Integrating spatially detailed micro-environmental attributes to a routable transport network for active travel modeling: A pilot study in Greater Manchester

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January 17, 2022

Summary

Prior studies show that the Built Environment (BE) can influence route and mode choice, increasing the uptake of active modes and reducing car dominance. One of the main challenges in establishing such relationships between the BE and travel behavior is the unavailability of micro-scale BE data. This study presents a methodology for harmonizing and joining multi-source spatial datasets to the unit level of the street segment (link). We observed significant link-level variations of the environmental characteristics which would have been missed with more traditional area-level approaches. Thus more detailed information of specific street segments can assist travel demand modelling.

KEYWORDS: Built environment, OpenStreetMap, Data harmonization, Transport network, Active travel

1. Introduction

Traditional research on urban environmental exposures often underestimates the health impacts of the outdoor environment because they focus on exposures around the home environment at the neighborhood scale (Orellana and Guerrero, 2019; Kim et al., 2014; Liu et al., 2020). Studies focused on residential locations or neighborhoods ignore exposures experienced by individuals away from home (Kwan, 2009), and they do not consider how the physical environment along travel corridors influences an individual's active travel behavior. Therefore, there is scope for developing methods to better integrate measurements at the neighborhood scale (i.e., meso-scale) with those at the micro-scale such as at street level.

Previous studies on transport and environmental health usually focus on multiple meso-scale area-based measurements of environmental exposures, such as the built and natural environment. These studies mostly have used the concepts of 3Ds (density, diversity, and design) or 5Ds (3D plus "destination accessibility" and "distance to transit") developed by Cevero et al. (2009). While the "D" variables are widely utilized in understanding travel-related behavior at meso-scale, they are vulnerable to variations in the size and scale of areal measurement units (Clark and Scott, 2014), and the modifiable areal unit problem (MAUP, Openshaw, 1981). The MAUP can cause the associations between exposures and health outcomes to vary based on the scale and size of the aggregation unit (Labib et al., 2020). Furthermore, aggregation of variables at the meso-scale unit results in uniformed values for the variables, which may not reflect the variation of conditions across the area (Krizek, 2003; Strominger et al., 2016). For example, a high-quality cycling route is only useful if it connects users to destinations. Therefore, such infrastructure may not be equally accessible to all users living within the neighborhood

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unit. Additionally, meso-scale measurements do not fully reflect travel experiences (Ettema et al., 2010; Liu et al., 2020). These issues with meso-scale measurements of environmental exposure can lead to erroneous assessments of environmental exposure, individual experience, and overall modeled relationships.

To reduce errors in environmental exposure assessments, a better representative individual travel experience and improved micro-environmental indicators of health are essential. The granular information allows not only to understand the level of people's exposure to different environments but also if and how these exposures modify users' behavior towards mode choice and route choice (Ettema et al., 2010; Liu et al., 2020). Considering these, we aimed to develop a spatial methodological approach that harmonizes micro-environmental characteristics of the transport network links, creating a routable transportation network.

2. Methods and Materials

2.1. Data Sources

In order to create a routable transport network with the micro-environmental attributes, we harmonized spatial data from multiple sources, including OpenStreetMap, Ordnance Survey, CycleStreets, Satellite images, and modeled the network spatial dataset (Figure 1).

