Computers, Environment and Urban Systems 119 (2025) 102270

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

Modelling active travel accessibility at the micro-scale using multi-source built environment data

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ARTICLE INFO

Keywords:
Accessibility
Walking
Cycling
Micro-scale
Built environment
MATSim

ABSTRACT

Accessibility models explore how land use and transport systems interact to facilitate access to activities and daily needs. Existing applications generally model accessibility based on distance or travel time. For pedestrians and cyclists, the street-level environment (e.g., green visibility, streetside amenities, dedicated infrastructure) significantly influences people's willingness and ability to travel. Incorporating these features into accessibility models can help them to be more representative of active travellers' experienced environment.

This study presents a methodology for incorporating the street-level environment into active mode accessibility. First, micro-scale built environment data from multiple sources are harmonised into a high-resolution digital representation of the land use and transport system. Second, a compute-optimised framework is developed for modelling accessibility at the micro-scale (i.e., each dwelling separately) incorporating the street-level environment. The methods build upon the open geodatabase OpenStreetMap and open-source MATSim project, facilitating expandability and transferability to other contexts. We apply this methodology to develop policy-relevant accessibility indicators for Greater Manchester.

In the results, we observe that the street-level environment can cause accessibility indicators to vary at the micro-scale, especially in less connected neighbourhoods where the choice of routes is limited. We also observed that for cyclists, the accessibility advantage over walking reduces substantially when traffic stress is considered. Our findings support further adoption of micro-scale built environment data and high-resolution analysis methods for active travel accessibility modelling in research and practice.

1. Introduction

Designing urban environments that support active travel (walking and cycling) has been identified as a pillar of healthy and sustainable urban development (United Nations, 2015). A growing multidisciplinary body of research aims to understand how our built environment (BE) can facilitate (or impede) active travel and assess the implications for climate, equity, health, and other markers of sustainability and liveability (Adkins, Makarewicz, Scanze, Ingram, & Luhr, 2017; Baobeid, Koç, & Al-Ghamdi, 2021; Cain et al., 2017; Cervero, Denman, & Jin, 2019; McCormack, Nesdoly, Ghoneim, & McHugh, 2022; Owen, Humpel, Leslie, Bauman, & Sallis, 2004; Sallis et al., 2011).

Accessibility models offer useful frameworks to assess how people's local environments support active travel. While they vary in complexity and scope, they commonly bring together multiple dimensions of people's local environment such as the availability of nearby destinations and structure of the street network (Merlin & Jehle, 2023). In general, accessibility models aggregate over destinations weighting them by their size and the impedance (i.e., difficulty) of reaching them (H. Wu & Levinson, 2020). A dwelling located near many easy-to-reach destinations will have relatively high accessibility, while a dwelling near fewer, smaller, or harder-to-reach destinations will have poorer accessibility.

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https://doi.org/10.1016/j.compenvurbsys.2025.102270
Received 9 September 2024; Received in revised form 19 December 2024; Accepted 24 February 2025
Available online 7 March 2025

Accessibility models can account for the co-dependency between the land use and the transport network: the advantage of having destinations nearby depends on how easily they can be reached through the network; similarly, the advantage of living near high-quality transport provision depends on how it facilitates access to destinations.

A challenge remains in qualifying the 'ease-of-reach' aspect of accessibility, especially for active modes. The environment at street-level can significantly influence people's ability and willingness to walk and cycle. For example, the presence of dedicated infrastructure, vehicle traffic, and streetside greenery can affect the routes active users take or whether they are comfortable using active modes at all. This has clear implications for accessibility; however, most active travel accessibility applications ignore the street-level environment and only consider travel distance or time (Merlin & Jehle, 2023; Van Wee, 2016).

Advances in geospatial data collection have enabled micro-scale mapping of the BE to capture street-level environments in detail. Common street-level indicators associated with active modes are infrastructural provision (e.g., dedicated paths and crossings), traffic volumes, gradient, green visibility, and street-side amenities (Bartzokas-Tsiompras, Bakogiannis, & Nikitas, 2023; Broach & Dill, 2016). These indicators can capture variations in walking and cycling environments at the micro-scale. For example, cycling infrastructure may differ between one street and the next, or there may be a change in safety from crime as a pedestrian turns a corner. This level of detail advances the traditional meso-scale BE indicators (e.g., measured at neighbourhood zones) dominating active travel literature (De Vos, Lättman, Van Der Vlugt, Welsch, & Otsuka, 2023). Micro-scale BE data are especially advantageous for accessibility because they can be used for evaluating the street-level environment along routes. This enables precise estimates of journey impedance that reflect active users' experiences as they move through the network.

We consider two challenges central to integrating the street-level environment with accessibility. First, a connected graph representation of the transport network is required to compute lowest-impedance (i.e., least-cost) paths, using an algorithm such as Dijkstra (1959). If impedance incorporates street-level environment features, then the relevant BE attributes must be incorporated into this graph. However, the relevant data can originate from various regional, national, and global sources which often have mismatching network geometries and varying levels of detail. Second, calculating accessibility at the household level is computationally intensive since it requires estimating impedance from all origins to all potential destinations. It is common to reduce computational demand by coarsening the network or spatially aggregating to zones. However, this is less suitable for active modes, especially walking, since trips are shorter and networks are denser, hence variations in the BE at the microscale matter more than for other modes.

This study presents a methodological and computational framework to address these challenges. First, we present methods for harmonising multi-source micro-scale BE data into a dense multimodal network graph, accounting for different data types, levels of detail, and mismatching networks. The methods include spatial joining, modelling, and simulation approaches to enhance a network graph from OpenStreetMap (OSM) with street-level attributes relevant to active travel. Second, we present a flexible and efficient framework for computing disaggregate accessibility measures incorporating the street-level environment. The code is written in Java and extends compute-optimised algorithms and data structures developed for the open-source MATSim project (Horni, Nagel, & Axhausen, 2016). It can efficiently compute lowest-impedance paths, incorporating the street-level environment, for billions of origin-destination pairs over a dense network. This enables fully spatially disaggregate (i.e., dwelling-level) mapping of walking and cycling accessibilities for entire city-regions. The framework is flexible, enabling many potential specifications for different modes, destination types, weights, decay types, impedance functions, and spatial resolutions. Using Greater Manchester as a case study, we apply our network harmonisation methods and accessibility framework to demonstrate their potential for developing policy-relevant indicators of residents' active travel environments.

2. Literature review

2.1. Emergence of Micro-scale indicators

The street-level environment as described through 'micro' scale BE indicators contrasts with the aggregate '*meso*' and 'macro' scale BE indicators dominant in walkability and cyclability literature. Traditionally, studies utilised the concepts of 3Ds (density, diversity, and design) or 5Ds (3D plus destination accessibility and distance to transit) or 8Ds (5Ds plus desirability, demand management and distribution of employment) in analysing the effects of BE on walking and cycling (Cervero, Sarmiento, Jacoby, Gomez, & Neiman, 2009; Giles-Corti et al., 2016). These 'D' variables can provide critical insights on active travel environments, but most applications use aggregated indicators at the meso-scale. This aggregation has several limitations because of the modifiable aerial unit problem (MAUP) (Openshaw, 1984). Strominger, Anthopolos, and Miranda (2016) found that BE indicators and their variability depend strongly on size, scale, and aggregation method. Labib, Lindley, and Huck (2020) observed how size and scale of aggregation changes the sensitivities of modelled relationships between the BE and health. Clark and Scott (2014) explored how the MAUP affected the modelled relationships between BE and active travel, concluding that the smallest aggregation unit has the most explanatory power. Similarly, Zhang (2023) tested multiple scales of BE aggregation and concluded that the most disaggregate resolutions are most effective for capturing pedestrian behaviour. However, Gehrke and Clifton (2014) performed a similar exploration for land use diversity indicators and obtained mixed results. A review of walking accessibility literature by De Vos et al. (2023) argues that the micro-scale BE strongly influences walkability and recommends further adoption in future studies. Micro-scale indicators have also been found to be more effective for understanding social equity than meso- or macro-scale indicators (Sallis et al., 2011).

A growing body of active travel studies collect micro-scale BE data. For example, Kim, Park, and Lee (2014) conducted a study to elicit pedestrians' satisfaction with the BE based on measurements in the exact location where pedestrians were surveyed. Cain et al. (2014) and Cain et al. (2017) modelled the impacts of the BE on physical activity through detailed streetscape audits of up to 120 street-level attributes along participants' key walking routes. This was expanded to a global framework for collecting street-level environment data relevant to active travel and health (Cain et al., 2018; Vanwolleghem et al., 2016). However, these approaches currently rely on manual data collection, which would be unsuitable for applications requiring data for full city-regions. More recently, technologies including crowdsourcing, remote sensing and computer vision simplify region-wide micro-scale BE data collection. For example, OSM includes crowdsourced data on pavement surfaces and cycling infrastructure and this has been used for region-level active travel studies (Cervero et al., 2019; Rhoads, Solé-Ribalta, & Borge-Holthoefer, 2023). Google street view (GSV) has been used to evaluate street-level environments through both manual evaluation of images (Bartzokas-Tsiompras, Photis, Tsagkis, & Panagiotopoulos, 2021; Blečić, Cecchini, Congiu, Pazzola, & Trunfio, 2013; D'Orso & Migliore, 2018; Koo, Guhathakurta, & Botchwey, 2022) and computer vision models (Blečić, Cecchini, & Trunfio, 2018; Koo et al., 2022; Lu, Sarkar, & Xiao, 2018; Lu, Yang, Sun, & Gou, 2019).

