**Developing urban biking typologies: quantifying the complex interactions of bicycle ridership,
bicycle network and built environment characteristics**

Ben Beck¹, Meghan Winters², Trisalyn Nelson³, Chris Pettit,⁴ Meead Saberi⁵, Jason Thompson⁶,
Sachith Seneviratne⁶, Kerry Nice⁶, Simone Zarpelon Leao⁴, Mark Stevenson^{6,7}

1. School of Public Health and Preventive Medicine, Monash University, Victoria, Australia
2. Faculty of Health Sciences, Simon Fraser University, British Columbia, Canada
3. Department of Geography, UC Santa Barbara, United States
4. City Futures Research Centre, University of New South Wales, New South Wales, Australia
5. School of Civil and Environmental Engineering, University of New South Wales, New South
Wales, Australia
6. Melbourne School of Design, The University of Melbourne, Victoria, Australia
7. Melbourne School of Population & Global Health, The University of Melbourne, Victoria,
Australia

Corresponding author:

Dr Ben Beck

School of Public Health and Preventive Medicine, Monash University, Australia

553 St Kilda Rd, Melbourne, VIC 3004

Telephone: +61 3 9903 0316

Email: ben.beck@monash.edu

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ABSTRACT

Background: Extensive research has been conducted exploring associations of built environment characteristics and biking. However, these approaches have often lacked the ability to understanding the interactions of built environment, population and bicycle ridership. To overcome these limitations, this study aimed to develop novel urban biking typologies using unsupervised machine learning methods.

Methods: We conducted a retrospective analysis of travel surveys, bicycle infrastructure and population and land use characteristics in the Greater Melbourne region, Australia. To develop the urban biking typology, we used a k-medoids clustering method.

Results: Analyses revealed 5 clusters. We highlight areas with high bicycle network density and a high proportion of trips made by bike (Cluster 1; reflecting 12% of the population of Greater Melbourne, but 57% of all bike trips) and areas with high off-road and on-road bicycle network length, but a low proportion of trips made by bike (Cluster 4, reflecting 23% of the population of Greater Melbourne and 13% of all bike trips).

Conclusion: Our novel approach to developing an urban biking typology enabled the exploration of the interaction of bicycle ridership, bicycle network, population and land use characteristics. Such approaches are important in advancing our understanding of bicycling behaviour, but further research is required to understand the generalisability of these findings to other settings.

INTRODUCTION

Spatial variation in bicycle ridership exists both within and between cities.¹⁻⁶ Understanding this variation is important for benchmarking and identifying inequities in participation and access to safe and connected bicycling infrastructure for all ages and abilities. It is well known that the presence and quality of bicycling infrastructure has a significant impact on bicycle ridership,⁷ and there is considerable scope for increases in bicycle ridership participation when high-quality and connected infrastructure is provided.⁸ Numerous studies have explored the association between bicycle network, population and land use characteristics, and measures of bicycle ridership (such as mode share).^{2, 9-15} These studies have been important in quantifying the importance of built environment characteristics and connected bicycle networks in enabling bicycling. However, these approaches have been limited in their ability to quantify the complex interactions of these factors. Quantifying this complexity is needed to advance our understanding of how the interplay of bicycle ridership, built environment and bicycle network characteristics vary across space, and to identify areas where previously established associations do not hold true (such as areas where there is a well-established bicycle network, but low bicycle ridership).

Quantifying the complexity of cities has been achieved through approaches such as the development of typologies. As an example, the urban form is often described as the physical configuration of a city that includes the complex relationships between elements such as land use patterns, population and housing densities, infrastructure and amenities, and transport and communication networks.¹⁶ Urban typologies have been developed to simplify this complexity and group areas into similar clusters. They have been used to compare city forms,^{17, 18} develop liveability indices¹⁹ and evaluate transport networks,²⁰ for example.

