relating to adult skills.
- The **Health Deprivation and Disability** Domain measures the risk of premature death and the impairment of quality of life through poor physical or mental health. The domain measures morbidity, disability and premature mortality but not aspects of behaviour or environment that may be predictive of future health deprivation.
- The **Crime** Domain measures the risk of personal and material victimisation at local level.
- The **Barriers to Housing and Services** Domain measures the physical and financial accessibility of housing and local services. The indicators fall into two sub-domains: ‘geographical barriers’, which relate to the physical proximity of local services, and ‘wider barriers’ which includes issues relating to access to housing such as affordability.
- The **Living Environment Deprivation** Domain measures the quality of the local environment. The indicators fall into two sub-domains. The ‘indoors’ living environment measures the quality of housing; while the ‘outdoors’ living environment contains measures of air quality and road traffic accidents.



Besides, **LSOAs** (Lower-layer Super Output Areas) are small areas designed to be of a similar population size, with an average of approximately 1,500 residents or 650 households. There are 32,844 Lower-layer Super Output Areas (LSOAs) in England. The household data is included in the LSOA unit.

<https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019>

### ***Roads, Railway Track and Rail Station***

The OS Open Map Local Dataset that includes detailed street-level vector data of roads and railways lines, from Digimap, the Ordnance Survey dataset.

<https://digimap.edina.ac.uk/roam/download/os>

### ***Highstreet***

Boundaries of High Streets as developed by the Regeneration team at the Greater London Authority.

<https://data.london.gov.uk/dataset/gla-high-street-boundaries-map>

### ***Space Syntax Model for M25 London***

A Dataset includes a detailed segment map on London's road network and the calculation of a series of attribute like integration and choice, by Space Syntax Limited.

<https://spacesyntax.com/>

## Appendix B. Details about MGWR Analysis

### *Difference between GWR and MGWR*

According to the MGWR 2.2 User Manual(<https://sgsup.asu.edu/sparc/multiscale-gwr>), the official document written by the MGWR 2.2 Development Team, the difference between GWR and MGWR models can be further defined.

For a GWR model, the linear regression model is as follows:

Assuming that there are  $n$  observations, for observation  $i \in \{1,2,\dots,n\}$  at location  $(u_i, v_i)$ ,

$$y_i = \beta_0(u_i, v_i) + \sum_j \beta_j(u_i, v_i) x_{ij} + \epsilon_i,$$

where  $\beta_0(u_i, v_i)$  is the intercept,  $x_{ij}$  is the  $j$ th predictor variable,  $\beta_j(u_i, v_i)$  is the  $j$ th coefficient,  $\epsilon_i$  is the error term, and  $y_i$  is the response variable.

For a MGWR model, the linear regression model is as follows:

Assuming that there are  $n$  observations, for observation  $i \in \{1,2,\dots,n\}$  at location  $(u_i, v_i)$ ,

$$y_i = \beta_0(u_i, v_i) + \sum_j \beta_{bwj}(u_i, v_i) x_{ij} + \epsilon_i,$$

Where  $bw_j$  in  $\beta_{bwj}$  indicates the bandwidth used for calibration of the  $j$ th conditional relationship.

As shown in the equations above, unlike GWR which assumes that the local relationships within each model vary at the same spatial scale, MGWR allows the conditional relationships between the response variable and the different predictor variables to vary at different spatial scales.

### *A Sample Result of MGWR Analysis*

To help interpret the MGWR analysis in Chapter 5, below lists a sample of analysis result, output from the MGWR 2.2 software.

```
=====
Model type: Gaussian
Number of observations: 457
Number of covariates: 10
Dependent variable: Crime Score
Variable standardization: On
Total runtime: 0:00:47
```

#### Global Regression Results

```
-----
Residual sum of squares: 347.411
Log-likelihood: -585.806
AIC: 1191.612
AICc: 1194.206
R2: 0.240
Adj. R2: 0.224
```

| Variable        | Est.   | SE    | t(Est/SE) | p-value |
|-----------------|--------|-------|-----------|---------|
| Intercept       | 0.000  | 0.041 | 0.000     | 1.000   |
| Centre Type A   | -0.052 | 0.050 | -1.041    | 0.298   |
| Centre Type B   | -0.083 | 0.050 | -1.680    | 0.093   |
| Centre Type C   | -0.119 | 0.044 | -2.682    | 0.007   |
| High Street     | -0.093 | 0.055 | -1.698    | 0.090   |
| Railway Track   | -0.018 | 0.058 | -0.311    | 0.756   |
| Railway Station | -0.084 | 0.063 | -1.334    | 0.182   |
| Motorway        | -0.226 | 0.046 | -4.933    | 0.000   |
| Road Density    | 0.146  | 0.051 | 2.892     | 0.004   |
| Household       | 0.056  | 0.045 | 1.246     | 0.213   |

#### Multiscale Geographically Weighted Regression (MGWR) Results

```
-----
Coordinates type: Projected
Spatial kernel: Adaptive bisquare
Criterion for optimal bandwidth: AICc
Score of change (SOC) type: Smoothing f
Termination criterion for MGWR: 1.0e-05
Number of iterations used: 36
```

#### MGWR bandwidths

```
-----
```

| Variable        | Bandwidth | ENP <sub>j</sub> | Adj t-val(95%) | DoD <sub>j</sub> |
|-----------------|-----------|------------------|----------------|------------------|
| Intercept       | 43.000    | 19.549           | 3.033          | 0.515            |
| Centre Type A   | 103.000   | 9.791            | 2.814          | 0.627            |
| Centre Type B   | 450.000   | 1.408            | 2.109          | 0.944            |
| Centre Type C   | 149.000   | 5.765            | 2.636          | 0.714            |
| High Street     | 58.000    | 16.638           | 2.983          | 0.541            |
| Railway Track   | 456.000   | 1.323            | 2.083          | 0.954            |
| Railway Station | 186.000   | 4.171            | 2.523          | 0.767            |
| Primary Road    | 47.000    | 17.690           | 3.002          | 0.531            |
| Road Density    | 142.000   | 5.925            | 2.646          | 0.710            |
| Household       | 427.000   | 1.841            | 2.216          | 0.900            |

#### Diagnostic Information

|  |          |
|--|----------|
| Residual sum of squares:                   | 90.047   |
| Effective number of parameters (trace(S)): | 84.101   |
| Degree of freedom (n - trace(S)):          | 372.899  |
| Sigma estimate:                            | 0.491    |
| Log-likelihood:                            | -277.290 |
| Degree of Dependency (DoD):                | 0.652    |
| AIC:                                       | 724.782  |
| AICc:                                      | 764.294  |
| BIC:                                       | 1075.798 |
| R2:  | 0.803    |
| Adj. R2:                                   | 0.758    |

#### Summary Statistics For MGWR Parameter Estimates

| Variable        | Mean   | STD   | Min    | Median | Max    |
|-----------------|--------|-------|--------|--------|--------|
| Intercept       | -0.072 | 0.509 | -1.112 | -0.110 | 1.067  |
| Centre Type A   | -0.052 | 0.133 | -0.446 | -0.023 | 0.156  |
| Centre Type B   | -0.010 | 0.013 | -0.022 | -0.018 | 0.026  |
| Centre Type C   | -0.027 | 0.102 | -0.200 | -0.034 | 0.160  |
| High Street     | -0.190 | 0.165 | -0.506 | -0.183 | 0.175  |
| Railway Track   | -0.080 | 0.009 | -0.095 | -0.081 | -0.064 |
| Railway Station | 0.029  | 0.080 | -0.174 | 0.042  | 0.166  |
| Primary Road    | -0.114 | 0.361 | -0.988 | -0.143 | 0.674  |
| Road Density    | -0.005 | 0.057 | -0.149 | 0.010  | 0.075  |
| Household       | -0.094 | 0.019 | -0.120 | -0.098 | -0.057 |

## Appendix C. Ranking of the Distance and Density Attributes of Communities

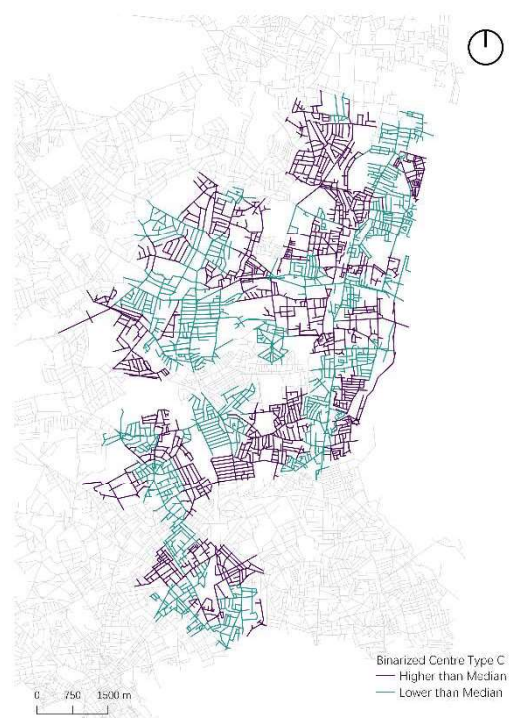
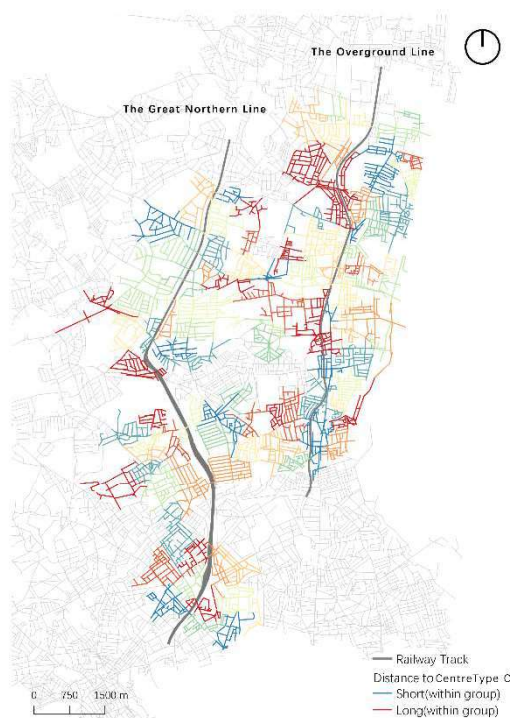
Here list the complete maps of the ranking and the binarized distance and density attributes of communities, mentioned in section 6.2.