Some studies harmonised street-level BE data from more than one source. Blečić et al. (2013, 2015) enhanced an OSM dataset with attributes visually audited from GSV. Cole-Hunter et al. (2015) and Krenz et al. (2023) combined regional air pollution and greenness data into their network. Faghih Imani, Miller, and Saxe (2019) combined several regional data sources into a harmonised cycling network. Rhoads et al.

(2023) combined OSM, GSV, and regional data to develop a harmonised pedestrian network enhanced with pavement widths, gradients, and accident risks. However, existing studies only developed single-mode network graphs with a limited selection of BE attributes. Expanding to a multimodal approach and incorporating more diverse spatial data sources could enable analysts to capture the various components of impedance more comprehensively, including multimodal interactions such as stress caused by walking and cycling in proximity to motor vehicles (Furth, Mekuria, & Nixon, 2016; Rodriguez-Valencia, Ortiz-Ramirez, Simancas, & Vallejo-Borda, 2022).

2.2. Walking and cycling accessibility

Accessibility is a broad concept that describes how easily amenities can be accessed from a particular origin (Geurs & van Wee, 2004). Building on Hansen's (1959) seminal study, accessibility models have been widely applied in transport and linked with activity-travel behaviour and social equity (Vickerman, 1974; Cervero & Kockelman, 1997; Wang, 2012; Cordera, Coppola, dell'Olio, & Ibeas, 2017; Li, Li Deng, H., Shu, H., & Xie, D., 2018; Zhang, Clifton, Moeckel, & Orrego-Oñate, 2019). There are many types of accessibility measures, with formulations varying greatly depending on the regional context and research application (H. Wu & Levinson, 2020). Most accessibility studies focus on private vehicles and public transport, with fewer applications to active modes (Van Wee, 2016).

The street-level environment is well-recognised to influence active mode impedance with a growing body of empirical evidence supporting this (Broach & Dill, 2016; Broach, Dill, & Gliebe, 2012; De Vos et al., 2023; Fosgerau, Łukawska, Paulsen, & Rasmussen, 2023; Lu et al., 2018; Lu et al., 2019; Reggiani et al., 2022; Sevtsuk, Basu, Li, & Kalvo, 2021). However, of existing walking and cycling accessibility studies, most use distance-based impedance (Merlin & Jehle, 2023; Van Wee, 2016). Exceptions include Kuzmyak, Baber, and Savory (2006) and Blečić et al. (2013, Blečić et al., 2015), who developed walking accessibility methodologies incorporating street-level environment attributes. Nassir, Ziebarth, Sall, and Zorn (2014) estimated cycling accessibility using results from a route choice model that considered street-level cycling infrastructure. Faghih Imani et al. (2019) explored cycling accessibility to populations and jobs for varying thresholds of traffic-induced stress. Rhoads et al. (2023) used percolation theory to evaluate the extent to which walking accessibility changes for different thresholds of pavement width, gradient, and accident risk.

These existing studies demonstrate the value of incorporating street-level BE features into accessibility. However, both Blečić et al. (2015) and Rhoads et al. (2023) pointed out challenges with spatial data standardisation and harmonisation and called for this to be addressed in future research. Additionally, Blečić et al. (2013) and Nassir et al. (2014) noted computational constraints restricting spatial scope and precision. Finally, the models applied in these existing studies used bespoke unimodal accessibility formulations for their research question, but generalisability to other modes and formulations was unclear.

2.3. Summary and research contribution

With micro-scale BE data becoming widely available, there is growing evidence to support incorporating street-level environment features into active travel accessibility models. However, this remains uncommon, partly due to challenges with spatial data harmonisation and high-resolution computation. By developing methods to address these challenges, we facilitate disaggregate (dwelling level) multimodal accessibility analyses for entire city-regions incorporating diverse micro-environmental data. We demonstrate these methods using the data-rich study region of Greater Manchester to develop detailed accessibility indicators incorporating a comprehensive and varied collection of street-level features, advancing active travel accessibility literature. This offers opportunities for new insight into the impact of the micro-scale BE on accessibility. Our methodology and framework are built upon the open geodatabase OSM and open-source MATSim, facilitating transferability and further development in other study areas and research contexts.

3. Study area

The methods described in this study area applied to Greater Manchester in north-west England. Greater Manchester has a population of 2.8 million and comprises England's third-largest urban area and second-largest economy (Fenton, 2023). The region's transport authority, Transport for Greater Manchester (TfGM), maintains high-quality spatial datasets of the street-level BE to support their active travel infrastructure projects and wider transport vision (Bee Network, 2023; Greater Manchester Transport Strategy 2040, 2021). Manchester is also notable for its diverse land use and social inequality (Hincks, 2015), making it a relevant case study for exploring spatial variation in accessibility and active travel equity.

4. Methodology

The methodology is divided into three sections. Section 4.1 describes the processing of geographic data, including developing a dense multimodal network graph incorporating street-level environment data. Section 4.2 describes the computational framework for computing disaggregate accessibility indicators incorporating the street-level environment. Finally, Section 4.3 describes four example applications of the accessibility model. This methodology is supplemented with a detailed technical documentation provided in parts A and B of the supplementary materials.

4.1. Geographic database

Spatial data from the following global, national, and regional sources were incorporated into a geographic database for Greater Manchester:

- Open Street Map (OSM), a global open crowdsourced geographic database
- Verisk Analytics, a multinational firm
- Sentinel-2 satellite imagery
- Ordnance Survey (OS), a national mapping agency
- Census data from the UK Office for National Statistics
- Police UK (data.police.uk), a national crime database
- CycleStreets (cyclestreets.net), a national journey planner for cyclists
- Transport for Greater Manchester (TfGM), the regional transport authority
- Greater Manchester Combined Authority
- UK Department for Transport
- UK Rail Delivery Group

The database contains a high-resolution multimodal graph representation of the transport network incorporating micro-scale BE attributes, described in Section 4.1.1. It also contains micro-scale land use data including precise dwelling and destination locations with corresponding access points, described in Section 4.1.2. The geographic database covers the entire Greater Manchester region plus a 10 km buffer to avoid edge effects (i.e., artificially cutting out relevant destinations close to the boundary).

4.1.1. Network

OSM formed our base network graph structure because it offered the most complete and spatially detailed active travel networks of all data sources based on validation in coordination with TfGM (see Supplementary A1.1 for further details). OSM network data (links and nodes) were queried and processed using an adapted version of the code developed for the Cycling Infrastructure Prioritisation Toolkit (Lovelace

& Parkin, 2018). This was converted into a multimodal directed graph which differentiated walking, cycling, and driving.

The base network was embedded with limited set of link attributes from OSM including length, speed limits, road classifications, surface type, and cycling infrastructure.

Through various spatial joining, modelling, and simulation methods, the links and nodes of the base network were enhanced with 43 additional street-level environment attributes relevant to active travellers. This section presents an overview of these attributes and spatial methods. Further details on network development, including a full attributes table with data sources, can be found in the technical documentation (Supplementary A.1.2–A.1.7).

Features from non-OSM sources were spatially joined to the base network to develop additional attributes. The joining methods and tolerances varied based on geometry type, precision, and degree of mismatch versus the base network. Some new attributes were copied directly from the joined data, including cycling infrastructure (in greater detail than OSM), observed 85th percentile speeds, road widths, modal filters (i.e., features which restrict through vehicle traffic), and crossing infrastructure. In other cases, the joined spatial data were further processed and synthesized to construct attributes more relevant to active travel impedance. An overview of these attributes and methods is provided in the remaining paragraphs.

Density attributes were created to describe the concentrations of certain point data along links, including streetlights, crime records, heavy vehicle infrastructure, positive points of interest (POIs), and negative POIs. The "positive" POI score considered POIs that make streets more attractive for walking and cycling (e.g., small shops, water features, museums, churches), inspired by Novack, Wang, and Zipf (2018), while the "negative" score considered POIs likely to have the opposite effect (e.g., parking and industrial sites). Detailed POI classifications and weightings for the heavy vehicle infrastructure, positive POI, and negative POI category are given in Supplementary B.1.

Diversity scores were modelled for high streets (i.e., primary business streets) using Shannon and Weaver's (1949) diversity information index to capture streets' vibrancy. This index is commonly used in ecological research as an indicator of the diversity of different species in a community. We repurpose this index as a measure of the diversity of POIs along high streets, using the classification in Supplementary B.1.

Elevations were estimated for nodes using a digital terrain model at 5-m spatial resolution. Gradients were then estimated for each link based on their length and the node elevations on each end.

