Walkable Newcastle

An assessment of urban accessibility under the framework of the '15-minute city'

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1 Goals

1.1 Initial Goals

The following aims and goals were identified in the project inception report:

- To assess Newcastle on how it meets the 15-minute city criteria of proximity, density, and diversity.
- To find out which areas of Newcastle provide a diverse range of services that can be reached within 15-minutes of walking. This will involve categorising buildings into local services, transportation, leisure, education, health services and green areas. *Network Analyst* in ArcGIS will then be used to calculate areas within a 15-minute walk.
- Assess Newcastle at the output area level through factors like land-use mix, population density, employment density, distance to work, and car ownership. Use census data and GIS data where possible to map values.
- Establish a relationship between these factors through multivariate analysis at the output area level by splitting the area covered by a 15-minute walk for all neighbourhoods into these regions.
- Use the results from the correlation analysis to find out which areas of Newcastle are most accurately fulfilling the requirements of a 15-minute city. Look at what changes could be made to better fit the model.

1.2 Revised Goals

As understanding of the analysis process developed and awareness of available tools and data changed, the goals have morphed slightly.

Understanding of the capability and availability of tools and data evolved throughout the project.

- To use the OS MasterMap highway and path network dataset to create a topologically accurate path network as a set of edges and nodes.
- To calculate walk times and distances from residential addresses to their closest amenities using the NetworkX and Pandana Python libraries.
- To use a range of amenities that are important to everyday life and assign a walkability score at different levels of granularity throughout the city.
- To investigate composite metrics for walkability (i.e., averaging walk times between several amenity types).
- To investigate scenarios that would improve the walk score of the study area and measure the effects they would have on walk times for neighbourhoods.

2 Literature Review

2.1 Introduction

15-minute cities have been suggested as a way forward for creating urban environments that promote sustainability through reducing the need for carbon-intensive travel and combatting the problems associated with urban sprawl. The core idea of the model is to design neighbourhoods around how people use their time, where urban necessities are available within a 15-minute walk. This project will involve assessing how Newcastle currently performs under the criteria laid out in the frameworks developed for 15-minute cities.

In order for an urban area to be 'walkable', it must first be 'accessible'. The former involves a grand confluence of environmental, behavioural, systematic, and non-systematic factors and is therefore inherently difficult to measure. This project will focus predominantly on the accessibility component – that being, how close in proximity can a diverse range of amenities be found.

The concept of walkability has evolved over the last few decades, but the core concepts have remained the same.

Neo-traditional design → New urbanism → Best-practice town planning → Walkability

2.2 Background

Global urban design largely remains a legacy of the industrial revolution when city centres became increasingly polluted and unpleasant places to live. As a result of advances in mobility technology and unprecedented growth in much of the developed world after WW2 (Crafts, 2018), the opportunity arose for individuals to escape the polluted inner-city and live in the suburbs (R. M. Hartwell, 1971). The subsequent mass migration of people away from the city centre lowered the land value and created more room for businesses to buy the land, building factories and offices in central locations for people to commute to by car or public transit. This resulted in the current urban model of large central business districts surrounded by suburbs on the outskirts of cities that we have today.

Modernist architects like Frank Lloyd-Wright and Le Corbusier paved the way for car-dominated cities with concepts like *Broadacre City* and *Towers in the Park* as a way for people to live in areas surrounded by nature whilst being a (less than) 30-minute commute by car to the business and manufacturing district located at the heart of the city (English, 2019). Over the course of the 20th century, the focus has been on increasing *mobility* rather than *accessibility*. Greater mobility has undoubtedly significantly increased the interconnectivity of communities, although it has resulted in considerable reliance on private vehicles. By focussing on mobility efficiency, underlying variables like which individuals make trips, to where; and by what mode have been neglected. As a result, over the last 200 years, the length of time individuals travel has not changed, only the distance that they travel (Marchetti, 1994; Venter, 2016).

Smart-city proponents predict a city with the attributes of a living organism capable of reacting to social and environmental changes, with a focus on driving efficiency increases for traffic and transit systems, i.e., *mobility* (Batty et al., 2012). While this is a reasonable goal, smart cities do not necessarily promote active modes of travel. Focus has also been placed on making vehicles more efficient to reduce total emissions, but the effect of this can sometimes rebound, leading to increased use (Herring & Roy, 2007). It is beginning to be recognised that to make a *truly smart city*, the fundamental '*dumb'* infrastructure needs to be designed with greater efficiency adhering to universal principles and more closely reflecting ancient rules of urban design (Alexander, 2004; Goldsmith, 2021). Most recently, COVID-19 has bought a new set of challenges that cannot be solved by technological ubiquity alone. The need for outdoor spaces and stronger local communities is more prevalent than ever. Despite the advances in virtual working and the inherent advantages it carries, it is still deemed that a balance of face-to-face and virtual work is the best way forward for productivity (Morrison-Smith & Ruiz, 2020).

With 18.3% of greenhouse gas emissions in the UK resulting from cars and taxis (BEIS, 2021), it would be prudent to investigate the effects of reorganising urban neighbourhoods to promote active modes of travel and discourage car use. To achieve this goal, a framework for better living is required. The 2021 Obel Award-winning 15-minute city concept conceived by Carlos Moreno in 2016 and currently being trialled in Paris offers a solution that seeks to improve accessibility via active modes of travel whilst also targeting a host of other environmental, social, and economic issues (Allam et al., 2022).

The model comprises 4 dimensions:

Proximity

Density

Diversity

Digitalisation

The policy aims of the EU are to create compact settlement structures with limited urban sprawl, high levels of environmental protection and quality in and around cities, and enhance socio-economic, cultural, generational, and ethnic diversity (EU, n.d.). Newcastle has embraced these concepts with its *2030 Net-Zero Action Plan*.

2.2.1 Newcastle 2030 Net-Zero Action Plan

The action plan highlights how the city plans to achieve its net-zero goals through a mixture of energy, transportation, and ecological enhancement schemes. It requires large capital upfront expenditure, so schemes that can improve resource efficiency by reducing transport demand and providing opportunities for creating ecological corridors without the need for significant public investment should be sought after. Looking forward, the issues of a growing population and increased demand for services (including social care, transport, and education) also need to be contended with (NCC, 2020).

A top transport priority for the city is to avoid carbon-intensive activities by promoting active modes. This is in line with the government's aims for ensuring active travel is the easiest choice for short urban journeys (DfT, 2019). Reducing demand for carbon-intensive transport will be important - approximately 29% of the city's emissions are from the transport sector. Part of the city's plan for enhancing sustainable transport involves a modal shift by 12% of commuters who currently use cars will walk or cycle and a transition of 1.3% of all car travel to the railway. A 21.6% increase in working at home and a reduction in face-to-face business meetings by 50% will reduce the need travel (NCC, 2020). Reducing travel demand, particularly motorised modes, is aimed to be achieved by reducing the need to travel, the number of trips and trip lengths.

2.2.1.1 Policy

15-minute city planning is briefly mentioned in a section of the transport documentation, with policies aimed at improving accessibility via active modes listed below (NCC, 2020).

- *CS13 Transport supports sustainable travel by protecting and enhancing pedestrian routes, cycle networks and Rights of Way and ensuring development provides direct, safe, secure, and continuous pedestrian and cycle links and the policy also seeks to reduce unnecessary traffic through, within and around the Urban Core. The policy seeks to minimise car trips and promote and enhance public transport.*
- *UC5 defines Primary and Secondary Pedestrian Routes within the Urban Core, that will be the focus for improvement over the Local Plan period.*
- *UC6 states that priority will be given to cycling in the Urban Core where appropriate and cycle infrastructure will be developed by promoting cycle improvements and links to the surrounding area.*
- *UC7 designates a bus loop in the Urban Core that will refocus routes so that they provide good service around the edge of the retail area with less reliance on the routes that cut across.*
- *UC9 seeks to minimise traffic in the Urban Core by focusing traffic on the designated Urban Core Distributor Road.*
- *UC10 states that within the Urban Core, the location and supply of safe, secure car parking will be managed by minimising car parking for development, promoting short stay over long stay car parking, and restricting the development of temporary car parks.*
- *DM10 states development must provide connections through developments both to the existing and future wider pedestrian and cycle network.*
- *DM11 requires major development to promote and facilitate the use of public transport and demonstrate accessibility by public transport to the Urban Core and other key local facilities.*

- *DM12 requires development to provide safe, secure, and useable vehicle and cycle parking that satisfies its operational requirement.*

2.2.1.2 The 15-Minute Opportunity

Much of the policy focus is on the urban core, which would likely meet many of the dimensions of a 15-minute city already; however, much of Newcastle is further than a 15-minute walk from the urban core. There does not appear to be an assessment of how Newcastle currently performs under these dimensions. This involves investigation into socio-economic factors, land-use mix and density, as well as accessibility to a range of services. The main goal of this project is to begin to understand how the 15-minute city concept can fit into the existing fabric of Newcastle. This will involve several layers of analysis.

2.3 How is Accessibility Measured?

The first step in determining how Newcastle performs under the 15-minute model will be through assessing accessibility to services. Diversity of services is key to the 15-minute city, defined in the following categories: living, working, commerce, caring, education, and entertainment (Allam et al., 2022). Research has found that locating retail stores and services near residences can "de-generate" vehicular trips for shopping by upwards of 25% (Cervero, 1996). Methodology for evaluating the potential for an area to become a 15-min city based on its existing essential urban functions has been previously developed (Correa-Parra et al., 2020; Gaglione et al., 2022).

(i) Identify essential urban functions of each city and collect georeferenced data that informs them
(ii) Apply principal component analysis to review how these georeferenced variables are grouped into synthetic components
(iii) Map these variables in GIS to evaluate the availability of the different components for each city, reviewing where concentrations occur and where there is a need to increase availability of these missing uses
(iv) Explore the existing essential urban functions in the city that could contribute to triggering a major transformation

(Correa-Parra et al., 2020)

Locations of services can be found in the GEOMNI datasets in Edina Digimap. The variety of buildings will need to be grouped for a proximity network analysis to be undertaken. A possible way of grouping urban functions for analysis in GIS are the following, as defined by (Correa-Parra et al., 2020):

Table 1 Urban Function Groupings

Local services	Food shops, post offices, banks, pharmacy
Transportation	Public transportation stops
Leisure	Recreational
Education	Primary and secondary education
Health services	GP service
Green Areas	Parks and other recreational spaces
Metropolitan Services	Hospitals, police stations, fire stations

GEOMNI use classifications can be found in section 5.4.1.1.

Once the services have been grouped into appropriate categories, One option is to use ArcGIS Network Analyst using a 15-minute travel time can be used to map areas of Newcastle that fulfil the requirements of a 15-minute walk for each category and the combined categories.

The City of Toronto have conducted an in-depth report into the walkability of the city to a range of amenities. They have used a variety of Python Libraries and have posted their work on GitHub. This is another option for how to approach the analysis but will depend on whether the data is of a compatible format (City of Toronto, 2019). An example of their work is shown below in Figure 1.

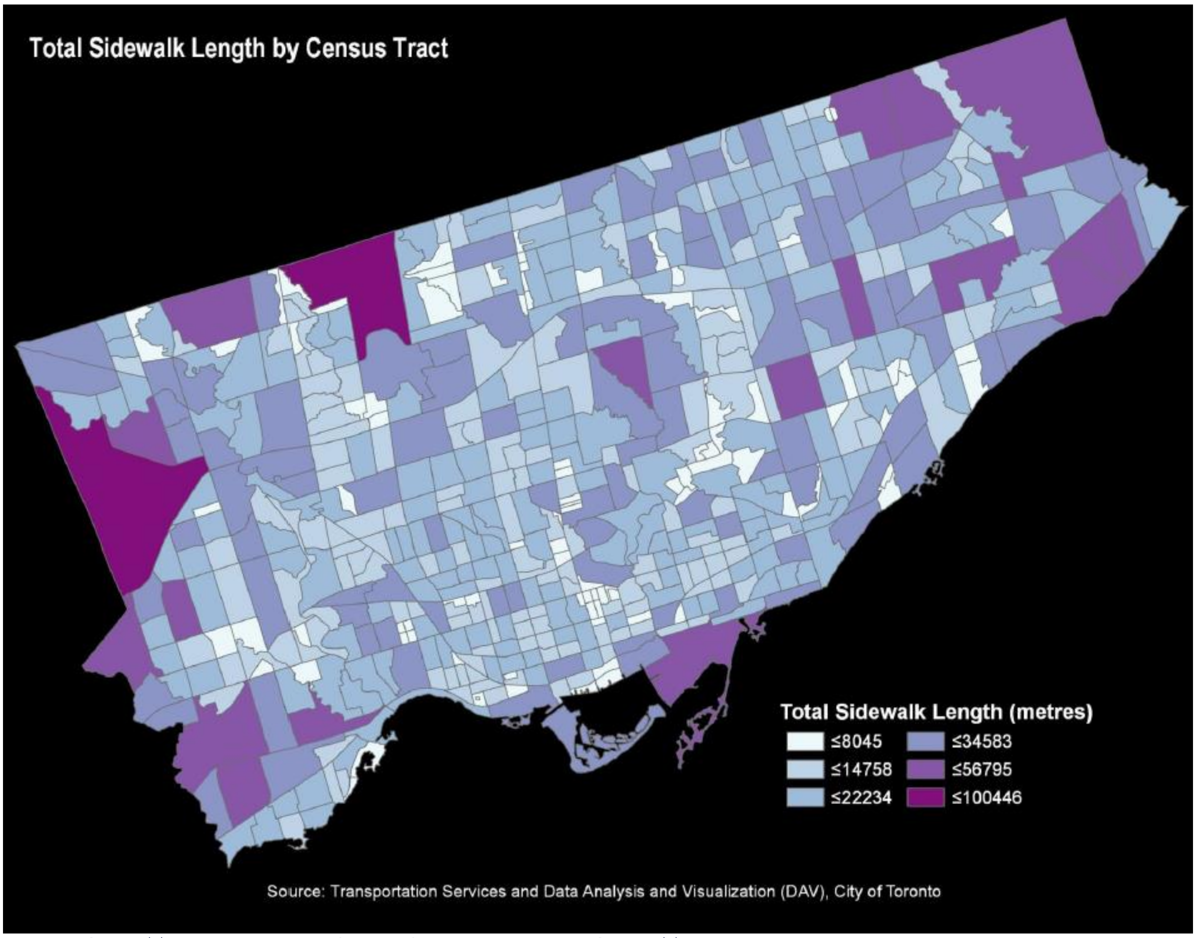


Figure 1 City of Toronto Walkability Study – Sidewalk Length by Census Tract

2.4 What Makes An Environment Walkable?

The next step will be assessing the walkability of the urban environment. Improving walkability is perhaps the biggest contributing factor to the success of a 15-minute city. Walkability can be defined "*as the extent to which the built environment supports and encourages walking by providing for pedestrian comfort and safety, connecting people with varied destinations within a reasonable amount of time and effort, and offering visual interest in journeys throughout the network*" (Southworth, 2005). Studies have indicated that proximity to destinations is the factor most affecting whether people decide to walk (Handy, 2019). However, the quality of the pedestrian environment is also key to encouraging people to choose walking over driving. Six criteria are presented for the design of a successful pedestrian network by (Southworth, 2005):

(1) connectivity
(2) linkage with other modes
(3) fine-grained land-use patterns
(4) safety
(5) quality of path
(6) path context

It is acknowledged by transport planners that certain micro aspects of urban form like landscape, path design or street furniture have an impact on pedestrian choices (Handy, 2019). Curbs, the presence of pavements, and pavement width are also associated with higher levels of walking (Ewing & Cervero, 2001). Spatial accessibility to green spaces and proximity to facilities, and the presence of cycle paths have also been identified as key determinants in the likelihood of walking (Charreire et al., 2012). It is also found that route directness and completeness of pedestrian facilities affect pedestrian volumes in both urban and suburban areas (Moudon et al., 1997). Certain aspects of this will be possible to determine through GIS analysis, like connectivity, linkage to other modes, and fine-grained land-use patterns; however, criteria 4, 5, and 6 six require qualitative data that may not be available for use. Relationships have also been established between the walkability of a place and the socio-economic status of its community - walkability is an indicator of accessibility to services, inclusiveness, and social equity (Ginevra et al., 2021). Therefore, the socio-economic statuses of the community will also need to be taken into consideration in the analysis.

2.4.1 Socio-Economic Factors

Important socio-economic influences on travel patterns in an area include car ownership, socio-economic group, and employment levels. Socio-economic characteristics have been found to typically explain around half of the variation in travel distance per person across different wards, whereas land-use characteristics are found to explain up to one-third of the variation in travel distance per person (Stead, 2016).

2.4.2 Proximity to Work

Creating a mix of jobs and housing in proximity can be estimated to reduce total vehicle miles travelled for a region by upwards of 15% (Ewing, 1996). Additionally, it has been found that jobs within 4 miles of the home significantly reduce vehicle miles travelled and vehicle hours travelled for work trips (Cervero & Duncan, 2008). A framework for assessing the spatial indicators for employment has been developed and used in Victoria, Australia, based on Census Data (H. Badland et al., 2016; Rae, 2017). Travel to work data on the fine grain scale is considered sensitive and not publicly available. The most applicable data currently published is the KS015 Travel to work from the 2001 census. It shows the percentage mode used for commuter journeys available at the super area output level. While only crude results would be able to be obtained, it would give some indication of the amount of work locally available based on the percentage of individuals using active modes to commute (NOMIS, 2001). This could be combined with the land-use mix, as the two may well be correlated.

2.4.3 Land Use Mix

Mixed land use has a significant association with whether residents decide to walk or ride a bike (Duncan et al., 2010; Kockelman, 1997; Stead, 2016). Analysing the land-use mix will be more complicated. Using land mix entropy and applying it to an output area would be one way of accomplishing this (Cervero, 1988; Frank & Pivo, 1994; Zagorskas, 2016).

Level of land use mix (entropy value) =

- [single family • log10 (single family)]

+ [multifamily • log10 (multifamily)]

+ [retail and services • log10 (retail and services)]

+ [office • log10 (office)]

+ [entertainment • log10 (entertainment)]

+ [institutional • log10 (institutional)]

+ [industrial/manufacturing • log10 (industry)]

This could then provide a score for each output area that can be correlated with the other factors being investigated in the study.

2.5 What Factors Influence Mode Choice?

The factors influencing mode choice are manifold, both human and physical (Boarnet & Crane, 2001a). There are a variety of urban and non-urban form factors that will influence whether an individual will make a trip by car. Built environments with higher levels of development density, land use diversity, street connectivity, destination accessibility, and a short distance to transit are considered compact (Ewing & Cervero, 2017). It is well established in urban design literature that compact development is correlated with less driving (Ewing & Cervero, 2017; Jencks & Burgess, 2000). However, the factors associated with density, like regional accessibility, land use mix, and walkability, are found to have far greater impacts on travel behaviour than density itself (Ewing & Cervero, 2001; Kockelman, 1997). Relationships between single occupancy vehicle usage and employment density, population density and land-use mix have been found to be consistently negative for both work and shopping trips, while for transit and walking; they are found to be consistently positive (Frank & Pivo, 1994). This is a strong indicator that to promote active travel, many factors need to be changed beyond the improvement of walking infrastructure.

Another study found significant associations between changes in travel behaviour and changes in the built environment, independent of travel attitudes, which concluded support for a *causal* relationship (Muller-Eie & Bjorno, 2015). However, a study in Glasgow found the effect of improving the walkability of the built environment has limited measurable effects on walking behaviour (Curl et al., 2018). This is thought to be due to, in part, the strong correlation between walking behaviour and perceived accessibility of a neighbourhood rather than to objective measures of accessibility (Curl, 2013). Understanding behaviour change will play a key role in reaching the targets laid out in the 15-minute city model.

While many of the travel-oriented components of the proximity model are aimed at encouraging pedestrian and transit travel, they often also include changes in street patterns that will reduce the distances required to drive between locations; therefore, initiatives to discourage car use also need to be implemented (Boarnet & Crane, 2001b).

While the *correlation* between mode choice and urban form is well established, it is, however, not clear on the direction of the relationship - whether the individuals attitude changes after their built environment changes or that their attitude changes beforehand, thus causing the individual to move environments (Jakovcevic & Steg, 2013; Schwanen & Mokhtarian, 2005). Changing human behaviour is not as simple as just changing the built environment. Effective policymaking for urban sustainability and changing individual behaviour is most effective when simultaneously applied to individuals, e.g., through campaigns; to the choice environment, e.g., the provision of infrastructure like cycling networks; and to economic systems, e.g., a ban on combustion engines (Londakova et al., 2021; Muller-Eie & Bjorno, 2015).

The 15-minute city model presents the opportunity to target the three parameters simultaneously, as the concept is built on community engagement to raise awareness, investment in new infrastructure to re-invigorate the neighbourhood and policy targeted at improving neighbourhood awareness of what is accessible (Allam et al., 2022). The carrot and stick approach to managing transport demand (when both enablers and deterrents are used in tandem) has been shown to be most effective in implementing behavioural change (Piatkowski et al., 2017). From a transport and travel behaviour perspective, this might involve increasing the implementation of fine-grain urbanism where possible to increase accessibility and pedestrianisation of high streets to discourage automobile use.

2.5.1 Disincentivising Car Use

Disincentives can have a major impact on car use when paired with improvements to the active travel environment. In Vienna, the share of trips by car has been reduced by a third between 1993 and 2014: from 40% to 27%. The key to Vienna's success was a coordinated package of mutually reinforcing transport and land-use policies that made car use slower, less convenient, and more costly while also improving conditions for walking, cycling, and public transport (Buehler et al., 2017).

Congestion charging has been shown to be the most effective way of reducing car use, but it is largely unpopular with the public (Saleh, 2007). A simulation study in Paris found the most effective way is likely to be through reducing car speed by reducing road or parking capacity with implementation at the hyperlocal level through community engagement (Massot et al., 2007). Increasing the distance between parking facilities and destinations is another factor in the reduction of car use (Smith & Butcher, 2008). These are effective ways of promoting walkability by appealing to our inherent 'nimbyism'.

2.5.2 Car Availability

In existing sustainable developments aimed to promote healthy lifestyles, and in line with previous studies, residents' car availability was a significant influence: it is the main factor that discourages public transport trips and reduces walking and cycling (Susilo et al., 2012). Therefore, car ownership levels of different neighbourhoods will need to be considered in the analysis. This data is available from Digimap at the output area level.

2.5.3 Land-Use

Studies into the effects of having local shopping and entertainment are mixed and inconclusive. A study in the US has found that simply having shops closer does not prove a particularly effective strategy for reducing vehicles and miles but does increase the quality of life of the neighbourhood residents (Handy & Clifton, n.d.). This is further support for a more integrated approach involving multi-variate analysis for looking at travel.

2.5.4 Urban Form Variables

Whilst some of the variables assessed independently do not necessarily provide obvious changes in mode choice, it is well established that when they are combined can have a significant impact. The current trend towards integrated communities and neo-traditional design is associated with an increase in active travel for work and shopping trips (Berman, 2016; Craig et al., 2002). Mixed-use development is often cited as a key factor in determining mode choice (Oueslati et al., 2015; Zagorskas, 2016). Trip lengths and frequency are primarily a function of the built environment, and secondarily a function of socioeconomic characteristics and several design variables are commonly accepted as the principal component of mode choice (Ewing & Cervero, 2001; Southworth, 2005).

- The mix of Land Uses (proximity of offices, residential development, retail development, personal services, open spaces)
- Availability of convenience services (proximity to restaurants, banks, child-care, dry cleaner, pharmacies, post office)
- Accessibility of services (presence and frequency of convenience services, presence of pavements, volume of traffic, public transport stops)
- Perception of safety (absence of vacant lots, pedestrian activity, pavements, streetlights)
- Aesthetically pleasing (absence of graffiti, presence of trees and shrubs in pavement zone, wide sidewalks, minimal building setbacks)

2.5.5 Proximity

Urban spatial networks are most like a geometric networks as spatially close nodes are more likely to be linked (Agryzkov et al., 2019). Results of centrality studies have shown that in the cities of Barcelona and Bologna, retail and service activities tend to concentrate in areas with better centralities, confirming the hypothesis that street centrality plays a crucial role in shaping the formation of urban structure and land use (Porta et al., 2007).

2.5.6 Variables Included in the Study

Outcome variables for how a community can attract and encourage residents who prefer to walk or how a neighbourhood might improve the perception of walking as a transportation option have been found as the following (Carlson et al., 2012):

Independent Variables

- Connectivity—the number of intersections (three-legged or greater) within the neighbourhood divided by the area of the neighbourhood.
- Businesses—the number of services falling within the bounds of each neighbourhood
- Pavements—presence and condition of pavements as a percentage
- Average lot size – the area of the neighbourhood divided by the number of lots

Confounding Variables

- Age
- Education
- Mean neighbourhood income

2.6 How Individuals Travel

2.6.1 UK Trip Data

Across Great Britain, 68% of workers typically travelled to work by car, though this varied by region, with London having a substantially lower proportion of people (27%). On average, between 2010 and 2019, 7% of trips by car/van were under 1 mile, 25% under 2 miles, and 53% under 5 miles (DfT, 2021b). Averaging over the same period, trip purposes by car/van are as follows: Commuting 21%, Business 5%, Education 6%, Shopping 21%, Personal 10%, Leisure 24% and Other 12% (DfT, 2021a).