Ranking of Distance to Centre Type B



Binarized Distance to Centre Type B

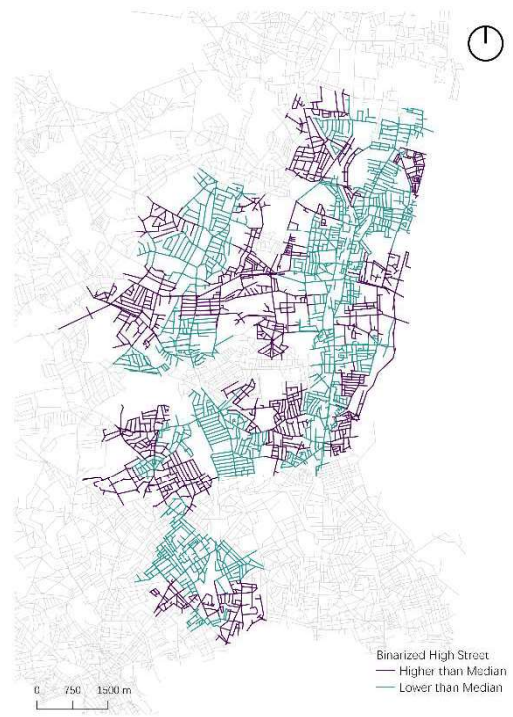




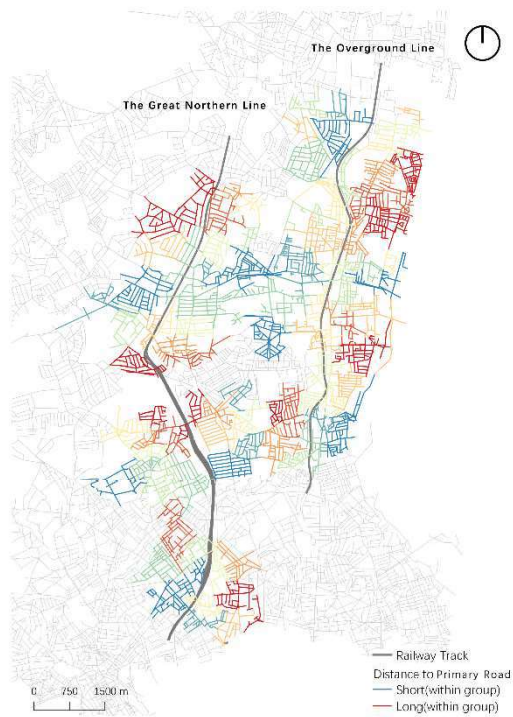
Ranking of Distance to Centre Type C



Binarized Distance to Centre Type C



Ranking of Distance to High Street



Binarized Distance to High Street

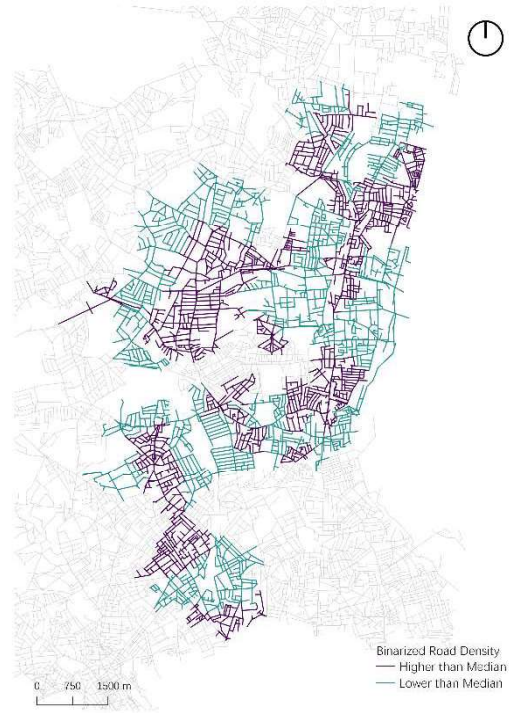


Ranking of Distance to Primary Road

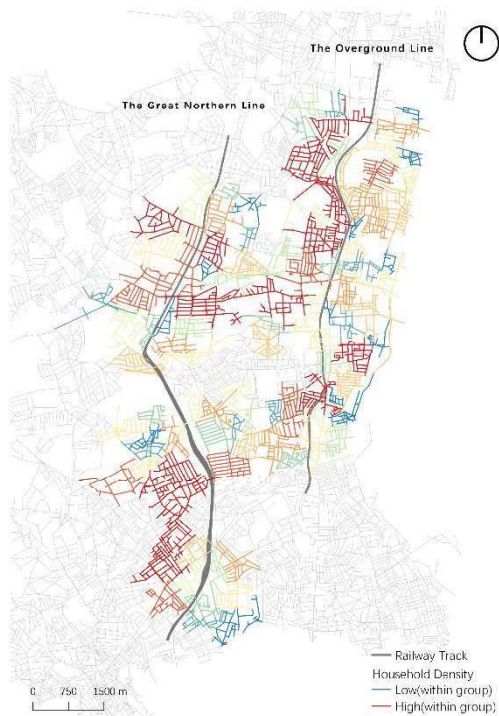
Binarized Distance to Primary Road



Ranking of Road Density



Binarized Road Density



Ranking of Household



Binarized Household

## Appendix D. Complete Tables of ‘Variables in the Equation’ in Binary Logistics Regression

Below list the complete tables of ‘Variables in the Equation’ in 6 models of binary logistics regression, as mentioned in section 6.2.

### Variables in the Equation-Crime Deprivation

|         |               | B      | S.E. | Wald   | df | Sig. | Exp(B) |
|---------|---------------|--------|------|--------|----|------|--------|
| Step 1a | Highstreet    | 1.580  | .420 | 14.126 | 1  | .000 | 4.853  |
|         | Constant      | -.916  | .296 | 9.595  | 1  | .002 | .400   |
| Step 2b | Centre Type C | .795   | .431 | 3.404  | 1  | .065 | 2.213  |
|         | Highstreet    | 1.451  | .429 | 11.418 | 1  | .001 | 4.267  |
|         | Constant      | -1.275 | .368 | 12.031 | 1  | .001 | .280   |
| Step 3c | Centre Type B | -.743  | .445 | 2.796  | 1  | .094 | .475   |
|         | Centre Type C | .762   | .437 | 3.037  | 1  | .081 | 2.142  |
|         | Highstreet    | 1.568  | .447 | 12.329 | 1  | .000 | 4.799  |
|         | Constant      | -.949  | .411 | 5.337  | 1  | .021 | .387   |

a. Variable(s) entered on step 1: Highstreet

b. Variable(s) entered on step 2: Centre Type C.

c. Variable(s) entered on step 3: Centre Type B.

### Variables in the Equation- Living Environment Deprivation

|                     |               | B      | S.E. | Wald   | df | Sig. | Exp(B) |
|---------------------|---------------|--------|------|--------|----|------|--------|
| Step 1 <sup>a</sup> | Road Density  | -1.422 | .414 | 11.789 | 1  | .001 | .241   |
|                     | Constant      | .611   | .285 | 4.596  | 1  | .032 | 1.842  |
| Step 2 <sup>b</sup> | Centre Type B | -1.208 | .431 | 7.874  | 1  | .005 | .299   |
|                     | Road Density  | -1.307 | .431 | 9.189  | 1  | .002 | .271   |
|                     | Constant      | 1.152  | .363 | 10.060 | 1  | .002 | 3.163  |
| Step 3 <sup>c</sup> | Centre Type B | -1.398 | .458 | 9.313  | 1  | .002 | .247   |
|                     | Highstreet    | .986   | .461 | 4.588  | 1  | .032 | 2.682  |
|                     | Road Density  | -1.144 | .444 | 6.626  | 1  | .010 | .319   |
|                     | Constant      | .691   | .413 | 2.799  | 1  | .094 | 1.997  |
| Step 4 <sup>d</sup> | Centre Type B | -1.338 | .472 | 8.050  | 1  | .005 | .262   |
|                     | Primary Road  | 1.110  | .487 | 5.195  | 1  | .023 | 3.035  |
|                     | Highstreet    | 1.293  | .503 | 6.622  | 1  | .010 | 3.645  |
|                     | Road Density  | -1.174 | .457 | 6.591  | 1  | .010 | .309   |
|                     | Constant      | -.063  | .534 | .014   | 1  | .906 | .939   |

a. Variable(s) entered on step 1: Road Density

b. Variable(s) entered on step 2: Centre Type B

c. Variable(s) entered on step 3: Highstreet

d. Variable(s) entered on step 4: Primary Road

### Variables in the Equation - Education Deprivation

|         |               | B      | S.E. | Wald  | df | Sig. | Exp(B) |
|---------|---------------|--------|------|-------|----|------|--------|
| Step 1a | Centre Type C | 1.099  | .405 | 7.360 | 1  | .007 | 3.000  |
|         | Constant      | -.693  | .297 | 5.445 | 1  | .020 | .500   |
| Step 2b | Centre Type C | .949   | .417 | 5.188 | 1  | .023 | 2.584  |
|         | Highstreet    | .822   | .416 | 3.904 | 1  | .048 | 2.274  |
|         | Constant      | -1.007 | .347 | 8.425 | 1  | .004 | .365   |