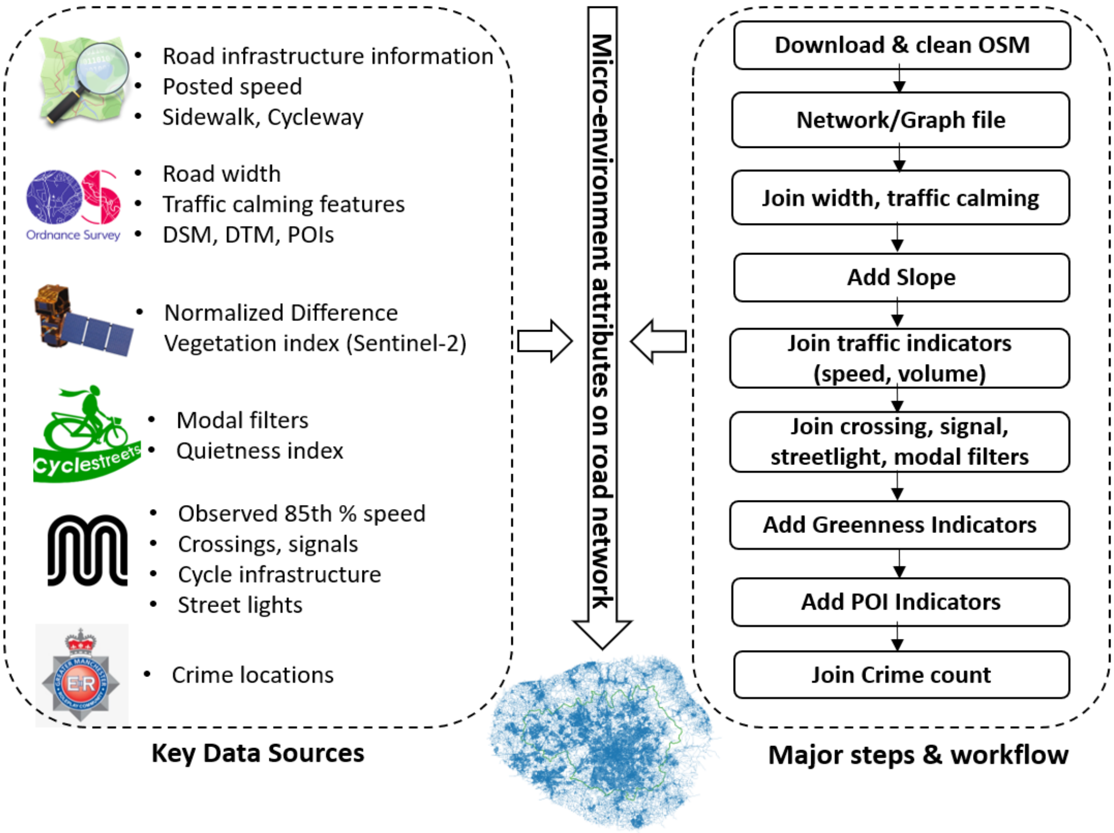

Figure 1 Multi-source spatial data for varying network and micro-environmental indicators and major methodological steps.

2.2 Methodological steps

2.2.1 Download and clean OSM data

We used OpenStreetMap (OSM) for the base road and path dataset for the study area. We downloaded the OSM dataset with the "highway" tag to create the road network. We then cleaned the dataset, keeping only tags for road indicators such as road types, maximum speed, direction, etc. We utilized code from the Cycling Infrastructure Prioritisation Toolkit (Lovelace and Parkin, 2018) to remove any unnecessary tags in the cleaning process.

2.2.2 Create a routable road network

We used the cleaned OSM line dataset to create a routable road network by converting line strings to a spatial graph object consisting of edges (links) and nodes. This process includes adding pseudo nodes, finding the largest connected cluster of links, and providing unique link and node IDs.

2.2.3 Adding micro-scale environmental variables

We added several physical, traffic, built, and natural environmental indicators to the network links created in the previous step. These micro-scale indicators were grouped under two broad categories of factors that can influence route and mode choice with respect to active travel: safety-related indicators; and, attractiveness indicators (Mertens et al., 2014; Liu et al., 2020).

For safety-related indicators, we joined additional road infrastructure information such as width and traffic calming features from the Ordnance Survey highway network. We also added traffic volume information on major and minor roads based on the Department of Transport's count and a model developed by Morley and Gulliver (2016). From Transport for Greater Manchester (TfGM), we obtained data on observed 85th percentile speed on each link, cycling infrastructure, crossing, signal, and street lights locations. And from CycleStreets, we collected data on modal filters and quietness index on each OSM link (Figure 1). To join the attributes from spatial lines, we created sampled spatial points on the lines. We spatially joined these points to the links within a distance threshold (identified iteratively using Hausdorff distance) and transferred the summary attributes. We also estimated the slope of each link using the Digital terrain dataset (5 m resolution).

To reflect the attractiveness of a link for cycling and walking, we added information about the surrounding greenness (e.g., normalized difference vegetation index- NDVI, eye-level visibility). We used Sentinel-2 satellite data for NDVI and applied a viewshed-based greenness visibility model developed by Labib et al. (2021). Additionally, we used the point of interest (POIs) database from the Ordnance Survey to identify POIs which may positively or negatively influence a link's attractiveness in terms of cycling and walking. Positive POIs include the presence of cafes, shops, and negative POIs include places that generate heavy traffic such as construction services or create an ambient of non-scenic walking such as large parking lots or office parks. We used spatial clustering algorithms such as KNN, and DBscan to identify POIs in proximity to each link and then spatially joined the POI score. Shannon and Simpson indices were used to quantify the diversity and dominance of POIs for each link. Finally, we joined the numbers of crimes attached to each link based on Greater Manchester's police dataset.