2.6.2 Time Travel Ratio for Different Activities

A study into time travel ratios for different activities value shows the ratio varies according to the nature of the journey. It depends on the type of activities, individual commitments, available travel mode, availability of activities location, and many other factors. The results show that education and work have the lowest ratios (which makes sense as these often occupy most of the day). Meanwhile, sport/recreation, as well as visits to 'other services' (bank, post office, city hall, tax office), had the highest ratio. Additionally, less-urbanised residents would spend longer travel times than residents who live in denser areas (Susilo & Dijst, 2009).

2.6.3 Short Trips

Short trips are the main target area of compact city design. Qualitative studies have revealed that trip characteristics (mainly trip purpose and complexity) influence mode choice to a great extent (alongside built environment, personal and household characteristics). There are a number of reasons why people drive a car over short distances like time constraints, convenience, the need to carry heavy goods, giving a lift to passengers, escorting children or lack of feasible alternatives and trip chaining. (Neves & Brand, 2019) used a GPS study in Cardiff to find the purpose of trips. It revealed similar results to those provided by DfT, with work and education accounting for 27%, business trips 5%, shopping and personal business 35% and social and leisure 33%. The study found over a third of short car trips could be eliminated by improving walking and cycling infrastructure. (Song et al., 2017) found that provision of new infrastructure did result in greater levels of use of active travel, but only in the medium-long term, typically a period of 1-2 years.

2.7 Benefits of the Model

The scope of potential for emissions reductions, improvement to health and the natural environment with this model has significant potential. Some impacts are easier to measure than others. The initial impacts on measurable emissions will likely be minimal and derive mostly from decreased reliance on non-active modes of travel.

2.7.1 Potential for Mode Substitution

Studies have found walking (<1.5km) or cycling (<5km) could realistically substitute for 41% of short car trips (Neves & Brand, 2019), saving nearly 5% of CO_2e emissions from car travel which would be 0.9% of total GHG emissions (BEIS, 2021). Meanwhile, (Lindsay et al., 2011) find shifting 5% of vehicle kilometres to cycling (all trips <7km) would reduce transport-related greenhouse gas emissions by 0.4% resulting in significant health benefits and a reduction in fatality related costs.

2.7.2 Industry Specialization

Since 2000, industry 4.0 has become standard practice, which is a long way from the polluting factories and relatively low standard of living of the industrial revolution (Leong et al., 2020; Nardinelli, 2019). This opens the potential for the industry to be part of the neighbourhood, reducing the spatial separation between work and home. Industrial agglomeration is correlated with better economic performance and, to an extent, reduced emissions from travel – there becomes a spatial point where the opposite is true, indicating that planning for a midpoint between the diversity of industry and agglomeration could provide emissions reductions (Shen et al., 2018).

2.7.3 Population Density

Population density and energy efficiency are intrinsically linked. (Morikawa, 2012) found that as the population doubles, energy efficiency increases by 12%. Another study has found that to mitigate against the effects of the increasing population; density will play a very important role in reducing energy use (Güneralp et al., 2017). Estimation range between a 7% and 40% increase in energy use over the next 30 years, depending largely on density. Higher population densities have been linked with economic vitality due to the intense movement of people. It has been found that population density enhances those qualities up until a certain threshold (around 3000 people/km^2 in the case of Vancouver). Above that, denser spaces start to become highly unaffordable when compared with lower density areas (Martino et al., 2021). The indicators of accessibility, social diversity and economic vitality are directly correlated with each other and inversely correlated with affordability (Martino et al., 2021).

2.7.4 Public Health

It is well known in the practice of clinical psychology that an individual's environment is correlated with the individual's health. Social determinants of health are recognised to the inhabitants' location and living conditions, educational attainment and opportunities, and income and levels of accumulated assets or wealth, and by other socioeconomic and political factors" (Dankwa-Mullan & Louis Rhee, 2012). Additionally, studies have found that regions with accessible public transport (<400m) experience higher levels of public health than regions that are reliant on cars for commuting (H. M. Badland et al., 2017). The presence of walkable environments is also correlated with greater levels of physical activity, leading to better health (Frank et al., 2007).

2.7.5 Safety

The prevalence of cars results in less safe roads for other transport users. In the UK in 2019, the rate of casualty per billion passenger miles was 4,891 for cyclists, 1640 for pedestrians, and 195 for cars (Murphy, 2019). The majority of cyclist and pedestrian accidents were attributed to "individual failed to look properly" (ROSPA, 2021), so reducing the number of cars on the road would likely have an impact on pedestrian and cyclist safety, in turn improving the likelihood of an individual changing to active modes.

New highway code measures that came into effect in 2022 require motorised vehicle users to give way to cyclist and pedestrians (DfT, n.d.), it will be interesting to see how much this impacts the causalty rate over the coming years.

2.8 Limitations In Model Implementation

Whilst the benefits of proximity, density, and diversity are clear; there are limitations in how they can be implemented. Generally, residents will not take kindly to the idea of increasing density (Ewing & Clemente, 2016), which is why planning must be community-led, and provide enough benefits through improvement of transport, access to services and enhancement of ecology to outweigh the perceived negatives of increased density (Allam et al., 2022). The infrastructure of cities provides the framework upon which individuals function. Having a long-term plan to restructure the fabric of urban areas to encourage walkability may provide the framework for changing the travel behaviour of individuals, but changing the built environment alone is not enough to change behaviour.

3 Methodology

The first stage in this project was to create a 'walkability' dataset that stored walk times from every residential address in the study area to the nearest 50 amenities, split into 10 categories (for example, the nearest 5 places of education to residential address X). This resulted in around 3.5-million unique walk times for 15 million journeys that could be used in the analysis.

3.1 Data Consolidation

3.1.1 About the Data

Several datasets from Edina Digimap have been used in the analysis. This includes Ordnance Survey network topology data, building use data from GEOMNI, and 2011 census data from the Office for National Statistics.

3.1.1.1 OS MasterMap Highways/Path Network

To create the pedestrian network, the *OS MasterMap Highways Network* dataset from March 2019 was chosen. (A 2021 version is available using Ordnance Survey's latest data structures, but it required multiple days of CPU time to process). The 2019 dataset is a combined Highways Roads and Paths dataset and was converted using the Esri UK Data Loader for ArcGIS into a File Geodatabase. The dataset is built from line segments categorised in the following ways. Certain segments have been excluded as they were either not present in the study area or duplicated existing line features with additional data.

Table 2 OS MasterMap Line and Node Features

Included			
Line / Node Feature	Description	Fields	Count
Street	A Street feature encompasses both Roads and Paths. Therefore, a Street feature will reference the Road Links or Path Links. Where a Street crosses an administrative boundary, a new Street feature will be created A Road Link or Path Link could be referenced by multiple Street features.	USRN, a unique and persistent identifier for a street. Every street, road, track, path, cycle track or way is assigned a USRN by a Roads Authority, Local Highway Authority or Highways England.	
Path Node	A topological node connecting to at least one Path Link	connectivity between path links, end of a road.	
Path Link	A line segment representing the alignment of a path.	name of the path, its length and its nature, alongside other attributes	
Ferry Node	A point feature which identifies where the Ferry Network terminates	-	
Ferry Link	A line segment that connects the road network and path networks across bodies of water	who operates the service, is service limited to pedestrians	
Connecting Node	A point feature which identifies where a Path would join the road network	-	
Connecting Link	A line segment and a logical connection between the road and path networks (connects the two independent topologically structured road and path networks without splitting the road network)	-	
Road Node	A topological node connecting to at least one Road Link - used to represent connectivity between road links or the end of a road	classification, junction number	
Road Link	A line segment representing the general alignment of the road carriageway (single carriageways, dual carriageways, slip roads, roundabouts)	road name, classification, form, length, and other attributes	
Highway Dedication	Provide an indication of the type of user who has access to that particular section of the Highway		
Excluded			

Special Designation	Statutory and advisory designations that can be applied to protect a highway when street works are to be undertaken		
Reinstatement	Reinstatement defines the standard to which the highway must be restored to, following opening due to works in the highway		
Maintenance	Maintenance provides information about whether a path is maintained at public expense by a national or local highway authority, by a road authority or is maintained by another responsible organisation (i.e., not maintained at public expense).		

3.1.1.2 GEOMNI

The Geomni *UKBuildings* dataset contains data about building use for every urban building in the UK. Use categories are shown below Use values associated are either observed from interpretation of buildings from modern, historic, and ground imagery or sourced from open data. (Geomni, 2021).

Table 3 UKBuildings 'Use' Field Categories

Use Values	Included	Amenity Name Used
AGRICULTURAL - UNCLASSIFIED	FALSE	-
COMMUNITY - EDUCATIONAL	TRUE	Education
COMMUNITY - EMERGENCY SERVICES	FALSE	-
COMMUNITY - GOVERNMENTAL (CENTRAL AND LOCAL)	TRUE	Government
COMMUNITY - HEALTH	TRUE	Health
COMMUNITY - INSTITUTIONAL AND COMMUNAL ACCOMMODATION	FALSE	-
COMMUNITY – RELIGIOUS	TRUE	Religious
DEFENCE	FALSE	-
GENERAL COMMERCIAL - MIXED USE	TRUE	Commercial
GENERAL COMMERCIAL - MIXED USE – DERELICT	FALSE	-
INDUSTRY - MANUFACTURING/PROCESSING	TRUE	Manufacturing
OFFICE ONLY	TRUE	Office
OFFICE WITH RETAIL ON GROUND FLOOR	TRUE	Office
RECREATION AND LEISURE	TRUE	Recreation
RESIDENTIAL ONLY	TRUE	Residential
RESIDENTIAL WITH RETAIL ON GROUND FLOOR	TRUE	Residential
RETAIL - PETROL STATION	FALSE	-
RETAIL - VACANT/DERELICT	FALSE	-
RETAIL - WITH MORE RECENT EXTENSIONS OF DIFFERENT TYPE CONSTRUCTION/AGE	TRUE	Retail
RETAIL ONLY	TRUE	Retail
RETAIL WITH OFFICE/RESIDENTIAL ABOVE	TRUE	Retail
STORAGE/WAREHOUSING	FALSE	-
STORAGE/WAREHOUSING WITH LINKED OFFICE BLOCK	FALSE	-
TRANSPORT	TRUE	Transport
UTILITIES	FALSE	-
UNCLASSIFIED	FALSE	-

3.1.1.3 Lower Super Output Areas and Census Data

Census data for a variety of socio-economic measures is available at the Lower Super Output Area (LSOA) level. The socio-economic data that is used in the analysis is car ownership, economic output, and population density.

Output Areas (OAs) are built from clusters of adjacent unit postcodes in the UK and are the base unit for Census data releases. LSOAs are built from groups of contiguous OAs and have been automatically generated to be as consistent in population size as possible, and typically contain from four to six OAs (NHS, 2021). The Minimum population is 1000 and the mean is 1500 which is not atypical in size for a new residential district and a useful level of granularity at which to look at walk times from individual addresses.

3.1.1.4 Unitary Authority Layer

The study area has been defined using the *District, Borough, and Unitary Authority* layer of the *OS Boundary-Line* dataset. It includes the Northern Section of the Tyne and Wear Metropolitan Borough. This area was chosen as it was the densest continuous section of path and highway network - also fits well in a rectangular image.

Figure 2 Tyne and Wear Metropolitan Borough with Highlighted Study Area

Figure 3 Highway and Path Network in the Study Area

3.1.2 Processing the Data

3.1.2.1 Pedestrian Network Data

The OS MasterMap Highways Network dataset was loaded into ArcGIS pro and the comprising line and node features were added as layers. The 'clip features' tool was used to refine the highway and path network to size of the study area shown in Figure 2 above. The six-line feature layers and four-point feature layers comprisng the highway and path network are shown in Table 2 above. The merge features tool was used on the six-line feature layers to create the Pedestrian Network Edges layer (Figure 3) and also on the four-point features to create the Pedestrain Network Nodes layer. The 'feature to line' tool was then used as the NetworkX script (see section 3.2.3) is unable to read the multipart geometries format that Ordnance Survey uses in the MasterMap dataset. The pedestrian network was then exported as shape files and zipped. Description of layers found in Table 7.

3.1.2.2 Building Use Data

The UKBuildings dataset was loaded into ArcGIS pro as a geodatabase (.gdb). The clip features tool was used to reduce the dataset to the size of the shown in Figure 2 above. As the buildings are stored as polygons features, two new fields containing the X and Y coordinates of the building centroids were needed. Using the 'feature to point' tool, a new layer called UKBuildingNodes was created. To create the 11 building use layers shown in Table 4 to Table 5 overleaf the UKBuildingNodes dataset was split using 'select by attribute' on the 'Use' field shown in Table 3 in section 3.1.1 (some of the the building use layers use multiple 'Use' attributes). All 11 of the building use layers were then exported as csv files for use in Jupyter Notebooks.

Table 4 Building Use Nodes

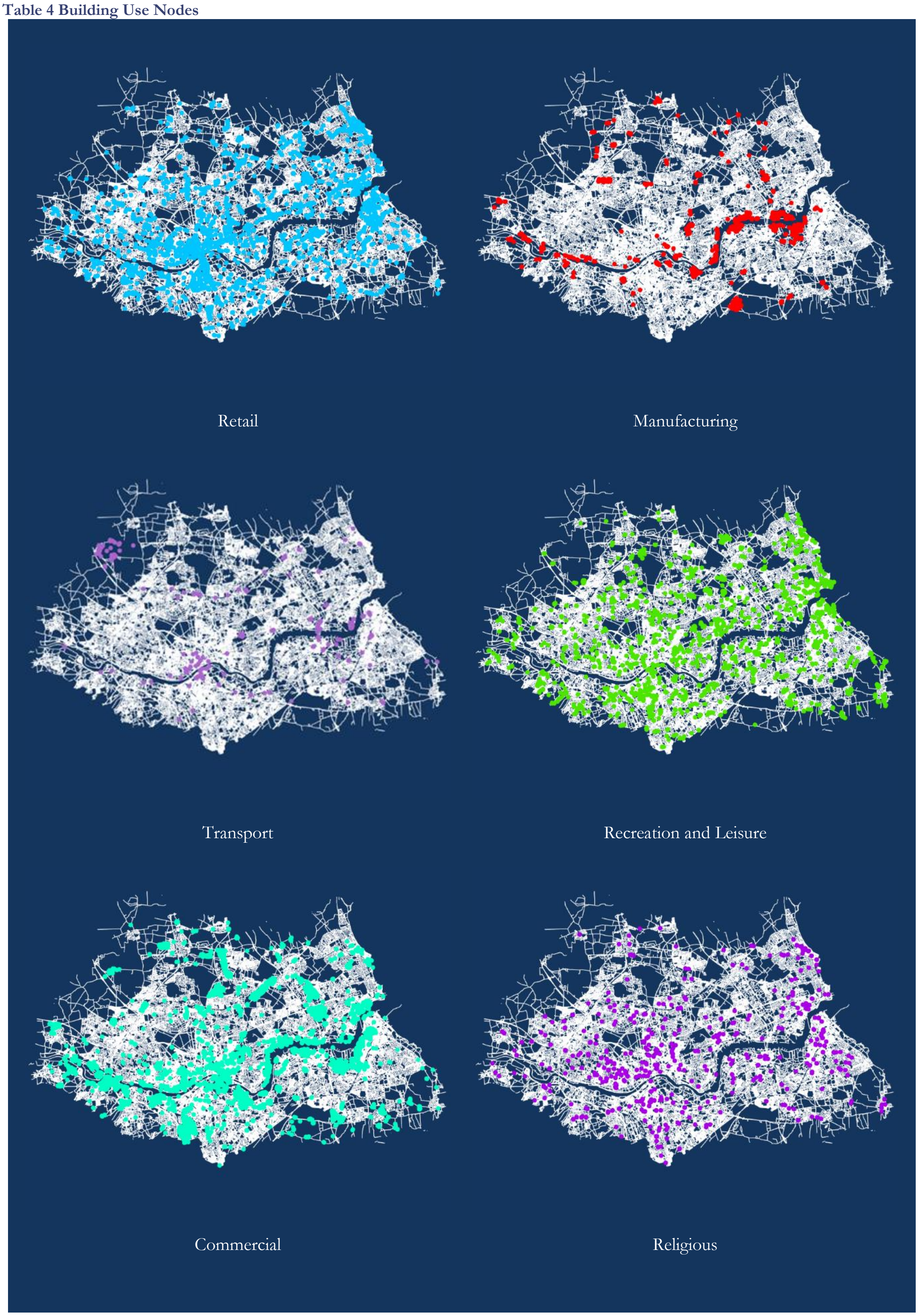
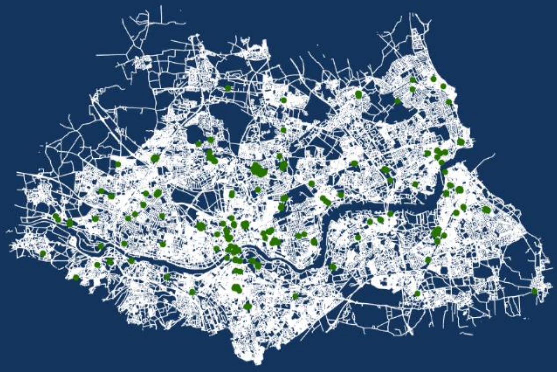
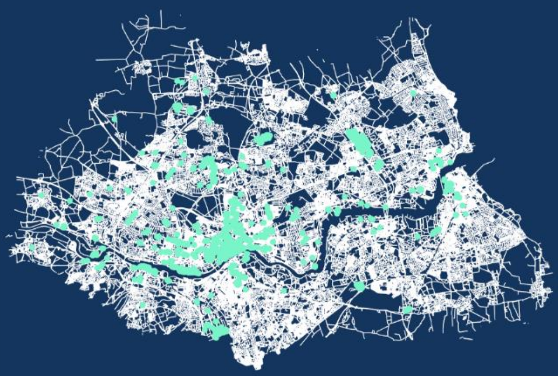


Table 5 Building Use Nodes (cont.)

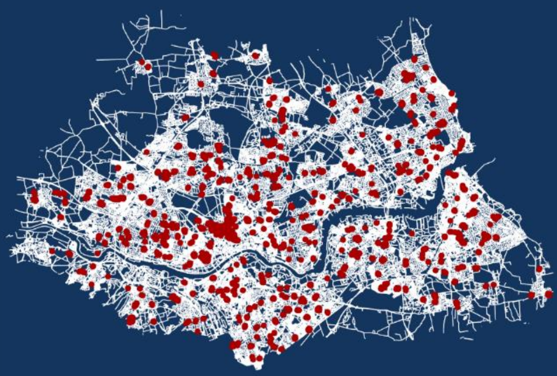
Health



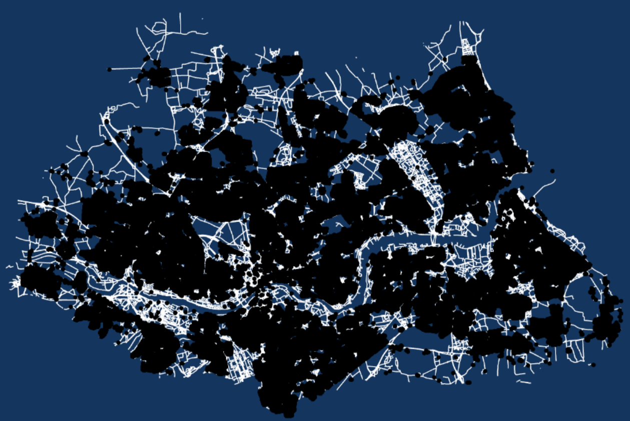
Governmental



Office



Education



Residential Nodes

3.1.2.3 LSOAs and Census Data

The census data at the LSOA level was loaded into ArcGIS as a geodatabase, and again the 'clip features' tool was used to reduce the dataset to the size of the study area shown in Figure **2** above. This yielded 507 complete area polygons available for the analysis shown in the figure below.

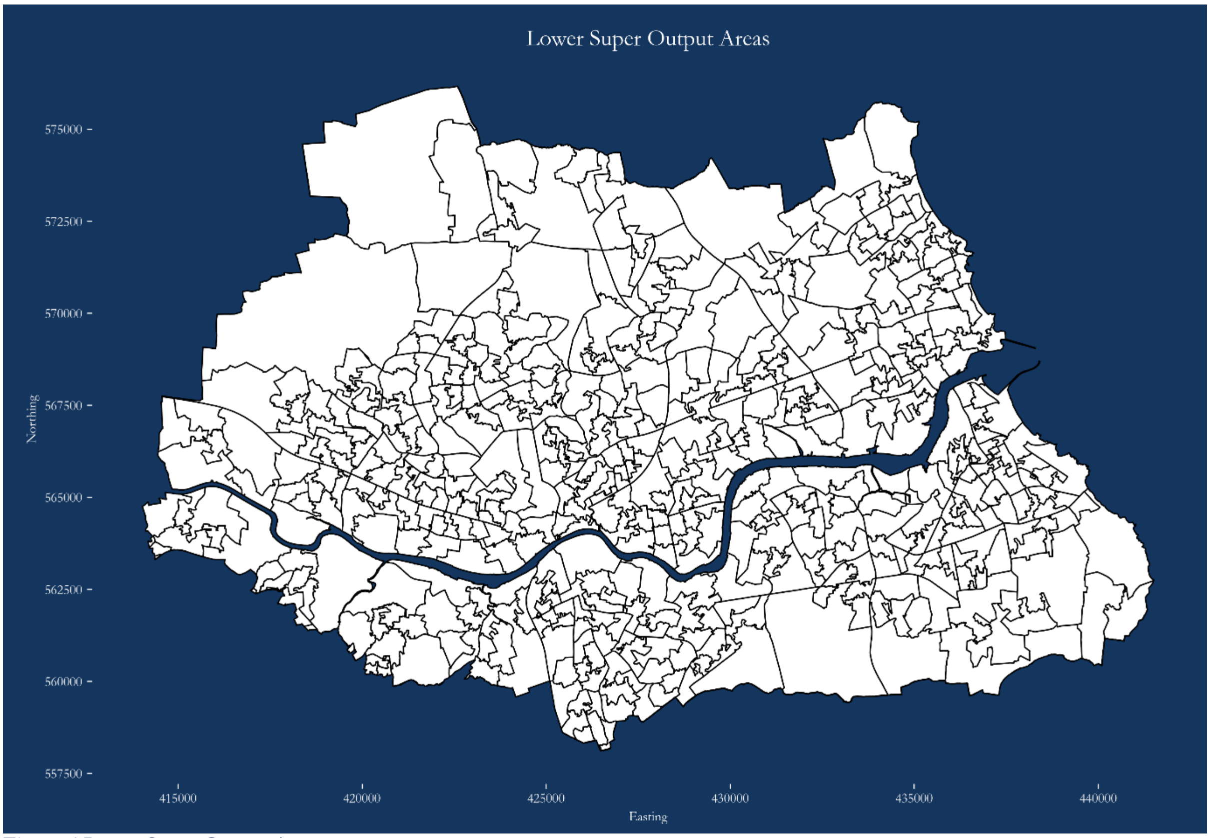


Figure 4 Lower Super Output Areas

3.1.2.4 Additional Infomation

Table 6 ArcGIS tool run-time

Process	Time	Runs
Clip features (OSMasterMapHighways)	<10s	10
Merge features (OSMasterMapHighways)	<10s	2
Feature to Line (OSMasterMapHighways)	<7mins	1
Clip (UKBuildings)	<2mins	1
Calculate Centroid Geometry (UKBuildings)	<1min	1
Feature to Point (UKBuildings)	<20s	1
Feature to Geodatabase (removes M and Z values - OSMasterMapHighways)	<10s	1
Feature Class to Shapefile (OSMasterMapHighways)	<2mins	1
Calculate Geometry Attribute (Nodes - OSMasterMapHighways)	<30s	1
Clip Features (CensusData)	<20s	14

Table 7 Metadata

Name	Python Name	Description	Feature Type	File Type	Row Count	Column Count
Unitary Authorities	UApolygons	Unitary Authorities included in the Study area	Polygon	.shp	79	18
Lower Super Output Areas	LSOApolygons		Polygon	.shp	507	4
Residential Addresses	res_df	Residential Address point – stores the distance and time	Point	.csv	307,943	26

		data from each address to each amenity				
Education Nodes	edu_df	Centroids of buildings listed as 'education' use	Point	.csv	1805	5
Recreation Nodes	recr_df	Centroids of buildings listed as 'recreation use	Point	.csv	2107	5
Transport Nodes	tran_df	Centroids of buildings listed as 'transport use	Point	.csv	254	5
Office Nodes	offi_df	Centroids of buildings listed as 'education' use	Point	.csv	1141	5
Retail Nodes	reta_df	Centroids of buildings listed as 'retail use	Point	.csv	5822	5
Religious Nodes	reli_df	Centroids of buildings listed as 'religious use	Point	.csv	599	5
Manufacturing Nodes	manu_df	Centroids of buildings listed as 'manufacturing use	Point	.csv	938	5
Commercial Nodes	comm_df	Centroids of buildings listed as 'commercial use	Point	.csv	4206	5
Health Nodes	heal_df	Centroids of buildings listed as 'health use	Point	.csv	646	5
Government Nodes	gov_df	Centroids of buildings listed as 'government use	Point	.csv	337	5
Network Nodes	nodes_df	The nodes from merged OS MasterMap Data	Point	.csv	125,005	20
Network Edges	edges_df	The edges from merged OS MasterMap Data	Line	.shp	523,401	18
Pedestrian Network	pednet	The network nodes and edges as two Pandas DataFrames in an HDFStore object	Point and Line	.hdf5	523,401	18
Walk times and Distances	walk times_df	The walk times and distances from each residential address to the nearest 5 of each amenity	Point	.shp	307,943	108
UA Walk times	UAWalk	Mean walk times to each amenity in each UA with additional compound measures	Polygon	.shp	80	78
LSOA Walk times	LSOAWalk	Mean walk times to each amenity in each LSOA with additional compound measures	Polygon	.shp	507	78
Economic Output	eco_df	Economic output at the LSOA level from the 2011 census				
Population Density	pop_df	Population density at the LSOA level from the 2011 census				
Car Ownership	car_df	Percentage of the population without a car at the LSOA level from the 2011 census				

3.2 Geospatial Analysis

There are are some powerful tools that have been developed as python libraries for conducting network analysis. Python is very efficient at handling large datasets like the ones used in this project. It provides greater transparency than more 'out of the box' technologies like ArcGIS and so aids clarity in the calculation process and identification of errors resulting in greater confindence in the results.