Greenness indicators included Normalised Difference Vegetation Index (NDVI), which was estimated using Sentinel-2 satellite imagery (Martinez & Labib, 2023; Tucker, 1979). Additionally, Viewshed Greenness Visibility Index (VGVI), which describes eye-level greenness visibility, was modelled using terrain, surface, tree crown circumference, land use and land cover data using the methodology described in Labib, Huck, and Lindley (2021).

Traffic volumes for cars and heavy vehicles were estimated using a vehicle simulation. We used MATSim to simulate vehicle movements over the network for a typical 24-h period using regional demand data provided by TfGM. Further details on the simulation and validation are given in Supplementary A.1.6.

Travel times for active modes were estimated based on link length and estimated speeds. Walking speed was a function of gradient, estimated using Tobler's (1993) hiking function. Cycling speed was a function of gradient and surface type, estimated using the MATSim bicycle extension (Ziemke, Metzler, & Nagel, 2017).

Ambience describes links in terms of their visual appeal, personal safety, and streetside amenities. An ambience indicator was created as a function of VGVI, POI density and diversity, and crime density, accounting for correlations between these. It is a continuous score between 0 and 1, where 1 indicates ideal ambience (high green visibility and/or high density and diversity of amenities), 0 indicates poor ambience (industrial and/or high crime areas), and 0.5 is a neutral score. The scoring model was developed heuristically in consultation with local experts and refined through several rounds of iteration to ensure a reasonable contribution of each component.

Stress describes the discomfort associated with proximity to motor vehicles. Two stress indicators were created: link stress (from travelling alongside traffic) and crossing stress (from crossing traffic). They were developed based on guidance from the UK Department for Transport's Cycle Infrastructure Design (2020) handbook which defines three categories of links and crossings:

- Green: "*suitable for most people*"
- Amber: "*will exclude some potential users and/or have safety concerns*"
- Red: "*will exclude most potential users and/or have safety concerns*"

Link stress is a function of the speed limit, 85th percentile speed, traffic volume, and infrastructural protection. Crossing stress is a function of the type of crossing infrastructure and the crossing links' speed limits, 85th percentile speeds, traffic volumes, and number of lanes. We computed discrete stress attributes based on the above categorisation and continuous stress attributes ranging from 0 to 1, where 0 indicates no stress (e.g., offroad paths and dedicated crossings) and 1 indicates high stress (e.g., no dedicated infrastructure and high vehicular speeds/volumes).

All street-level attributes were validated visually using large-scale overview maps, small-scale district maps, and street-level imagery in key areas. Examples of the visual outputs used for validation are provided in the network results (Section 5.1).

4.1.2. Land use

Household dwelling footprints (1,123,574 in Greater Manchester) were obtained from the Verisk (2023) under an educational license.

We considered 12 categories of activity destinations, based on the classification system developed for the Australian Urban Liveability Index (Higgs, Badland, Simons, Knibbs, & Giles-Corti, 2019) and then refined and extended for the UK context based on the study by Olsen, Thornton, Tregonning, and Mitchell (2022). The categories are social/cultural locations, primary schools, primary healthcare, pharmacies, recreational facilities, early years services, food retail, eating establishments, financial establishments, services, public transport, and public open spaces. The OS POI dataset (2023b) was the data source for the first 10 categories, using the classification given in Supplementary B.2. The public transport category used digitised regional and national timetable data, and the public open spaces category used OS Open Greenspace (2023a). Further details on the selection and classification of destinations are provided in Supplementary A.2.

Destination weights were estimated to indicate their size and relative attraction. For all categories except public transport and public open space, this weight was the estimated number of employees, which is standard practice in the transport field (de Ortúzar Salar, 2011). For public open spaces, weight was the product of their area and the variety of amenities offered within (e.g., gardens, sports courts). For public transport, the weight was based on the frequency of timetabled services.

4.2. Accessibility framework

We developed a flexible and compute-efficient framework to calculate accessibilities at the micro-coordinate level. It is written in Java, employing multi-threading and highly optimised graph and least-cost-path tree data structures to efficiently compute accessibilities over large city-regions. It is available open-source at https://doi.org/10.5281/zenodo.14963057.

We compute the accessibility of location i as an aggregate function over all destinations j:

$$A_i = \sum_j W_j^{\alpha} f(c_{ij}) \tag{1}$$

Where W_j is the weight of destination j, α is a weight parameter, f is a decay function, and c_{ij} is the cost (impedance) of travelling between i and j along the least-cost path on a network graph with link costs c_l. This link cost can be any non-negative impedance indicator such as travel time, distance, or a composite incorporating street-level environment attributes (e.g., stress, gradient). Infinite costs can be used to describe links that are effectively impassable. Depending on the application, c_{ij} can be computed for an outbound, inbound, or round-trip journey. The decay function f can be any decreasing function such as cumulative, exponential, power, gaussian, or logistic. To reduce computational burden, a cut-off cost c_{ij} can optionally be specified, beyond which $f(c_{ij})$ becomes 0 (i.e., the destination is ignored if cost exceeds the cutoff). All these input parameters should be specified by the analyst based on their research objectives and local context. Templates are included in the code for common specifications of cost and decay, including those listed above.

The computational approach adapts Rieser and Scherr's (2019) methodology for computing origin-destination matrices. Their methods use efficient graph data structures and least-cost path tree algorithms to efficiently compute costs between many origins and destinations simultaneously. We have expanded this to evaluate least-cost path trees from micro-coordinate origin points, splitting links at the origin point rather than snapping them to network nodes. This enables detailed dwelling-by-dwelling analyses of results even within the same street segment.

For each origin i, the tool computes accessibility using the following computation:

1) Define $A_i := 0$
2) Compute a least-cost path tree C_{in} between i and all network nodes n (stopping at a specified cut-off, if applicable)
3) For each destination j:
   a. For each access point j_n:
      i. Identify the nearest network node to j_n
      ii. Query c_{ij_n} from C_{in}
   b. Define $c_{ij} := \min_n(c_{ij_n})$
   c. Redefine $A_i := A_i + W_j^{\alpha} f(c_{ij})$
4) Store A_i

Computing least-cost path trees for every origin i is the most computationally demanding aspect of the algorithm. For all 1,123,574 dwellings in our study area, the process takes 7.5 h on a desktop workstation with an 8-core Intel Xeon 2.6HGz CPU and 64GB RAM. However, specifying a cut-off value, which stops each tree computation once the cut-off is reached, can reduce this. Furthermore, the trees only need to be computed once for each impedance type and can be re-used (e.g., for multiple destination types) provided the impedance specification does not change.

4.3. Example applications

We demonstrate four example applications based on our harmonised geodatabase and accessibility framework. The first two are accessibility scores computed directly from the framework described in Section 4.2. The latter two are accessibility-based indicators which combine separate accessibility scores to further explore residents' active travel environments.

4.3.1. Accessibility using travel time only

We first compute walking and cycling accessibilities using only travel time as impedance. Like many existing accessibility applications, this does not consider the street-level environment. We define $c_l = t_l$, where t_l is the estimated travel time along each link. We compute walking and cycling accessibilities for all household dwellings in Greater Manchester.

We apply weight parameters $\alpha = 0.25$ for social/cultural locations, recreational facilities, and public open spaces, $\alpha = 1$ for education, and $\alpha = 0.5$ for remaining types. These parameters were selected to reflect the local context and ensure similar weight distributions throughout the study area (further details in Supplementary A.3.1).

We apply the cumulative gaussian decay function recommended in Vale and Pereira (2017). This function assumes indifference (i.e., no decay) up to a specified threshold, beyond which it decays according to a gaussian function. It is defined by

$$f(c_{ij}) = \begin{cases} 1 \ if \ c_{ij} \le a \\ e^{\frac{-(c_{ij}-a)^2}{v}} \ otherwise \end{cases} \tag{2}$$

Where c_{ij} is path impedance, a is a parameter specifying 'acceptable' impedance and v is the gaussian decay parameter. For this study we fix $a = 300$ and $v = 129843$, creating a curve which decays from 300 s (5 min one-way) reaching 0.5 at 600 s. We chose this parametrisation to align with the 20 min neighbourhood urban planning concept (Gower & Grodach, 2022), supported by empirical evidence from local travel diary data supplied by TfGM and evidence and guidance in Vale and Pereira (2017), Wu, Lu, Lin, and Yang (2019), Martínez and Viegas (2013), and Higgs et al. (2019). Further details on the selection, parametrisation, and validation of this decay function are in Supplementary A.3.2.

4.3.2. Accessibility incorporating the street-level environment

This application builds from the previous one, incorporating street-level environment into impedance. We define $c_l = \tilde{t}_l$, where $\tilde{t}_l$ is an 'equivalent travel time' which is equal to t_l for 'average-quality' street-level environments but can be smaller for high-quality environments and larger for poor-quality environments.