Clustering approaches, such as those used to develop urban form typologies, have been used in bicycling research as applied to classifying mode share,⁴ bike share schemes,²¹ and bicycle crashes.²² Previous research has also develop bicyclist/population typologies based on individual

characteristics, such as the Geller Typology, which characteristics individuals based on their confidence riding in a variety of road/street/path configurations.^{8, 23, 24} However, to our knowledge, typologies have not previously been used to measure the complexity of the interaction between bicycle mode share, bicycle infrastructure, and population and land use characteristics. Therefore, this study aimed to develop novel urban biking typologies using unsupervised machine learning methods to classify the complex interaction of bicycle ridership, bicycle network, population and land use characteristics.

METHODS

Study design

We conducted a retrospective analysis of travel surveys, bicycle infrastructure and population and land use characteristics in the Greater Melbourne region, Australia.

Setting

The State of Victoria, Australia, has a population of 6.7 million people of which 67% reside in the Greater Melbourne area.²⁵ The Australian Bureau of Statistics (ABS) define seven hierarchical classifications of functional areas in Australia, from mesh blocks (the smallest unit) to the country level (the largest unit). Within these is a functional area known as Statistical Areas Level 2 (SA2), which are medium-sized general-purpose areas, reflecting a community that interacts together socially and economically. SA2s generally have a population range of 3,000 to 25,000 persons, with an average of approximately 10,000 persons. For this study, analyses were restricted to the 309 SA2 areas within Greater Melbourne, reflecting an area of 9,986 km².

Data sources

Bicycle ridership data

Travel survey data were captured through the Victorian Integrated Survey of Travel & Activity (VISTA), coordinated by the Victorian Department of Transport. VISTA is the most robust data available on bicycling in study area. We used data from three waves (2012-14, 2014-16, 2016-18) of the VISTA. VISTA is a survey of day-to-day travel conducted in the Greater Melbourne area and in a single regional centre in Victoria. VISTA randomly selects households to complete a travel diary for a single specified day, using a stratified, clustered sampling methodology. The survey and resulting data are then weighted to generate population-representative data. Since 2012, 16,000 households and 66,000 people have contributed to the VISTA survey. Further information on the VISTA is provided elsewhere.⁶ In this study, we employed a set of combined weights that use the full data set from 2012-2018 to produce statistics weighted to the 2017-18 population. Weights were applied to the SA2 in which the trip originated, and therefore, data reflect where trips commenced and not trip routes or destinations. Unless otherwise specified, data reflect trips made within Greater Melbourne on an average day across the study period. Eligibility for inclusion in this study were participants aged 18 years and older, and trips that had trip origins and destinations within the Greater Melbourne region. The metric of bicycle ridership reported in this study is the proportion of all trips (all modes) made by bike within a SA2 area (based on trip origin).

Bicycle network data

We used Open Street Map (OSM) data to characterise bicycle infrastructure in the study region. We captured infrastructure at a single time-point, which was the final year of the study period (2018). 2018 OSM data was downloaded for the Greater Melbourne region from Geofabrik.²⁶ Bicycle infrastructure is coded by OSM contributors according to the OSM Wiki²⁷ and stratified into: on-road bicycle lanes, protected on-road bicycle lanes, and off-road paths (off-road dedicated bicycle path, off-road shared path (shared with pedestrians), and footways where bicycling is legal). Further information on this method is described previously.⁶

Population and land use characteristics

Population characteristics (population density) were sourced from the ABS.²⁸ Land use characteristics were derived from ABS Mesh Blocks. Mesh Blocks are the smallest geographical area defined by the ABS and broadly identify land use (e.g. residential, commercial, primary production, parks).²⁹

Procedures

The development of an urban biking typology was informed by our previous research that explored the association between bicycling network characteristics and bicycle ridership,³⁰ and prior research. Specifically, measures of the length of the bicycle network, network centrality, and topography have previously been demonstrated to be associated with bicycle ridership.^{11, 13, 15, 31} Other population and land use characteristics, such as population density, and land use mix, have also previously been demonstrated to be associated with bicycle ridership.^{10, 12, 15}

Similar to prior studies that have developed typologies/indices,^{14, 19} the final set of indicators chosen for inclusion in the urban biking typology reflected a balance of parsimony and pragmatism. We acknowledge that the included indicators do not capture the full complexity of bicycle ridership and urban form, but represent key attributes that have previously been associated with bicycle ridership.