a. Variable(s) entered on step 1: Centre Type C

b. Variable(s) entered on step 2: Highstreet

### Variables in the Equation-Barriers Deprivation

|                     |              | B     | S.E. | Wald  | df | Sig. | Exp(B) |
|---------------------|--------------|-------|------|-------|----|------|--------|
| Step 1 <sup>a</sup> | Primary Road | .844  | .398 | 4.505 | 1  | .034 | 2.325  |
|                     | Constant     | -.438 | .287 | 2.335 | 1  | .127 | .645   |
| Step 2 <sup>b</sup> | Primary Road | 1.044 | .423 | 6.079 | 1  | .014 | 2.841  |
|                     | Highstreet   | .854  | .424 | 4.061 | 1  | .044 | 2.350  |
|                     | Constant     | -.945 | .393 | 5.770 | 1  | .016 | .389   |

a. Variable(s) entered on step 1: Primary Road

b. Variable(s) entered on step 2: Highstreet

### Variables in the Equation- Income Deprivation

|                     |            | B     | S.E. | Wald  | df | Sig. | Exp(B) |
|---------------------|------------|-------|------|-------|----|------|--------|
| Step 1 <sup>a</sup> | Highstreet | .911  | .400 | 5.186 | 1  | .023 | 2.486  |
|                     | Constant   | -.588 | .279 | 4.442 | 1  | .035 | .556   |

a. Variable(s) entered on step 1: Highstreet

### Variables in the Equation- Employment Deprivation

|                     |            | B     | S.E. | Wald  | df | Sig. | Exp(B) |
|---------------------|------------|-------|------|-------|----|------|--------|
| Step 1 <sup>a</sup> | Highstreet | .829  | .399 | 4.323 | 1  | .038 | 2.291  |
|                     | Constant   | -.588 | .279 | 4.442 | 1  | .035 | .556   |

a. Variable(s) entered on step 1: Highstreet



## **Appendix E. Author's Previous Educational Project Report**

### **The Life along the Tracks**

A Study of the Railways' Impact on Spatial and Socio-Economic Conditions of Communities Along the Lines

#### **Abstract**

The criss-crossing railway system of London can be the epitome of the city's modern development. As a long-standing urban infrastructure, the railway provides convenient transportation services for commuting across regions; while as a physical barrier, it may also have a continuous impact on the local development. This research aims to explore, to what extent, the existence of railway tracks may have an impact on the spatial and socio-economic conditions of communities around the track. The research is carried out on two scales. On a global scale, there is an attempt to compare the distribution differences in the Index of Deprivation data between the areas along and not along the railway tracks in London. It is concluded that the existence of railway can be related to the distribution difference in socio-economic attributes. On a community scale, the Emirates Stadium and Hornsey Station areas are selected as the research objects. Firstly, detailed community structures in the areas are detected, together with their positional difference relative to the tracks. On this basis, a correlation test is carried out between the positional difference and the configurational and socio-economic characteristics of communities. It has been found that communities closer to the railway usually receive a more significant impact of the railway. However, whether it is a positive or negative impact may further depend on the spatial relationship between the railway and the regional integration centres, as well as the density of the built-up environment in the background. In addition, the research has inspired thinking about the spatial and temporal pattern between the railway development and the expansion of built-up area in historical London.

**Key words:** Railway; Socio-economic Difference; Space Syntax; Community Detection

#### **1. Introduction**

Tobler's First Law (TFL) states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p236). However, in real urban space, significant differences in socio-economic conditions, such as crime rate and ethnic composition, can be frequently observed between adjacent communities. In this regard, physical barriers like railways are commonly assumed to be related to these differences. There are some famous hypotheses, like "border vacuums" by Jane Jacobs (Jacobs, 1961, p257), highlighting the railway's disruptive impact in restricting movement and breeding illegal activities. However, it is questionable whether the railway may have the same impact in cities with different social or spatial contexts, and the impact mechanism of these physical barriers on urban space requires more empirical research.

As one of the earliest cities to build rail transit, London's development has greatly benefited from the railways. By the 1850s, there have been rail tracks reaching the fringes of built-up London, and thousands of passengers disembarked at Euston, Paddington or King's Cross stations to make their way into workplaces ('History of rail transport in Great Britain 1830–1922', 2020). The railway system played



an important role in enhancing the spatial connection between London and other early industrial cities. In the meanwhile, the densely distributed railway lines were closely intertwined with the road network, which formed a unique texture of space.

With the expansion of the city, the interaction between railways and the urban space can be inevitable (Bolton, 2018), and there are also local differences observed in a series of socio-economic conditions in London. Considering the widespread existence of railway lines, it is significant to ask what the possible role of railways in these local differences is, and how the railways are involved in the community development of London. In space syntax theory, the configuration of space can be the embodiment of existing social relations, and play a generative role in new social activities (Hillier, & Hanson, 1984). From this point of view, the possible movement restriction by a railway track may shape and reinforce the unbalanced configurational development of communities on the two sides, and further result in socio-economic difference. Conversely, the railway's possible impact can be revealed by analysing the relevant spatial and socio-economic difference. Study below is an attempt to develop this hypothesis.

## **2. Research Questions**

The paper aims to explore, to what extent the existence of railways may have an impact on the spatial and socio-economic conditions of the surrounding communities. The research question can be divided into three parts.

Firstly, is there a typical social difference between local areas along and not along the tracks in London?

Secondly, what's the specific content of railways' impact and how does this impact spread in space?

Thirdly, is there a universal mechanism of railway's impact, which can be applicable to communities with different social and spatial contexts?

## **3. Literature Review**

Questions above constitute a logical chain to learn the railways' possible impact on the surrounding communities. On this basis, additional questions are how to define the possible spatial and socio-economic difference related to the railways, and how to define the communities to compare. These rely on the literature review on previous work .

### **3.1 Indicators Related to the Impact of Physical Barriers**

In previous empirical studies, indicators such as ethnic composition (Kramer, 2012), Index of Multiple Deprivation (Mitchell & Lee, 2014) and some distance-based urban function attributes (Noonan, 2005) have been applied to reveal the possible social impact of urban physical barriers. There is a confirmed correlation between physical barriers and the distribution difference of these indicators, though the significance may vary on global and local scales. To be more specific, Kramer (2012) compares the proportion of black people in different areas of Philadelphia and finds that barriers may not have a substantial impact on global segregation. Instead, they are able to shape the local distribution of different ethnic groups, and somehow protect white neighbourhoods in areas with a higher proportion of non-white residents. Mitchell and Lee (2014) examine the correlation between physical barriers that coincide with the community boundary, such as rivers, parks, railways and highways, and the socio-economic difference from the Scottish Index of Multiple Deprivation (SIMD) in Glasgow. With the linear regression method on global scale, there is a weak association between barriers and deprivation differences. From the research above, it is an effective method to identify the dissimilarity between statistical data and explore the relationship between dissimilarity and the existence of railway.

Besides the social aspects, there are also spatial indicators related to the physical barriers' impact. In space syntax theory, integration and choice as morphological attributes are widely used as indicators to detect the possible isolated structure in urban space. For example, in *Space is the machine*, Hillier(1996) picked out three housing estates around King's Cross in London with segregated lines in the global integration map. These estates become problematic due to the complex inner structure and a lack of connection with global network. And the physical barriers surrounding King's cross play an important role in reducing the connection. In addition, Bolton (2018) also applied space syntax measurement to identify the long-term segregation impact of London railway terminals in urban space. A decrease of integration and choice value can be observed in neighbourhoods with the development of most terminals(Bolton, 2018, p354).

In conclusion, the empirical research above provides a good reference for indicators and methods possibly revealing the social and spatial impact of the railway. Especially, the findings from social indicators suggest the necessity of testing the impact from a smaller spatial scale.

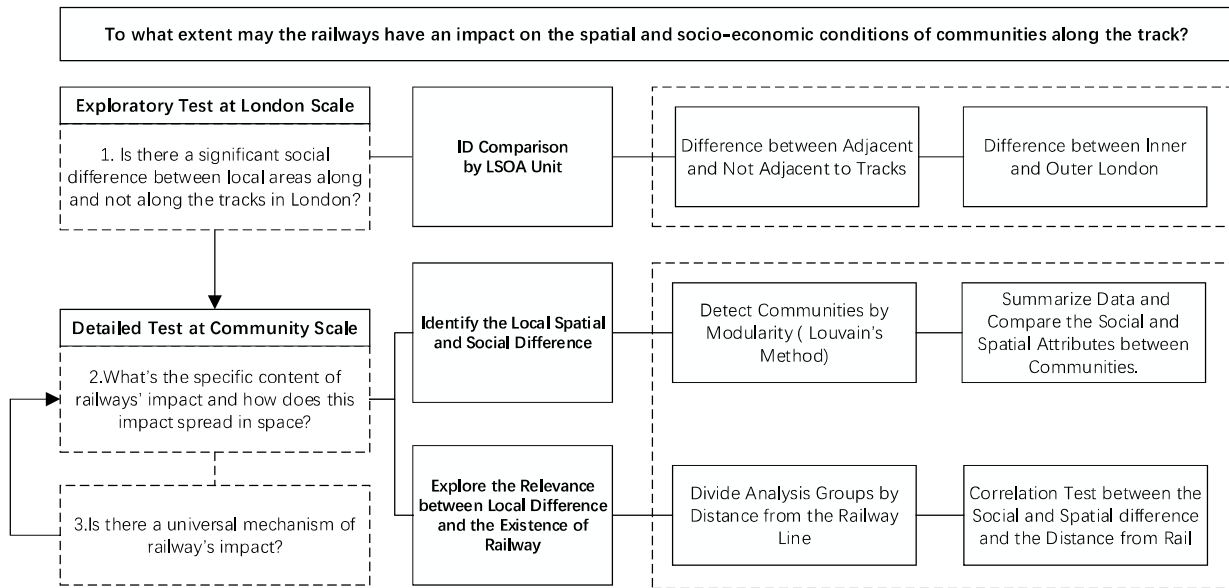
### **3.2 Community Defining Method**

In order to measure the impact of physical barriers on communities, it is necessary to define the boundary and the cross-boundary relationship of communities and control the irrelevant variables. Adjacent census tracts or block groups are commonly used as observation units, and spatial or socio-economic characteristics can be summarised and compared by units (Noonan, 2005; Mitchell & Lee, 2014). However, for research with a higher resolution requirement, Law (2018) argues that the census tracts may not accurately reflect the physical boundary and the distribution of internal characteristics of the community. Instead, Street-based-Local-Area (St-LAs) is put forward to define communities based on street segments and capture subtle perceptual differences in the urban environment (Law, 2018, p65). Law uses the method to identify the communities in Greater London and studies the relationship between housing prices and spatial network configuration. The study proves the practicability of the method in urban community detection.