3.2.1 Python Libraries

A number of python libraries are used in the analysis for a variety of purposes. Geopandas, Shapely, Shapefile and Geoalchemy2 assist in handling geospatial data and shapefile formats. NetworkX studies the structure dynamics and functions of complex networks, and Pandana provides tools for calculating vectoried shortest path algorithms. The others are mostly for data presentation and data interoperability.

Table 8 Description of Python Libraries

Library	Description
Pandas	Data manipulation and analysis

GeoPandas	Extends the datatypes used by pandas to allow spatial operations on geometric types
Shapely	Manipulation and analysis of geometric objects in the Cartesian plane
Numpy	Support for large, multi-dimensional arrays and matrices and high-level mathematical functions to operate on these arrays
Network X	Creation, manipulation, and study of the structure, dynamics, and functions of complex networks
MultiProcessing	Supports spawning processes using an API similar to the threading module
Pandana	Network analysis that uses contraction hierarchies to calculate super-fast travel accessibility metrics and shortest paths
h5py	Pythonic interface to the HDF5 binary data format to store huge amounts of numerical data for easy manipulation
Shapefile	Provides read and write support for the Esri Shapefile format
Pyproj	Performs cartographic transformations
Matplotlib	Comprehensive library for creating static, animated, and interactive visualizations in Python
Fiona	Reading and writing data in standard Python IO style
MPL Toolkits	Interface to natgrid C library for gridding irregularly spaced data
PySAL	Wide range of tools for a systematic and exhaustive analysis of urban form

3.2.1.1 Pandana

Pandana is a Python library for network analysis that uses contraction hierarchies to calculate super-fast travel accessibility metrics and shortest paths (UrbanSim, 2021). The network data used in this project did not contain route priority values and therefore the use of contraction hierarchies was not used. Nevertheless, the computations ran within a reasonable time frame.

3.2.2 Assumptions

A mean walkspeed of 1 m/s was used for the analysis as this is a standard walk speed used by transport planners in the UK (Crabtree et al., 2014).

3.2.3 Part 1 – Creating the Pedestrian Network

The first step in the walkability analysis was to turn the *Edges* and *Nodes* shape and csv files into a format that can be used to run shortest path queries. The Data and Visualisation at the City of Toronto (DAVCoT) have provided a workflow using the Python library 'Pandana' for network analysis that is available on GitHub. This script has been adapted using the comprehensive set of tutorials available on Pandana's GitHub to work with the datasets in this project.

3.2.3.1 Reading in the Edge and Node Data

This code reads in the *edges* data as a GeoPandas DataFrame and the *nodes* as a standard Pandas DataFrame.

```
# network files
nodes = path + r"\.csv\Newcastle\Nodes.csv"
edges = path + r"\PedNet\PedNet.zip"

nodes_df = pd.read_csv(nodes, delimiter= ',', low_memory=False)
edges = gpd.read_file(edges)

# keep useful columns
nodes_df = nodes_df[['OID_','TOID','CentroidX','CentroidY']]
edges_df = edges_df[['identifier','formOfWay','length','roadClassi','geometry']]
```

3.2.3.2 NetworkX Graph

The following block of code uses the *edges* GeoDataFrame (line features) to create a graph which the NetworkX library defines as a collection of nodes (vertices) along with identified pairs of nodes (i.e., edges). The following script from DAVCoT was applied to the *edges* dataset. For this to work, the objects in the GeoSeries needed be stored as singular line objects 'Line' format rather than the 'MultiLine' objects that Ordnance Survey provides. This was done using the feature to line tool in ArcGIS. Each line corresponds to two directional graph edges. Each node will be where end points meet and will store a clockwise ordering of incoming edges.

```python
# creating network graph code
def create_graph(gdf, precision=3):

    G = nx.Graph()

    def make_node(coord, precision):
        return tuple(np.round(coord, precision))

    # Edges are stored as (from, to, data), where from and to are nodes.
    def add_edges(row, G):
        geometry = row.geometry
        coords = list(geometry.coords)
        geom_r = LineString(coords[::-1])
        coords_r = geom_r.coords
        start = make_node(coords[0], precision)
        end = make_node(coords[-1], precision)
        # Add forward edge
        fwd_attr ={}
        for k,v in row.items():
            fwd_attr[k]=v
        fwd_attr['forward']= 1
       #fwd_attr['geometry']=  geometry
        fwd_attr['length']=  geometry.length

        fwd_attr['visited']= 0

        G.add_edge(start, end, **fwd_attr)

    gdf.apply(add_edges, axis=1, args=[G])

    return G

# creating network graph
G = create_graph(edges)

# get network "from" and "to" from nodes
edges = nx.to_pandas_edgelist(G,'from','to')
to = edges['to'].tolist()
fr = edges['from'].tolist()
fr = list(set(fr))
to = list(set(to))
to.extend(fr)
nodes = list(set(to))
nodes = pd.DataFrame(nodes)
nodes.columns=['x', 'y']
nodes['xy'] = nodes.apply(lambda z: (z.x,z.y),axis=1)

# Assigning node ids to to_node and from_node
nodes['id'] = nodes.index
edges['to_node']=edges['to'].map(nodes.set_index('xy').id)
edges['from_node']=edges['from'].map(nodes.set_index('xy').id)
```

3.2.3.3 Pandana Network

With the *nodes* and *edges* dataframes now storing 'to' and 'from' data the Pandana network can be created. The modified DAVCoT script below shows how this is done. Pandana structures the data using an index comprising the id of the node and its x-y position. Edges are then used as ids and **'from' node ids** and **'to' node ids** index directly to the original *nodes* dataframe. The *pednet* network dataframe is then saved as a new file. The precomputed horizon distance was left at the same value of 1000m used by DAVCoT despite Pandana's recomended value of 3000m. This is discussed further in section 3.3.1.4.

```python
# establishing the pandana network
pednet = pdna.Network(nodes["x"],
                               nodes["y"],
                               edges["from_node"],
                               edges["to_node"],
                               pd.DataFrame([edges['length']]).T,
                               twoway=True)

#precompute a given horizon distance of 1000 meters so that aggregations don't perform the n
etwork queries unnecessarily
pednet.precompute(1000)

# save the pednet and res_df files
pednet.save_hdf5(r'D:\Dissertation\Excel\savedfiles\pednet.hdf5')
```

3.2.4 Part 2 – Calculating the Walk Distances and Times

3.2.4.1 Reading in the Amenity and Residential Address Data

The csv files are read in and stored as pandas DataFrames. The workflow from this point is identical for all 10 amenities shown below, so for the rest of the section, only operations performed on the 'edu_df' (Education) dataframe will be shown.

```
# amenities
edu = path + r"\.csv\Newcastle\Education.csv"
gov = path + r"\.csv\Newcastle\Government.csv"
heal = path + r"\.csv\Newcastle\Health.csv"
manu = path + r"\.csv\Newcastle\Manufacturing.csv"
offi = path + r"\.csv\Newcastle\Office.csv"
comm = path + r"\.csv\Newcastle\Commercial.csv"
recr = path + r"\.csv\Newcastle\Recreation.csv"
reli = path + r"\.csv\Newcastle\Religious.csv"
reta = path + r"\.csv\Newcastle\Retail.csv"
tran = path + r"\.csv\Newcastle\Transport.csv"
edu_df = pd.read_csv(edu, delimiter= ',')
gov_df = pd.read_csv(gov, delimiter= ',')
heal_df = pd.read_csv(heal, delimiter= ',')
manu_df = pd.read_csv(manu, delimiter= ',')
offi_df = pd.read_csv(offi, delimiter= ',')
comm_df = pd.read_csv(comm, delimiter= ',')
recr_df = pd.read_csv(recr, delimiter= ',')
reli_df = pd.read_csv(reli, delimiter= ',')
reta_df = pd.read_csv(reta, delimiter= ',')
tran_df = pd.read_csv(tran, delimiter= ',')

# addresses
res = path + r"\.csv\Newcastle\Residential.csv"
res_df = pd.read_csv(res, delimiter= ',')
```

3.2.4.2 Creating the GeoPandas Dataframes

GeoDataFrames need geometry data to be stored as a *shapely* object in order to read and plot coordinate data. As the exported csv have the point coordinates stored as X and Y centroid values in separate fields, they need to be first wrapped into a shapely objects and then converted to a GeoDataFrame.

```
# amenities
# keep useful columns
edu_df = edu_df[['unique_property_number','unique_building_number','CentroidX','CentroidY']]
# create geopanda dataframe
edu_df['geometry'] = list(zip(edu_df.CentroidX, edu_df.CentroidY))
edu_df['geometry'] = edu_df['geometry'].apply(Point)
edu_df = gpd.GeoDataFrame(edu_df, geometry='geometry')

# addresses
# keep useful columns
res_df = res_df[['unique_property_number','unique_building_number','CentroidX','CentroidY']]
# create geopanda dataframe
res_df['geometry'] = list(zip(res_df.CentroidX, res_df.CentroidY))
res_df['geometry'] = res_df['geometry'].apply(Point)
res_df = gpd.GeoDataFrame(res_df, geometry='geometry')
```

3.2.4.3 Computing Distances and Times

With the pedestrian network created, and the residential and amenity addresses now stored as GeoDataFrames, Pandana's vectorised shortest path algorithm can now run using the modified DAVCoT script. The algorithm first searches for the nearest amenity point for each residential address on the network by computing shortest paths. The shortest paths are the distance from the closest node to the beginning and end of the pedestrian network path (not the actual distance between building centroids along the network). There are some minor limitations with this method resulting from the distribution of residential addresses and line lengths in the *edges* dataset which are discussed further in section 3.3.1.2.

```
# get node_ids for points for each amenity layer
# map the variables x and y to node_ids
x, y = edu_df.CentroidX, edu_df.CentroidY
edu_df["OID_"] = pednet.get_node_ids(x, y)
pednet.set(edu_df["OID_"], name="edu_df")

# using x and y coordinates from address
x, y = res_df.CentroidX, res_df.CentroidY
res_df["OID_"] = pednet.get_node_ids(x, y)

# get nearest points with id
# finds the 5 nearest amenities to the each residential address point in the data set

n=5
maxdistance = 10000

pednet.set_pois("edu_df", maxdistance , n, edu_df.CentroidX, edu_df.CentroidY)
education_walk_distances = pednet.nearest_pois(maxdistance , "edu_df", num_pois=n,
include_poi_ids=False)

# rename columns 1 to 5 to d_education_0 to d_education_4.

n=5
columns =  ['d_educat_'+str(i) for i in range(0,n,1)]
education_walk_distances.columns = columns

for i in range(5):

res_df['d_educat_{}'.format(i)]=res_df['OID_'].map(education_walk_distances['d_educat_{}'.fo
rmat(i)])

res_df['m_educat_0'] = res_df.apply(lambda row: row.d_educat_0/(60), axis=1)
res_df['m_educat_1'] = res_df.apply(lambda row: row.d_educat_1/(60), axis=1)
res_df['m_educat_2'] = res_df.apply(lambda row: row.d_educat_2/(60), axis=1)
res_df['m_educat_3'] = res_df.apply(lambda row: row.d_educat_3/(60), axis=1)
res_df['m_educat_4'] = res_df.apply(lambda row: row.d_educat_4/(60), axis=1)
```

3.2.4.4 Network Analysis Walk times

Once the computation has run for all amenities, a dataset with following fields for each residential address point is created:

Table 9 Walk Time and Distance Fields

Amenity Class	Measurement	Field Name	Relative Position of Amenity from Residential Address
Education	Distance (metres)	d_educat_0	Nearest
		d_educat_1	2nd nearest
		d_educat_2	3rd nearest
		d_educat_3	4th nearest
		d_educat_4	5th nearest
	Time (minutes)	m_educat_0	Nearest
		m_educat_1	2nd nearest
		m_educat_2	3rd nearest
		m_educat_3	4th nearest
		m_educat_4	5th nearest
Government	Distance (metres)	d_ govern _0	Nearest
		d_ govern _1	2nd nearest
		d_ govern _2	3rd nearest
		d_ govern _3	4th nearest
		d_ govern _4	5th nearest
	Time (minutes)	m_ govern _0	Nearest
		m_ govern _1	2nd nearest
		m_ govern _2	3rd nearest
		m_ govern _3	4th nearest
		m_ govern _4	5th nearest
Health	Distance (metres)	d_health_0	Nearest
		d_ health _1	2nd nearest
		d_ health _2	3rd nearest
		d_ health _3	4th nearest
		d_ health _4	5th nearest
	Time (minutes)	m_ health _0	Nearest
		m_ health _1	2nd nearest
		m_ health _2	3rd nearest
		m_ health _3	4th nearest
		m_ health _4	5th nearest

Manufacturing	Distance (metres)	d_ manufa_0	Nearest
		d_ manufa _1	2nd nearest
		d_ manufa _2	3rd nearest
		d_ manufa _3	4th nearest
		d_ manufa _4	5th nearest
	Time (minutes)	m_ manufa _0	Nearest
		m_ manufa _1	2nd nearest
		m_ manufa _2	3rd nearest
		m_ manufa _3	4th nearest
		m_ manufa _4	5th nearest
Office	Distance (metres)	d_office_0	Nearest
		d_office_1	2nd nearest
		d_office_2	3rd nearest
		d_ office _3	4th nearest
		d_ office _4	5th nearest
	Time (minutes)	m_ office _0	Nearest
		m_ office _1	2nd nearest
		m_ office _2	3rd nearest
		m_ office _3	4th nearest
		m_ office _4	5th nearest
Commerce	Distance (metres)	d_commer_0	Nearest
		d_ commer _1	2nd nearest
		d_ commer _2	3rd nearest
		d_ commer _3	4th nearest
		d_ commer _4	5th nearest
	Time (minutes)	m_ commer _0	Nearest
		m_ commer _1	2nd nearest
		m_ commer _2	3rd nearest
		m_ commer _3	4th nearest
		m_ commer _4	5th nearest
Recreation	Distance (metres)	d_recrea_0	Nearest
		d_ recrea _1	2nd nearest
		d_ recrea _2	3rd nearest
		d_ recrea _3	4th nearest
		d_ recrea _4	5th nearest
	Time (minutes)	m_ recrea_0	Nearest
		m_ recrea _1	2nd nearest
		m_ recrea _2	3rd nearest
		m_ recrea _3	4th nearest
		m_ recrea _4	5th nearest
Religious	Distance (metres)	d_religi_0	Nearest
		d_ religi _1	2nd nearest
		d_ religi _2	3rd nearest
		d_ religi _3	4th nearest
		d_ religi _4	5th nearest
	Time (minutes)	m_ religi _0	Nearest
		m_ religi _1	2nd nearest
		m_ religi _2	3rd nearest
		m_ religi _3	4th nearest
		m_ religi _4	5th nearest
Retail	Distance (metres)	d_retail_0	Nearest
		d_ retail _1	2nd nearest
		d_ retail _2	3rd nearest
		d_ retail _3	4th nearest
		d_ retail _4	5th nearest
	Time (minutes)	m_ retail _0	Nearest
		m_ retail _1	2nd nearest
		m_ retail _2	3rd nearest
		m_ retail _3	4th nearest
		m_ retail _4	5th nearest
Transportation	Distance (metres)	d_tranps_0	Nearest
		d_ tranps _1	2nd nearest
		d_ tranps _2	3rd nearest
		d_ tranps _3	4th nearest
		d_ tranps _4	5th nearest
	Time (minutes)	m_ tranps _0	Nearest
		m_ tranps _1	2nd nearest
		m_ tranps _2	3rd nearest

m_ tranps _3	4th nearest
m_ tranps _4	5th nearest

3.2.5 Part 3 – Examining the Results

3.2.5.1 Distribution of Results

Due to the nature of the data used there were a few irregularities resulting from the calculation process. These are discussed further in sections 3.3.1.1 - 3.3.1.3. The first objective was to understand the causes of errors, and the second, to elimate any errors resulting from data irregularities. As walk times and distances should be normally distributed, histograms have been frequently used. Below is an example of how the maximum errors were identified and removed.

In order to be certain that none of the addresses being removed, had genuinely calculated a distance of 10,000m from an amenity (unlikely but possible), a field containing the mean walk time to the nearest 1 of each amenity category was created. This meant any addresses that still had max errors could be removed with confidence (the likelihood of an address being more than 10,000m from all amenities is diminishingly small).

```
# create mean fields for times and distances

walktime_df['d_ave_0'] = walktime_df[['d_educat_0','d_govern_0', 'd_health_0','d_manufa_0','
d_office_0','d_recrea_0','d_religi_0','d_retail_0','d_transp_0']].mean(axis=1)
walktime_df['m_ave_0'] = walktime_df[['m_educat_0','m_govern_0', 'm_health_0','m_manufa_0','
m_office_0','m_recrea_0','m_religi_0','m_retail_0','m_transp_0']].mean(axis=1)

# plot mean distances as a histogram

ax = walktime_df.d_ave_0.plot.hist(figsize= [6,5], bins=500, cmap='cool')
ax.set_title('Distance to Nearest Amenities - Mean of the 9 Categories')
ax.set_xlabel('Distance to Nearest X (m)')
plt.box(False)
```

3.2.5.2 Remove Max Errors

2,033 max errrors are removed. The reasons for this are discussed in 3.3.1.1.

```
# remove max errors

walktime_df = walktime_df.loc[walktime_df['d_ave_0'] < 10000.0]
```

3.2.5.3 Mean and Compound Walk Times

To aid the analysis, some compound measures have been created using the .mean() function. This is an attempt to try and emulate the activities or classes of trips that people are likely to participate in. By grouping together categories that fulfil people trip objectives, it may present a more useful picture of how much diversity of amenity there is in a neigbourhood. The method used presents many limitations which are discussed in 5.3. The compound walk times have then been added to the Walk Times and Distances dataset shown in Table 9.The sample size of the data everytime the .mean() is applied is identical (305,920), so no weighting was required.

3.2.5.3.1 Recreation and Leisure

Firstly, walk times to the nearest office, commercial and manufacturing nodes are combined to create a new field ‘employment’. This has been repeated for the next four closest nodes in each of the three categories.

```
# walk time to ‘employment’
walktime_df["m_employment_0"] = walktime_df.loc[:,[
"m_manufa_0","m_commer_0","m_office_0"
]].mean(axis = 1)

walktime_df["m_employment_1"] = walktime_df.loc[:,[
"m_manufa_1","m_commer_1","m_office_1"
]].mean(axis = 1)
```

```
walktime_df["m_employment_2"] = walktime_df.loc[:,[
"m_manufa_2","m_commer_2","m_office_2"
]].mean(axis = 1)

walktime_df["m_employment_3"] = walktime_df.loc[:,[
"m_manufa_3","m_commer_3","m_office_3"
]].mean(axis = 1)

walktime_df["m_employment_4"] = walktime_df.loc[:,[
"m_manufa_4","m_commer_4","m_office_4"
]].mean(axis = 1)
```

3.2.5.3.2 Leisure Mean

Another new field 'leisure' follows the same process as above, this time combining walk times to 'recreation' and 'religious' nodes.

```
# walk time to 'leisure'
walktime_df["m_leisure_0"] = walktime_df.loc[:, [
"m_religi_0","m_recrea_0"
]].mean(axis = 1)

walktime_df["m_leisure_1"] = walktime_df.loc[:, [
"m_religi_1","m_recrea_1"
]].mean(axis = 1)

walktime_df["m_leisure_2"] = walktime_df.loc[:, [
"m_religi_2","m_recrea_2"
]].mean(axis = 1)

walktime_df["m_leisure_3"] = walktime_df.loc[:, [
"m_religi_3","m_recrea_3"
]].mean(axis = 1)

walktime_df["m_leisure_4"] = walktime_df.loc[:, [
"m_religi_4","m_recrea_4"
]].mean(axis = 1)
```

3.2.5.3.3 Relative Distance Mean

This compound measure has not been used later in the discussion. However, it was used during the project as a way of investigating the data in an attempt to understand how mean of walk times for amenities changed as the relative distance changed. It is the mean walktime to the closest amenity of each type. This is then repeated for 2nd closest of each type, 3rd closest etc.

```
# mean walk time to each amenity
walktime_df["m_ave_0"] = walktime_df.loc[:, [
'm_educat_0','m_govern_0',
'm_health_0','m_manufa_0','m_office_0','m_commer_0','m_recrea_0','m_religi_0','m_retail_0'
]].mean(axis = 1)

walktime_df["m_ave_1"] = walktime_df.loc[:,[
'm_educat_1','m_govern_1',
'm_health_1','m_manufa_1','m_office_1','m_commer_1','m_recrea_1','m_religi_1','m_retail_1'
]].mean(axis = 1)

walktime_df["m_ave_2"] = walktime_df.loc[:,[
'm_educat_2','m_govern_2',
'm_health_2','m_manufa_2','m_office_2','m_commer_2','m_recrea_2','m_religi_2','m_retail_2'
]].mean(axis = 1)

walktime_df["m_ave_3"] = walktime_df.loc[:,[
'm_educat_3','m_govern_3',
'm_health_3','m_manufa_3','m_office_3','m_commer_3','m_recrea_3','m_religi_3','m_retail_3'
]].mean(axis = 1)

walktime_df["m_ave_4"] = walktime_df.loc[:,[
'm_educat_4','m_govern_4',
'm_health_4','m_manufa_4','m_office_4','m_commer_4','m_recrea_4','m_religi_4','m_retail_4'
]].mean(axis = 1)

]].mean(axis = 1)
```

3.2.5.3.4 Nearest 5 Mean

As a walkable neighbourhood would generally demand more than one of each type of amenity (not true for all amenities – as discussed in 5.3.3), a compound measure calculating the mean walk time to each amenity type has also been created. (for example, the mean trip time taken to walk to the 5 nearest retail nodes – each trip is counted as between the residential address and the retail node).

```
# mean walk time to the nearest 5 amenities
walktime_df["m_employment_all"] = walktime_df.loc[:,[
"m_employment_0","m_employment_1","m_employment_2", 'm_employment_3','m_employment_4'
]].mean(axis = 1)

walktime_df["m_leisure_all"] = walktime_df.loc[:,[
"m_leisure_0","m_leisure_1","m_leisure_2", 'm_leisure_3','m_leisure_4'
]].mean(axis = 1)

walktime_df["m_retail_all"] = walktime_df.loc[:, [
"m_retail_0","m_retail_1","m_retail_2", 'm_retail_3','m_retail_4'
]].mean(axis = 1)
walktime_df["m_commer_all"] = walktime_df.loc[:, [
"m_commer_0","m_commer_1","m_commer_2", 'm_commer_3','m_commer_4'
]].mean(axis = 1)
walktime_df["m_office_all"] = walktime_df.loc[:, [
"m_office_0","m_office_1","m_office_2", 'm_office_3','m_office_4'
]].mean(axis = 1)
walktime_df["m_recrea_all"] = walktime_df.loc[:, [
"m_recrea_0","m_recrea_1","m_recrea_2", 'm_recrea_3','m_recrea_4'
]].mean(axis = 1)
walktime_df["m_manufa_all"] = walktime_df.loc[:, [
"m_manufa_0","m_manufa_1","m_manufa_2", 'm_manufa_3','m_manufa_4'
]].mean(axis = 1)
walktime_df["m_religi_all"] = walktime_df.loc[:, [
"m_religi_0","m_religi_1","m_religi_2", 'm_religi_3','m_religi_4'
]].mean(axis = 1)
walktime_df["m_transp_all"] = walktime_df.loc[:, [
"m_transp_0","m_transp_1","m_transp_2", 'm_transp_3','m_transp_4'
]].mean(axis = 1)
walktime_df["m_educat_all"] = walktime_df.loc[:, [
"m_educat_0","m_educat_1","m_educat_2", 'm_educat_3','m_educat_4'
]].mean(axis = 1)
walktime_df["m_health_all"] = walktime_df.loc[:, [
"m_health_0","m_health_1","m_health_2", 'm_health_3','m_health_4'
]].mean(axis = 1)
walktime_df["m_govern_all"] = walktime_df.loc[:, [
"m_govern_0","m_govern_1","m_govern_2", 'm_govern_3','m_govern_4'
```

Lastly, a mean of all the walk times which is the mean amount of time taken to reach the closest 50 amenities (5 in each of the 10 categories). This has essentially been used as an all ecompassing indicator of how diverse building use in a neighbourhood is and how use diversity varies throughout the study area.