We define $\tilde{t}_l$ using a composite impedance specification inspired by Ziemke, Metzler, and Nagel (2017), but reformulated and extended to incorporate the attributes in our network:

$$\tilde{t}_l = \gamma t_l \left[1 + m_g g_l + m_p p_l + m_a (1 - a_l) + m_s \left(s_l + \frac{w_{lj}}{x_l} s_{lj} \right) \right] \tag{3}$$

where t_l is link travel time (seconds), g_l is gradient (uphill slope between 0 and 0.5), p_l is a surface comfort score (between 0 and 1), a_l is the ambience score (between 0 and 1), s_l is link stress (between 0 and 1), s_{lj} is crossing stress (between 0 and 1), w_{lj} is the width of the junction at the end of the link (metres), x_l is the link length (metres), m_g, m_p, m_a and m_s are marginal cost parameters, and γ is a scale parameter.

The marginal cost parameters determine the influence of each BE component. They can be interpreted as the proportional travel time penalty for a unit increase in the corresponding component. For example, $m_g = 10$ would indicate that each 1 % increase in upward gradient corresponds to a 10 % travel time penalty.

The scale parameter γ adjusts impedance so that $\tilde{t}_l$ becomes for t_l average-quality street-level environments. We define this average using observed walking and cycling journeys in Greater Manchester.

We parametrised this impedance formula for 'typical' pedestrians and cyclists and this is presented in Table 1. These specifications were chosen through an iterative process and validated in consultation with regional experts (e.g., transport engineers and planners at TfGM), referring to evidence and heuristics from previous studies where possible. For cycling, we referred to the MATSim bicycle extension (Ziemke, Metzler, & Nagel, 2017), Broach and Dill (2016) and Lu et al. (2019). For walking, we referred to Sevtsuk et al. (2021), Merlin and

Table 1
Impedance parameters.

Mode	Scale parameter γ	Gradient m_g	Surface m_p	Ambience m_a	Stress m_s
Cycling	0.392	15	0.15	1	3
Walking	0.442	4	0	3	1

Jehle (2023), and Mason, Kearns, and Livingston (2013). Further details on these parametrisations and the validation process are provided in Supplementary A.3.3.

We apply the same destinations, destination weights, and decay function as described in the previous section.

4.3.3. Sensitivity to the street-level environment

This application defines an indicator Q_i to explore the sensitivity of accessibility to the street-level environment. We define it as

$$Q_i = log_{10}\frac{A_i(\tilde{t})}{A_i(t)} \tag{4}$$

where $A_i(\tilde{t})$ is accessibility according to equivalent travel time (Section 4.3.2) and $A_i(t)$ is accessibility according to travel time only (Section 4.3.1). It indicates the suitability of the street-level environment for facilitating access to destinations by foot or bike. A score of $Q_i = 0$ indicates an 'average' quality environment for reaching destinations while positive scores indicate better quality and negative values indicate poorer quality.

4.3.4. Varying thresholds of cycling stress

This final application is specific to cycling and explores how cyclists' differing tolerances toward stress influence their personal accessibility. While stress is uncomfortable for everyone, many cyclists become unwilling to cycle after stress reaches a certain level. From an accessibility perspective, a person's stress threshold determines what parts of the network are available to them for cycling. Depending on a person's household location and stress tolerance, their accessibility may be dramatically lower versus if this threshold were ignored.

We develop an example indicator to explore how differing thresholds of cycling stress influence accessibility. This builds from the work by Faghih Imani et al. (2019) who explored how different tolerances toward traffic stress influence cycling accessibility. Their indicator followed a simple approach that used a cumulative decay function (up to 30 min) and assumed links exceeding the stress threshold are impassable. We advance this by defining a more continuous measure that uses a smooth decay function and assumes links exceeding the threshold slow the cyclist down to walking speed (i.e., they must dismount and walk) but do not stop them entirely. For simplicity, this example assumes indifference toward other aspects of the street-level environment besides stress.

First, we define three cycling personas based on guidance in the Cycling Infrastructure Design (2020) handbook using the green/amber/red stress classifications described in Section 4.1.1:

- The 'cautious' persona can only cycle on green links,
- The 'typical' persona can also cycle on amber links, and
- The 'confident' persona can cycle on any link that permits cycling.

Second, we defined custom impedance functions for each persona. If a link is cyclable by the persona, impedance is the cycling travel time $(c_l = t_{l,bike})$. Otherwise, the user must dismount, so impedance becomes equal to walking travel time $(c_l = t_{l,walk})$.

Finally, accessibility is re-computed for each persona using the modified impedance functions, with the specification otherwise remaining the same as Section 4.3.1. Confident personas have no stress threshold, so their accessibility is not affected. However, accessibility for typical and cautious cyclists can be lower. We define the indicator $T_{i,p}$ for each dwelling i and persona p to explore to what extent their cycling accessibility is reduced by stress:

$$T_{i,p} = \frac{A_{i,bike} - A_{i,p}}{A_{i,bike} - A_{i,walk}} \tag{5}$$

Where $A_{i,p}$ is the persona-specific bike accessibility, $A_{i,bike}$ is full (confident) bike accessibility and $A_{i,walk}$ is the full walk accessibility. The result falls on a scale between 0 and 1, where 0 indicates that stress has no effect on the person's ability to cycle to the relevant destinations, and a value of 1 indicates that the person cannot save any time by cycling to destinations (rather than walking) because stress is too high. This extreme case would occur if there are no routes the cyclist is comfortable using that could help them reach surrounding destinations faster than walking.

5. Results

Results are presented in two sections: Section 5.1 presents the final network graph with selected street-level environment attributes, and Section 5.2 presents results from the example accessibility applications.

5.1. Network

The final network for Greater Manchester is visualised in Fig. 1 with a selection of attributes. Additionally, street-level examples detailing ambience and stress with their contributing components are shown in Table 2. VGVI scores, indicating eye-level green visibility, are highest in and around green areas, around one-half on tree-lined streets (e.g., Table 2b), and low in the city centre (upper left corner of inset area). Shannon diversity is highest in the city centre. Ambience scores are highest in busy shopping areas and open green spaces but becomes poorer near industrial areas and other negative POIs (e.g., Table 2a). Streetlighting is high in the centre and on primary roads but low in greenspaces and some residential streets.

Link stress varies substantially for cyclists even at small scales, while for pedestrians it is generally lower and relatively constant owing to pedestrian's increased separation from vehicles. Link stress can be high, even when infrastructural protection exists, if the protection is not suitable given the traffic volumes and speeds (e.g., the cycle lane in Table 2c). Similarly, it can be low even without dedicated infrastructure if traffic speeds and volumes are low (e.g., Table 2a). Crossing stress is variable for both pedestrians and cyclists and generally poorer around primary roads (e.g., Table 2d), retail parks and roundabouts. Zebra crossings and/or dedicated signals can substantially reduce crossing stress (e.g., Table 2e).

5.2. Accessibility

5.2.1. Accessibility using estimated travel time

Results for accessibility ignoring the street-level environment (Section 4.3.1) are not presented, since similar applications exist in current accessibility literature. Examples of micro-resolution accessibility studies using basic impedance specifications include Krenz et al. (2023) and Vale and Pereira (2017). While we do not present these results independently, they are used within the indicators Q_i and $T_{i,p}$ presented in Sections 5.2.3 and 5.2.4 respectively.

5.2.2. Accessibility incorporating the street-level environment

A sample of walking and cycling results for green open spaces, early years services (i.e., childcare), and food stores incorporating the street-level environment (Section 4.3.2) are presented in Figs. 2 and 3.

Walking accessibility decays faster with distance to destinations due to the lower speed of walking. Therefore, the highest walking accessibility scores are more concentrated around the destinations themselves. Walking accessibility to green open spaces is high just north and south-east of the centre (inset area of Figs. 2 and 3) but poor in the centre. Walking accessibility to food stores is highly concentrated in the centre due to its density of food stores and high-ambience streets.

Cycling accessibility scores are higher overall than walking accessibility and more evenly distributed. The influence of cycling stress is highly visible in the results; for example, scores are higher just south of the city-centre, which is a more affluent university area with many low-stress cycle links (as shown previously in Figure 1vii).