For measures of bicycle ridership, we selected the proportion of trips that were made by bike, per SA2. For characteristics of the bicycle network, we drew from our previous research to calculate measures of bicycle network length (stratified by bicycle infrastructure that was off-road and on-road), network centrality (degree centrality), and topography.³⁰ To calculate degree centrality, we firstly characterised the OSM bicycle network data as a graph, where the links represent the bicycle network infrastructure (e.g. off-road path or on-road bike lane) and the nodes represent the intersections between network links (e.g. street and bicycle network links). To process the OSM data, we ‘contracted’ the network to remove network artefacts and ensure that the networks contained only edges that directly connected junctions. Topography was measured using the average weighted slope of the bicycle network within the SA2. Elevation data was sourced from the

Victorian Government ‘Vicmap Elevation’ product, which includes a Digital Elevation Model (DEM) at 10m grid resolution³² and applied to the OSM network using the ‘slopes’ package in R.³³ Further information on these methods is described previously.³⁰

To quantify land use mix, we used the Entropy Index.³⁴ The Entropy index, which varies from 0 to 1, takes into account the relative percentage of land use types within an area. Therefore, higher levels of Entropy correspond with greater land use mix. Similar to prior research,^{10, 35} we selected a subset of land use types that have been shown to be associated with cycling^{9, 10, 36}: residential, commercial and education. To calculate the Entropy Index, the distribution of land use types in each SA2 was determined through the use of ABS Mesh Block land use classifications. The Entropy Index was then calculated using the following equation³⁴:

$$ENT = \frac{-[\sum_{j=1}^k P^j \ln(P^j)]}{\ln(k)}$$

Where ENT is the Entropy Index; P^j is the percentage of each land use type j in the area (with the denominator being the summed area for land use classes of interest); and k is the number of land use types.

Analysis

To develop the urban biking typology, we used a commonly employed unsupervised machine learning clustering approach known as Partitioning Around Medoids (PAM),³⁷ also simply referred to as k-medoids.³⁸ K-medoid is a robust alternative to k-means clustering, which is sensitive to noise and outliers.³⁹ K-medoid applies clustering algorithms to find k clusters in n objects by firstly identifying representative objects (the Medoids) for each cluster (the representative example of the members within that cluster), and then assigns each object to the nearest Medoid.³⁹ The following indicators were included: the proportion of trips made by bike, population density, land use entropy, network density, off-road bicycle network length, on-road bicycle network length, and average

weighted slope. Data for each SA2 were standardised and z-scores are presented. The number of clusters was guided by use of 'NbClust' (an R package for determining the relevant number of clusters in a dataset)⁴⁰ and the authors' knowledge of the study area. A sensitivity analysis was conducted to evaluate the impact on the urban bicycle typology of applying weights to the SA2 in which the trip was completed (the destination), as opposed to the SA2 in which the trip originated. To summarise the characteristics of each cluster, we report the proportion of land area and population captured by each cluster, and report the following measures of bicycle ridership drawn from the VISTA travel survey data: the proportion of all bike trips that are captured within each cluster, the proportion of bike trips made by females, and the proportion of bike trips made for work and recreational purposes.

Data were prepared using the statistical software package R v4.0.3 (R Core Team, 2021) and the integrated development environment RStudio (RStudio 2020, Boston, MA, USA), using the 'survey', 'srvyr', 'dodgr', 'igraph', 'slopes', 'cluster', 'factoextra', 'NbClust' and 'tmap' libraries.

Ethical approval

Ethical approval for this study was provided by the Monash University Human Research Ethics Committee (Project ID: 29210).