3.2.5.3.5 Mean of all means

Whilst not an ideal measure of walkability, this was the most appropriate concievable way of summarising all of the data in a single field. In order to maintain the unweighted approach to different amenities, every uncompounded mean walk time has been included (except transport for the reasons discussed in 3.3.2.2).

```
# mean walk time to the nearest 45 amenities (5 in each category
walktime_df["m_ave_all"] = walktime_df.loc[:,
["m_office_all","m_manufa_all","m_commer_all","m_religi_all","m_recrea_all","m_retail_all",'m_
educat_all','m_health_all','m_govern_all'
]].mean(axis = 1)

# save walk times and distances file
walktime_df.to_file(r'D:\Dissertation\Excel\savedfiles\walktime_df.shp')
```

3.2.5.4 Spatial Data as Individual Nodes

From *walktime_df*, the data can easily be plotted as coloured points using custom class intervals to show how walk times vary throughout the city. In this example, the walk time to the nearest education has been discretised with 2-minute class intervals (Figure 21 to Figure 27). Binary discretisation (<=15 min class interval) has been used in Figure 28 and Figure 29.

```
# plot walk times from each address with 2-minute bins


ax = walktime_df.plot(figsize=(15, 15), column='m_educat_0', scheme='userdefined',
cmap='cool', classification_kwds={'bins':[2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26,
28, 30]}, legend=True,markersize = 1)

ax.set_title(('North Tyneside Mean Walking Times To Closest Amenities'),
fontdict={'fontsize':'20', 'fontweight':'3'})

ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)

plt.savefig(path + r"/SavedPNGs/Results/Overview/North Tyneside Mean Walking Times to
Closest Amenities", dpi=300)
```

3.2.6 Part 4 – Unitary Authorities

In order to find the mean walk times within Unitary Authorities, a spatial join was performed between *walktime_df* and *UApolygons*. This created a new data set with 80 rows and the mean walktime to each amenity for the UA. The coordinates and name of any chosen UA are then stored to create plots centred on that UA - see Figure 19. **m_Series_X** is a string series storing all the walk time field names.

```
# include columns needed for the project
UApolygons = UApolygons[['NAME','UNIT_ID','CODE','geometry']]

# change the name of the geometry column before spatial join - GeoPandas DataFrames can only
have one geometry column
UApolygons["centre"] = UApolygons["geometry"].centroid

# spatial Join where Unitary Authority polygons intersect address points
UA_walktime_df = gpd.sjoin(UApolygons, walktime_df, op='intersects', how='left')

#  UA address count DataFrame
value_counts = UA_walktime_df.NAME.value_counts()
#value_counts

# renaming axis to NAME and resetting index to UA_walktime_df_counts
UA_walktime_df_counts =
value_counts.rename_axis('NAME').reset_index(name='UA_address_count')

# merge UA_walktime_df_counts with UA_walktime_df using the NAME field which is shared by
both DataFrames
UA_walktime_df = pd.merge(UA_walktime_df, UA_walktime_df_counts)


# create a new DataFrame called UA_ave_walktime_df (with 80 rows)
UA_ave_walktime_df = UA_walktime_df.groupby('NAME')[m_Series_X
                                              ].mean()

UAWalk = pd.merge(UA_walktime_df, UApolygons, on='NAME')

# Add row number column in UAWalk dataframe
UAWalk['row_num'] = np.arange(len(UAWalk))

# Change datatype of 'NAME' to string (from Object) and remove 'Ward' from column
UAWalk['NAME'] = UAWalk['NAME'].astype("string")
UAWalk['NAME'] = UAWalk['NAME'].str.replace(' Ward', '')

# store variables for UA bounding box coordinates
minx,miny,maxx,maxy = UAWalk.bounds.iloc[51].values

# store variables for UA name
UA_NAME = UAWalk.NAME.iloc[51]
```

3.2.7 Part 5 – Lower Super Output Areas

A similar process to Part 4 is repeated with the LSOA polygons (which are extracted from the economic dataset) to create a dataframe with 536 rows. 29 'empty' polygons are removed, discussed in section 393.3.1.5. After this, the socio-economic data is added.

```
# import socio-economic data
eco_df = eco_df.rename(columns={'area_name':'NAME'})
pop_df = pop_df.rename(columns={'area_name':'NAME'})
car_df = car_df.rename(columns={'area_name':'NAME'})
LSOA = eco_df[['NAME','geometry']]

# find the centre points, copy the original df to a new df
LSOA["centre"] = LSOA["geometry"].centroid

# spatially join where LSOA area polygons intersect with address points
LSOA_walktime_df = gpd.sjoin(LSOA, walktime_df, op='intersects', how='left')

LSOA_ave_walktime_df = LSOA_walktime_df.groupby('NAME')[m_Series_X
                                            ].mean()
LSOAWalk = LSOA_ave_walktime_df
# data frame containing all 29 of the null LSOA polygons
LSOAWalkNull = LSOAWalk[LSOAWalktime.isna().any(axis=1)]

# 507 complete LSOA polygons
LSOAWalk = LSOAWalk.dropna()

# add the socio-economic data to the DataFrame
ECO = pd.merge(LSOAWalk, eco_df, on='NAME')
POP = pd.merge(ECO, pop_df, on='NAME')
CAR = pd.merge(POP, car_df, on='NAME')
LSOAWalk = CAR
```

3.3 Issues and Limitations

3.3.1 Calculation Issues

3.3.1.1 Minimum / Maximum Error

Minimum errors i.e., 0m walk distance, occur as a result of the centroids of residential addresses being located closer to the amenity centroids it is trying to find, than the nearest node of the pedestrian network.

Maximum errors occur as a result of the residential addresses not being topologically connected to an amenity on the pedestrian network. Before the maximum computation distance was set to 10,000m (section 3.2.4.3), it was set at 5000m. If the shortest path algorithm couldn't find an amenity within this distance, a value of 5000m was recorded as the walk time for that address. This helped to pick up on problems with the calculation process.

3.3.1.1.1 *Edges* Shapefile Export

An unexpectedly large number of 5000m distance values were found after the calculations had initially been performed. This was due to a portion of the *Edges* dataset shown in Figure 5 disappearing when exporting from ArcGIS (the white section as a result of a 2gb file size limit on shapefiles. 5000m walk distances to all amenities were being recorded for most of the addresses located in the white region of Figure 5.

The shapefile size problem was fixed by removing some unneccessary data columns before exporting *Edges* to shapefile, allowing the full network to be imported to Jupyter notebooks. The impact on the number of maximum and minimum errors of importing the full network is shown in white. The number of 0m errors increases as a result of more addresses being incoporated in the network, and the number of 5000m errors drops dramatically.

Figure 5 Shapefile size limit for the *Edges* dataset (white region was cut during export to shapefile in ArcGIS)

Table 10 shows how the number of max errors drop from 16,954 to 2,033 once the entire *edges* dataset is imported. The number of zero errors increases slightly due to a larger portion of the network being available for analysis.

Table 10 Impact of removing columns in the *Edges* dataset before exporting to shapefile (counts are for the entire dataset)

Distance Value	Equivalent Time Value	Count (Before)	Count (After)
0	0	2353	2388
5000	69.444	16954	2033

3.3.1.1.2 Minimum Errors

The 0m errors are kept in the dataset as they only occur when residences are in very close proximity to the amenity in question. It is therefore of greater accurate to keep them in than remove them (Figure 6 shows the addresses with minimum errors clustered around education nodes). Figure 7 shows that the number of minimum errors occur frequently for education compared to transport. This is unsurprising as schools are generally located in residential neighbourhoods.

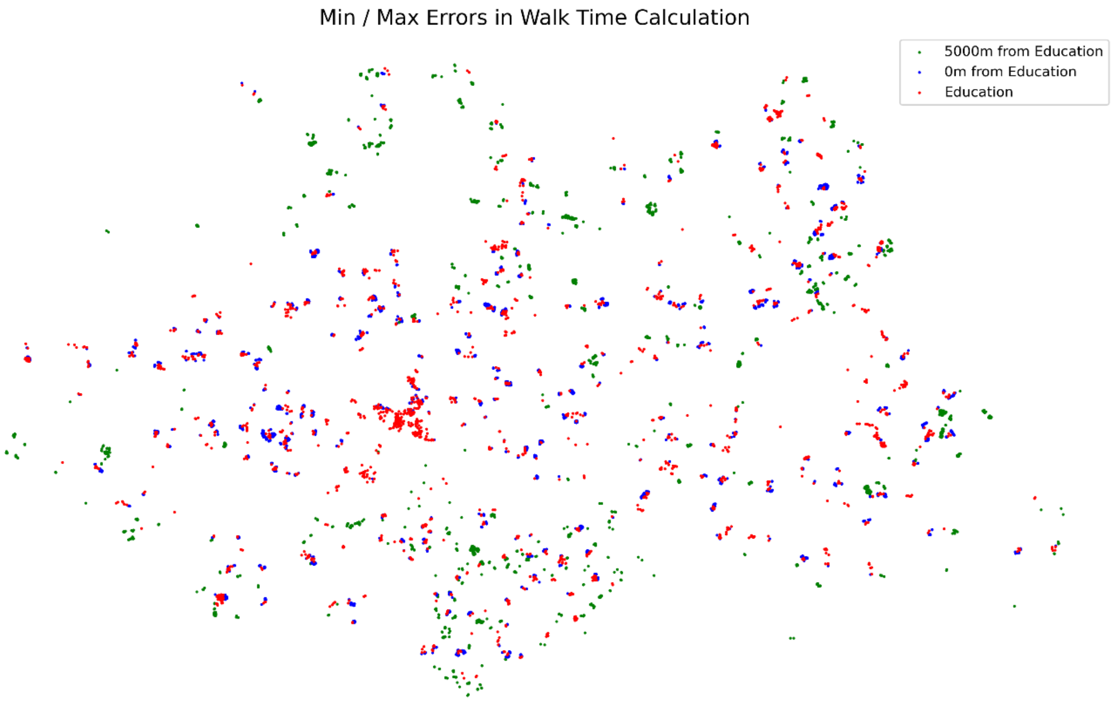
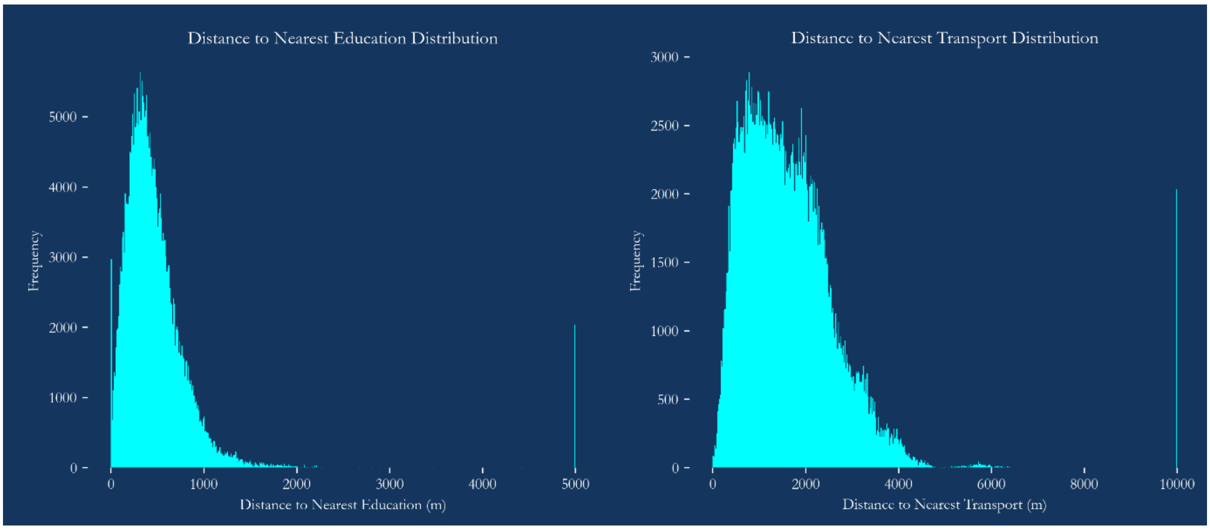


Figure 6 Spatial Distribution of Min / Max Errors for Education

3.3.1.1.3 Incomplete Pedestrian Network

After changing the max compute distance to 10,000m and re-running the analysis, Figure 7 shows that some calculations over 5000m appear to be valid. The valid distances beyond 5000m become more frequent as the n^{th} nearest amenity moves from 1 to 5. Tranport is used as the example here. However, there is still a large spike at 10,000 indicating that something was going awry. When averaging the walk distances across all nine categories, the total count for number of residences with the maximum error remained at 2,033, indicating that the maximum error occurred independent of the category of amenity. The cause of the maximum errors are topologically disconnected edges that were present in the OS MasterMap dataset. This is discussed briefly in 3.3.2.1 and can be seen in Figure 14. The 2,033 maximum distance errors were removed before any analysis of the walk times, because these are definitley artefacts and would skew the results.



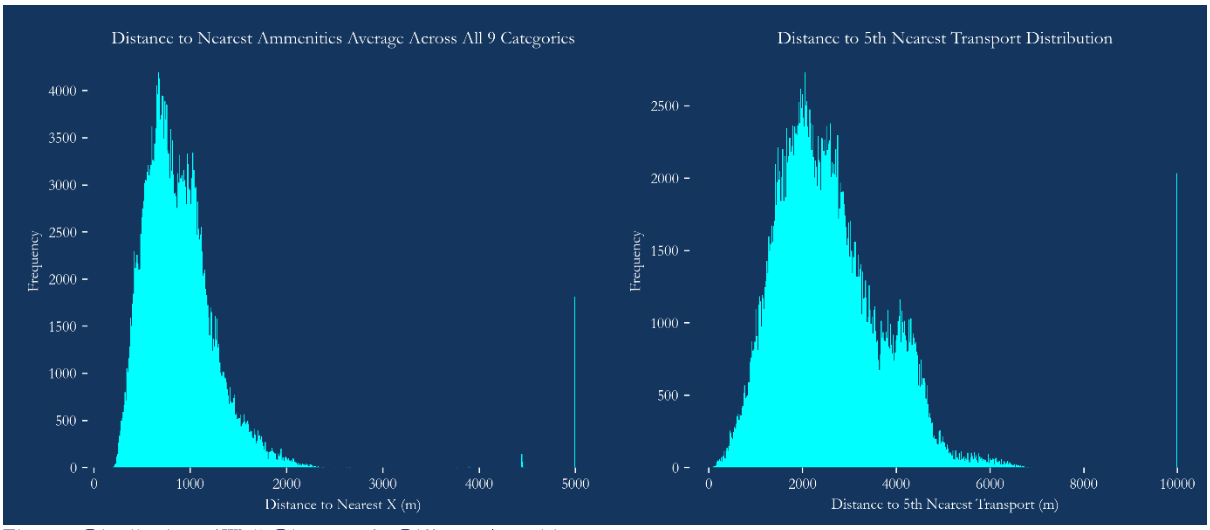


Figure 7 Distribution of Walk Distances for Different Amenities

3.3.1.2 Distribution of Edge Lengths

In initial runs of the walkability analysis, the 'split line' tool in ArcGIS was used to break the *edges* layer down into 10m sections. However, this created a dataset with over 10-million-line segments (approximately 20x more than the original *edges* layer). Using the *edges* layer in its original form resulted in substantially faster processing time for both reading the file (~2mins instead of ~10mins) and for running the shortest path queries (~40s per amenity instead of ~2mins). Another added benefit of this was that the longer road segments were generally confined to sections of dual carriageway or paths through parks (the left image shows the paths through the town moor and sections of the A167). This means that residential address points are less likely to 'jump' to one of these road types when searching for the nearest node to begin calculating shortest paths, and instead use the residential roads. The residential neighbourhoods typically have a high node density.

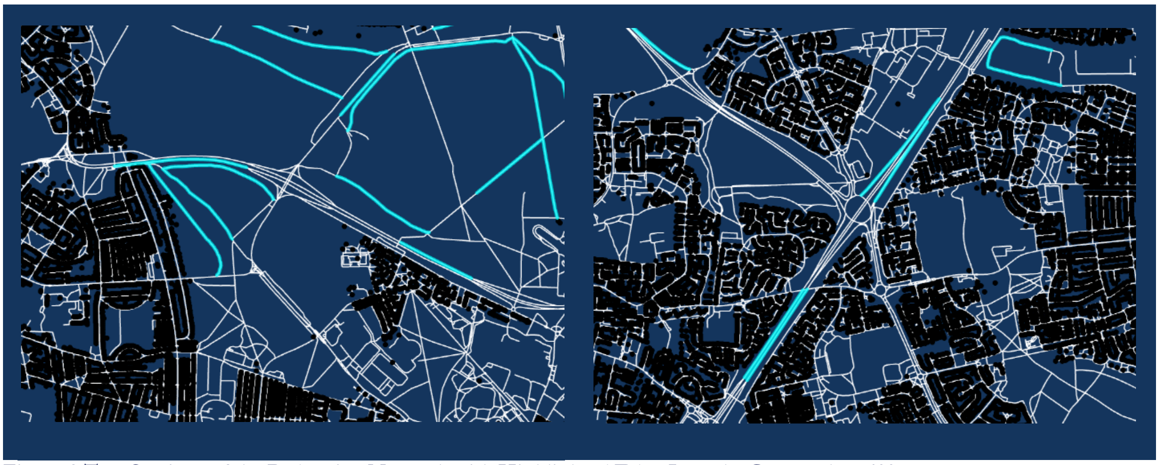


Figure 8 Two Sections of the Pedestrian Network with Highlighted Edge Lengths Greater than 400m

Distribution of edge lengths follows a Poisson distribution with a mean edge length of 29.36m and a standard deviation of 43.47m.

Table 11 Line Length Descriptors

count	523401
mean	29.36
std	43.47
min	0.001
max	1701
25%	5.720

50%	16.12
75%	35.72
99%	200.0

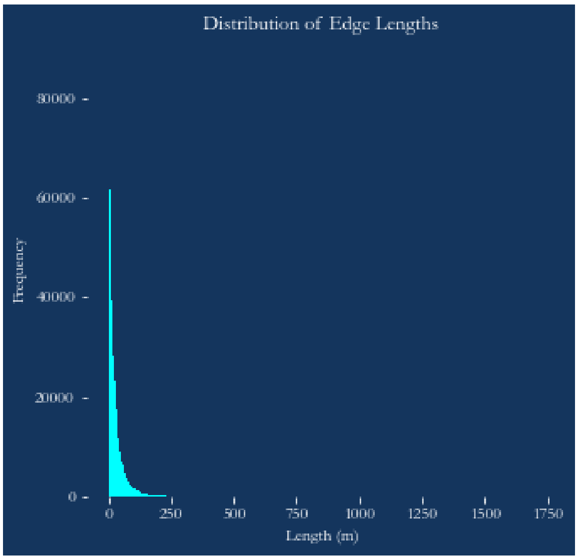


Figure 9 Distribution of Edge Lengths

3.3.1.3 Address Aggregation

As a result of the distribution edge lengths discussed above, when the network aggregation runs, between 70,000 and 77,000 unique distance and time values are calculated depending on the amenity being queried. This means approximately 1 in 4 addresses are being aggregated to the same point. (i.e., 4 addresses start the shortest path query from the same node on the pedestrain network). The spatial distribution with which this occurs this is fairly even (although more residential addresses will be aggregated in neighourhoods with a greater density of long terraced roads). This should not significantly impact the mean walk time of the LSOA's or provide much visual variation from reality at the address point level (it will reduce the mean walk distance for areas with a high density of long terraced roads slightly, as the middle terrace houses will be treated as end of row terraces and therefore closer to the network node at the end of the road. Ideally the analysis would be run with a greater number of nodes, but for now the overall loss of information can be described as small and all 307,953 addresses will still be used in the analysis.

As can be seen from Figure 10 the spatial aggregation of addresses is fairly even, but aggregation occurs at higher rates in more central and high-density areas.

m_SERIES_X are all of the fields in Table 9.

```
# create new dataframe without duplicates
resnd_df = res_df.drop_duplicates(subset=('m_SERIES_X'))
```

Figure 10 Address Aggregation Spatial Distribution

3.3.1.4 Precomputing Horizon Distances

Pandana recommend precomputing the horizon distance, so network aggregations are not performed unnecessarily, at a distance of 2000m-3000m. However, at this value, the kernel used for the calculation dies, and the calculation stops. Instead, a distance of 1000m is used, which is the same value used by DAVCoT. It would be of interest to explore the impact of increasing this number, as it does not appear to make any difference to the results at values below 1000m (100m and 500m were also tested).

3.3.1.5 ArcGIS clipping

When spatially joining the walktime dataframe with the LSOA polygons, it was found that 29 of the LSOA regions contained no walktime information. This resulted from the ArcGIS clipping tool leaving sections of external LSOA polygons in the LSOA dataframe. These regions have been removed from the dataframe as they contain no addresses and did not impact the analysis.

Figure 11 Sunderland 004E

Figure 12 Northumberland 032D

3.3.2 Data Issues

3.3.2.1 Ordinace Survey - MasterMap

The OS MasterMap data set contains segments that are not topologically connected to the rest of the network which means that some of the address points cannot find a path to an amenity. As a result, these addresses have been removed as discussed further up 3.2.5.2.

Ideally, the pedestrian network would not include sections of dual-carriageway that are not walkable, however, as the OS dataset does not include information about the sidewalk presence on dual-carriageway sections, there was no way to automate the removal these sections. Doing this manually using google street view or visiting the sites would have been very time consuming. No concievable method was found to assess which sections of 'unwalkable dual-carriageway' was used by the algorithm in the shortest path analysis. However, in addition to the reasons highlighted in 3.3.1.2, most motorway sections have pedestrian walkways nearby, so the impact of leaving these sections in is likely to be minimal.

Figure 13 Sample Section of Dual-Carriageway with Mixed Walkability

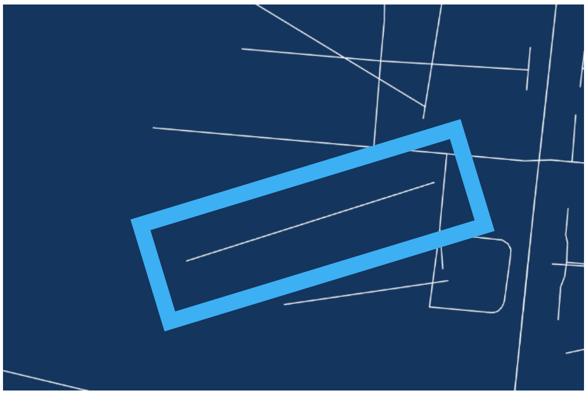


Figure 14 Disconnected Edge Example

3.3.2.2 Geomni – UKBuildings

The quality of the 'use' field in the Geomni – UKBuildings dataset is very sporadic.

The TRANSPORT category presents some of the greatest irregularities. Occasional auxillary structures like electrified rail substations are included (Figure 15). The stations on the metro network are generally accurate and well documented, but some stations are missed completely or listed as RETAIL, as is the case with both Jesmond and West Jesmond Metro Station (Figure 16 and Figure 18). The bus network is very poorly documented with very few examples to be found (Figure 17).

Figure 15 Rail Substation on Whitley Road

Figure 16 Longbenton and Four Lane Ends Metro Stations

Figure 17 Bus Stop in Whiteley Bay

Figure 18 West Jesmond Metro Categorised As Retail

3.3.2.3 Census Data

The census is from 2011 so for newer neighbourhoods like Newcastle Great Parks, it is unuseable. The first release of 2021 census data will be in June 2022, which provides an oppurtunity to conduct a comprehensive bivariate analysis.

4 Results

The results are laid out predominantly at two spatial levels, the whole study area, and then in-depth analysis on 3 selected case studies at the Lower Super Output Area Level.

The following two graphs use the mean of all means (**m_ave_all**) field to indicate how walk times vary throughout the North Tyneside study area (see 3.2.5.3 for a breakdown of how mean walktimes are generated). Unsurprisingly, the central polygons have the lowest average walk times, and the outer polygons have the highest average walk times.