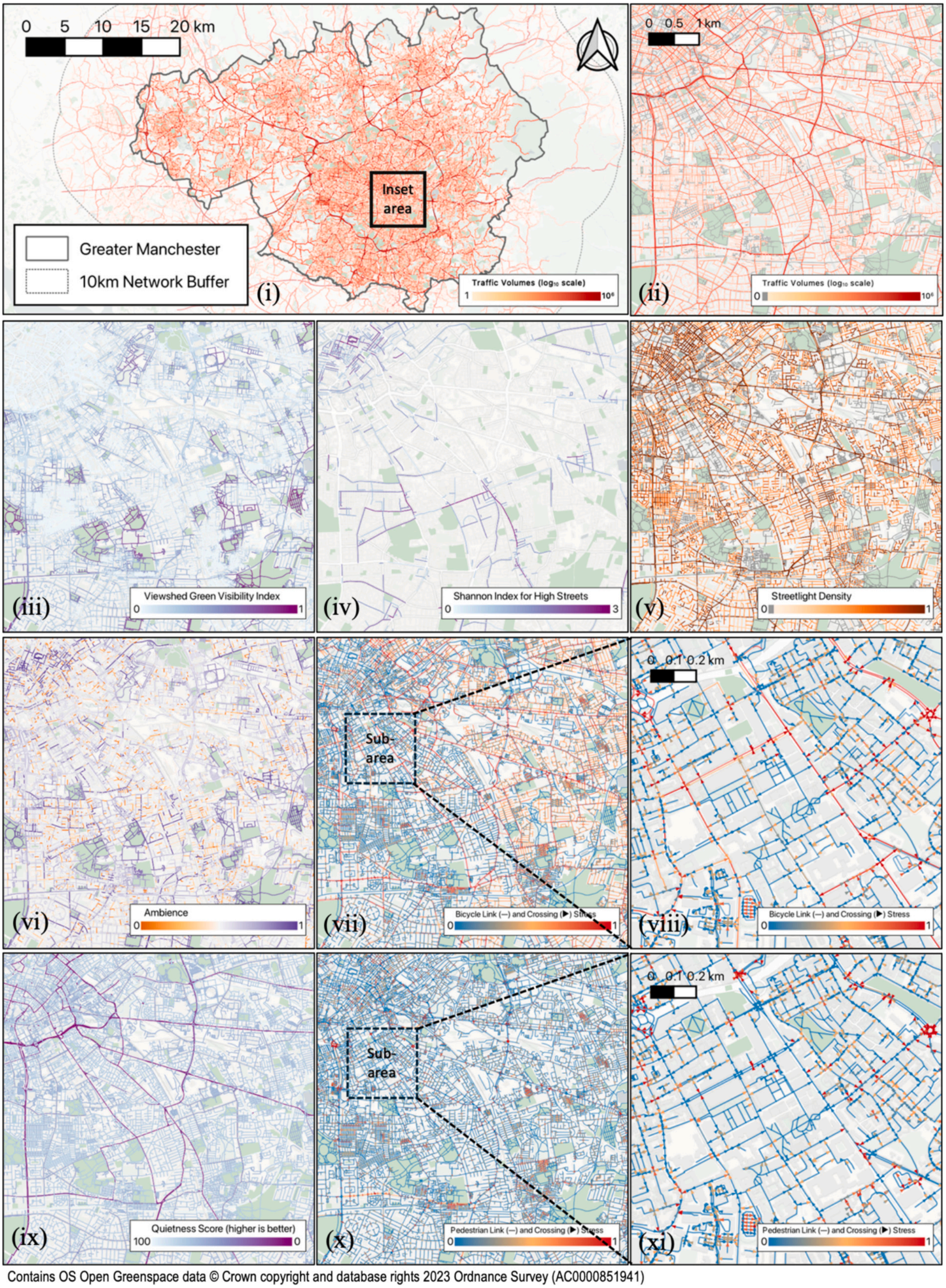

Fig. 1. Network examples showing (i) traffic volumes for Greater Manchester, (ii) traffic volumes for inset region, (iii) viewshed greenness visibility index, (iv) high street diversity, (v) streetlight density, (vi) ambience, (vii/viii) bike stress, (ix) quietness score from Cyclestreets.net, (x/xi) pedestrian stress.

Table 2
Street-level examples of ambience and stress.

	Street view	Ambience	Link stress
(a)		VGVI: 0.03 Shannon: 0.00 +POIs: 0.31 –POIs: 0.94 Crime: 0.00 **Score: 0.20**	Protection: mixed AADT: 1552 Speed limit: 20 Speed 85th perc: 18 Heavy inf: 1.00 **Bike score: 0.34** **Walk score: 0.00**
(b)		VGVI: 0.50 Shannon: 0.00 +POIs: 0.10 –POIs: 0.00 Crime: 0.00 **Score: 0.80**	Protection: protected AADT: 9268 Speed limit: 20 85th perc. speed: 29 Heavy inf: 0.00 **Bike score: 0.00** **Walk score: 0.00**
(c)		VGVI: 0.60 Shannon: 0.00 +POIs: 0.00 –POIs: 0.00 Crime: 0.00 **Score: 0.80**	Protection: lane AADT: 35820 Speed limit: 40 Speed 85th perc: 38 Heavy inf: 0.00 **Bike score: 1.00** **Walk score: 0.50**
	Street view (perspective of approaching link)	**Crossing Stress**	
(d)		**Approaching link details:** Walk stress: 0 Bike stress: 0 **Crossing details:** Walk type: Uncontrolled Bike type: Uncontrolled AADT: 2168 Speed limit: 20 85th percentile speed: 30 Lanes: 3 **Walk score: 0.91** **Bike score: 0.91**	
(e)		**Approaching link details:** Walk stress: 0 Bike stress: 0 **Crossing details:** Walk type: Dedicated signal Bike type: Dedicated signal AADT: 2964 Speed limit: 30 85th percentile speed: 30 Lanes: 4 **Walk score: 0** **Bike score: 0**	

Variables: *VGVI* viewshed greenness visibility index, *+POIs* positive POIs, –POIs negative POIs, *Protection* infrastructural protection type, *AADT* vehicle volume, *Speed 85th perc* 85th percentile speed, *Heavy inf* heavy vehicle infrastructure. Speeds in miles per hour. Full definitions in Supplementary Table A1.

5.2.3. *Sensitivity to the street-level environment*

Sensitivity indicator Q_i results for both walking and cycling to all 12 destination types are provided in Supplementary C. This section presents an interpretation in the context of childcare destinations. Ensuring access to childcare provision is a policy focus in the UK (Langford, Higgs, & Dallimore, 2019) and we can use this indicator to explore how the street-level environment influences childcare accessibility for pedestrians and cyclists.

Results for childcare destinations are presented in Fig. 4. Recall that Q_i is not an indicator of accessibility; instead, it describes the influence of the street environment on accessibility.

Dwellings shaded blue experience above-average street-level environments for reaching destinations, whereas dwellings shaded red suffer poorer environments. Dwellings closer to destinations appear lighter because both types of impedance fall within the cumulative part the decay function $\left(c_{ij} \leq a\right)$, so $f\left(c_{ij}\right) = 1$. Therefore, under this model, the street-level environment is less relevant when destinations are in the immediate vicinity. Dwellings with mixed street-level environments to destinations also appear lighter in colour. To better illustrate the causal mechanism behind the variation in Q_i, the most influential street-level attributes in each mode's impedance specification (Table 1) are shown in the zoomed inset maps (Figures 4iii and 4iv).

For walking, Q_i is predominantly influenced by ambience. Fig. 4i shows above-average street-level environments for reaching childcare facilities in most of the area, particularly the city centre and many neighbourhoods to the south. However, there are some exceptions, with poor ratios in certain council estates (e.g., bottom left of Fig. 4i) where higher crime links must be traversed to reach destinations. Poor ratios also occur in neighbourhoods near freight and industrial facilities (e.g., top centre of figure 4iii) that must be walked past to reach childcare. Lack of connectivity is a major contributor to low Q_i: while similar levels of crime and negative POIs also exist in other parts of the region, they are more easily avoided due to the availability of alternate routes and therefore have a smaller influence on accessibility.

For cycling, the most influential factor is stress. Ratios for cycling accessibility to childcare closely reflect the link stress results presented previously in figure 1viii. The worst performing areas are those in which one must traverse stressful routes to reach childcare, which is especially