RESULTS

On an average day in Greater Melbourne, there were 180,393 trips made by bicycle, reflecting 1.7% of all trips. The median proportion of trips made by bicycle per SA2 was 0.74% (Q1: 0.26%; Q3: 1.61%) with the highest proportion of trips concentrated in the inner Melbourne region (Figure 1). The median length of off-road bicycle infrastructure per SA2 was 5.98 km (Q1: 2.51 km; Q3: 10.47 km) and the median length of on-road bicycle infrastructure per SA2 was 2.33 km (Q1: 0.23 km; Q3:

5.78 km). Network characteristic data are provided in Table 1 and Figure 2. Median land use entropy was 0.24 (Q1: 0.15; Q3: 0.37) (Table 1 and Figure 3).

K-medoid analysis identified 5 clusters (Figure 4 and Figure 5):

- Cluster 1: High population density, high bicycle network density and a high proportion of trips made by bicycle
- Cluster 2: Average population density, average on-road bicycle network length, below average proportion of trips made by bicycle
- Cluster 3: Below average population density, low land use entropy, below average bicycle network density, low proportion of trips made by bicycle
- Cluster 4: Below average population density, high off-road and on-road bicycle network length, average network density, below average proportion of trips made by bicycle
- Cluster 5: Low population density, low land use entropy, low network density, high average weighted slope, below average proportion of trips made by bicycle

A map of clusters by SA2 is presented in Figure 5. Cluster 1 was generally observed in inner city areas, Cluster 2 was generally observed in inner urban areas surrounding Cluster 1, Clusters 3 and 4 were generally observed in middle and outer fringe areas, and Cluster 5 was observed exclusively in outer fringe areas. Cluster 1 captured 12% of the population of Greater Melbourne, but 57% of all bike trips (Table 2). Cluster 2 captured 43% of the population of Greater Melbourne and 26% of all bike trips. The proportion of bike trips made by females varied from 23% in Cluster 3 to 41% in Cluster 1. The proportion of bike trips made for work purposes varied from 16% in Cluster 5 to 40% in Cluster 1, while the proportion of bike trips made for recreational purposes varied from 16% in Cluster 1 to 53% in Cluster 5 (Table 2).

Summary characteristics across SA2s in each cluster are presented in Table 3. Median values of the proportion of trips made by bike varied from 0.05% in Cluster 3 (Q1: 0%, Q3: 0.57%) to 5.39% in

Cluster 1 (Q1: 3.61%, Q3: 6.53%). Median network density ranged from 0.05 in Cluster 5 (Q1: 0.02, Q3: 0.17) to 4.1 in Cluster 1 (Q1: 2.61, Q3: 5.15).

A sensitivity analysis was conducted using data on where the trip was completed (the destination), as opposed to where the trip originated. The clustering and spatial distribution of clusters was similar between the two methods (see Supplementary Material) with 280 of 309 SA2s (91% of all SA2s) having the same cluster assignments between the two methods.

DISCUSSION

In this study, we developed a novel urban biking typology that combined measures of bicycle ridership, bicycle network, and population and land use characteristics, and mapped these clusters across a large metropolitan region. These findings are important as they provide a mechanism to understand the complex interactions between a diversity of factors related to bicycle ridership.

Extensive research has been conducted exploring associations of built environment characteristics and bicycle ridership.^{15, 41} These studies have demonstrated the importance of bicycle network accessibility, connectivity and comfort, land use mix, population characteristics (including socioeconomic status) and topography have on bicycle ridership.^{9, 10, 12, 14, 15} The vast majority of these prior studies have used various forms of regression modelling to explore associations between these built environment and population characteristics, and bicycle ridership, typically generating single coefficients to quantify the association. These approaches are limited in their ability to understand the interactions of built environment, population and bicycling characteristics. For example, numerous studies have demonstrated positive associations between bicycle network length and bicycle ridership.^{11, 31, 42} However, there may be areas in which there is a relatively high bicycle network length, but low bicycle ridership. In this study, we overcome these limitations by

applying a novel clustering approach that integrates built environment, population and bicycling characteristics.