The overall workflow and spatial operations can be reproduced for any other city-regions in the UK. We created a GitHub Organization and multiple repositories for this project, https://github.com/jibeproject. The majority of the code was developed in R-programming language using multiple packages, including osmdata, sf, sfnetworks, tidygraph, igraph, nngeo, slope, qgisprocess, terra, dbscan, vegan, tidyverse, and GVI (Brinkmann and Labib, 2021).

3. Results and Discussion

The outcome of our overall process and workflow is a routable transport network (graph: links and nodes) with 40 key road and micro-environmental attributes of each link. Figure 2 illustrates a few selected physical and built attributes on the links for the Manchester city center area. From Figure 2, it is clear that creating detailed attribute information of each link allows exploring spatial variability and spatial pattern of different attributes of the network at a fine scale. For instance, the highest speed is observed on the Mancunian way (Fig 2A), a motorway link road. We also observed that the majority of the roads have sidewalks (Fig 2B), but only a few links have cycling infrastructure or marked cycling lanes (Fig 2C); which is common in the UK. Also, the majority of the roads have a width between 8-12 m (Fig 2D), within this zoomed-in area of interest.

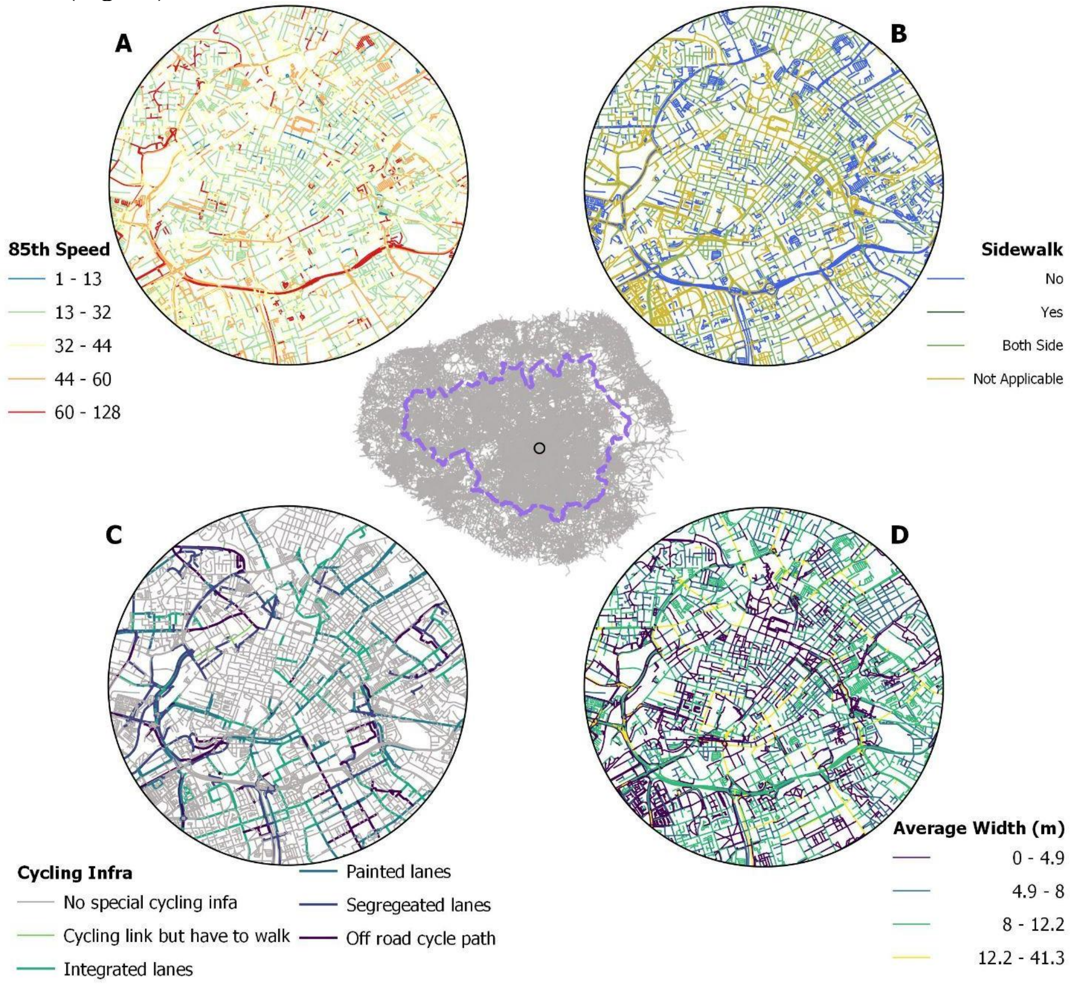

Figure 2 Selected safety-related physical and built link attributes for Manchester city center area.

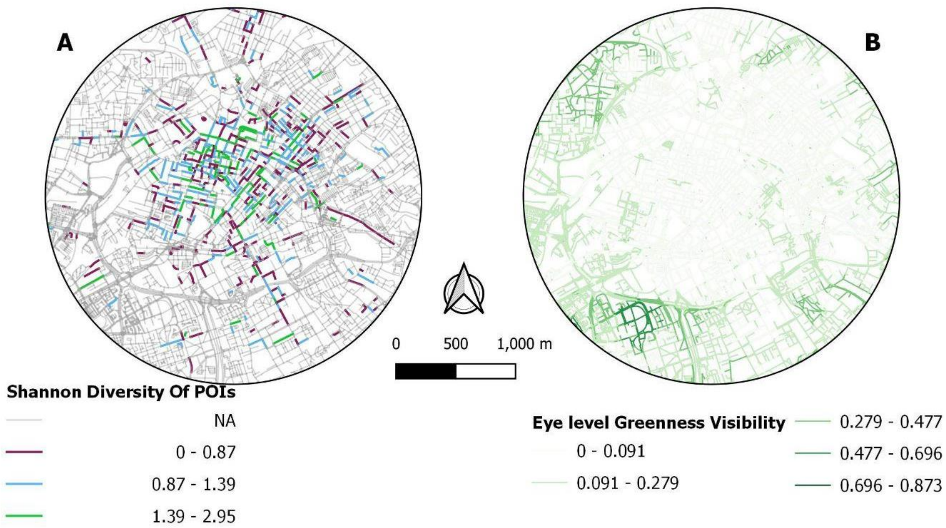

Figure 3 Selected attractiveness-related attributes for Manchester city center area.

Additionally, we also identified spatial patterns of attractiveness attributes for each link (Figure 3). As expected, Figure 3B indicates for the city center area, that eye-level greenness is very low (less than

10% on most links), but the links within this area have a high diversity of POIs (Figure 3A). The contrasting patterns of attractiveness attributes indicate that the road links can be both attractive and unattractive simultaneously depending on the micro-scale environmental attributes surrounding them.