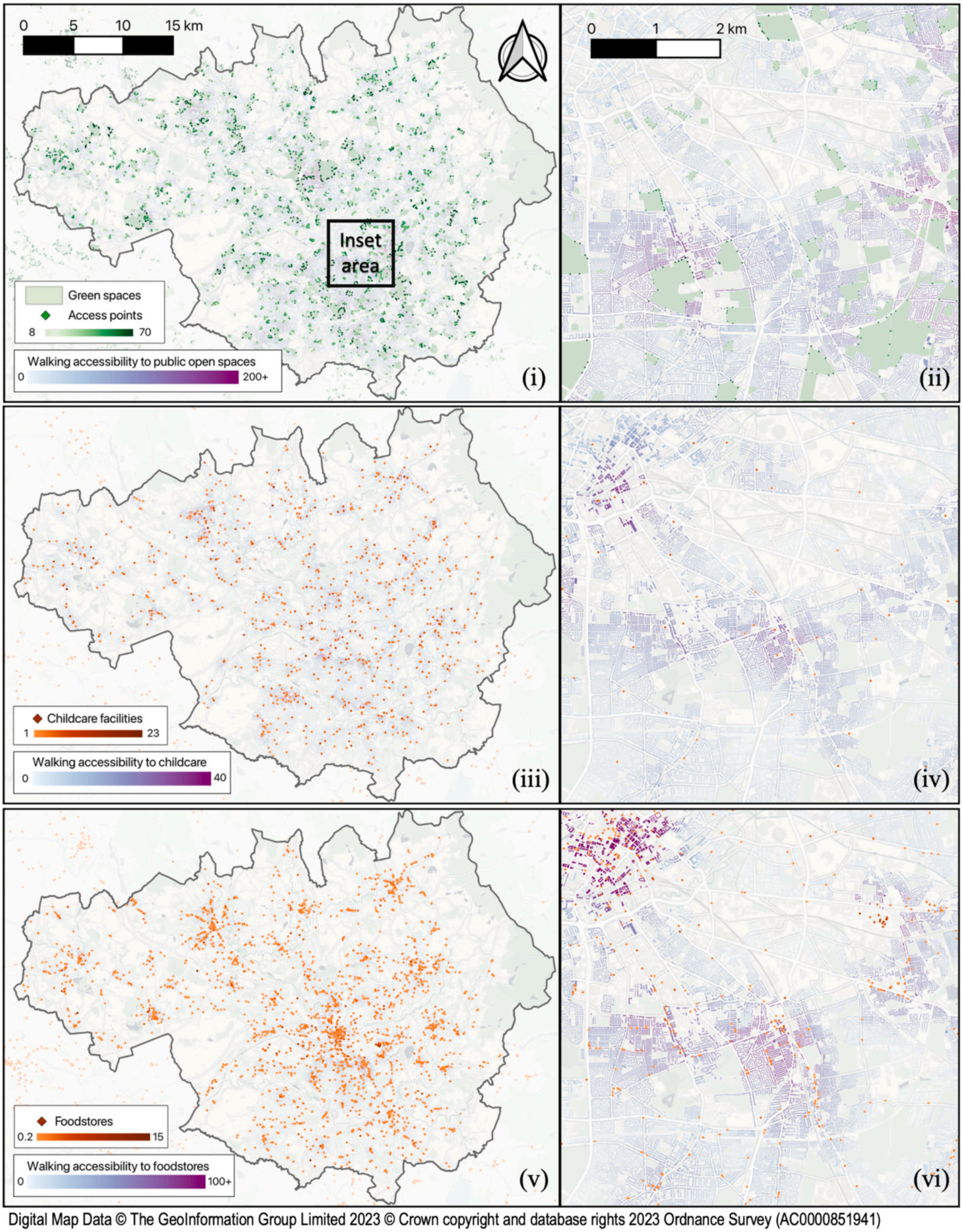

Fig. 2. Walking accessibility results for public open spaces (i/ii), childcare facilities (iii/iv), and food stores (v/vi).

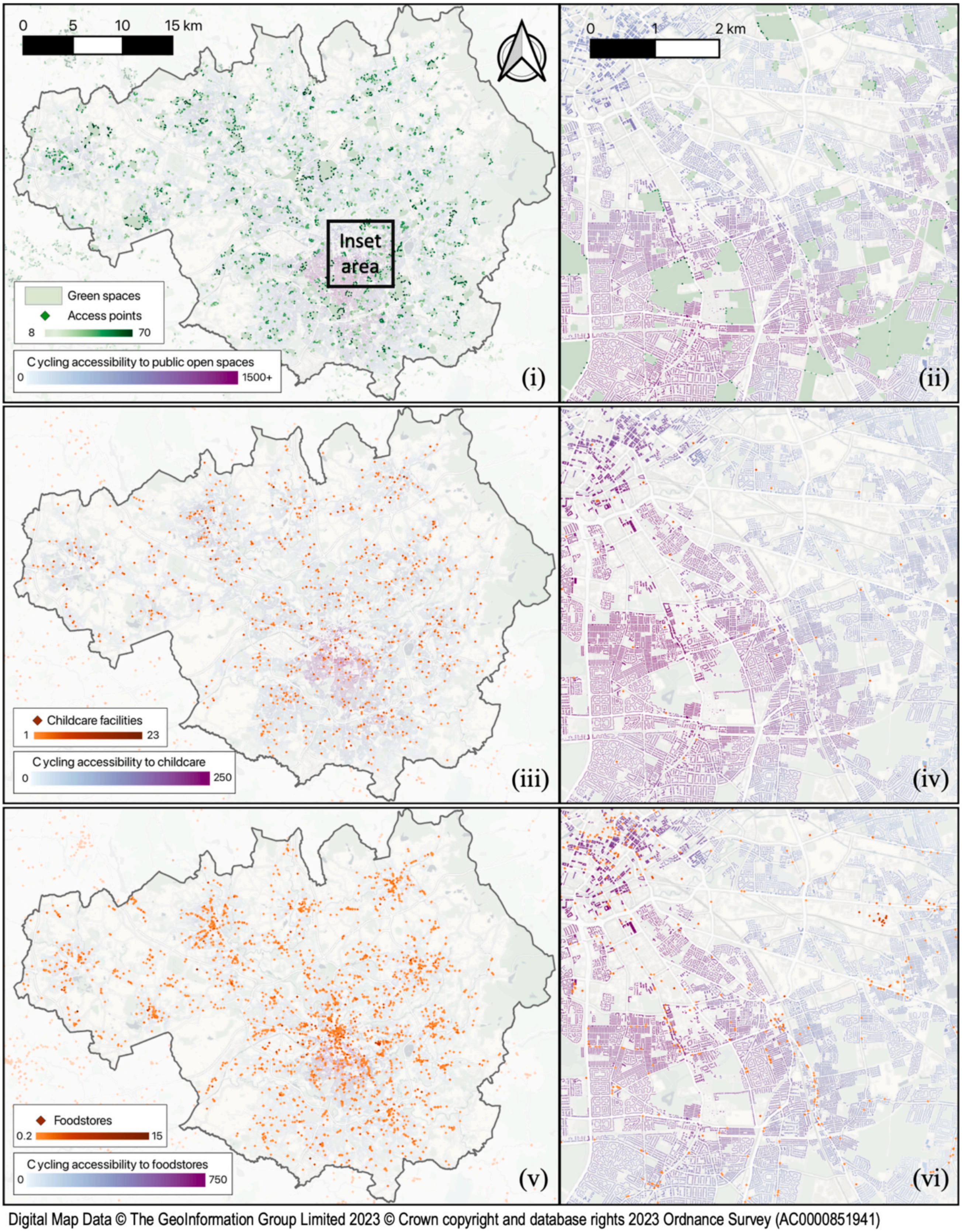

Fig. 3. Cycling accessibility results for public open spaces (i/ii), childcare facilities (iii/iv), and food stores (v/vi).

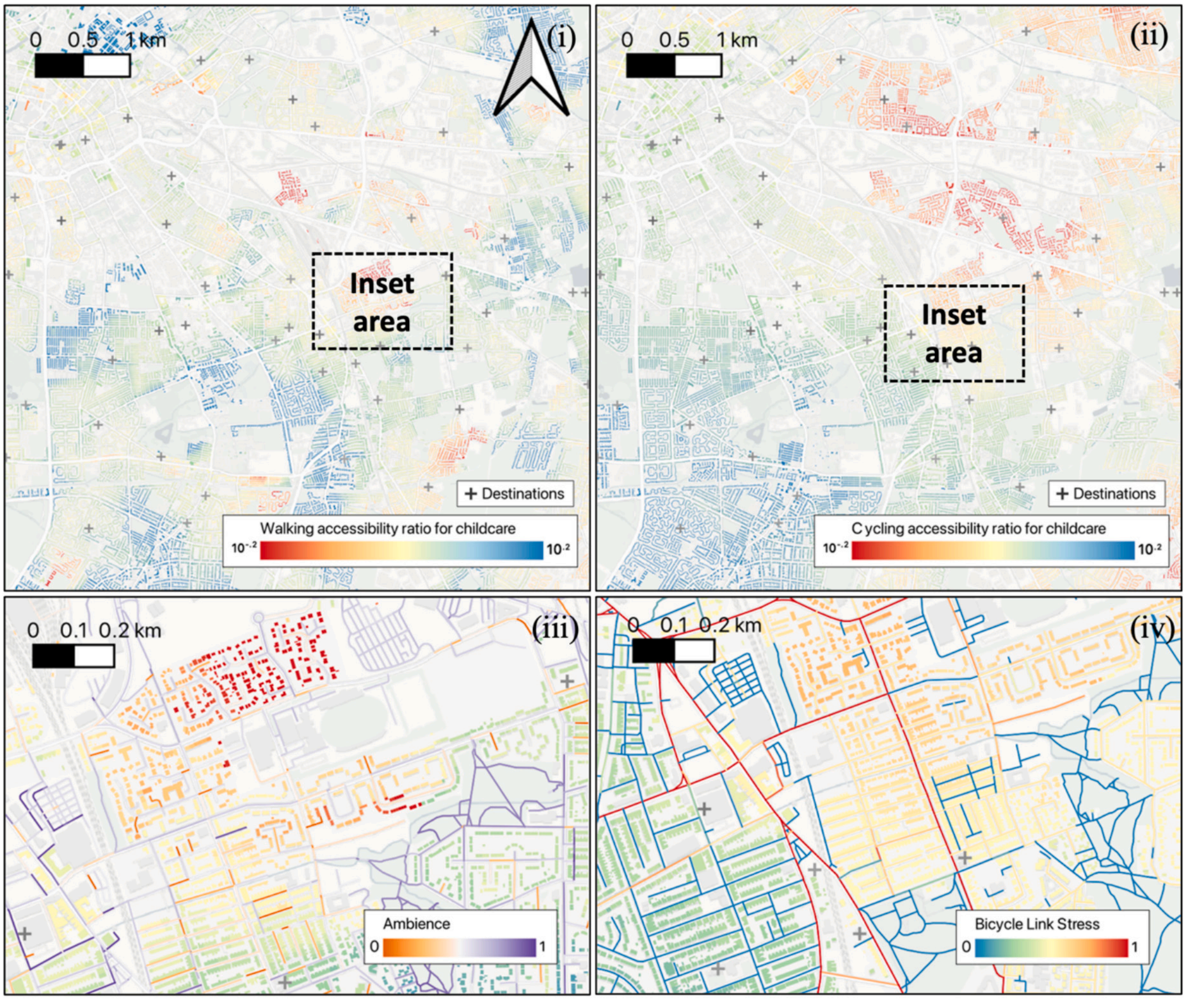

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Fig. 4. Sensitivity indicator Q_i describing the influence of the street-level environment on accessibility for walking (i/iii) and cycling (ii/iv) to childcare.

notable in neighbourhoods east of the centre (top right of figure 4ii). Areas to the south of the city (bottom left of figure 4iv) perform consistently better despite the presence of some high-stress links, since sufficient low-stress routes are available to reach childcare destinations.