To sum up, census boundary as a community can be more suitable for a large-scale socio-economic comparison, and it can be regarded as an indirect method to reveal the barrier's impact (Roberto, & Hwang, 2015). While the community detection based on street segment and distance can play a more critical role in research requiring higher resolution, and sensitive to environmental or physical characteristics.

## **4. Methodology**

Based on the literature review, the research questions in section 2 can be transformed as the tests of spatial relevance between railway tracks and the distribution difference of a series of spatial and social attributes on London and community scales. The methodology framework is designed as below (Figure 1), corresponding to different research questions and analysis methods.



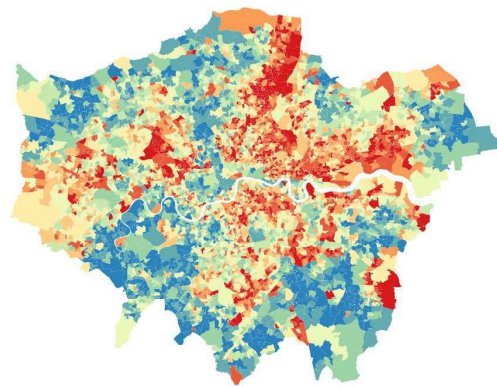
**Figure 1.** Methodology framework (Self-drawing)

### 4.1 London Scale

On London scale, it is a preliminary test about whether the existence of railway tracks near communities makes a typical social attribute difference. The test is mainly based on the data of census boundary of Lower Super Output Areas (LSOA) (Figure 2a) and the corresponding Index of Deprivation (ID) data in Greater London (Figure 2b). The LSOA boundary divides urban space into areas with a similar population, and ID data provides eight types of residents' socio-economic attributes, such as income, employment, health, and crime. On this basis, the data of ground-level railway lines and the boundary of inner and outer London are used to divide LSOA units into four groups (Figure 3), according to whether they are adjacent to the railway and whether they are located in the Inner London area. The average values of ID scores are respectively calculated in each group and also, compared among different groups.

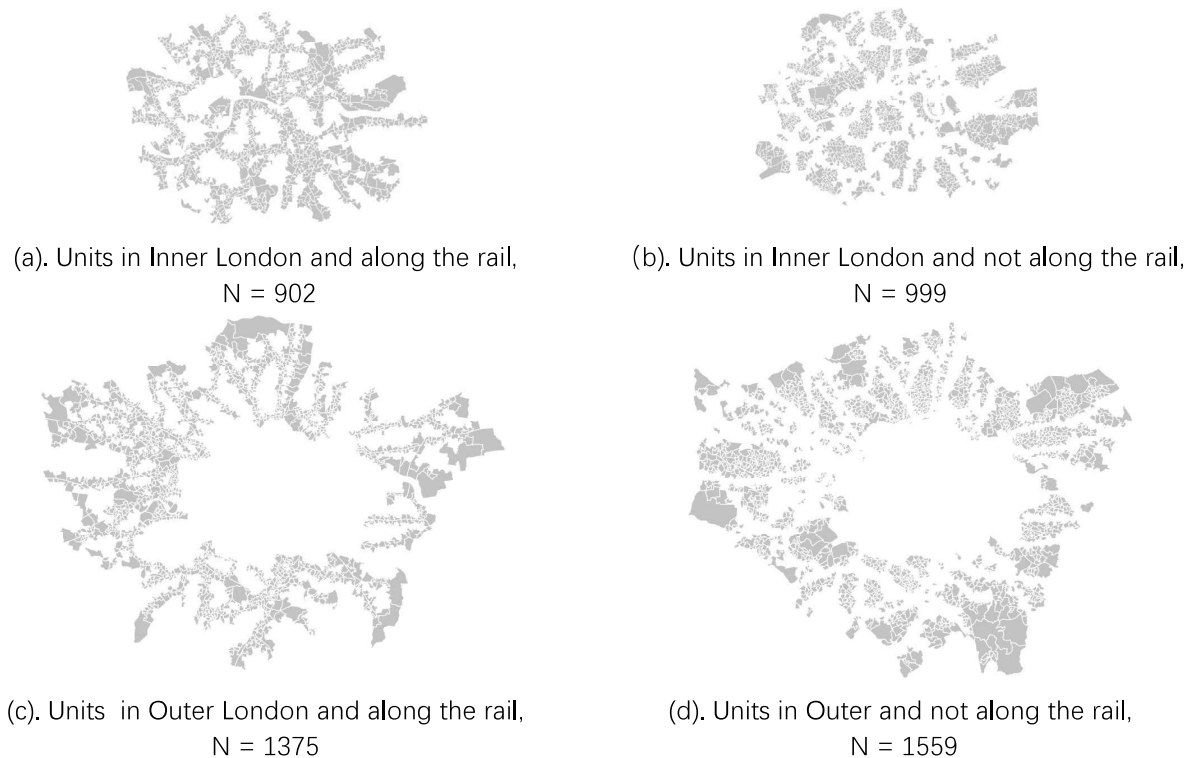


(a). Boundary of Inner London and outer London



(b). LSOA units in all London boroughs

**Figure 2.** LSOA boundaries and the corresponding ID values in the Greater London

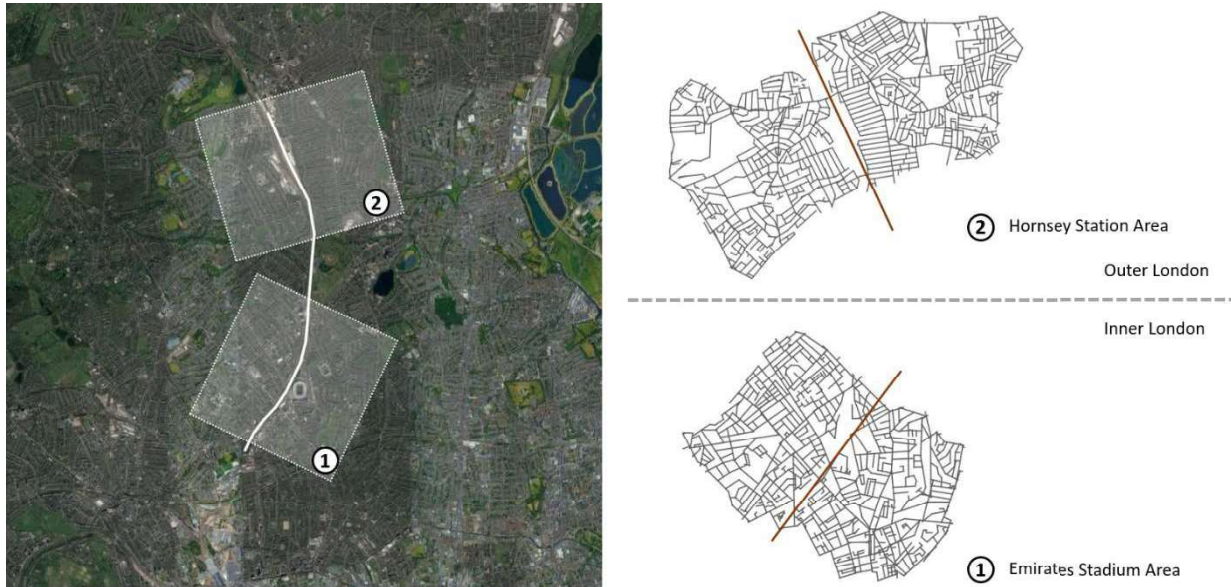


**Figure 3.** 4 groups of LSOAs divided in the Greater London (Self-drawing)

## 4.2 Community Scale

On a community scale, taking a group of typical communities along the railway as research objects, it is a detailed test to explore the distribution property of significant spatial and social difference, and their relevance with the distance from railway. On this basis, more research objects with similar size can be tested to see, whether there is a universal mechanism of railway impact in different contexts.

Communities near Emirates Stadium in inner London and communities near Hornsey station in outer London are selected as the research objects (Figure 4). Two groups of communities are located along the same railway line, "the Great Northern Line", and with similar size. Among them, communities in the Emirates stadium area are mainly used to analyse and identify the specific spatial and social difference related to the railway and the possible mechanism. The objects in the Hornsey area are taken as a control to test further whether the mechanism is universal or not. In terms of data, the Index of Deprivation data can be applied to reveal the socio-economic conditions of the area and the road network data is added to reflect the spatial configuration characteristics with space syntax measurement. Besides, data such as historical maps, Point of Interest (POI) and street crime are also collected as a reference. Details about the data source are listed in the Appendix 1.



**Figure 4.** Research areas of Emirates Stadium (object 1) and Hornsey station (object 2)

In order to identify the local spatial and social difference, units of observing and summarising the community conditions can be defined first. Considering that the LSOA data may not accurately describe the community boundary in real space, the Louvain method is applied to find road segments with stronger connection and form communities in the road network (in Appendix 2) (Blondel et al., 2008; Law, 2018). On this basis, linear distance from the centroid of community to the railway line is calculated, which defines the spatial relationship between units and railway tracks. Four communities along the railway and four communities away from the railway are selected respectively on both sides. The average score of integration by space syntax analysis and attributes of Index of Deprivation (IMD) are compared among communities.