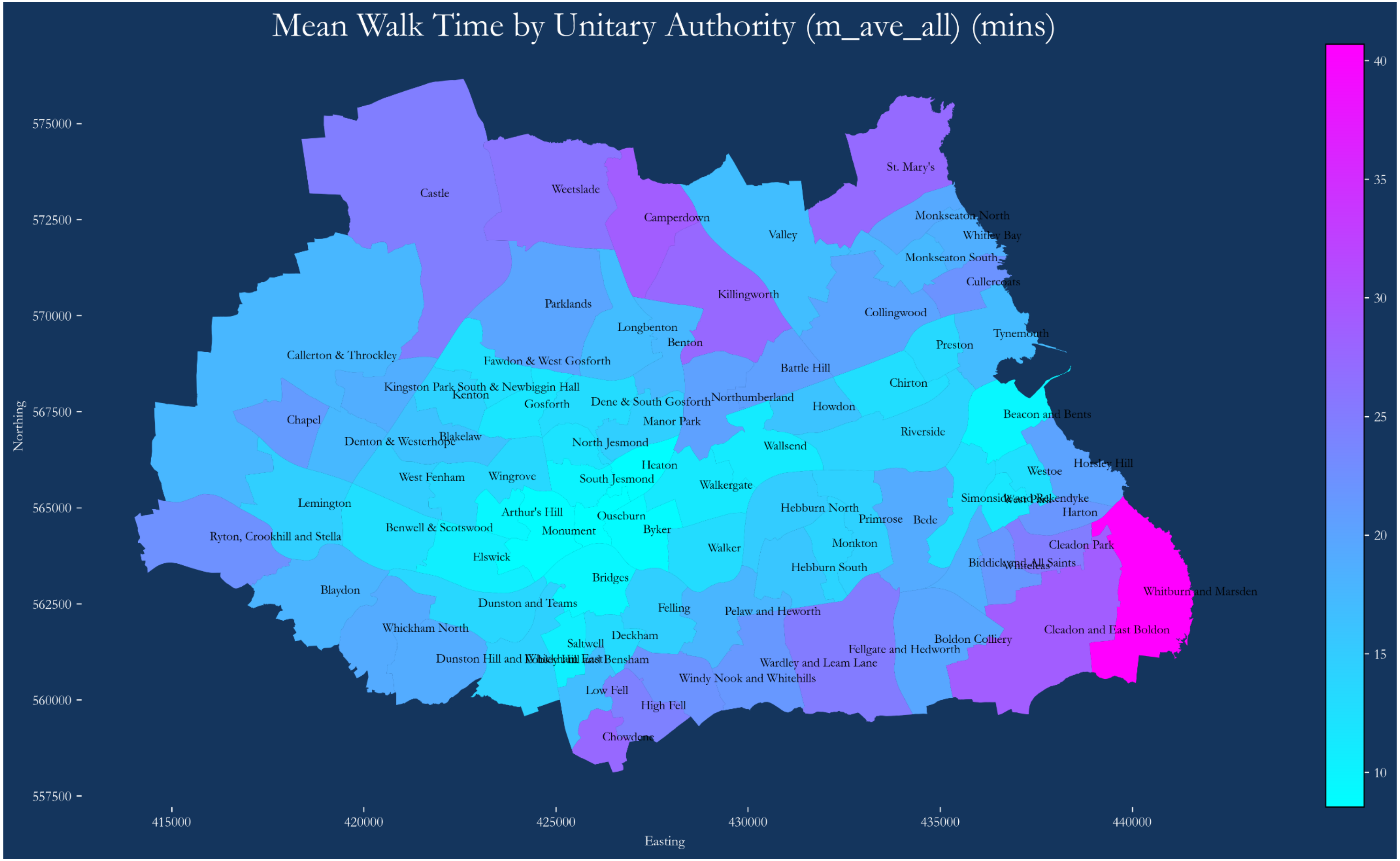


Figure 19 Mean Walk Time by Unitary Authority (m_ave_all)

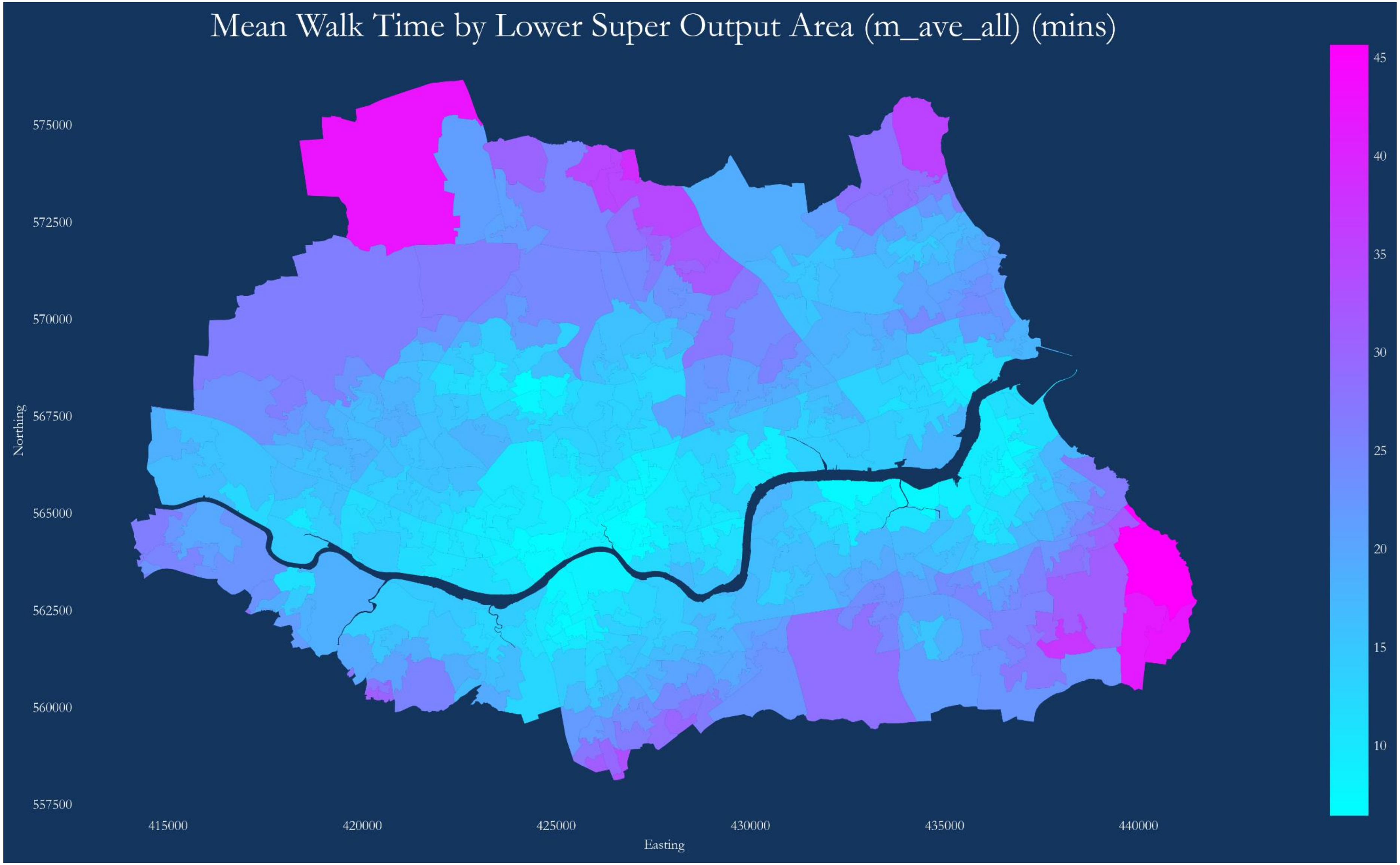


Figure 20 Mean Walk Time In Lower Super Output Areas

4.1 North Tyneside Metropolitan Area

4.1.1 What Does The Distribution Of Walk Times Look Like?

For a higher resolution view of the variation of walk times, the walk times from individual residential addresses can be plotted using the compound and mean walk times. Table 12 shows the statistical descriptors for the different mean and compound walk times. Retail has the lowest mean (6.89 mins) and tightest distribution with a standard deviation of (4.21) followed by Education.

Table 12 Statistical Descriptors of Nearest 5 Means and Mean of all Means

	m_ave_all (Mean)	m_employment_all (Employment)	m_leisure_all (Leisure)	m_health_all (Health)	m_govern_all (Government)	m_educat_all (Education)	m_retail_all (Retail)
count	305920	305920	305920	305920	305920	305920	305920
mean (mins)	17.50	23.73	12.37	18.56	25.96	10.20	6.89
std (mins)	6.61	10.85	5.36	10.68	13.72	5.52	4.21
min (mins)	4.64	2.09	1.59	0.02	0.00	0.00	0.00
25% (mins)	12.81	15.82	8.58	11.25	16.25	6.46	3.82
50% (mins)	16.58	21.90	11.45	16.73	23.63	9.23	6.24
75% (mins)	21.00	29.28	15.18	23.03	33.51	12.66	9.07
max (mins)	80.58	85.06	88.51	88.93	129.34	80.48	50.30

-inf (overleaf) shows in the legend where there are no values are contained in the lowest class interval.

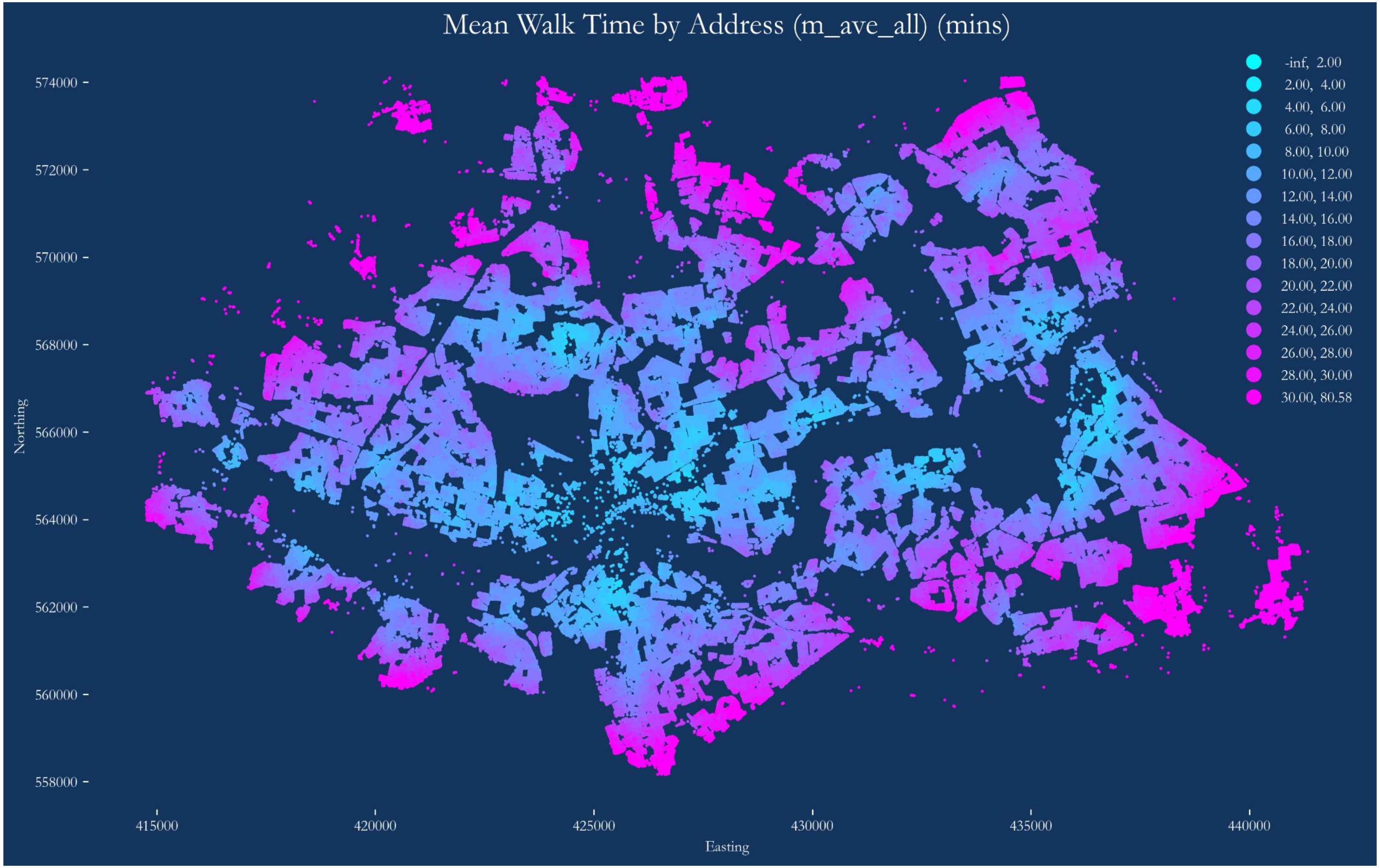


Figure 21 Mean Walk Time by Address (m_ave_all)

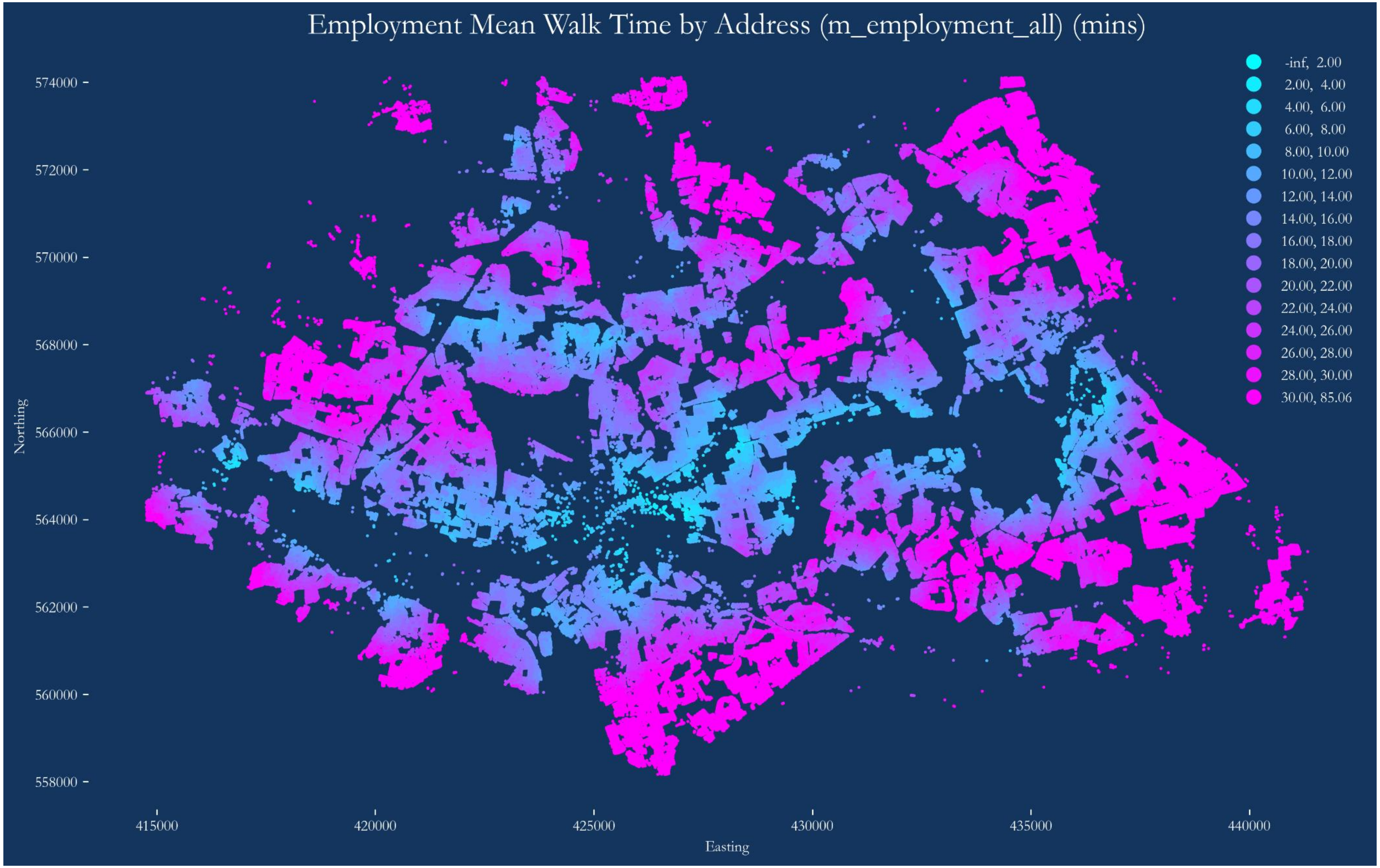


Figure 22 Mean Employment Walktime (m_employment_all)

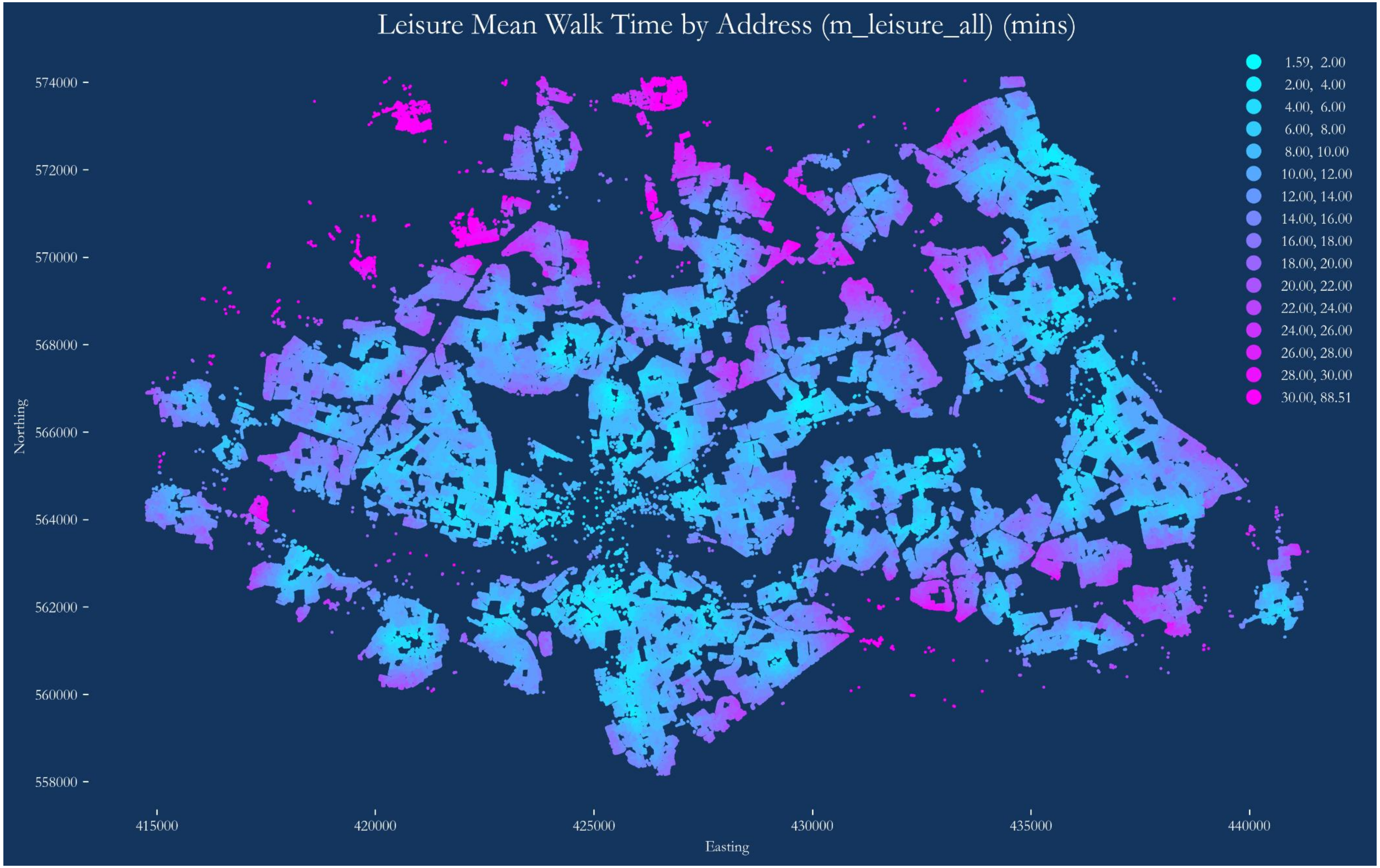


Figure 23 Mean Leisure Walk Time by Address (m_leisure_all)

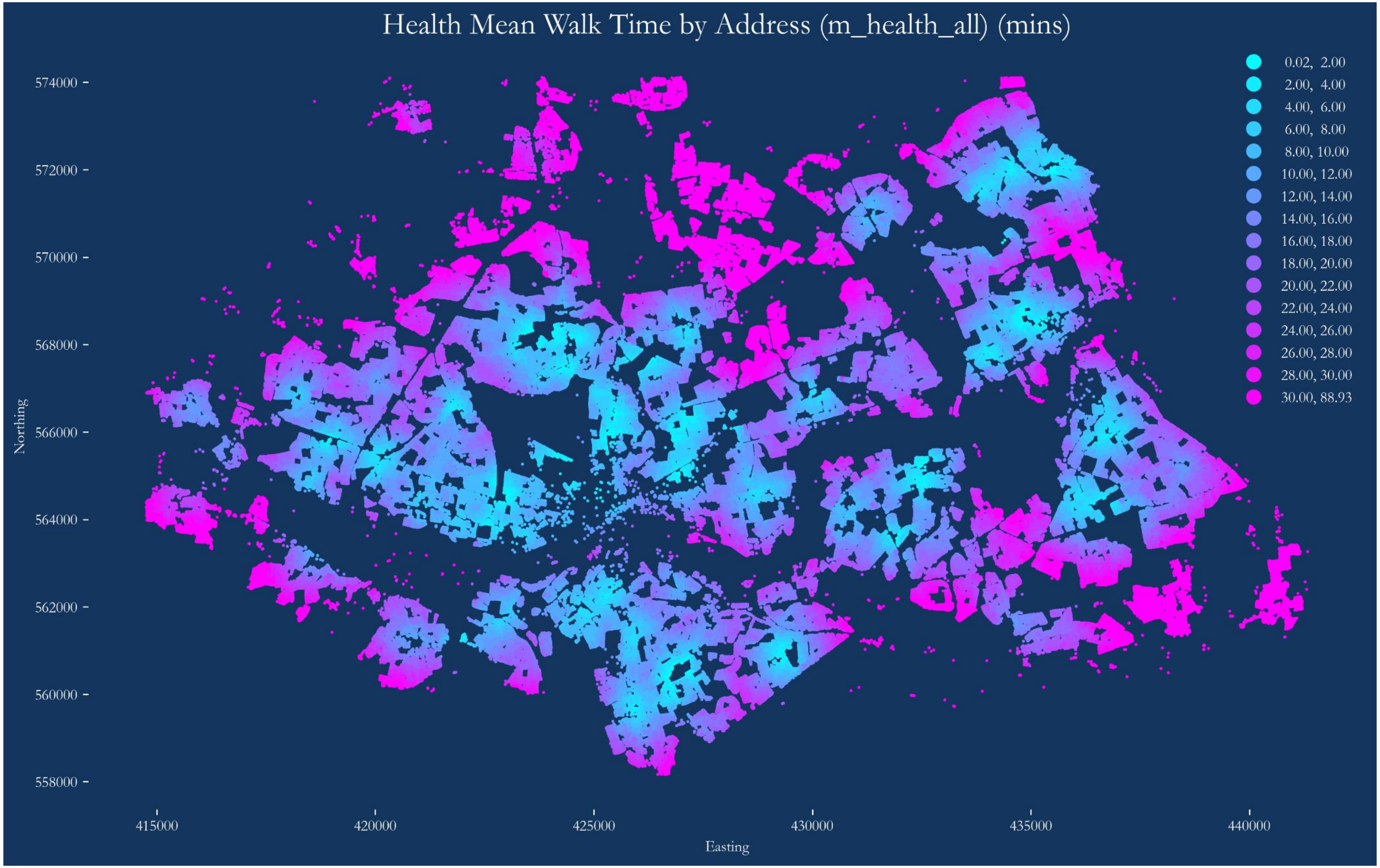


Figure 24 Mean Health Walk Time by Address (m_health_all)