5.2.4. *Varying thresholds of cycling stress*

Building on the previous results, we present and interpret tolerance indicator $T_{i,p}$ results for childcare destinations. Stress thresholds are especially relevant for childcare since people often have a lower stress tolerance when travelling with children (Hardinghaus & Papantoniou, 2020), reducing their effective accessibility.

Indicator $T_{i,p}$ scores for 'cautious' and 'typical' cyclist personas are presented in Fig. 5. Results can be interpreted as the extent to which stress reduces cycling accessibility to childcare. For example, a dwelling that scores 0.5 would imply that traffic stress has caused the potential for cycling to access childcare facilities to be reduced by half.

These results reveal a dramatic reduction in cycling access to childcare. For 'typical 'cyclists, the average dwelling scores 0.5 in the childcare category; however, only the top 5% score above 0.7 and the top 1% score above 0.8. For 'cautious' cyclists, the potential for cycling to childcare reduces even further: the average dwelling scores 0.1, only the top 1% of dwellings score above 0.5 and only the top 0.003 % score above 0.7. The best-scoring dwellings are in the university region just south of Manchester city centre, owing to its higher density of childcare destinations and high-quality cycling infrastructure in this area.

While we identified a substantial reduction in cycling accessibility due to stress, our findings are not as severe as those by Faghih Imani et al. (2019) who found that average cycling accessibility to workplaces reduced by 99.8 % for the lowest stress threshold and by 98 % for the second-lowest threshold. The difference in results is likely because their methodology assumed links exceeding the stress threshold were impassable whereas ours allowed these links to be traversed but slowed users down to walking speed. Therefore, a relatively short high-stress road segment would only slightly reduce accessibility under our approach, rather than cutting off access entirely.

6. Discussion

This study introduces a methodology for incorporating multi-source BE data into accessibility using a micro-scale approach. Using the case study area of Greater Manchester, we observed how street-level features influence policy-relevant accessibility indicators for active modes. For example, we observed substantial but spatially varied reductions in cycling accessibility after incorporating traffic stress indicators and thresholds aligning with government policy guidance (indicator $T_{i,p}$ in Section 5.2.4). Micro-scale variations in results were especially apparent when exploring sensitivity to the street-level environment (indicator Q_i in Section 5.2.3): even within a neighbourhood or street (i.e., within the meso-scale), some dwellings benefit from above-average street environments for reaching relevant destinations while nearby dwellings experience a below-average environment. Living in a neighbourhood with good network connectivity dampens the effects of poor-quality

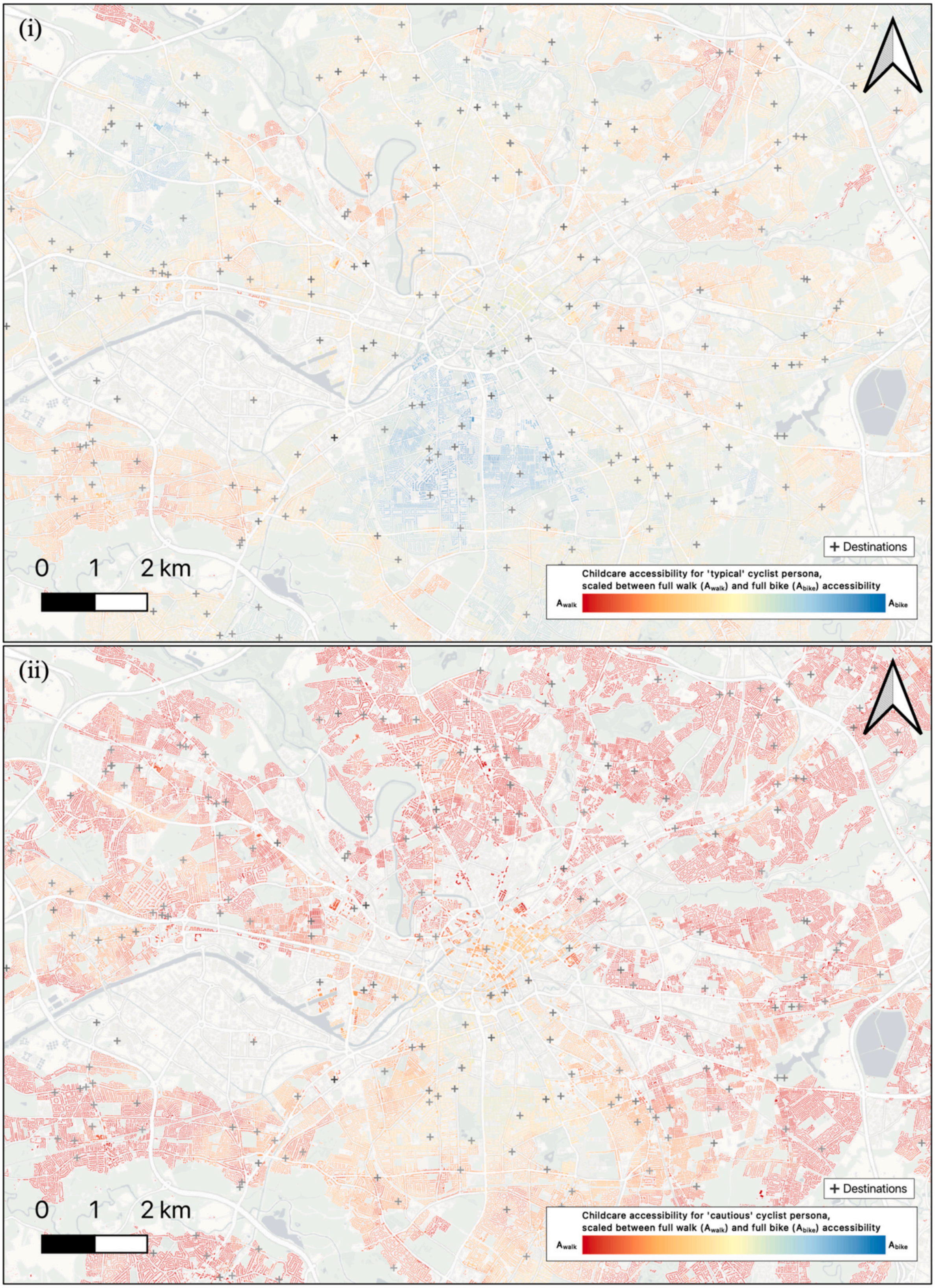

Fig. 5. Indicator $T_{i,p}$ describing the reduction in accessibility due to traffic stress for 'typical' (i) and 'cautious' (ii) cyclists, expressed on a scale between walking accessibility and full cycling accessibility.

links because alternate routes are available to reach destinations. However, in neighbourhoods with limited access routes, a poor-quality experience on a crucial link can substantially worsen accessibility for dwellings that rely on it.

The results highlight the value of high-resolution BE data and computational methods for active travel accessibility modelling. This evidence supports existing literature calling for and applying higher resolution BE data and more detailed accessibility models (Blečić et al., 2015; Krenz et al., 2023; Merlin & Jehle, 2023; Rhoads et al., 2023). The methodological and computational framework herein is unique from previous published accessibility studies in terms of the diversity of data sources and street-level environment features incorporated into the multimodal transport network, and efficiency of the algorithm.

We incorporated many street-level features from diverse data sources to demonstrate the possibilities for a data-rich study area. Our example specifications were selected from a limitless range of potential options. Their results demonstrate that when using intuitive indicators (based on policy and empirical evidence and developed and validated in consultation with the local authority), the street-level environment clearly influences accessibility at the micro-scale.