Correlation analysis is applied to further explore the possible relevance between local difference and the existence of railway. A preliminary hypothesis is that impact of the railway on communities on both sides may spread with distance, and communities closer to the railway receive a larger impact. To test the hypothesis, each road segment is regarded as an analysis unit at different road distance from the railway line. Calculation of the distance is based on the catchment analysis of the Space Syntax plug-in in QGIS. On this basis, correlation analysis is carried out by segment to identify further the relationship between the distance from the railway and the spatial and social attributes. In order to test whether there is a universal mechanism of railway's impact, similar correlation analysis can be repeated in areas along different track segments.

## 5. Analysis & Interpretations

### 5.1 Does the Existence of Railway Tracks Make a Social Difference?

In the preliminary test of railway's impact, it is found that for inner London, LSOAs adjacent to the railway have a higher mean score in almost all the ID attributes (Figure 5), which means the social conditions get worse. For scores of Crimes and Barriers to Housing and Services, LSOA units adjacent to tracks are 59% and 124% higher than those not adjacent to the railway tracks. This shows that the existence of railway may be related to the aggregation of some negative social attributes in the surrounding areas. However, for outer London, units adjacent to tracks only have a higher mean score in Crime, Barriers to Housing and Services and Living Environment Deprivation. Moreover, for Income,



Employment, Education and Health Deprivation, LSOAs adjacent to the tracks get lower scores, which means a better situation. The difference shows that in outer London, although the aggregation of negative social attributes such as crime may still be associated with the railway, residents living close to the track may maintain a better economic condition than those far away from the track.

To sum up, the existence of railways does make some difference on communities nearby, while the explicit impact may be significantly different between inner London and outer London. In order to study the possible forms and mechanism of the railway's impact, small-scale objects and accurate spatial analysis are required to learn about the interaction between the railway and the surrounding environment.

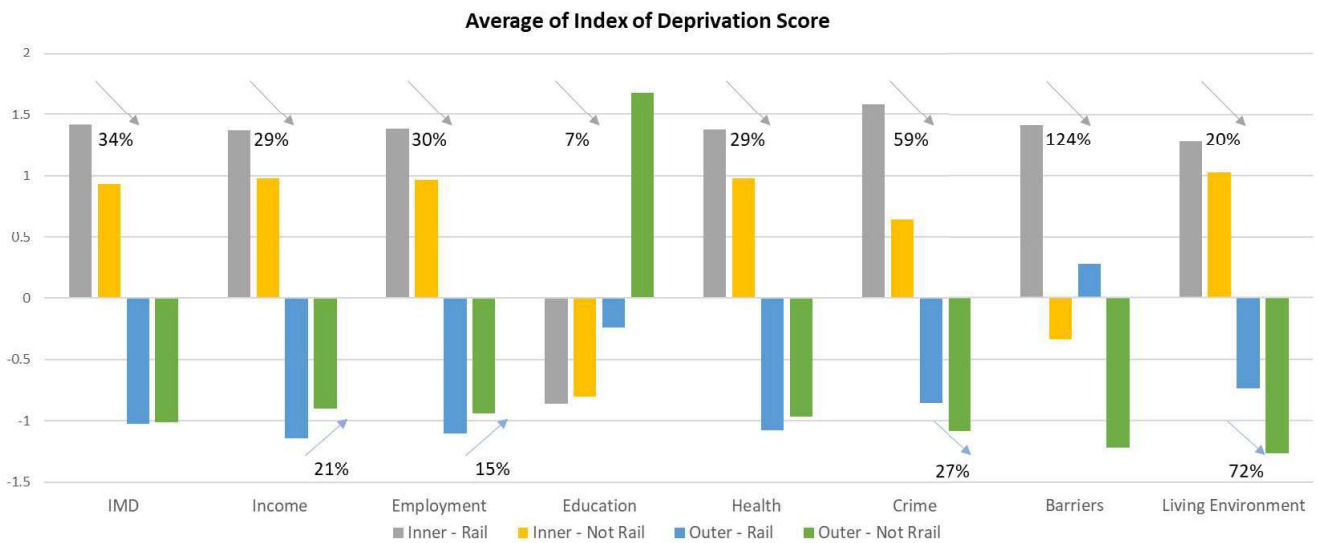


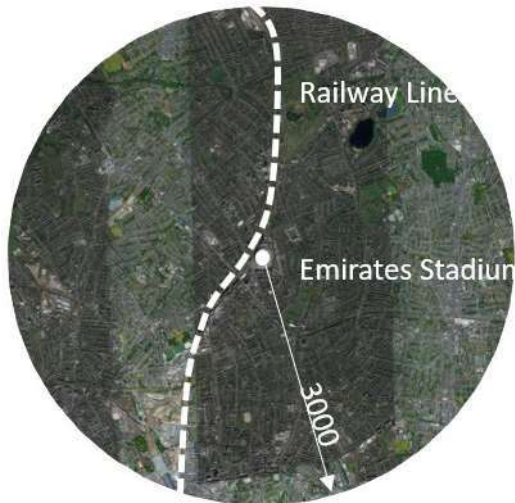
Figure 5. Comparison of Average ID scores in 4 LSOA groups (Self-drawing)

## 5.2 What are the possible local differences associated with the railway?

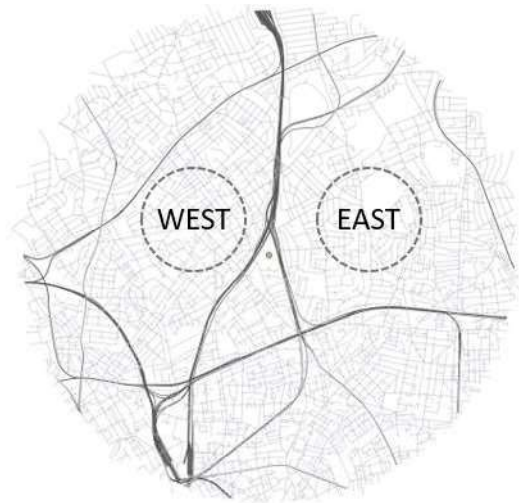
For communities along the railway track in the Emirates Stadium area, the general distribution of a series of spatial and socio-economic attributes is firstly analysed. On this basis, the attribute differences between communities on the same side and on both sides of the railway are further compared.

### 5.2.1 General Distribution of Spatial and Socio-economic Attributes

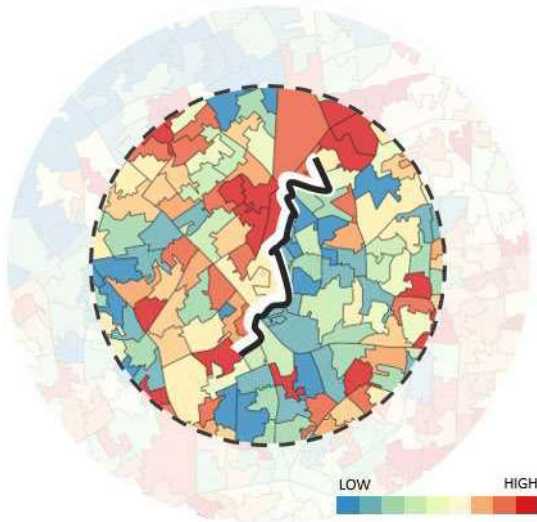
Communities in the Emirates Stadium area can be divided into the east and the west parts by the railway line, and there is a continuous physical barrier restricting the daily movement.(Figure 6a & 6b). It has been preliminarily found that the IMD score on the west side is much higher than that on the east (Figure 6c), and the existence of the railway is assuming related to the difference of IMD distribution. Besides, the integration value and the count of street crimes and POIs also show an unbalanced distribution like IMD between two sides (Figure 6.d,e,f). On this basis, Normalized Angular Integration of R2000 (NAIN2000) and IMD score are selected as two typical spatial and socio-economic attributes of the region, and the relation between their distribution characteristics and the railway can be further analysed.



(a). Position in Satellite Map



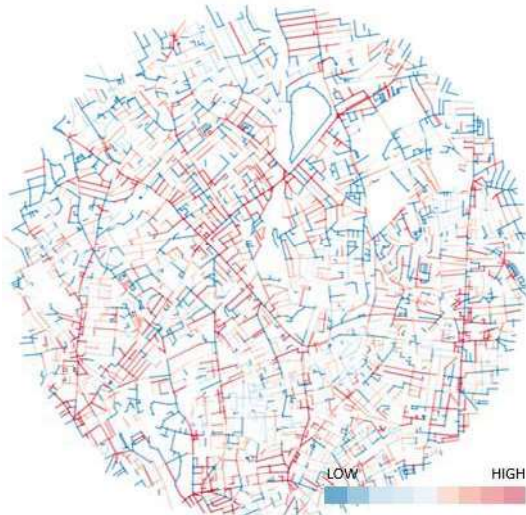
(b). Railway and Road Network



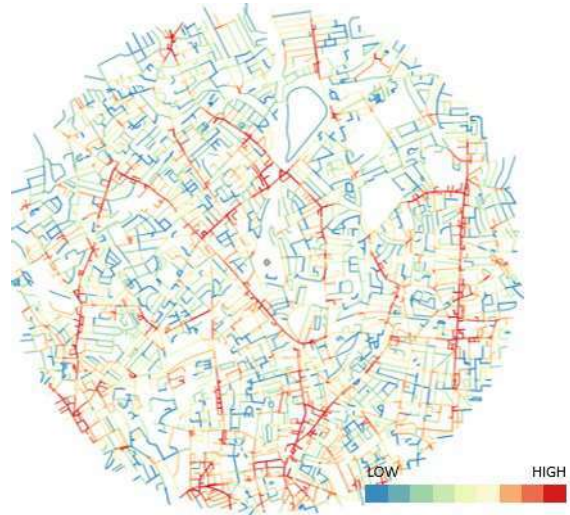
(c). Average IMD Scores by LSOA units



(d). NAIN R2000



(e). Crime on Street



(f). POIs on Street

**Figure 6.** The distribution of a series of spatial and socio-economic characteristics in Emirates Stadium Area (Self-drawing)



### 5.2.2 Community Based Comparison

Eight communities along the track and eight communities away from the track are selected based on the community detection method (Figure 7a & 7b), and the mean values of NAIN2000 and IMD in pairs of communities symmetric to the railway are compared, respectively (Figure 8a & 8b). For communities along the railway, higher mean values are observed on the west side, both in integration and IMD score. Besides, the closer to the connecting road across the railway, the weaker the contrast between communities on both sides. For communities gradually away from the railway, the contrast between the two sides can be prominent within four communities along the railway, while for the other four communities away from the railway, the contrast is weakened. In conclusion, the value of IMD and integration follows a similar pattern to change with communities' distance from the rail. The closer to the central area, communities can be more severely separated by the railway track and the more significant the contrast in social and spatial attributes. However, there may be a lack of continuity in the measurement of distance from the rail because of the division of communities. The correlation between railway and the local difference is further tested by segments in the next section.