Our results demonstrate a number of interesting findings. Firstly, Cluster 4 reflects areas with average bicycle network density (and above average on-road and off-road bicycle network length) but a low proportion of trips by bicycle. Understanding the drivers of low bicycle riding in these areas, particularly as many of these areas in middle and outer urban areas, is needed to advance our understanding of how to enable bicycle riding and how to enhance equity. It may be in these areas that on-road painted bicycle lanes (99.3% of on-road bicycle infrastructure in Melbourne⁶) are inadequate in providing safe and comfortable spaces for bicycle riding; the limitations of on-road painted bicycle lanes are well established in the literature.⁴³ It may also be that distance required to reach destinations of interest by bike exceeds a tipping point, and consideration for support of e-bikes or integration with public transport may assist in increasing bicycle mode share in these areas. Secondly, Cluster 5 reflects areas with low network density (but average off-road bicycle network length), high average weighted slope, low population density, but a near-average proportion of trips made by bicycle. This is somewhat surprising as these network, built environment and population characteristics are normally negatively associated with bicycle ridership. It may be that in these areas a limited but well-connected network of off-road bicycle paths facilitates recreational bicycling. This is supported by our finding that 53% of trips in this cluster were for recreational purposes. It is, however, important to note that even an 'average' proportion of trips made by bicycle in Greater Melbourne is still a very low mode share (0.74% of all trips) and significant investment is required to increase bicycle mode share, particularly to ensure equitable access to safe and connected infrastructure across entire metropolitan regions.

The approach developed in this study has multiple potential applications. It provides a methodological approach for how bicycle ridership and bicycle infrastructure can be monitored and evaluated within and between cities. However, clustering approaches can be unstable and are

sensitive to model inputs.⁴⁴ Therefore, generalising this approach to other cities, both in Australia and internationally, requires further development and refinement. There are opportunities to leverage this typology when considering how to understand behaviour and develop interventions to increase bicycling. For example, identifying a discrete set of homogenous areas within cities enables more efficient tailoring of interventions (whether behavioural or infrastructural). It may also assist with sampling when considering capturing the heterogeneity of populations across large geographical areas. It is well recognised that challenges exist in ensuring that samples are either fully or proportionally representative of the populations or activities being considering in spatial and transport planning.⁴⁵ By reducing the often large number of spatial areas that comprise metropolitan regions, for example, into a discrete set of homogenous clusters, we reduce these sampling biases and provide a sampling framework that can be used to maximise representativeness when collecting mobility data. In our specific application, the urban biking typology enables targeted sampling of mobility data, such as GPS data, to maximise representativeness across a heterogenous area of bicycle ridership, infrastructure, population and land use characteristics.

Given the massive increase in big spatial data relevant to urban environments,^{46, 47} the need for tools to aggregate data into typologies is critical for data integration and allows characterization of the city using multiple data sets. Unsupervised machine learning approaches to clustering data is an important approach to characterizing and mapping cities. However, the typologies generated will be dependent on the input variables. Here, we define topologies based on variables known to be important to bicycling and that support our goals of stratifying urban settings to optimize bicycling related data sampling. A similar approach can be used for other transportation and urban planning applications, and by modifying input variables the typology can reflect the needs of the application of interest. As such, our approach is a useful framework.

We acknowledge a number of study limitations. Further, survey weights were applied to the SA2 in which the trip originated, and the data presented do not reflect trips that occurred across multiple