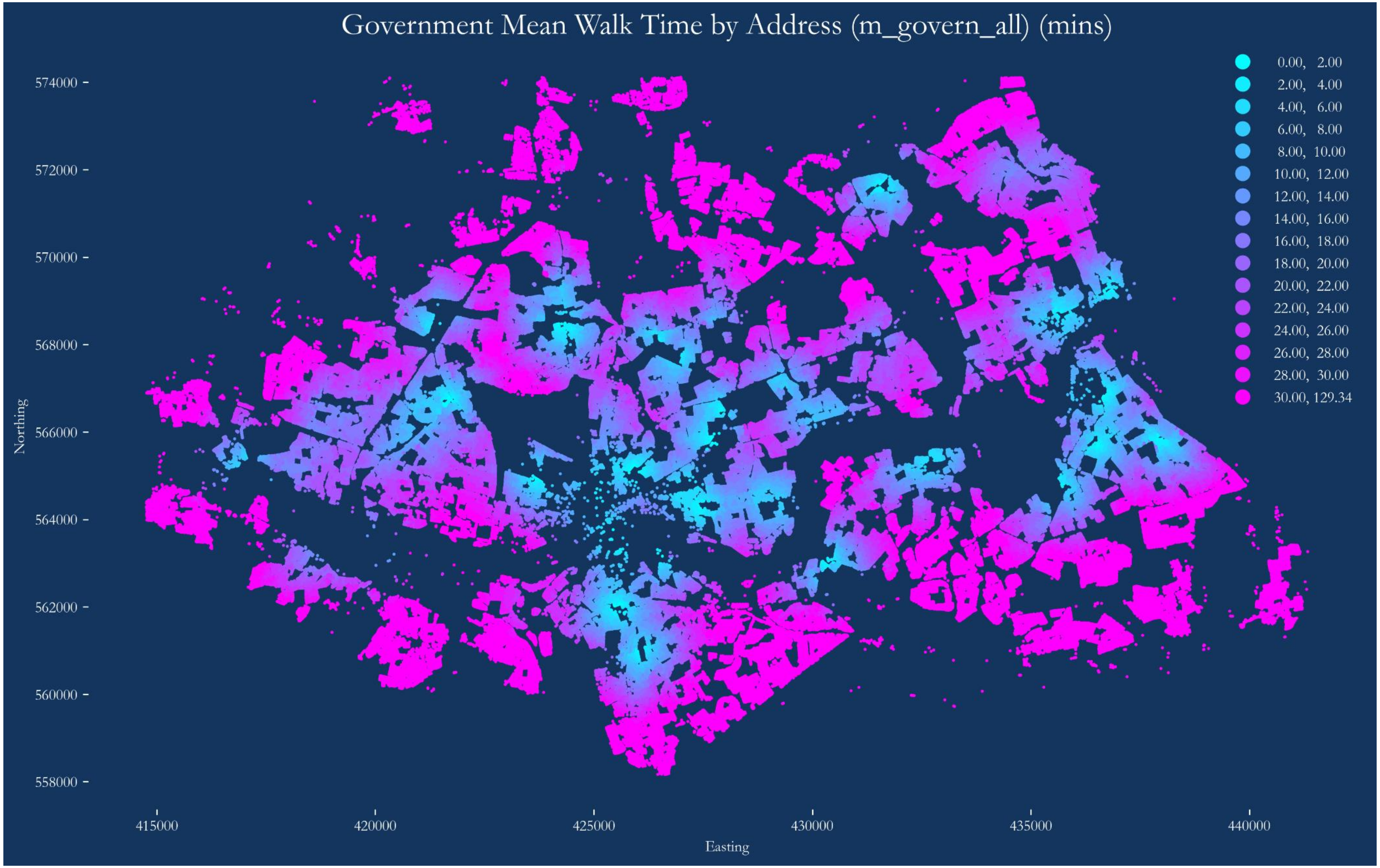


Figure 25 Mean Government Walk Time by Address (m_govern_all)

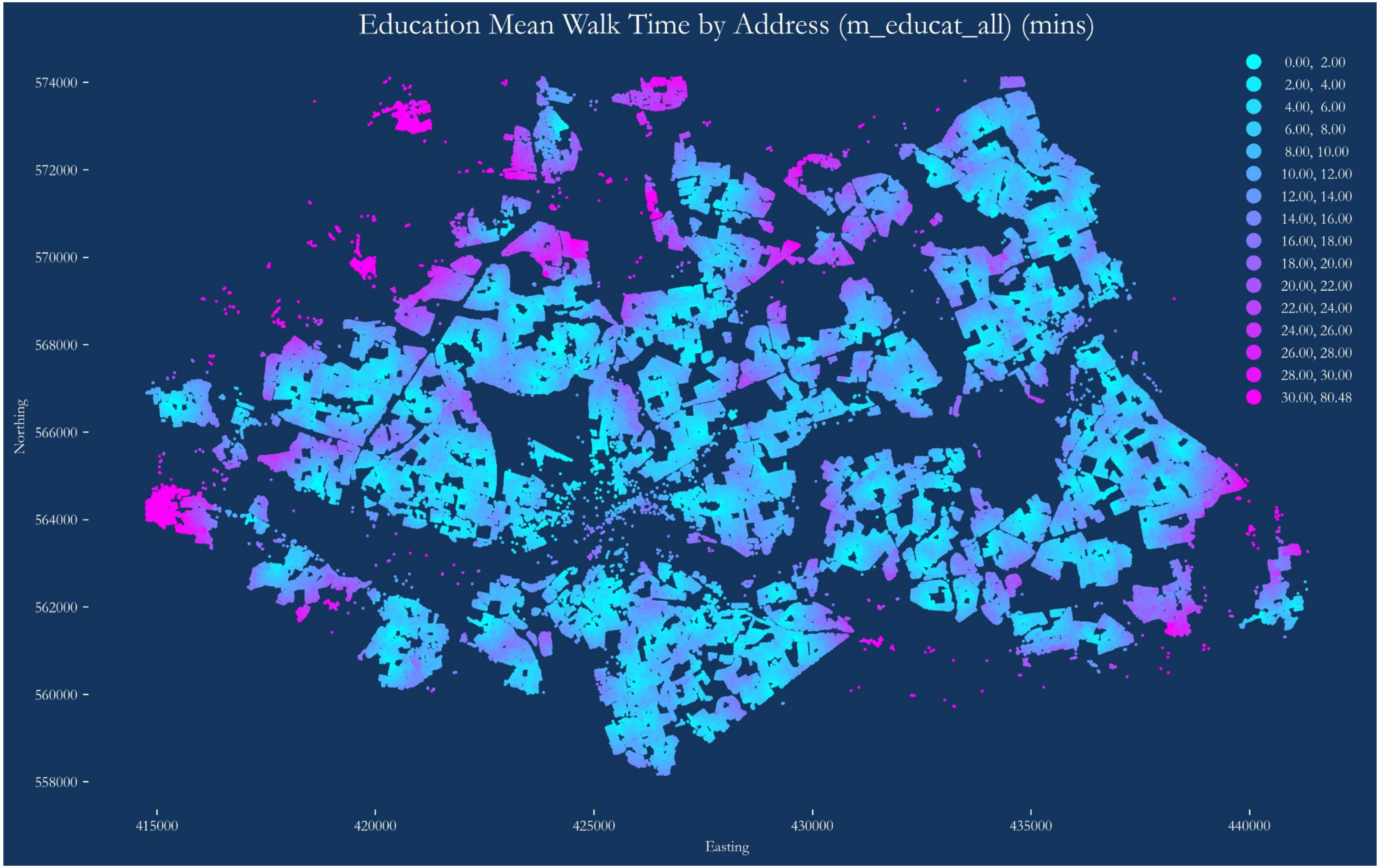


Figure 26 Mean Education Walk Time by Address (m_educat_all)

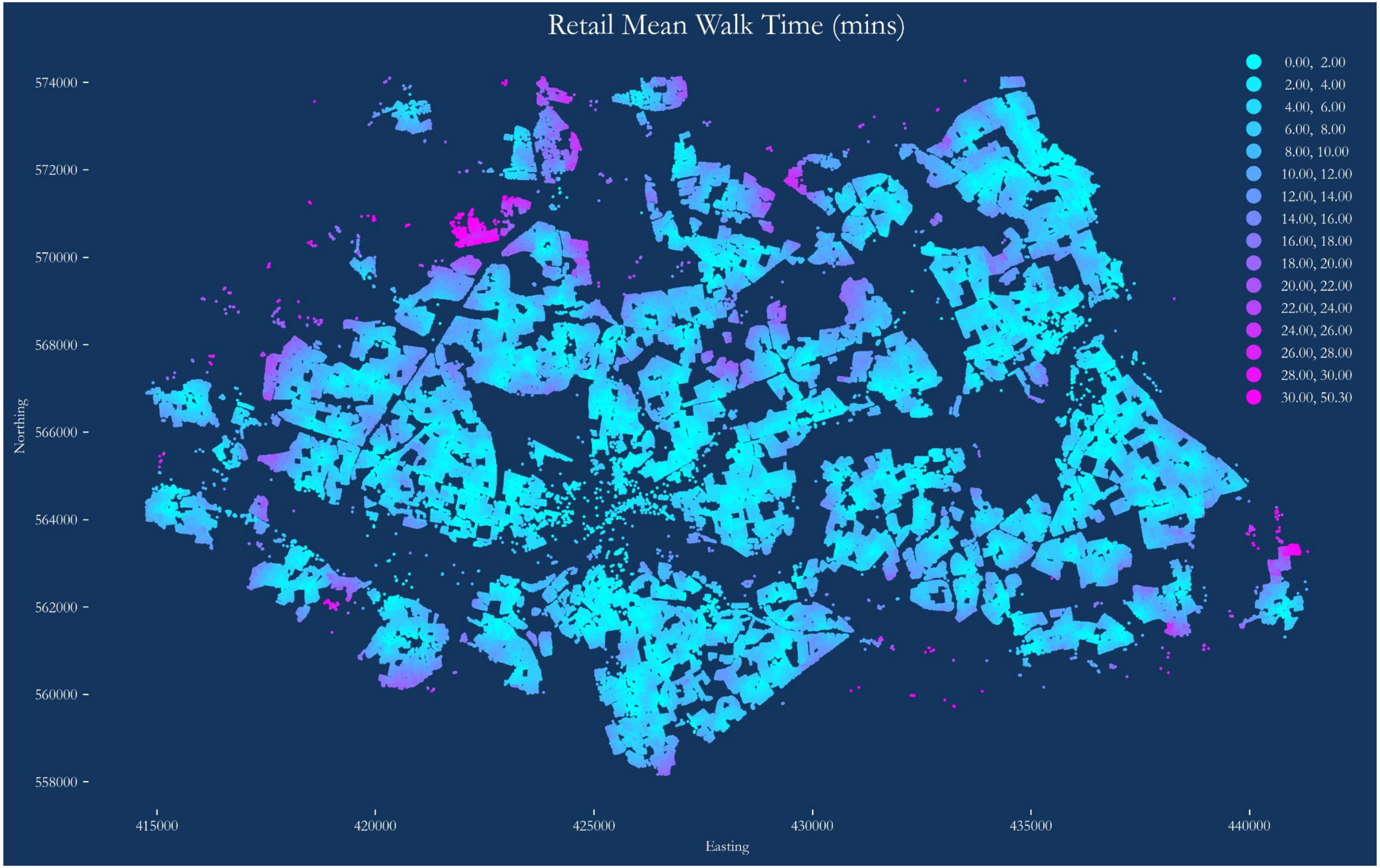


Figure 27 Mean Retail Walk Time by Address (m_retail_all)

4.1.2 Where Are Walk Times Less Than 15 Minutes? (Mean Walk Times to the 5 Closest Nodes)

The previous figures show a detailed breakdown of how walk time values to different amenities vary spatially. However it is not particularly clear exactly which parts of the study area meet the 15-minute walk time criteria. It is also quite difficult to compare amenities. Figure 28 shows a comparison between amenities with the same data that is used in the previous six figures but using a binary interval class of 15 minutes. It can be seen that there is significant variation in coverage between amenity types. Using the mean values works well for some of the amenity categories such as retail and employment where nodes are confined to one company or institution, but for others, where there are many listed points for one entity (at least 5 separate buildings are typical in a single school), taking the mean has less impact when compared to the 'nearest' amenity class (see the **Δ % from m_X_all** values in Figure 29 overleaf).

address count	**m_employment_all**	**m_leisure_all**	**m_health_all**	**m_govern_all**	**m_educat_all**	**m_retail_all**
<15 mins	66511	226516	128745	65733	259705	293039
>15 mins	239409	79404	177175	240187	46215	12881
% < 15 mins	**21.7**	**74.0**	**42.1**	**21.5**	**84.9**	**95.8**

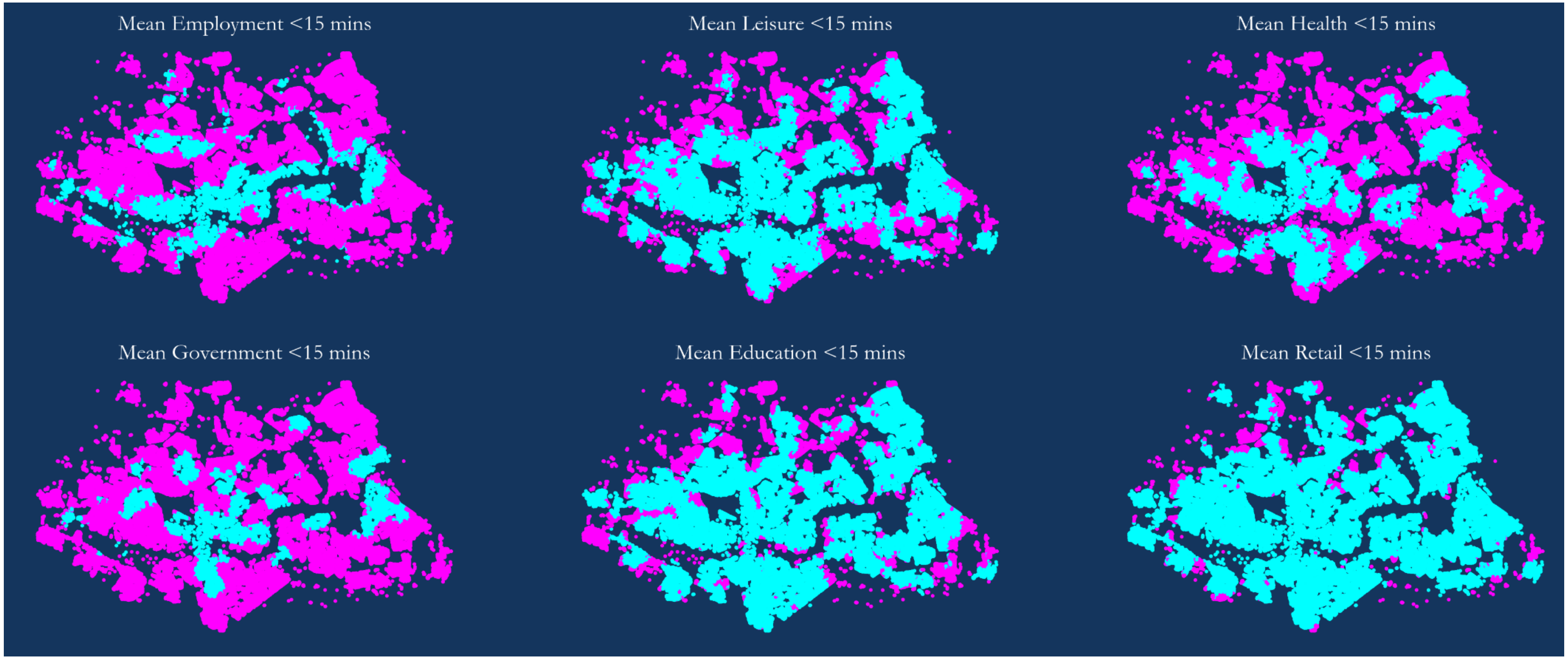


Figure 28 Mean Walk Times to Amenities <= 15 mins (shown in cyan)

4.1.3 Nearest Amenity In Each Category

There are some limitations with a binary measure of proximity to the closest amenity. 15-minutes of walking covers a relatively large area, and it only takes one erroneously labelled data point to give the indication that a neighbourhood is 'walkable'. Due to the inherent limitations in the 'use' classification of the dataset, a more accurate measure of walkability may be using mean walk time to the nearest 5 amenities (as above). Retail does not change significantly due to the large number of nodes in the dataset (see Table 7 in 3.1.2.4). This presents some significant limitations in the usefulness of the amenity category. The mean measures in Figure 28 above should slightly reduce uncertainty around the data accuracy and also provide a better indicator of the general land-use mix.

address count	**m_employment_0**	**m_leisure_0**	**m_health_0**	**m_govern_0**	**m_educat_0**	**m_retail_0**
<15 mins	122,052	287,685	221,765	140,949	284,577	299,347
>15 mins	183,868	18,235	84,155	164,971	21,343	6,573
% < 15 mins	**39.9**	**94.0**	**72.5**	**46.1**	**93.0**	**97.9**
Δ % from m_X_all	18.2	20.0	30.4	24.6	8.1	2.1

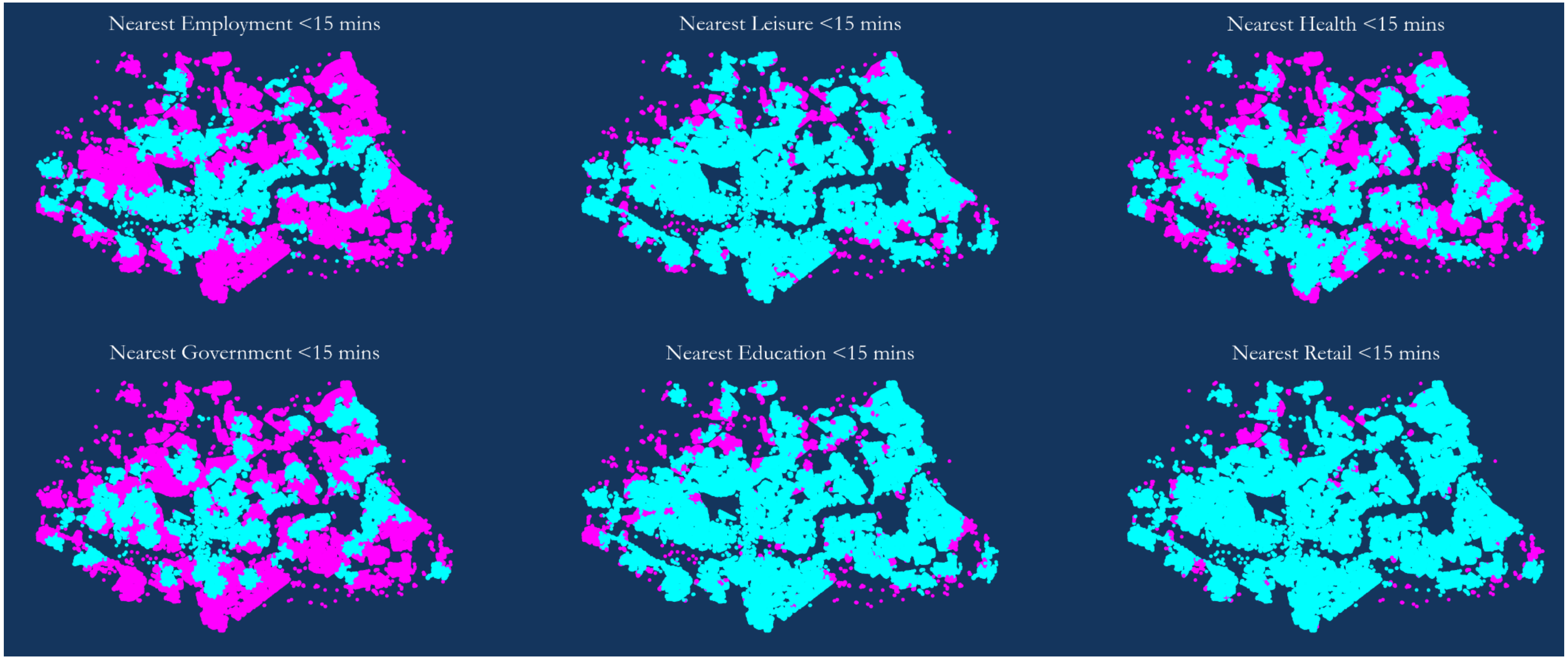


Figure 29 Walk Times to Nearest Amenities <= 15 mins

4.1.4 Socio-Economic Bivariate Relationships

In order to locate some LSOAs that might be suitable candidates for 15-minute neighbourhoods, a simple bivariate analysis between **[population density, percentage no car, economic output]** and **walk time** has been undertaken. The Splot python package adds functionality to easily create bivariate chloropleths.

- **Walk time** (m_ave_all) on the **y-axis** uses **'value by RGB'**
- **Socio-economic data** on the **x-axis** uses **'value by transparency'** (alpha)
- Both x and y axes use **quintiles** as the interval classes

The first plot uses population density from the 2011 census. The alpha value for the bottom quintile of population density is set to 0, meaning they are not visible on the map. This helps to identify the LSOAs that best meet the minimum criteria to become 15-minute neighbourhoods (i.e., higher population densities). Bright pink indicates high population density and low walkability.

The second plot uses percentage of the population that do not own a car from the 2011 census. Again the alpha value for the bottom quintile is set to 0, meaning areas with high car ownership are not visible on the map. A significant proportion of central Newcastle scores in the top quintile for no car ownership and the bottom quintile for walk time.

The final plot uses economic activity data ('all usual residents aged 16 to 74') from the 2011 census. This should provide some indication of the affluence of the neighbourhood – Office for National Statistics (ONS) neighbourhood descriptors have also been looked at further on for individual LSOAs. The economic activity bivariate seems to have been fairly similar to the percentage of no car ownership – with a few exceptions like Gosforth – higher levels of car ownership and higher levels of economic activity.

Unsurprisingly, central Newcastle scores in the top quintile for all three socio-economic values, and the bottom quintile for walk time, indicating a correlation between high values of **[population density, no car ownership, economic output]** and low **walk times**. This area also has very few residential addresses present, however. It can however be seen that the St Anthony's/Walker region of Newcastle is an exception to the rule (highlighted by the red square). This region is centrally located, in the top quintile for walkability, whilst being in the second-highest quintile for population density, second-highest quintile for no car ownership, and middle quintile for economic output.