For applications in other study areas, the street-level features and accessibility specifications will depend on context such as data availability, local policy, and research agenda. The spatial methods presented in section 4.1 can guide the network harmonisation, but analysts would need to identify relevant micro-environmental data for their area and adapt the methods accordingly. The accessibility framework presented in section 4.2 is open-source and can be applied in other study areas (assuming harmonised network and destination data are available) with flexibility for a range of specifications. A more focused analysis might use fewer data sources (e.g., OSM only) and/or consider fewer features (e.g., cycling stress only) in the accessibility specification. Developed on the basis of the open geodatabase OSM and open-source MATSim project, our code base is accessible to a growing community of transport researchers and practitioners with potential to be further expanded by developers worldwide.

6.1. Limitations of the greater Manchester case study

Our network does not offer the highest spatial detail resolution for the active travel networks. While OSM has a high density of links, these links were still simplified along centrelines. A more realistic representation of the pedestrian environment would model the pavement on each side of the road separately, as in Blečić et al. (2015) and Rhoads et al. (2023). Ideally, such a representation would explicitly specify designated pedestrian crossing points (Merlin & Jehle, 2023), which could allow for more detailed models of crossing stress than possible for this study.

The example specifications were prepared with limited empirical evidence related to accessibility, behaviour, and perceptions toward the BE in the study area. The only region-specific behavioural data was a local travel diary, which was used to validate the decay function parametrisation (Eq. 2) and calibrate the scale parameter (Eq. 3). Other aspects of the specification, including the parametrisation of impedance and marginal costs, were prepared using guidance and evidence from other regions. The presented accessibility results were assessed visually for plausibility, but did not undergo formal validation.

Incorporating empirical findings such as parameters from an active travel route or mode choice models could enable a more evidence-based specification, like in Nassir et al. (2014). However, empirical approaches also have limitations regarding data quality and statistical assumptions. In practical applications, it may be most effective to combine empirical evidence with guidance and input from stakeholders. Our examples followed this principle, using evidence from previous studies and empirical findings where possible, but then validating the chosen parametrisations in consultation with the local government through trial-and-error and visual examples to ensure results were interpretable and reasonable. Nonetheless, like Blečić et al. (2015), our specification still relies on the authors' assumptions and expertise about how the street-level environment influences walking and cycling.

6.2. Further applications

The network development methods (Section 4.1.1) have significant potential for transport and urban planning research besides measuring accessibility. By enhancing network graphs with multi-source BE data, behavioural models such as route and mode choice can use a broader range of street-level environment predictors than feasible in existing studies (Broach et al., 2012; Broach & Dill, 2016; Cervero et al., 2019; Cole-Hunter et al., 2015; Grudgings, Hughes, & Hagen-Zanker, 2023; Tribby, Miller, Brown, Werner, & Smith, 2017). This would in turn improve representation of active travel behaviours, enabling better sensitivities to the street-level environment in simulation and appraisal, e.g., building from Ziemke, Metzler, and Nagel (2019) and De Nazelle, Rodríguez, and Crawford-Brown (2009).

The accessibility framework is highly suitable for exploring how the street environment, network structure, and destination availability interact to influence walkability and cyclability. One-dimensional concepts based on the "D" indicators (e.g., connectivity, destination density, cycle lane density) are common in literature and simple to compute but behaviourally limited if assumed to be independent. This framework enables evaluation of the combined effect of these concepts in high detail. For example, cycling infrastructure density and destination density were not computed explicitly, but high-quality cycling infrastructure improved cycling accessibility in many neighbourhoods due to reduced cycling stress to destinations. Similarly, network connectivity was not calculated explicitly, but households in more connected neighbourhoods often scored better because travellers could avoid poor-quality links to reach destinations. There is potential for this to be applied to enhance walkability and cyclability evaluation in various applications related to transport and urban systems, as follows.

From an equity perspective, we observed micro-scale variations that potentially reflect sociodemographic differences (e.g., poor Q_i in some council estates, high Q_i near Manchester university). Because of the small scale of variation, potentially equity-relevant observations could be difficult to capture using aggregate indicators. Further applications could explore accessibility equity in detail by linking dwelling-level results with disaggregate population data (e.g., microcensus or synthetic population), e.g., building from Ziemke, Joubert, and Nagel (2017).

Travel behaviour is influenced by accessibility. Where micro-behavioural data is available (such as a travel diary survey with spatial data), empirical analyses could link accessibility indicators with observed behaviour such as mode choice, destination choice, trip/activity generation or walking and cycling volumes.

Health is also linked with accessibility. Access to green space can influence physical activity including recreational walking and cycling, access to different types of food can influence diets, and access to healthcare services can influence appointment attendance and survival rates (Glazener et al., 2021). Mental health is affected by social exclusion, which is a consequence of poor access. Health researchers can use this framework to explore how the street-level environment impacts health-oriented accessibility indicators. Empirical analyses could link results with micro-spatial health data, e.g., building from Krenz et al. (2023).

Purpose-built accessibility indicators could be developed for reflecting specific observed behaviours and/or health states. Empirical micro-spatial data on travel behaviour and health could be used to quantitatively calibrate and validate these specifications. This could enable evidence-driven accessibility indicators which could be useful for prediction models.

From a planning perspective, the indicators clearly pointed out dwellings and neighbourhoods that could be targeted for accessibility improvements. Practical tools could be developed based on this framework to enable policymakers to examine potential improvements to connectivity, street-level features, and/or destination placement and examine their impact on accessibility and equity. Indeed, the UK Cycling Infrastructure Design (2020) handbook highlights the importance of network planning approaches that can evaluate how to connect people to facilities using high-quality and low-stress routes.

Simulation studies could use empirical findings and prediction models based on accessibility to estimate how proposed changes to street-level infrastructure and land use impact active mode accessibility and thereby population behaviour, equity and health, e.g., building from De Nazelle et al. (2009). Micro-spatial accessibility methods can be especially powerful within microsimulation models, which simulate residents and dwellings individually to explore detailed spatial and sociodemographic variations in the population.

6.3. Further development

The accessibility framework is written in Java using MATSim methods and data structures wherever possible, including the format for the network, travel time, and impedance specification. This facilitates further development, especially from those with expertise in object-oriented programming and those in the MATSim community.

The current accessibility framework applies a two-component model that considers the land use and transport network. This could be extended to incorporate the individual (e.g., varying needs, abilities, preferences) and temporal (e.g., constraints of scheduling and opening hours) components of accessibility (Geurs & van Wee, 2004). It could also be extended to consider interactions between supply and demand (McGrail, 2012). Future research could expand the concepts of the impedance in this framework to explore accessibility in the context of specific population segments (e.g., children, older adults, people with disabilities). Alternatively, a more comprehensive individual-level accessibility analysis could incorporate multiple sociodemographic parameters into the impedance function, potentially linked with dwelling-level population (e.g., microcensus) data.

The framework does not provide a user-friendly graphic interface and is mainly relevant to MATSim developers and others with expertise in object-oriented programming. Nonetheless, developing a more accessible accessibility tool is a clear opportunity for further development.

7. Conclusion

Encouraging active travel is increasingly at the forefront of transport and public health policy because of its potential to reduce carbon emissions and improve population health. The growing availability of micro-scale BE data offers new opportunities for insight into people's active travel environments. Researchers and practitioners can use this data within accessibility models to facilitate sustainable and equitable urban designs.

This study addressed two key challenges with incorporating micro-scale BE data into active travel accessibility, namely multi-source spatial data harmonisation and efficient disaggregate computation. Through an example application, we demonstrated how the street-level environment can influence policy-relevant accessibility indicators at the micro-scale. This contributes to a growing body of evidence showing that micro-scale analysis methods are important for understanding and modelling the active travel environment. Going beyond the state of the art, the methodology and computational framework presented in this study are generalisable to many contexts and specifications, aiming to support further research exploring the interactions between accessibility and the street-level environment.

CRediT authorship contribution statement

Corin Staves: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Irena Itova:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Belen Zapata-Diomedi:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Audrey de Nazelle:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Jenna Panter:** Writing – review & editing, Funding acquisition, Formal analysis, Conceptualization. **Lucy Gunn:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Alan Both:** Writing – review & editing, Validation, Resources, Funding acquisition, Conceptualization. **Yuchen Li:** Writing – review & editing, Validation, Software. **Ismail Saadi:** Writing – review & editing, Formal analysis. **James Woodcock:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **S.M. Labib:** Writing – review & editing, Visualization, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

Links to code on GitHub within manuscript and technical documentation. Some data for our study area can be made available on request.

Acknowledgements

This work was supported by the United Kingdom Research and Innovation (UKRI) – Australian National Health and Medical Research Council (NHMRC) (MR/T038578/1, APP1192788) and the European Research Council under the Horizon 2020 research and innovation program (grant agreement No 817754). This material reflects only the author's views and the Commission is not liable for any use that may be made of the information contained therein. We are grateful to Transport for Greater Manchester for their support in providing built environment and travel diary data, as well as CycleStreets for providing spatial data. We are grateful to John Gulliver and Dhirendra Singh for the guidance on spatial methods, Billie Giles-Corti and Rachel Aldred for their advice on classifying spatial data including points of interest, and Anna Goodman for her guidance on accessibility. We would also like to thank Luke Knibbs for proof reading manuscript drafts.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2025.102270.

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