Overall, the spatial patterns of attractiveness and safety-related variables are crucial to understanding the overall experience of journeys on the network, in particular for active travel. These micro-environmental attributes contribute to the perceived impedances for different routes and modes, especially cycling (Orellana and Guerrero, 2019). Currently, we are testing a varying combination of indicators to develop composite indices which might reflect the cycling and walking experience for different uses based on a collection of safety and attractiveness indicators. We would also further validate the combined indicators based on empirical evidence (such as Strava cycling data) and active travel demand modeling. In addition to these activities, further research will address several limitations of this study, such as the inaccuracy of the variables' values stemming from the methodological limitations in the spatial joining process. Another limitation is the incompleteness of the input datasets for the variables' values across unit areas and road classes.

4. Acknowledgements

This study is part of Joining Impact models of transport with spatial measures of the Built Environment (JIBE) project. JIBE was supported by the UKRI-NHMRC Built Environment Prevention Research Scheme (#MR/T038578/1, APP1192788) and this funding is gratefully acknowledged. Papers using background IP or data from other projects with other funders should ensure that this is acknowledged either by citing relevant papers or as appropriate, in the acknowledgments. Sources of fellowship funding for relevant investigators on the manuscript should also be acknowledged: e.g., BGC is supported by an NHMRC Senior Principal Research Fellowship (1107672). The authors acknowledge the support of Cyclestreet (https://www.cyclestreets.net/) for their support in providing Quietness and modal filter data. We also acknowledge the contributions of the TfGM team for their support in collecting data and discussing TfGM's policies.

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