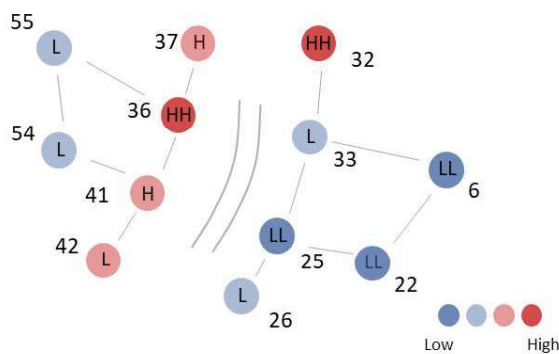


(a) Eight communities along the track

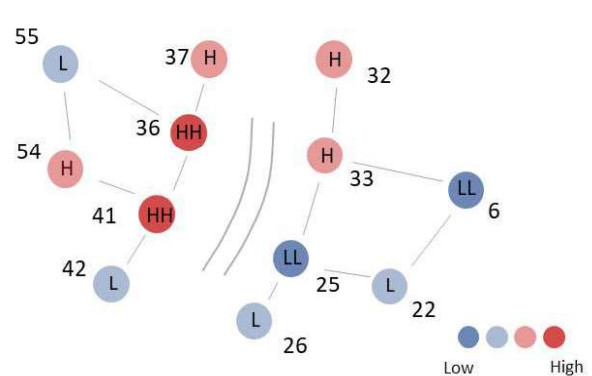


(b) Eight communities away from the track

**Figure 7.** Communities detected on two sides of the railway line (Self-drawing)



(a) Index of Multiple Deprivation



(b) NAIN2000

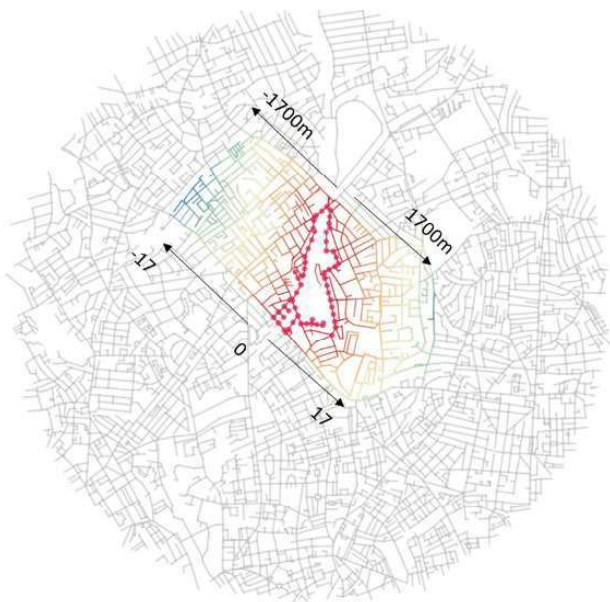
**Figure 8.** Comparison of Index of Multiple Deprivation and NAIN2000 between communities (Self-drawing)

### 5.3 Spatial Correlation between Local Differences and the Railway

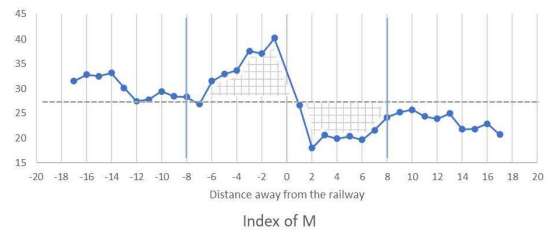
Further compare the distribution of IMD and integration values within different distance groups and street segments (Figure 9a). Similar to the previous comparison, the distribution of IMD values on the east sides shows a great contrast within 800m away from the railway (Figure 9b), while for distance beyond 800m, the value goes back to an average level. The difference further indicates that there may be a clear distance limit on the railway's impact on surrounding communities, and the impact can be weakened with the increase of distance from the railway. On this basis, street segments within 800m on both sides of the railway are selected to study further the correlation between the distance from the railway and the distribution of ID scores and integration values (Figure 9c).

#### 5.3.1 ID Scores and Distance from the Railway

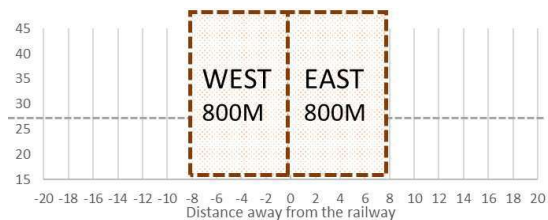
As shown in Table 1, within 800m of the west, most ID scores show a significant and robust negative correlation with distance, in which income is the most prominent. This indicates that residents with better social conditions are distributed in areas relatively far away from the railway. However, for 800m of the east, in addition to the weak negative correlation between Health, Barriers and Living environment, ID scores no longer have a strong correlation with distance, as on the west side. To sum up, the distance from the railway is commonly and negatively correlated with the ID scores on both sides, which means the further from the rail, the better the social situation. However, the correlation on the west is significantly more potent than that on the east, which indicates that the distance from railway may not fully explain the ID distribution on two sides. The direct impact of railway by distance may not be as significant as assumed. It is necessary to consider the role of integration value further.



(a) Distribution of distance from the railway



(b) IMD scores distribution in different distance groups



(c) Distance range for correlation analysis

**Figure 9.** Distance and ID distribution of segments from the railway track (Self-drawing)

**Table 1.** Correlation analysis between ID scores and distance from the railway track

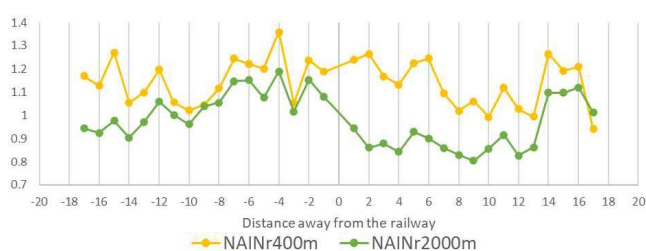
| Correlations         |         |         |            |           |         |       |          |                    |
|----------------------|---------|---------|------------|-----------|---------|-------|----------|--------------------|
|                      | IMD     | Income  | Employment | Education | Health  | Crime | Barriers | Living Environment |
| Distance In the West | -.593** | -.636** | -.462**    | -.435**   | -.464** | -.058 | -.246**  | -.071              |
| Distance In the East | -.098   | -.027   | .031       | .000      | -.205** | -.097 | -.252**  | -.246**            |

\*. Correlation is significant at the 0.05 level (2-tailed), \*\*. Correlation is significant at the 0.01 level (2-tailed).

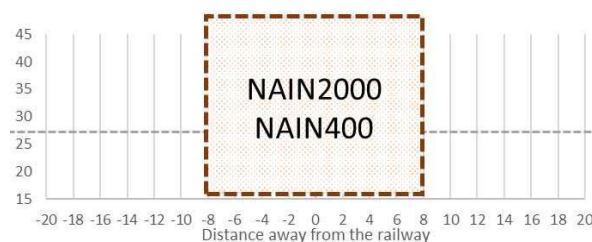
### 5.3.2 Integration and Distance from the Railway

NAIN2000 and NAIN400 are selected as the global and local measurement of spatial configuration, respectively, to test their correlation with 8 ID attributes in 800m distance from the railway (Figure 10). Within 800m from the railway, NAIN 2000 shows a relatively strong and positive correlation with crime, health and barriers score (Table 2), which means the higher the global integration, the worse the situation. In comparison, NAIN400 show a weak and negative correlation with income, employment and education, which means the higher the local integration, the better the situation. In conclusion, the global and local integration degrees are correlated with different ID indexes, and their roles to communities are possibly opposite.

Besides, the distribution of NAIN2000 within distance groups show a similar pattern as the distribution of IMD. If the NAIN 400 is also added into comparison, the difference between NAIN400 and NAIN2000 can be an even better explanation of the change of IMD. Furthermore, when comparing the correlation between NAIN2000 and NAIN400 on both two sides, it can be found that there is a higher R-value on the west (Figure 11a), and the roads with high global integration overlap more frequently with locally integrated road (Figure 11b & 11c).