SA2s. However, our sensitivity analysis showed that the clustering and spatial patterns of clusters were similar when using trip origins and trip destinations. It is also important to acknowledge the variation in size of the spatial areas (SA2s) used in this study; we acknowledge the modifiable areal unit problem and the potential statistical biases this produces. Additionally, due to the relatively low number of trips made by bicycle, we were unable to stratify by trip purpose at the SA 2 level to include in clustering (for example, the proportion of trips that were for recreational purposes). To characterise bicycle infrastructure, we were reliant on OSM data. OSM data has been reported to have varied accuracy in international settings,⁴⁸ and the accuracy of OSM data is unknown in our region. Further, the bicycle network measures that we employed in this study were simplistic due to the absence of bicycle infrastructure data that would enable a more robust evaluation of the accessibility, connectivity and comfort of infrastructure. Further research is required to advance the measurement of these bicycle network parameters. Land use measures were based on ABS Mesh Blocks, which reflect dominant land use and therefore may not pick up mixed land use at a finer scale. Furthermore, while we used a data-driven approach to the development of typologies, clustering methods are sensitive to model inputs.⁴⁴ For the selection of variables, we took an approach that was driven by availability of data and with the approach of achieving a balance of parsimony and pragmatism. We did not consider factors such as access to public transport, social infrastructure, employment and greenspace. Similarly, the selection of the number of clusters is a balance between achieving sufficient separation of clusters and complexity. Additionally, we chose not to use a spatially-weighted clustering approach as we were interested in cluster variation in near neighbours. Regardless, the final typology demonstrated substantial spatial clustering. Finally, and as noted above, validation of this approach and the typology developed in other Australian and international cities is needed to confirm generalisability.

CONCLUSION

In this paper, we present a novel approach to developing an urban biking typology, which classifies the interaction of bicycle ridership, bicycle network, population and land use characteristics. This methodological approach may be used to explore bicycle ridership and bicycle networks within and between cities, be used to enhance sampling of mobility data, and be used to inform the development of transport policies and targeted interventions to increase bicycle ridership.

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DISCLOSURE STATEMENT

There are no conflicts of interest to declare.

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TABLES

Table 1: Summary statistics of biking, network, population and land use data across SA2s in Greater Melbourne.

Measure	Greater Melbourne [median (Q1, Q3)]
Bicycle ridership data	
Proportion of trips made by bike (%)	0.74 (0.26, 1.61)
Network data	
Off-road bicycle network length (km)	5.98 (2.51, 10.47)
On-road bicycle network length (km)	2.33 (0.23, 5.78)
Network density	1.19 (0.50, 1.97)
Average weighted slope (%)	1.84 (1.15, 2.84)
Population and land use data	
Population density (persons per square km)	2075 (947, 3010)
Land use entropy	0.24 (0.15, 0.37)

Note: Q1 = quartile 1; Q3 = quartile 3.

Table 2: Summary characteristics for each cluster. Note that the bicycle ridership data reflects the distribution of each measure of ridership across the five clusters (ie. the rows sum to 100%).

Characteristics	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Coverage					
Proportion of land area	1%	11%	40%	24%	24%
Proportion of population	12%	43%	18%	23%	4%
Bicycle ridership data					
Proportion of all bike trips	57%	26%	3%	13%	2%
Proportion of bike trips made by females	41%	24%	23%	33%	25%
Proportion of bike trips made for work purposes ^a	40%	30%	18%	16%	18%
Proportion of bike trips made for recreational purposes ^a	16%	34%	61%	40%	53%

Note: a) Education, social and other trip purposes not shown.

Table 3: Summary characteristics for each cluster reflecting the median, Q1, Q3 and minimum and maximum values across SA2s in each cluster.