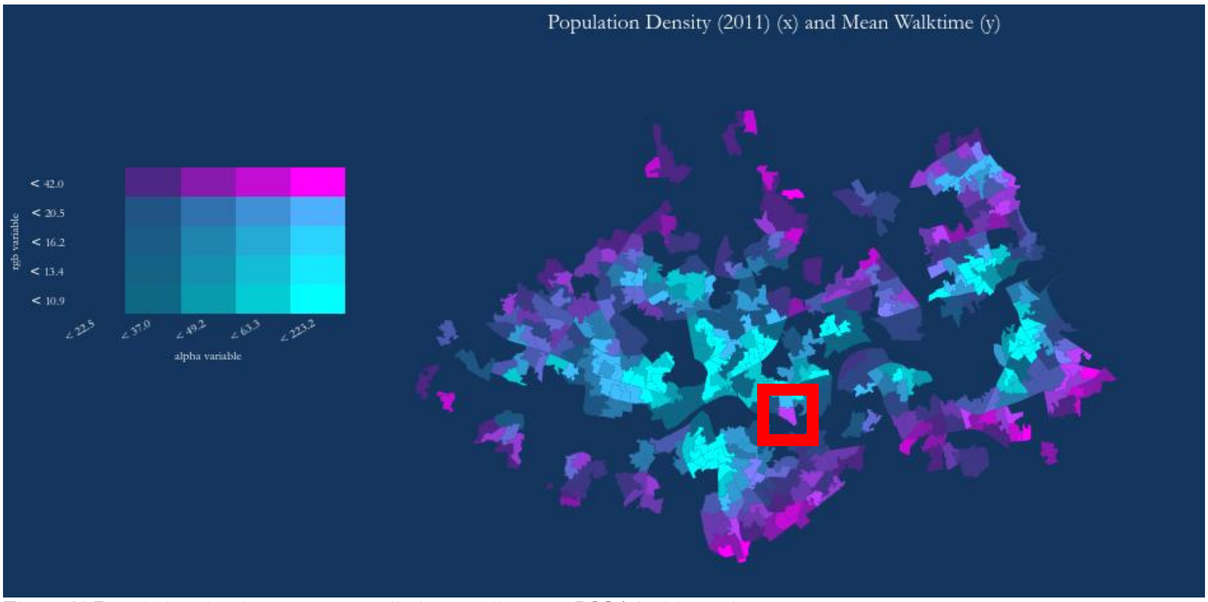


Figure 30 Population density and mean walk time (walker road LSOA inside red box)

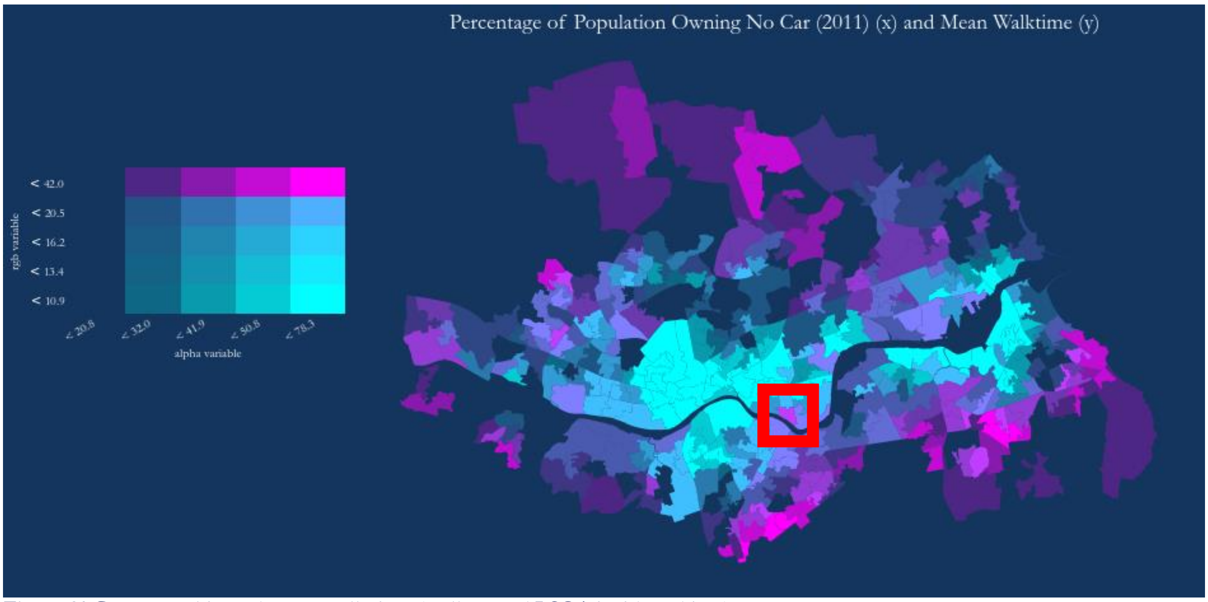


Figure 31 Car ownership and mean walk time (walker road LSOA inside red box)

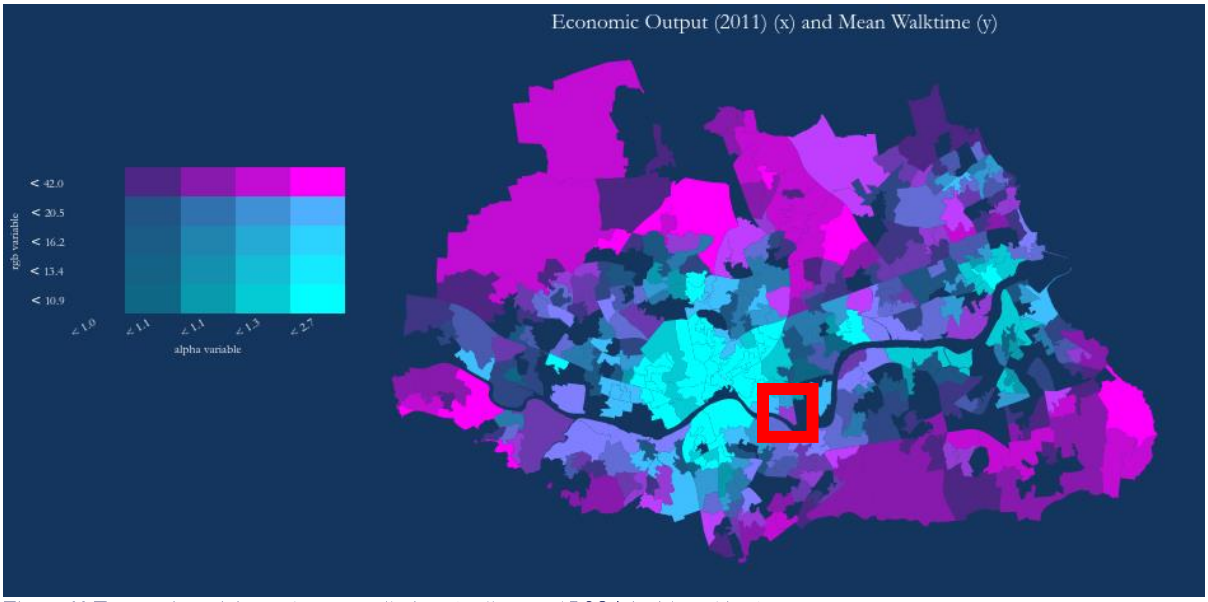


Figure 32 Economic activity and mean walk time (walker road LSOA inside red box)

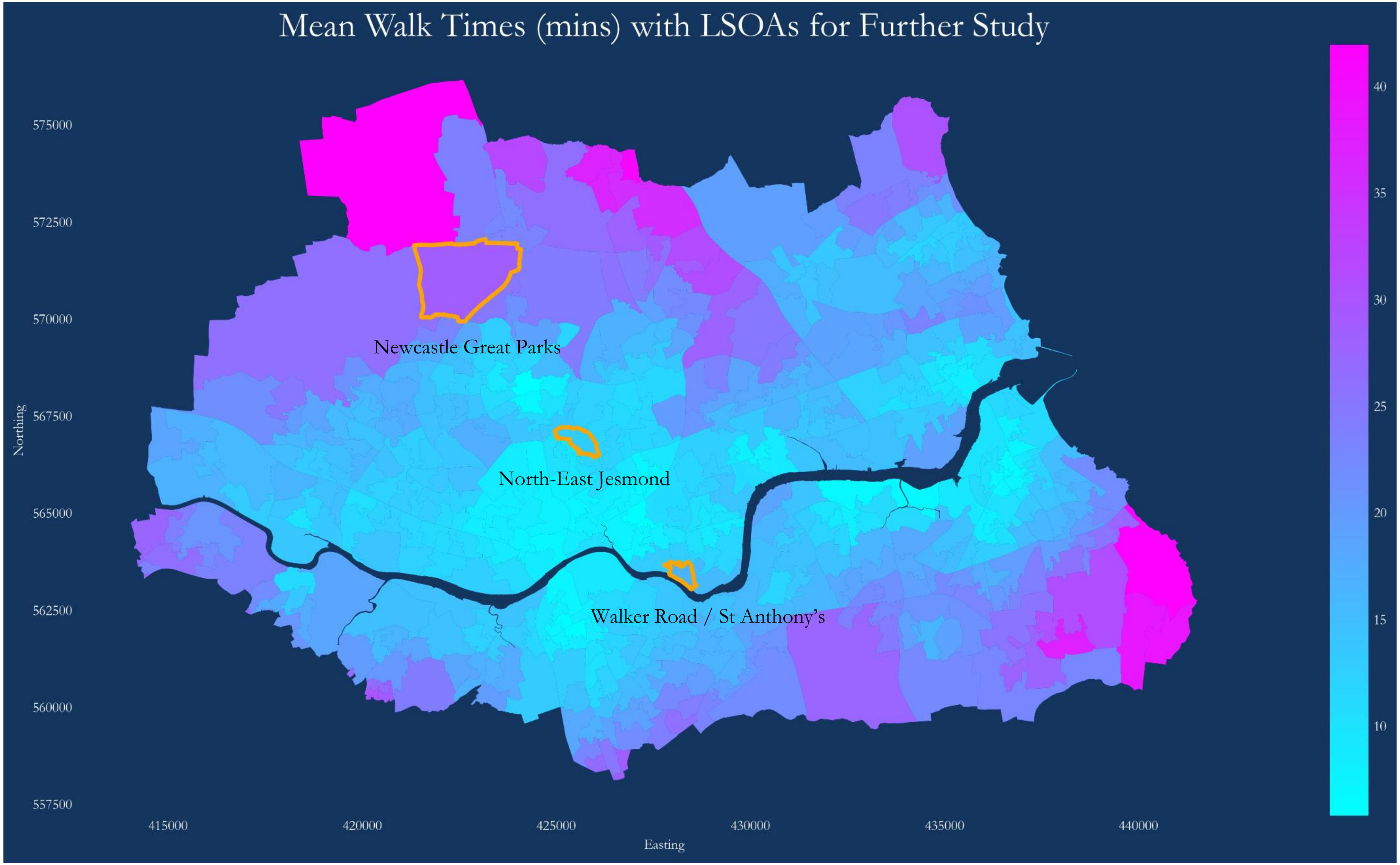


Figure 33 Mean walk times by LSOA (m_ave_all) with regions for detailed analysis highlighted

4.2 LSOA Case Studies

4.2.1 Overview

4.2.1.1 Newcastle Great Parks Development – 001D

This reason has been chosen as it is the largest new suburb built in Newcastle in the last 15 years. It is located in the north of Newcastle upon Tyne, England. Much of Newcastle Great Park is still under development and is sandwiched in between older areas of Newcastle, namely Gosforth, Fawdon and Kingston Park to the south, and Hazlerigg to the north. In the calculation there are 1,203 residential nodes as part of the Great Parks Developments included in the LSOA, with an additional 109 residential nodes included from Hazlerigg.

Based on a very crude estimate of 8,500 people (sourced from a 2020 Newcastle Chronical article) the population density of Great Parks currently sits in the region of 20-30 people per hectare ([8,500/ 300 hectares] ~ 28 people per hectare). This depends on how the new LSOA areas in Great Parks are redefined when the 2021 census data is released (typically area packets of between 1,000-2,000 people – see section 3.1.1.3). 300 hectares is very roughly the area of the LSOA when the Hazlerigg Estate portion is removed (~0.75*404 hectares).

From the analysis we can see that it performs very poorly with mean walk times to amenities.

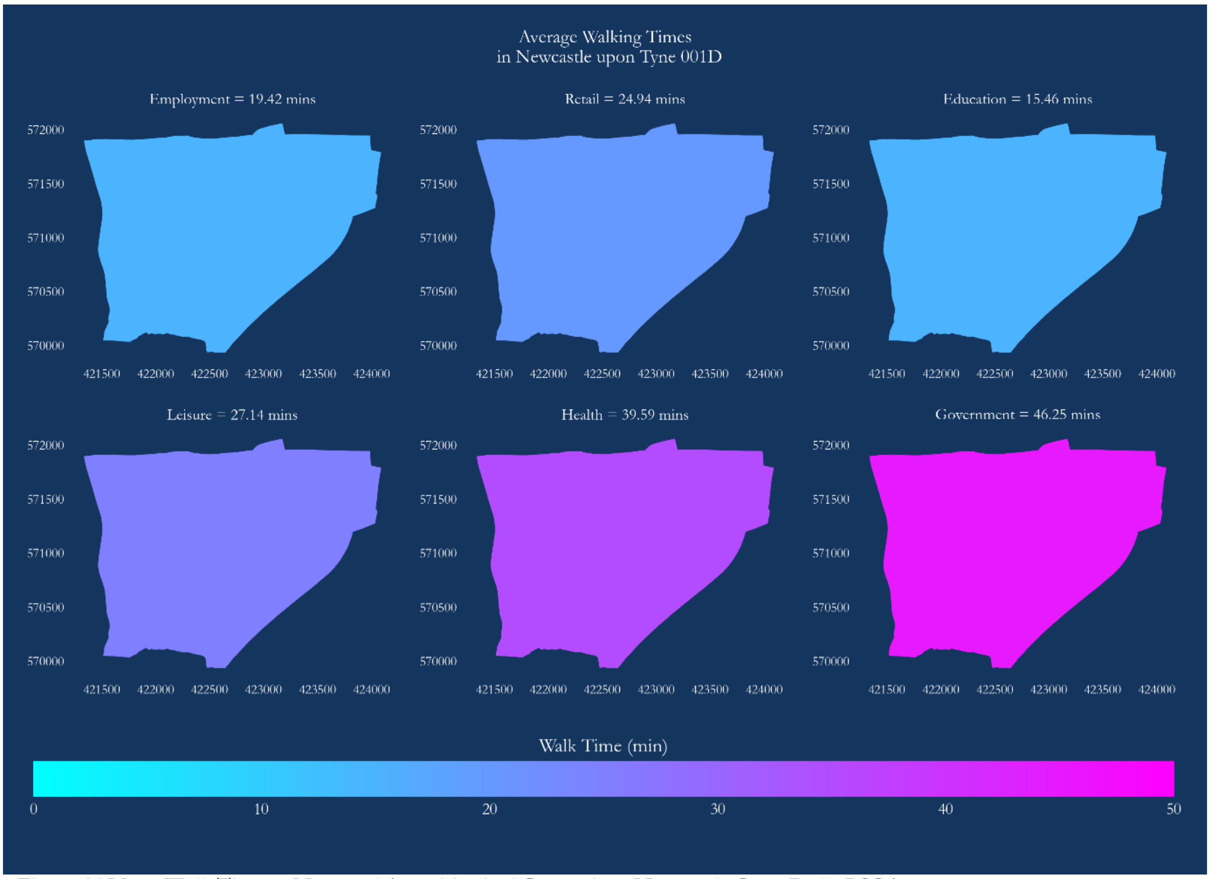


Figure 34 Mean Walk Time to Nearest 5 Amenities in 6 Categories - Newcastle Great Parks LSOA

4.2.1.2 Walker Road – West St Anthony's – 030A

This region has been chosen due to its high population density, centrality in Newcastle, and relatively low walkscore compared to other central regions of similar population density.

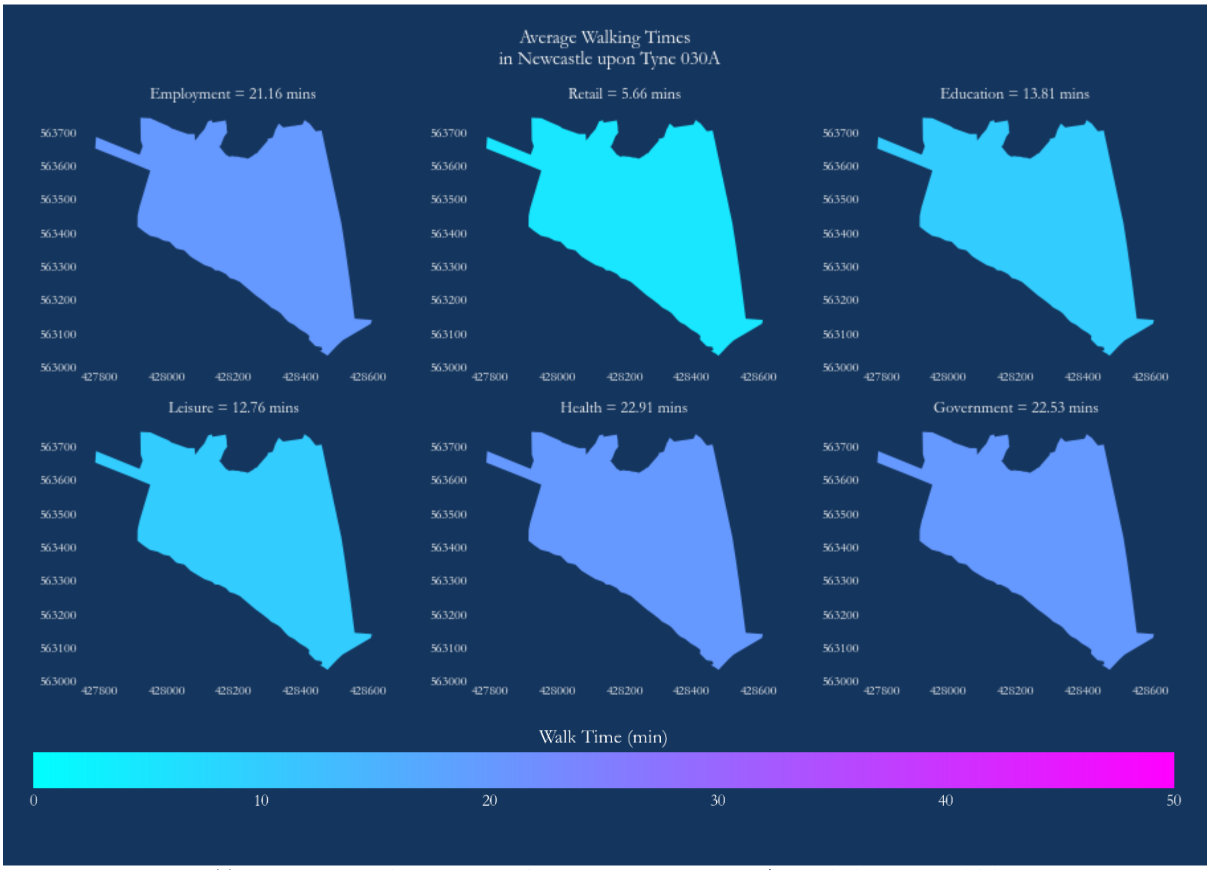


Figure 35 Mean Walk Time to Nearest 5 Amenities in 6 Categories – Walker Road / West St Anthony's LSOA

4.2.1.3 North-East Jesmond – 013C

This region has been chosen as it is one of the older regions of Newcastle, but also has a comparible population density to Great Parks (however, North-East Jesmond does border some very densely populated neighbourhoods in excess of 150 people per hectare). North-East Jesmond performs relatively well under the 15-minute city analysis. It is however, one of the most affluent neighbourhoods in Newcastle. Whilst the relationship between affluence and walkability appears to be, at some level, correlated 2.4 - 2.5, it is not clear if they are causally linked. If the relationship is indeed causal, it is also not clear on direction of causation, i.e., whether improvements in walkability increase house prices, or if pre-existing affluence results in neigbourhoods becoming more walkable resulting in a 'chicken or egg' scenario.

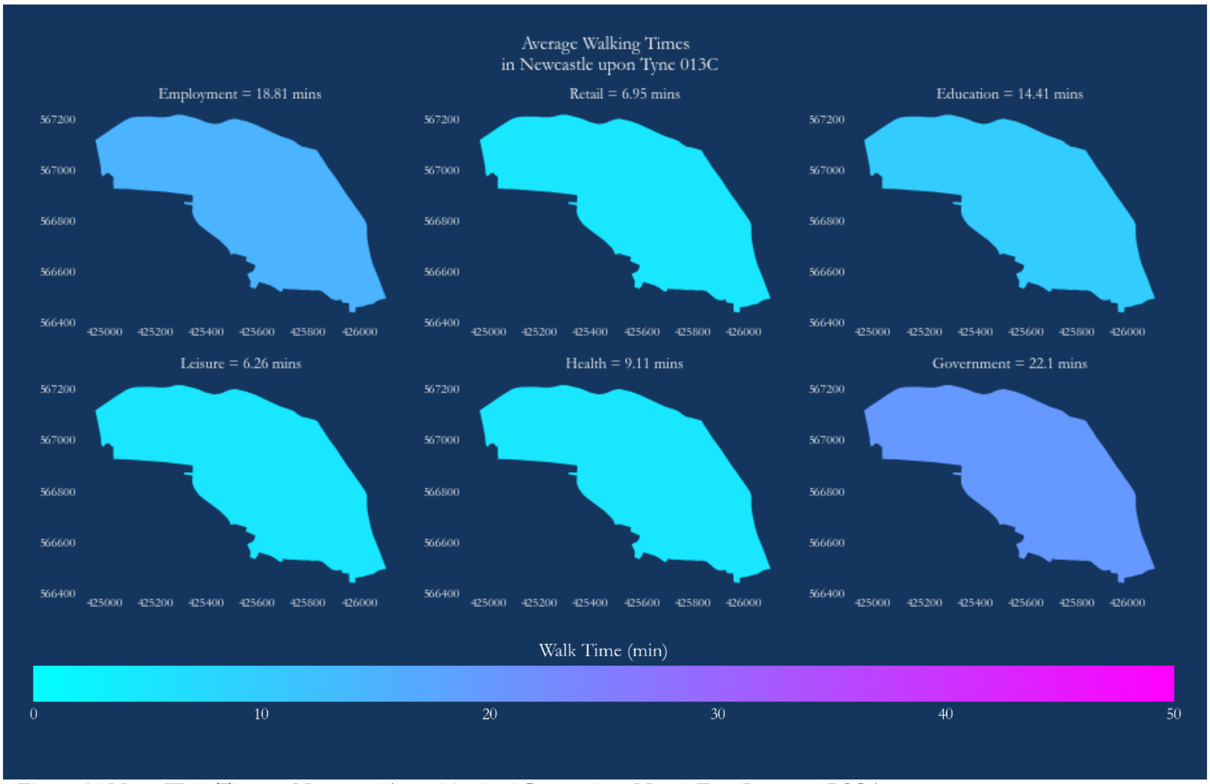


Figure 36 Mean Walk Time to Nearest 5 Amenities in 6 Categories - North-East Jesmond LSOA

4.2.2 Statistical Descriptors

Looking at a breakdown of the statistical descriptors for different walk time metrics in the 3 LSOAs, it is clear that there is greater variation for some amenity types than others.

Values greater than 30% have been highlighted in yellow. Any values equal to 100% result from the minimum error (3.3.1.1) and are highlighted in red. For example, leisure shows significant difference between the value for **m_leisure_all** and the value for **m_leisure_0**, for all three locations. Large differences suggest that the coverage of leisure amenities is well distributed but sparse in these neighbourhoods.

Looking at the **m** values it is evident that while Walker Road neighbourhood has relatively low **m_ave_0** values, the walk time increases by 34.2% when looking at **m_ave_all**. This suggests a sparser distribution of different amenities, compared with North-East Jesmond which has similar walk time values (26.4%). Due to inverse square law, it is expected that as **m_X_0 increases**, the difference to **m_X_all** should decrease (as there is a larger area of the city in which to find subsequent amenities). There is no point therefore comparing the difference in neigbourhoods with very different **m_X_0** values like Newcastle Great Parks and North-East Jesmond.

From the **m** values for Great Parks, it is clear that there is currently not much amenity within walking distance. The lowest walk time category – nearest education – has a value of 13.56 mins. There is already a school on the development, so it surprising that this value is so high. It is possible that the connectivity of paths may be poor, however further investigation is required.

It is surprising to see that of the 3 case studies, the Great Parks development has the highest walk time to **m_X_0** in every category, and the highest **m_X_all** in every category bar employment. The high employment walk times are perhaps the most surprising as there is an industrial park included in the development (this is also included in the analysis data).

North-East Jesmond and Walker Road both show relatively similar walk times. North-East Jesmond has the lowest **m_ave_0** and **m_ave_all** and scores the lowest walk times for most **m_X_0** and **m_X_all**, except for [**m_retail_0**, **m_retail_all**, **m_educat_0** and **m_educat_all]** – which are all in Walker Road. This indicates that the Walker Road region has both good accessibility to retail and education as well as a diversity of options.

However, the difference between **m_leisure_0** and **m_leisure_all** for Walker Road is 46.1% indicating there is a lack of diversity in leisure options in and around the LSOA.