(a) Value distribution of NAIN200 and NAIN400



(b) Distance range for correlation analysis

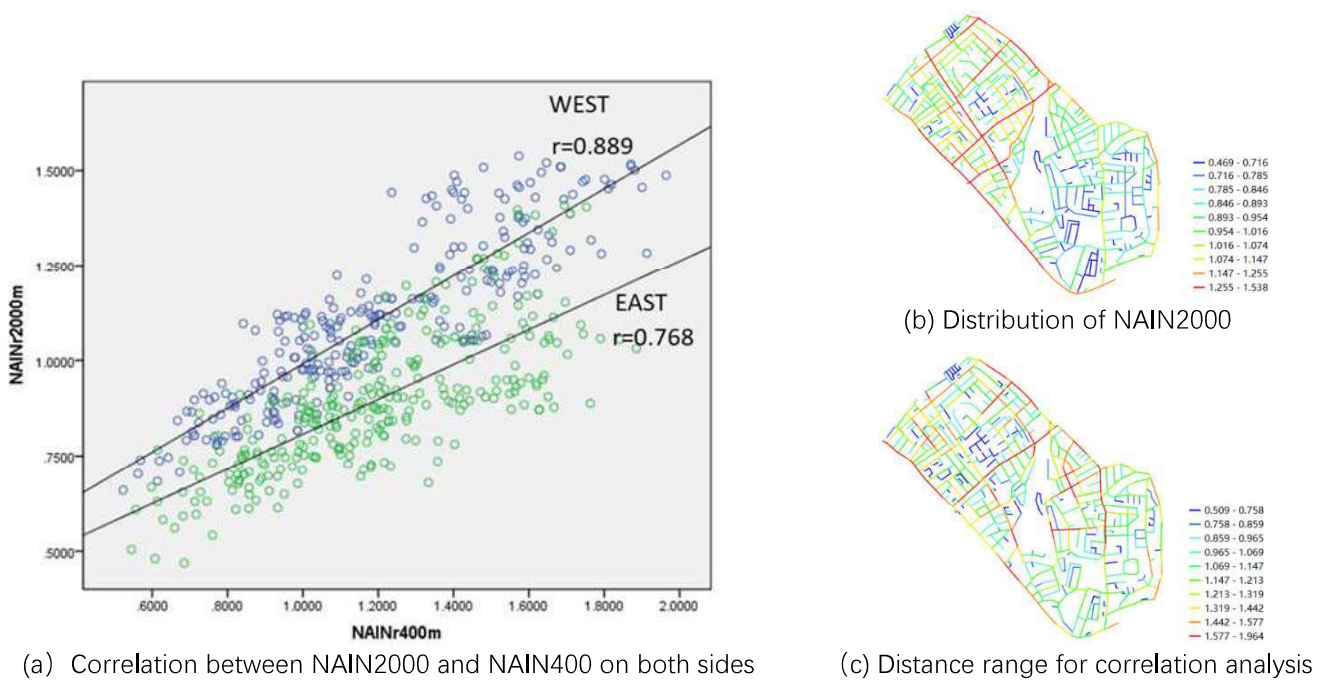
**Figure 10.** Value distribution of NAIN2000 and NNAIN400 in distance group (Self-drawing)

**Table 2.** Correlation analysis between NAIN2000, NAIN400 and ID scores

| Correlations |          |        |         |            |           |        |        |          |                    |
|--------------|----------|--------|---------|------------|-----------|--------|--------|----------|--------------------|
|              | Distance | IMD    | Income  | Employment | Education | Health | Crime  | Barriers | Living Environment |
| NAIN2000     | -.446**  | .274** | .099*   | -.024      | .147**    | .363** | .408** | .398**   | .216**             |
| NAIN400      | -.051    | -.086  | -.126** | -.159**    | -.100     | .031   | .002   | .072     | -.025              |

\*. Correlation is significant at the 0.05 level (2-tailed), \*\*. Correlation is significant at the 0.01 level (2-tailed).





**Figure 11.** Spatial distribution and the correlation of NAIN2000 and NAIN400 (Self-drawing)

### 5.3.3 Findings about the Possible Mechanism of Railway's Impact

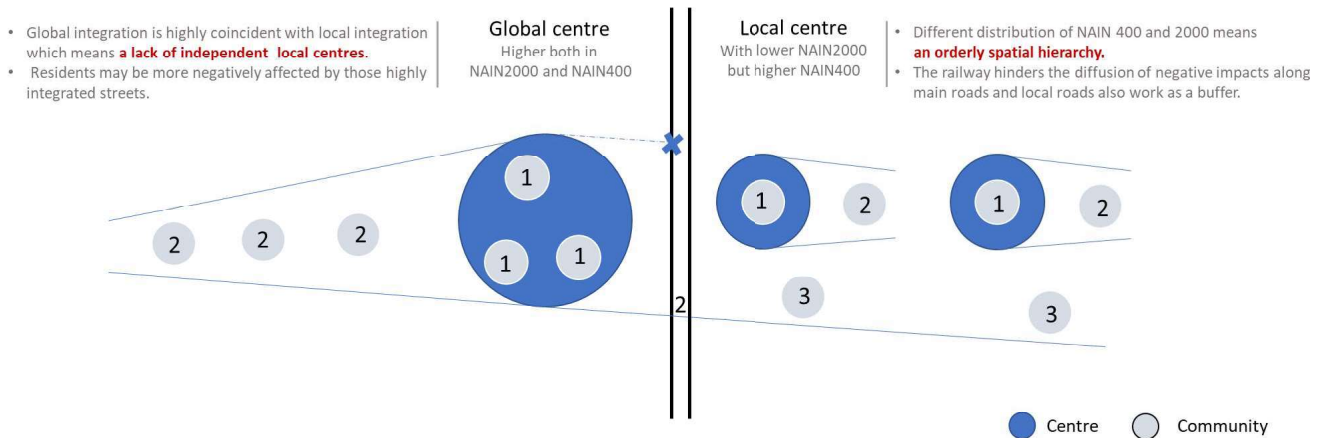
In section 5.22, it is found that the value of IMD and integration follows a similar pattern to change with communities' distance from the rail. This seemingly means that there is a direct impact of railway spreading by distance. However, based on the correlation analysis above, the possible mechanism of impact can be explained in a different way.

Firstly, the railway may only have a weak direct impact on the surrounding communities, and the impact is partly overlapped by that of global integration. To be more specific, the distribution of ID score can be more correlated with the regional integration centre. Considering that there is a regional centre - the Holloway centre adjacent to the railway, the measurement of distance from the railway may be actually the distance from the integration centre. This can be further supported by the east-west difference of correlation between ID distribution and distance.

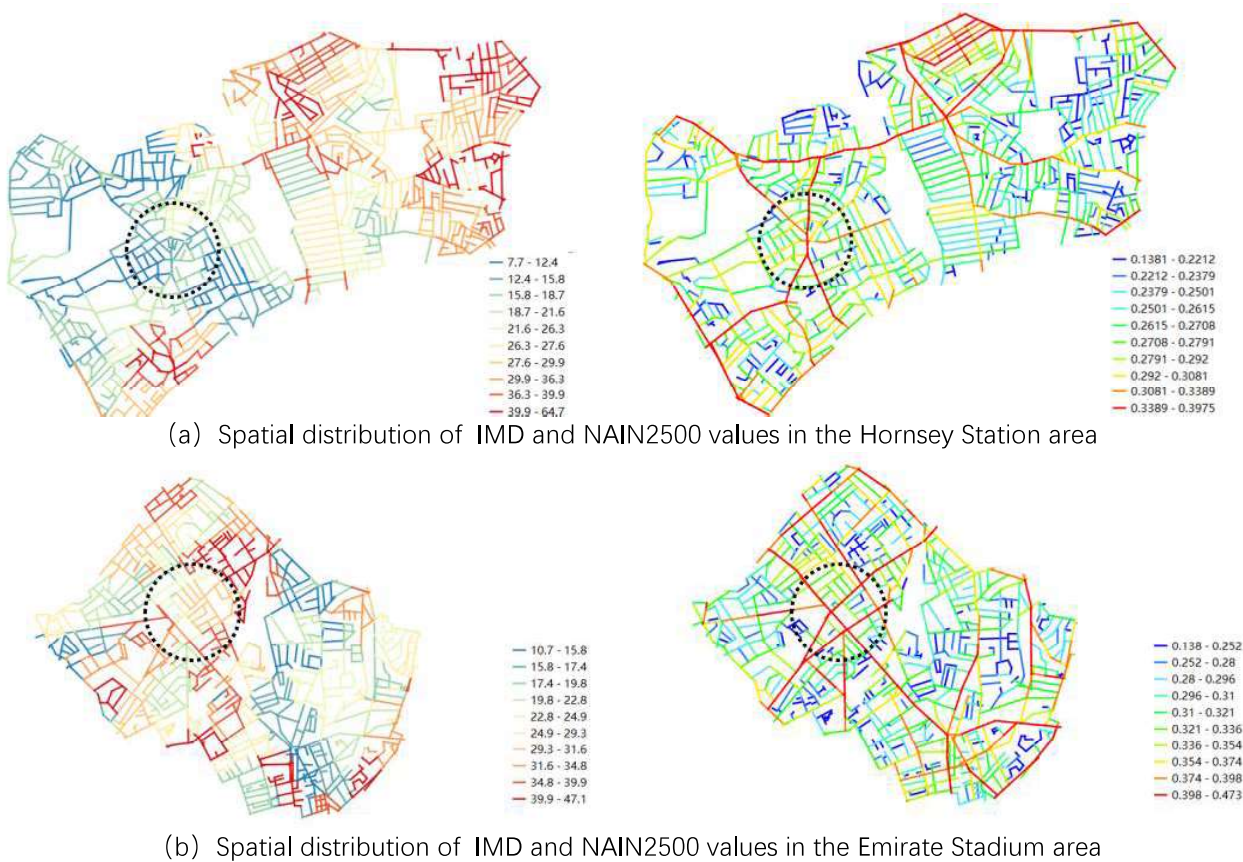
Secondly, although the direct impact of railway is limited, it may indirectly affect the regional ID distribution through its impact on the distribution of integration. In the King's Cross estates examples mentioned before, Hillier argues that the integration core can be peripheralised because of the global block of physical barriers (Hillier *et al.*, 1993, p62). This may result in a lack of interior structure in estates and the disruption of probabilistic social interfaces. Similarly, space on the west side near the railway can be over-integrated because of the spatial restriction of the barriers, and this covers up the local structure beneficial to communities. As a result, for both sides of the rail, there may be different centre structures (Figure 12). For the west, global integration is highly coincident with local integration, which possibly means a lack of independent local centres. On this basis, the residents who live in the centre of global integration may suffer more from the adverse effects of the integration centre. In contrast, residents who are relatively far away from the rail may benefit more from opportunities and convenience brought by the global centre. For the east, different distribution of NAIN 400 and 2000 form an orderly

spatial hierarchy, where communities gather around the local centre and are blocked from the negative impact from the other side.