Characteristics	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Number					
Number of SA2s	33	132	70	55	19
Bicycle ridership data					
Proportion of trips made by bike (%)	Median: 5.39, Q1: 3.61, Q3: 6.53; [Min: 2.12, Max: 10.84]	Median: 0.97, Q1: 0.42, Q3: 1.47; [Min: 0, Max: 3.22]	Median: 0.05, Q1: 0, Q3: 0.57; [Min: 0, Max: 2.53]	Median: 0.74, Q1: 0.46, Q3: 1.27; [Min: 0, Max: 3.49]	Median: 0.54, Q1: 0, Q3: 1.32; [Min: 0, Max: 3.25]
Network data					
Off-road bicycle network length (km)	Median: 4.21, Q1: 1.88, Q3: 7.16; [Min: 0.11, Max: 15.11]	Median: 5.04, Q1: 2.29, Q3: 7.96; [Min: 0, Max: 15.27]	Median: 6.12, Q1: 2.01, Q3: 9.89; [Min: 0, Max: 18.59]	Median: 17.14, Q1: 11.06, Q3: 25.31; [Min: 1.56, Max: 58.86]	Median: 3.55, Q1: 0.93, Q3: 10.43; [Min: 0, Max: 25.12]
On-road bicycle network length (km)	Median: 6.3, Q1: 4.18, Q3: 11.04; [Min: 0, Max: 25.43]	Median: 2.23, Q1: 0.58, Q3: 3.76; [Min: 0, Max: 11.14]	Median: 0.7, Q1: 0, Q3: 2.19; [Min: 0, Max: 7.14]	Median: 8.08, Q1: 4.58, Q3: 10.64; [Min: 0, Max: 19.18]	Median: 0, Q1: 0, Q3: 0.17; [Min: 0, Max: 4.23]
Network density	Median: 4.1, Q1: 2.61, Q3: 5.15; [Min: 0.78, Max: 8.88]	Median: 1.15, Q1: 0.77, Q3: 1.65; [Min: 0, Max: 3.15]	Median: 0.66, Q1: 0.11, Q3: 1.45; [Min: 0, Max: 3.58]	Median: 1.76, Q1: 0.66, Q3: 2.44; [Min: 0.08, Max: 6.58]	Median: 0.05, Q1: 0.02, Q3: 0.13; [Min: 0, Max: 1.05]
Average weighted slope (%)	Median: 1.56, Q1: 1.19, Q3: 2.12; [Min: 0.3, Max: 3.72]	Median: 2.11, Q1: 1.21, Q3: 2.8; [Min: 0, Max: 5.42]	Median: 1.53, Q1: 0.86, Q3: 2.62; [Min: 0, Max: 4.55]	Median: 1.27, Q1: 0.96, Q3: 2.18; [Min: 0.41, Max: 5.35]	Median: 7.24, Q1: 5.48, Q3: 8.01; [Min: 4.16, Max: 17.66]
Population and land use data					
Population density (persons per square km)	Median: 5658, Q1: 4132, Q3: 7581; [Min: 1896, Max: 20725]	Median: 2544, Q1: 1948, Q3: 3149; [Min: 38, Max: 7078]	Median: 1250, Q1: 130, Q3: 2004; [Min: 0, Max: 3424]	Median: 1411, Q1: 599, Q3: 2111; [Min: 23, Max: 3505]	Median: 124, Q1: 44, Q3: 653; [Min: 0, Max: 2135]
Land use entropy	Median: 0.46, Q1: 0.28, Q3: 0.65; [Min: 0.08, Max: 0.86]	Median: 0.3, Q1: 0.22, Q3: 0.39; [Min: 0.08, Max: 0.9]	Median: 0.11, Q1: 0.06, Q3: 0.16; [Min: 0, Max: 0.24]	Median: 0.28, Q1: 0.19, Q3: 0.38; [Min: 0.05, Max: 0.97]	Median: 0.1, Q1: 0.05, Q3: 0.12; [Min: 0, Max: 0.42]

FIGURES

Figure 1: Proportion of all trips that were made by bike (per SA2).

Figure 2: Network characteristics (per SA2). A) Off-road bicycle network length; B) On-road bicycle network length; C) Network density; D) Average weighted slope.

Figure 3: Population and land use characteristics (per SA2). A) Population density (persons per square km); B) Land use entropy.

Figure 4: Plot of cluster characteristics with the y-axis reflecting the Z-score.

Figure 5: Map of the clusters by SA2.

SUPPLEMENTARY MATERIAL

Sensitivity analysis: the impact of trip origin vs trip destination

An additional sensitivity analysis was conducted using data on where the trip was completed (the destination), as opposed to where the trip originated. The results for data reflecting where the trip was completed are presented below.

Figure 6: Plot of cluster characteristics with the y-axis reflecting the Z-score.

Figure 7: Map of the clusters by SA2.