Max mean walk times values for the 3 LSOA's are highlighted in bold

Table 13 Comparison of Walk Time Statistical Descriptors for 3 LSOAs (|x|>30% dark yellow, |x| = 100% dark red)

	Newcastle Great Parks			Walker Road / St Anthony's			North-East Jesmond		
node count		1,336			785			599	
	5 Mean m_X_all (mins)	**Nearest m_X_0 (mins)**	**Change**	**5 Mean m_X_all** (mins)	**Nearest m_X_0 (mins)**	**Change**	**5 Mean m_X_all (mins)**	**Nearest m_X_0 (mins)**	**Change**
Mean (m_ave_all, m_ave_0)									
mean	**26.53**	**22.06**	**-16.8%**	17.1	11.26	**-34.2%**	13.5	9.94	**-26.4%**
std	3.85	4.48	**16.4%**	1.34	0.98	**-26.9%**	1.85	2.13	**15.1%**
min	18.7	11.99	**-35.9%**	13.92	9.47	**-32.0%**	10.23	6.02	**-41.2%**
25%	22.81	18.43	**-19.2%**	16.07	10.44	**-35.0%**	12.15	8.33	**-31.4%**
50%	27.6	22.96	**-16.8%**	16.81	11.23	**-33.2%**	12.89	9.71	**-24.7%**
75%	29.75	25.54	**-14.2%**	17.87	12.04	**-32.6%**	15.21	11.72	**-22.9%**
max	33.9	30.11	**-11.2%**	20.72	13.69	**-33.9%**	19.01	15.73	**-17.3%**
Employment (m_employment_all, m_employment_0)									
mean	19.42	**17.38**	**-10.5%**	**21.16**	16.78	**-20.7%**	18.81	15.76	**-16.2%**
std	4.93	5.35	**8.5%**	2.13	1.3	**-39.0%**	1.84	1.86	**1.1%**
min	9.38	7.43	**-20.8%**	15.91	13.84	**-13.0%**	16.03	12.19	**-24.0%**
25%	14.88	12.07	**-18.9%**	20	15.91	**-20.5%**	17.14	14.29	**-16.6%**
50%	21.42	19.36	**-9.6%**	21.25	16.73	**-21.3%**	18.57	15.58	**-16.1%**
75%	23.48	22.05	**-6.1%**	22.69	17.84	**-21.4%**	20.62	17.11	**-17.0%**
max	27.84	26.83	**-3.6%**	25.28	19.53	**-22.7%**	23.26	20.81	**-10.5%**
Retail (m_retail_all, m_retail_0)									
mean	**24.94**	**22.25**	**-10.8%**	5.66	4.05	**-28.4%**	6.95	6.49	**-6.6%**
std	6.77	6.6	**-2.5%**	1.69	2.03	**20.1%**	2.78	2.73	**-1.8%**
min	2.51	0.49	**-80.5%**	2.33	0	**-100.0%**	0.91	0.52	**-42.9%**
25%	23.07	20.2	**-12.4%**	4.23	2.87	**-32.2%**	5.07	4.72	**-6.9%**
50%	27.21	23.93	**-12.1%**	5.51	4.21	**-23.6%**	6.69	6.3	**-5.8%**
75%	29.42	26.75	**-9.1%**	7.04	5.47	**-22.3%**	8.6	8.17	**-5.0%**
max	35.24	33.07	**-6.2%**	9.47	8.89	**-6.1%**	15.27	14.15	**-7.3%**
Education (m_educat_all, m_educat_0)									
mean	**15.46**	**13.56**	**-12.3%**	13.81	6.33	**-54.2%**	14.41	10.19	**-29.3%**
std	6.28	5.21	**-17.0%**	1.9	2.5	**31.6%**	2.34	3.13	**33.8%**
min	1.64	0	**-100.0%**	8.88	0	**-100.0%**	9.99	3.2	**-68.0%**
25%	11.46	10.39	**-9.3%**	12.48	4.71	**-62.3%**	12.65	8.01	**-36.7%**
50%	14.94	13.61	**-8.9%**	13.5	6.12	**-54.7%**	13.57	9.87	**-27.3%**
75%	19.38	17.35	**-10.5%**	15.01	8.37	**-44.2%**	16.69	12.86	**-22.9%**
max	31.06	29.63	**-4.6%**	18.08	11.67	**-35.5%**	20.16	16.89	**-16.2%**
Leisure (m_leisure_all, m_leisure_0)									
mean	**27.14**	**18.22**	**-32.9%**	12.76	6.88	**-46.1%**	6.26	4.59	**-26.7%**
std	5.43	4.43	**-18.4%**	1.17	1.96	**67.5%**	2.17	2.01	**-7.4%**
min	12.83	7.55	**-41.2%**	10.61	2.09	**-80.3%**	1.81	0.34	**-81.2%**
25%	24.45	16.16	**-33.9%**	11.96	5.52	**-53.8%**	4.91	3.24	**-34.0%**
50%	28.73	18.41	**-35.9%**	12.85	7.17	**-44.2%**	6.33	4.53	**-28.4%**
75%	31.01	20.79	**-33.0%**	13.43	7.93	**-41.0%**	7.92	6.5	**-17.9%**
max	36.07	32.06	**-11.1%**	15.73	11.13	**-29.2%**	11.43	8.51	**-25.5%**

Health (m_health_all, m_health_0)									
mean	39.59	30.96	**-21.8%**	22.91	6.84	**-70.1%**	9.11	6.01	**-34.0%**
std	4.24	7.85	**85.1%**	2.5	2.94	**17.6%**	2.83	3.28	**15.9%**
min	26.52	10.68	**-59.7%**	16.31	0	**-100.0%**	4.83	0	**-100.0%**
25%	38.4	27.43	**-28.6%**	21.12	5.33	**-74.8%**	6.59	3.57	**-45.8%**
50%	40.8	31.07	**-23.8%**	23.12	6.63	**-71.3%**	8.88	5.36	**-39.6%**
75%	42.19	36.99	**-12.3%**	24.82	8.65	**-65.1%**	11.2	9.03	**-19.4%**
max	45.99	44.84	**-2.5%**	27.1	14.29	**-47.3%**	16.52	15.03	**-9.0%**
Government (m_govern_all, m_govern_0)									
mean	46.25	43.16	**-6.7%**	22.53	19.99	**-11.3%**	22.10	10.34	**-53.2%**
std	3.86	5.73	**48.4%**	2.9	3.35	**15.5%**	1.52	3.4	**123.7%**
min	32.37	20.61	**-36.3%**	14.11	10.79	**-23.5%**	18.61	2.69	**-85.5%**
25%	44.58	42.62	**-4.4%**	20.38	17.75	**-12.9%**	21.03	7.69	**-63.4%**
50%	46.72	44.64	**-4.5%**	23.02	20.56	**-10.7%**	21.99	10.23	**-53.5%**
75%	48.77	46.48	**-4.7%**	24.49	22.09	**-9.8%**	23.17	12.79	**-44.8%**
max	54.44	53.59	**-1.6%**	28.24	26.41	**-6.5%**	26.46	17.9	**-32.4%**

5 Discussion

5.1 Interpretations

Although the quality of data and amemity categorisation is poor, and therefore the conclusivity of any results is limited, the project does provide some further avenues of study.

5.1.1 What Do The Results Mean?

It is clear from the analysis that, in some regards, large parts of Newcastle already meet the benchmarks laid out in the 15-minute city framework. However, it seems that there is still a significant opportunity to improve the city's walkability, especially in the more densely populated and less affluent central regions like Walker and St Anthony's, as well in some of the denser suburbs. It is also not evident that the modern developments like Great Parks are making significant effort to promote low-carbon modes of transport despite claiming sustainability credentials. Whether this is true of other modern developments remains to be seen and further analysis will need to be conducted.

There is also a lot of variation in accessibility between different categories of amenity. It is not clear which amenities are most critical for promoting walkability and further work will need to be done in this area.

5.1.2 Performance of modern developments compared to more traditional neighbourhoods

Great Parks is an isolated analysis case of modern housing developments in this project - so there is little to directly compare it to – but it can still be assessed according to the 15-minute city framework. Whilst it is too early in the development of the Great Parks area to definitively say how walkable the neighbourhood is, work on the project started 15 years ago and over a third of the 3,300 planned homes (Newcastle City Council & Gateshead Council, 2015) have been completed . This provides a reasonably large sample size to examine how current urban residential development trends perform in terms of walkability. There are more amenities planned; including a supermarket, but whether that alone will be close enough to most of the development remains to be seen. The average walkscore of 15.46 to the 5 education nodes that comprised the primary school suggest that just under half of the development will be able to reach it in under 15 minutes walk. It is also unlikey that people would walk for 15 minutes with shopping (see 5.3.3.4).

The evidence suggests that the area has very poor walkability shown in Table 13 and Figure 34. Mean walk times are far higher when compared with other regions of similar population density. It is however up to the local authorities and urban planning regulators to make sure new developments are encouraging use of low-carbon transport modes. It would seem that Great Parks is currently poorly connected to the rest of the city (via walking paths) and does not currently contain enough amenity to allow residents to be self-sufficient without means of a private vehicle.

5.1.3 Socio-economic Indicators

In the literature review it was established that socio-economic characteristics can typically explain around half of the variation in travel distance per person. Neighbourhood descriptors are an official classification created by the Office for National Statistics (ONS) and University College London (UCL) from the 2011 Census data.

North-East Jesmond - This LSOA comprises the following neighbourhood descriptors: Multi-Ethnic Professionals with Families, Delayed Retirement and Professional Service Cosmopolitans, which are subgroups of Urbanites and Cosmopolitans.

Walker Road / St Anthony's - This LSOA comprises the following neighbourhood descriptors: Multi-Ethnic Hardship, Young Hard-Pressed Families, and Constrained Young Families, which are subgroups of the Hard-Pressed Living and Constrained City Dwellers.

It is evident that there is a large disparity in the affluence of the residents in the two neighbourhoods. However the average walk times to amenities are not widely different, as the literature might predict. This could be for a number of reasons. The first is that the density of Walker Road is double that of North-East Jesmond at 63.4 people per hectare, however, the surrounding LSOAs have lower population density, which is not true of North-East Jesmond. The second is that investment from the local councils may already be targetted at ensuring suitable provision of amenity is this area. There is an existing history of attempts to rethink what social housing could look like with the nearby Byker Wall development. The most significant target areas for the Walker Road / St Anthony's region look to be provision of leisure, employment, and health.

5.2 Implications

5.2.1 Why Do The Results Matter?

Walkability is becoming increasingly important to the global climate action agenda - it is becoming recognised that the pedestrian network should comprise the core of the city's transportation network, and the default option for as many trip types as possible. Proximity was identified as the single most important factor as to whether a person would decide to walk or not (Handy, 2019). This project has demonstrated (not for the first time) that with the powerful geospatial data analysis tools available today, it is relatively easy to measure accessibility to services over an entire city region. Whilst the results as they are do not tell us anything novel or groundbreaking, it is a step towards understanding and mapping what a walkable Newcastle could look like.

5.2.2 Industrial Application of Walkability

As investors are increasingly applying Environmental, Social and Corporate Governance (ESG) in their analysis process to identify material risks and growth opportunities, concepts like walkability that straddle ESG are likely to become increasingly important for property developers to remain competitive.

The Global Real Estate Sustainability Benchmark (GRESB) has included a measure for walkability in its guidance since 2020, which they define as: a score designed to measure the walkability of a given address to community amenities (GRESB, 2022). Sustainability reporting has become better understood and of far greater importance to the real estate industry in the last 10 years. The value of the global 'wellness real-estate industry' – defined as "properties that are proactively designed and built to support the holistic health of their users" - almost doubled from $148 to $275 Billion between 2017 and 2020, according to the Global Wellness Institute (GWI, 2021).

Estimates from City Observatory suggest that for each additional WalkScore point a property earns, the value of the home increases by $3,500 (GWI, 2021). Developers are increasingly looking at 'health' as a way to differentiate their projects by applying third-party certification systems like Fitwel®, which also incorporates walkability scores for the developments.

5.2.3 Social Equity

As walkability scores inevitably end up as a corporate tool for selling real estate, it is of vital importance that there are also strategies that help the less affluent and reinvigorate historically neglected neighbourhoods. The leading voices in walkability and 15-minute city planning highlight the importance of community engagement and bottom-up development in this transformation (Allam et al., 2022). Speck highlights the importance of encouraging communities to participate in city council meetings – this is easier than ever with Zoom, to ensure city planning does not end up as 'the tragedy of the commons' (Speck, 2012). There is a need to respect 'nimbyism' whilst also aligning it with the goals of the community (as was show in Paris– see 2.5.1).

The estimates from the GWI highlight the impact walkability can have on house prices, and the importance of managing this change in a fair and equitable manner is of vital importance to maintaining existing communities. Schemes like community land trusts could be implemented in tandem with the development of walkable neighbourhoods to ensure that benefits remain within the community and that gentrification doesn't result in largely negative impacts for the residents. A fundamental law of complexity theory was established by Christopher Alexander in the 'Nature of Order' - "All the well-ordered complex systems we know in the world, all those anyway that we view as highly successful, are generated structures, not fabricated structures". In order to make truly walkable and livable neighbourhoods, community agents must drive the organisation of space and amenity.

5.3 Limitations

5.3.1 What Can't The Results Tell Us?

The limitations in the conclusions that can be drawn from the analysis in this project largely arise from the quality of the data that was chosen. However, the methodology in itself is somewhat limited in what it can actually tell us about the 'real' walkability of a given neighbourhood. As the literature review established, travel is the grand confluence of many factors – many of which are far beyond the scope of this project.

5.3.1.1 Intermodality

A significant gap in the analysis was the lack of reliable public transport data. From the literature, proximity to public transport was found to be an important factor in measuring the walkability of a neighbourhood (2.5.4). Beyond direct implications as to how walkable a place is, proximity to public transport provides an indication of whether an individual is likely to use a car for journeys longer than a 15-minute walk (H. M. Badland et al., 2017).

5.3.2 Compound Measures

There are many limitations with the use of compound measures; those that have been used in this project should be viewed as a 'first iteration' attempt at combining different amenities to produce a walkability score. The compound walk times like *employment* and *leisure* were an attempt to create something along the lines of Table 9 above, given the use categories that were available (Correa-Parra et al., 2020).

There are significant limitations with how the **m_ave_all** category has been created. As no weightings have been applied to the significance of different amenity categories, the less typicaly 'useful' amenities like *government* are weighted equally to *retail*. It is likely that being in proximity to multiple retail outlets contributes significantly to walkability, however proximity to multiple *government* buildings is likely less significant. Methods to improve this are discussed in 5.4.2.2.

The same limitation principle can be applied to the **m_X_all** categories. It is unlikely that there is a need to include mean walk times to the nearest 5 *government* - 1 or 2 nodes might provide a more useful indication. From the results in Table 13 above, it is seen that the difference between **m_govern_all** and **m_govern_0** is a factor of 2. As a result **m_ave_all** is probably skewed unhelpfully to longer walk times.

5.3.2.1 Employment

The inclusion of *manufacturing* in the *employment* field likely significantly reduces the mean walk times for the *employment* field. However, it is generally desirable to silo manufacturing areas for a multitude of reasons, like the increased efficiency that occurs due to agglomeration of similar industries in specialised estates, as well as containment of negative environmental effects. In the literature review, the industrial specialisation of neighbourhoods was highlighted as a target area in emissions reductions for cities. Whether we see hyperlocalised manufacturing as a result of Industry 4.0 remains to be seen (Shen et al., 2018).

5.3.2.2 Leisure

The combination of *religious* and *recreation* was predominantly to reduce the impact of the comparitively small number of religious nodes on the mean walk scores. In future it might might be prudent to investigate the impact of proximity to religious nodes on trip generation, as there was little literature regarding this.

5.3.3 Use Categories

5.3.3.1 Education

When taking the mean for the closest 5 education, most of the time this can be regarded as one school comprising 5 separate buildings. However, this measure does provide the benefit of eliminating education nodes like test centres and libraries, which are likely to be less important to improving walkability than proximity to a primary school that would generate daily trips for hundreds of people.

5.3.3.2 Government

Some of the amenity categories are less likely to promote walking than others. In the *Government* attribute in the North-East Jesmond LSOA, the only node was the Newcastle and Northumberland Society which is a voluntary member society with the goal of 'protecting and enhancing our landscape, culture and built environment for future heritage'. Whilst having 'amenities' such as this in the local neighbourhood may result in fewer car trips, the reduction in trip generation is by no means comparable to the effect of a local supermarket and therefore should be weighted accordingly in a future attempt to create a compound walkability metric.

5.3.3.3 Health

The *Health* category is another category that is too 'all encompassing'. For example, it would be unreasonable to expect a hospital within a 15-minute walk radius, but a GP practice could be expected. It also presents the same calculation irregularity described in education due to multiple buildings on one site. Furthermore, the category includes private health care clinics which should not ideally be included in an analysis for public walkability.

5.3.3.4 Retail

The issues with the *Retail* field are more obvious. Supermarkets and convienience stores really need to be seperated out to provide meaningful insights. The literature is clear that groceries contribute to a large proportion of trips, but there have been very few studies on the impact of high-street clothing stores, or laundrettes for example. One of the most important reasons to separate out supermarkets and convienience stores, is that 15-minutes walk time becomes unreasonable for a large proportion of the population where multiple heavy bags are involved. It is likely that this figure would need to be more in the region of 5 mins.

5.3.4 What Even Is Walkability?

As the literature review established, the variables included in the definition of 'walkability' are not fully defined, and most are beyond the scope of this study. The 15-minute framework highlighted **proximity**, **density**, **diversity**, and **digitalisation** as the core dimensions. This project has gone some of the way towards measuring proximity, has briefly covered density - and diversity has been looked at as a by-product of the proximity calculations. More in-depth analysis of density and closer examination of fine-grained land use patterns would aid future development of this project. Digitisation was well beyond the scope of this project.

Further variables highlighted by urban planning experts as important measures of urban walkability require paths to be **useful**, **safe**, **comfortable,** and **interesting.** These variables are extremely difficult to measure quantitatively and on a city-wide scale (Speck, 2012).

5.4 Recommendations

These recommendations would address some of the issues and limitations I have identified in the methodology and discussion.

5.4.1 Data Inputs

There are several external improvements that will / are likely to occur in the coming years. These mostly involve the release of higher quality data.

5.4.1.1 GEOMNI

GEOMNI UK provides data with pavement widths that can be used to further assess walkability within a neighbourhood (GEOMNI, 2021). This would help to address some of the other elements of the 15-minute framework beyond proximity and land-use mix, like safety and comfort.

5.4.1.2 Open Street Map Data

A much more detailed breakdown of building use is available through OSM (OSM, 2021); however, the completeness of this dataset will have to be investigated. There is also currently no way of accessing the building data for a city like Newcastle without downloading the 115GB data set for the globe.

5.4.1.3 Updated Census Data

The 2021 census data will be available in June 2022 and will include information about developments in the last decade, which were missing in the analysis – for example, accurate population density for Newcastle Great Parks.

5.4.2 Model Refinement

5.4.2.1 Contraction Hierarchies

Pandana uses contraction hierarchies to speed up calculation times. However, this involves providing a hierarchy score for each edge piece. Finding a way to automate the assignment of hierarchies to paths would make this possible. Ordnance Survey provide hierarchy rankings for the highway network, but they were removed for this analysis to prevent the algorithm preferentially using motorways. The modified version of Dijkstra's algorithm that Pandana uses can then find the shortest path in a fraction of a millisecond, visiting only a few hundred nodes. It can generate several million shortest paths in less than a minute (Bast et al., 2016).

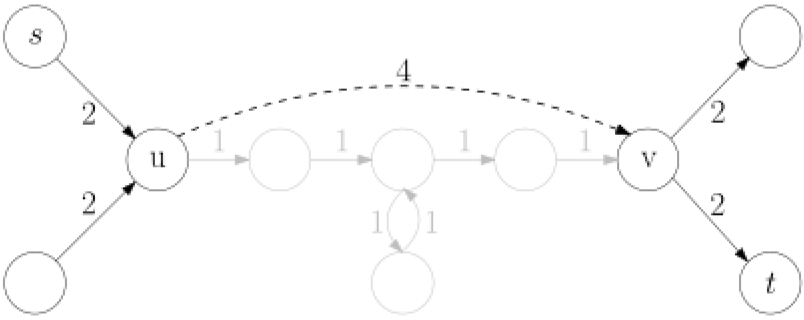


Figure 37 Calculating path from s to t using contraction hierarchies

5.4.2.2 Compound Measures

There are plenty of improvements that could be applied to the compound measures. In future iterations of walkability analysis for Newcastle, it would be interesting to see the effect of weighted averages on walk times. As the literature review highlights, the categories of amenity that generate trips by private vehicle use are not evenly distributed. *Education*, *retail*, *employment*, and leisure make up a very large proportion of trips by private vehicles and should ideally be weighted more heavily than government or health for example. Within *leisure*, features like parks should also have some extra weighting on a walkability score due to the impact on the perception of walk desirability, despite not generating many trips by private vehicle. *Education* could also be weighted according to the average age of a community.

The combination of recreation with religion was arbitrary and a compound with greater justification would be ideal. The same goes for *employment* with *offices*, *manufacturing*, and *commerce*, which were combined as they are likely to be predominantly visited by the people working there rather than customers. *Retail* would employ a large number of staff, but relative to the number of customers, employee visits would be less significant.

5.4.2.3 Graph Connectivity

Investigation into some of the properties of the pedestrian network that was generated using NetworkX would be useful. It would be of interest to investigate the properties of the network more thoroughly (beyond edge and vertex count). There is a variety of measures from graph theory that could help to understand why some neighbourhoods are more walkable than others.

- Vertex Connectivity - the number of vertex-independent paths between two vertices
- Edge Connectivity - the number of edge-independent paths between two vertices
- Closeness Centrality - inverse average distance to every other vertex
- Betweenness Centrality - fraction of shortest paths that pass through the vertex
- Degree Centrality - gives a list of vertex degrees for the vertices in the underlying simple graph
- Edge Betweenness Centrality - gives a list of betweenness centralities for the edges in the graph

5.4.3 Further Investigation

There were several ideas mentioned in the literature review that are beyond the scope of this project.

These include:

- Examine land use entropy using a method similar to 2.4.3
- Investigating the impact of land-use change on walk times
- Investigating the impact of new amenities on walk times
- Investigating the impact of new pedestrian routes on walk times
- Connectivity of neighbourhood networks
- Analysing linkages with other modes
- Investingating correlation between walkability and age of housing stock

6 Conclusion

The conclusions that can be drawn from this study are limited due to the nature of the categories of amenities and further analysis is required. However, it has provided a picture of what is required to create a comprehensive measure of walkability over a city-wide region. It also suggests that modern housing developments may not be fulfilling the requirements for meeting net-zero by passively encouraging people to use low carbon modes.

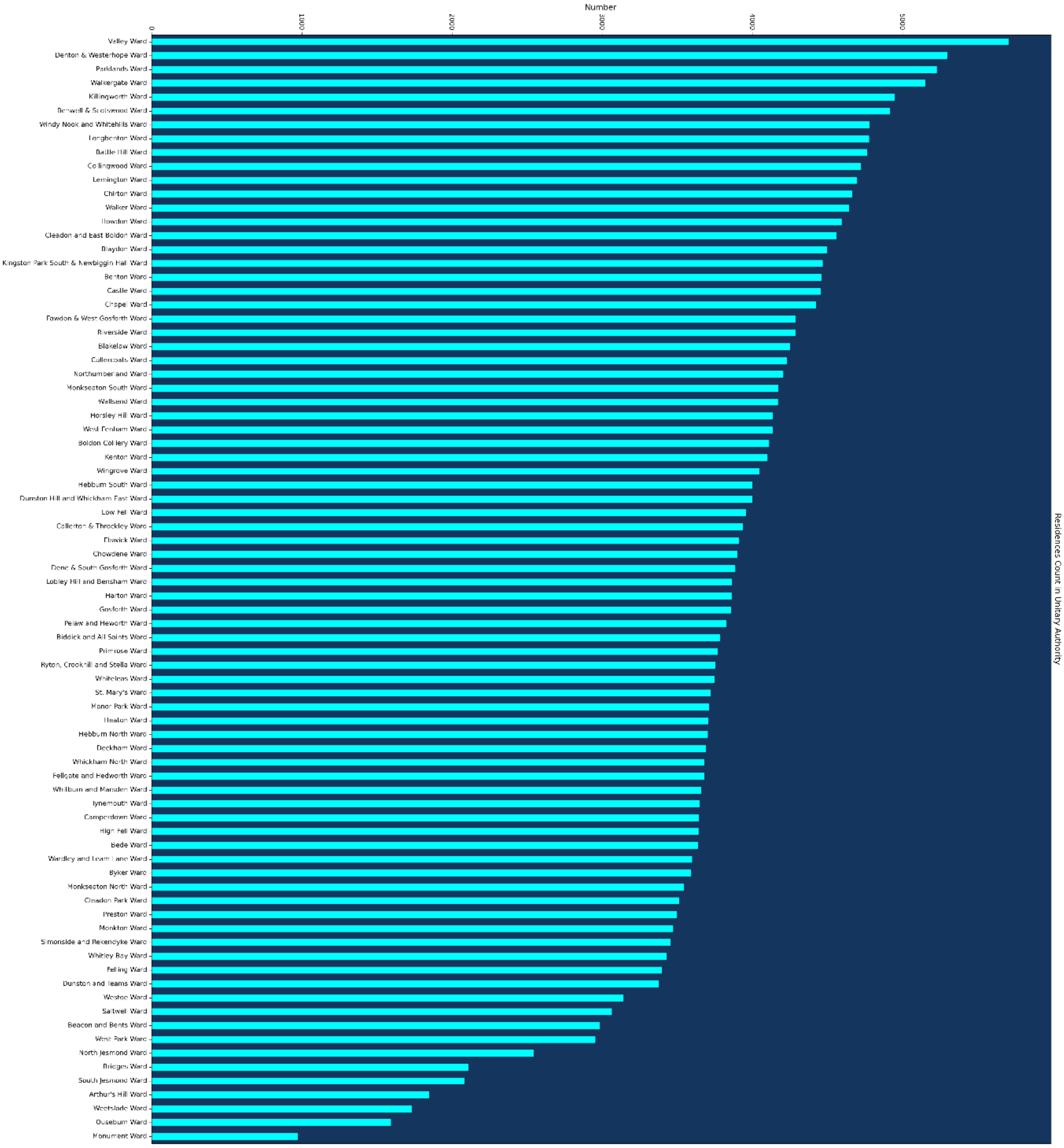
The most fundamental improvement to this analysis would be through higher resolution use categorisation. In particular 'supermarkets' and 'convenience stores' would be independent datasets, rather than under the umbrella of retail. The exisiting literature showed that groceries made up a significant proportion of trips made by cars and are therefore an important metric on which to score neighbourhoods on their walkability. However, it does provide a good indication of the general land use mixes of various parts of Newcastle.

Walkability is gaining interest in both public and political spheres. As the impertive on cities to transition to net-zero increases, it seems that walkability and the 15-minute city framework could play a vitally important role in mitigating the effects of climate change. The model is highly compatible with other net-zero trends like hyperlocalisation of manufacturing and retail, and key low-carbon transport initiatives like micro-mobility and multi-modal trip models. Meeting 15-city minute city criteria for much of Newcastle does not seem out of reach and, with foresight in policy and investment, achievable by 2030 as per the Newcastle Net-Zero 2030 Strategy.

In order to reduce the number of trips made by private vehicle the only real solution is to remove the need to travel far. To poorly paraphrase Francis Bacon, 'If the (destination) will not come to Mohamet, then Mohamet must go to the (destination)' - and probably drive.

7 Appendices

7.1 About the Data



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