In conclusion, the impact of the railway on the ID distribution of surrounding communities may be indirect, depending on the spatial relationship between railway lines and the global integration centres, and more cases are required to study the universality of the assumptions.



**Figure 12.** Possible structure difference of integration centres and communities on both sides of the railway track (Self-drawing)



**Figure 13.** Comparison of high and low aggregation of IMD score and the integration centres (Self-drawing)

## 5.4 Is There a Universal Mechanism of the Railway's Impact?

In order to learn whether the assumptions from Emirate Stadium can be a universal mechanism of the railway's impact on the ID distribution, similar methods are used to analyse the distribution of integration and ID scores in Hornsey station. Hornsey station is located to the north of Emirate Stadium, adjacent to the same railway line, but subordinate to outer London in administrative division. It has been found that two integration centres are corresponding to the high and low value aggregation of IMD, respectively on the west and east sides of the railway (Figure 13). At the same time, both of them are not adjacent to the rail. On the one hand, it is clear that in the Hornsey station area, the distribution of ID scores mainly changes according to their distance from integration centres while the railway itself has little impact. On the other hand, the ID contrast between the two sides around Hornsey station can be gentler than that in the Emirates Stadium Area. Considering that the difference between the two groups is whether the integration centre is adjacent to the railway, it can be inferred that the location relationship between the railway and the integration centres plays a vital role in determining the explicit impact of the railway. The correlation analysis results support the findings above, listed in Appendix 3.

## 6. Discussion

The findings from Hornsey station support the assumptions in the Emirate Stadium area and partly prove that there could be a universal mechanism to explain how the railway has an impact on the surrounding communities. In this section, the question is further discussed from a historical view and focuses on the evolution of spatial morphology.

By comparing historical maps, it is found that the mutual position of railways and highly integrated roads have been basically established in the early stage of urban construction. Furthermore, the intersecting or parallel relationships between them may play different roles in the extension of the regional road network. As in Figure 14, for example, the railway in the Emirate Stadium area intersected with the main road on the west side and formed a narrow triangle area in the 1870s. The extension of the road network to the east is hindered by the railway, and the triangle area is directly affected by a highly integrated centre, which shows greater negative characteristics. However, in the vicinity of Hornsey station, the railway and the main roads are almost parallelly distributed, which brings less interference to the development of communities along the railway. The railway plays mainly a role of separation, without further intensifying the negative impact of the high integration centre.

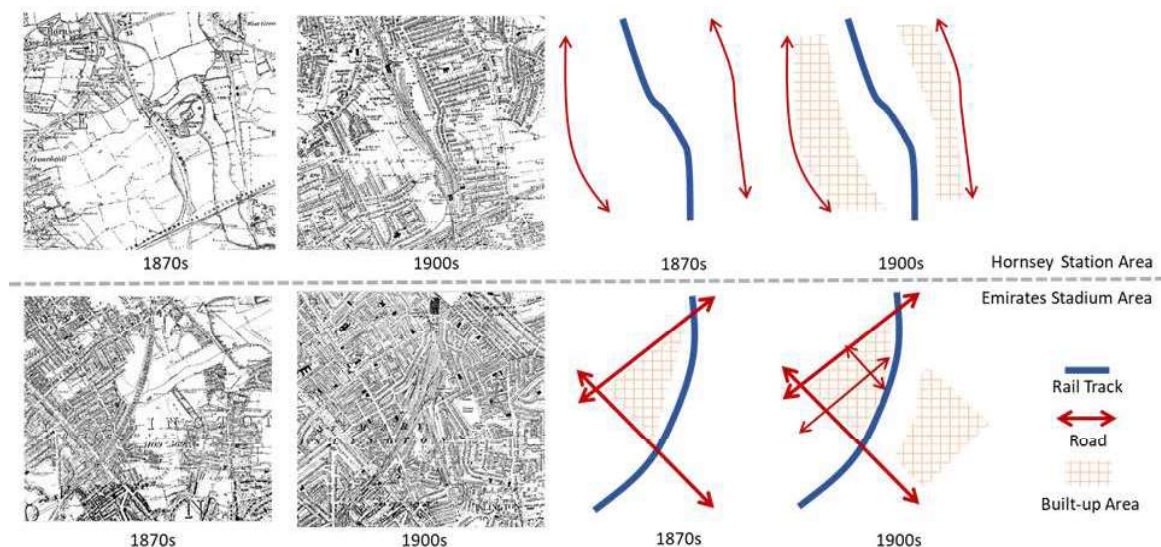
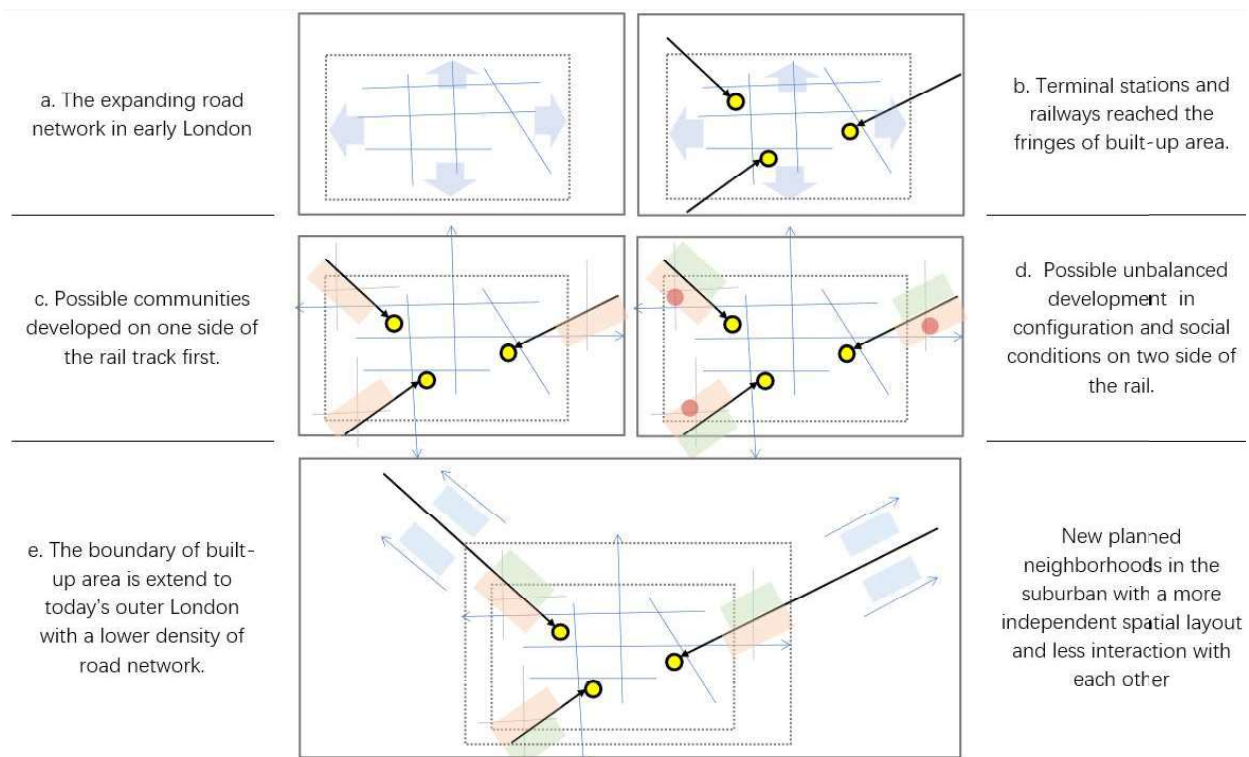


Figure 14. Possible spatial evolution of communities based on history map comparison (Self-drawing)



If the view above make sense, then a complete storyline may be suggested by reviewing the history of London's early development. By the 1850s, several railway lines have reached the edge of the built area of London, and the road network was expanding rapidly from the traditional city centre to the countryside (Figure 15a & 15b). In this process, some of the main roads may first intersect with the railway lines in the inner city or suburb with high density, and brought about the unbalanced development on both sides of the railway (Figure 15c & 15d). In this stage, railway lines may have played an important role in shaping the urban function and residents' life. With the further expansion of London's built-up boundary, the distance between railway lines in the new urban fringe areas may have been looser, with a decreasing built-up density. This reduced the probability of intersection between railway and road networks and weakened the railways' constraints on the residential structure and residents' lives (Figure 15e).

On the one hand, the above hypothesis integrates the findings from Emirate Station and Hornsey station areas. On the other hand, it also adapts to the spatial dependence of railway impact mentioned in the literature review. As far as London is concerned, the expansion of built-up area follows an apparent temporal sequence. As long-standing infrastructure built since early London, the railways should also have a temporal sequence impact on the surrounding area. Thus, for different segments of the railway track, there may be different impacts on the surrounding communities, and it depends on the local spatial contexts and the way the railway track is integrated with the background road network.



**Figure 15.** Possible spatial evolution of community forms along the railway lines (Self-drawing)

## 7. Conclusion

In conclusion, the railway may have had an autonomous impact on the surrounding communities since its first construction. With the development of a modern London, the morphologic structure and social activities in communities can be indirectly changed during their interaction with rail tracks. On this basis, a significant socio-economic difference may occur depending on the location of railway segments in the city as well as the way railways are combined with the surrounding street network. For historical districts or areas with higher built density, the railway's restriction on road extension may aggravate the overlapping of the global and local centres and produce adverse effects. In contrast, for areas with low building density, or weak connection between road network and railway, in contrast, the influence of the railway on the communities is limited. Nevertheless, spatial segregation from the railway may always magnify the differences between the communities on the two sides.

The limitation of the research lies in that, the existing conclusions are mainly based on the comparison of the two groups of communities, and there is still a lack of universality. Similar research methods can be extended to a broader range of urban objects. Besides, more systematic correlation and regression analysis methods can be introduced to explain the spatial autocorrelation and local difference in the community scale of research.



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