AGILE: GIScience Series, 5, 56, 2024. https://doi.org/10.5194/agile-giss-5-56-2024
Proceedings of the 27th AGILE Conference on Geographic Information Science, 4–7 Sept. 2024.
Editors: Alison Heppenstall, Mingshu Wang, Urska Demsar, Rob Lemmens, and Jing Yao.
This contribution underwent peer review based on a full paper submission.


# Impact of transit catchment size on the integration of shared e-scooters in the public transport system

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**Abstract.**
E-scooter sharing has been commonly used to integrate public transport systems in many cities worldwide. Accurately modeling integration between shared e-scooters and public transport is important for multi-modal urban transportation development and management. However, the effects of catchment size are scarcely considered while modeling their integration by widely adopting the method based on the transit catchment area in previous studies. In this paper, we systematically quantify the impact of the size of the transit catchment area on the integration of shared e-scooters in the public transport system from statistical, temporal, and spatial perspectives. A case study is implemented in Stockholm, Sweden. The results indicate that the transit catchment size has a significant impact on their integration, especially on spatial patterns. This research calls for more attention to consider such catchment size effects to ensure the validity of integration results for urban mobility research and practice.

**Keywords.** Shared e-scooter, Public transport, Integration, Transit catchment size, Spatial and temporal analysis

## 1 Introduction

E-scooter sharing services, known as an environmentally friendly, convenient, and flexible transport mode, have been popularized in many cities worldwide over the past few years (Li et al., 2022). Since e-scooter usage is mainly for short trips, shared e-scooters are particularly suitable for supporting public transport to deal with the first-mile-last-mile (FMLM) problem. (Zuniga-Garcia et al., 2022; Huang et al., 2024). The FMLM problem in public transport is often perceived as the disconnectivity between public transport stations and an individual's origin or destination during travel (Chandra et al., 2013), which is one of the most important factors determining whether an individual will choose public transport. Hence, solving the FMLM problem is crucial for creating a seamless and efficient transportation network for sustainable urban mobility.

The research on the integration between shared micromobility and public transport to tackle the FMLM problem has attracted notable attention in recent years. The related studies are mainly concentrated on bike-sharing services (Campbell and Brakewood, 2017; Lu et al., 2018; Radzimski and Dzięcielski, 2021; Kim, 2023), with relatively limited attention to e-scooter sharing services. It is thus required to further investigate the integration between shared e-scooters and public transport to extend current knowledge and understanding to facilitate their proper integration into the existing public transport systems.

A number of scholars attempted to explore the interplay relationships between shared e-scooters and public transport based on e-scooter trip data and public transport station data over the past three years (Luo et al., 2021; Ziedan et al., 2021; Guo et al., 2023; Li et al., 2024). It is found that the relationships between them can be both complementary and competitive. The commonly used method to recognize the relationships between them is by defining a transit catchment area based on walking distance. If both the origin and destination of an e-scooter trip are within transit catchment areas, the trip can be considered competitive. In contrast, if either the origin or destination of an e-scooter trip is within a transit catchment area, the trip can be considered complementary (Luo et al., 2021). The size of the catchment area is often determined as the range between 50m and 250m (Yin et al., 2024). One obvious problem with the method is that the predefined transit catchment area may significantly influence the findings obtained from modeling the integration between shared e-scooters and public transport. However, it is still unclear to what extent the size of the transit catchment area can impact their integration.

To fill the above-mentioned research gap, this study aims to conduct a sensitivity analysis to identify how the predefined size of the transit catchment area influences the derived spatial and temporal patterns of the integration between shared e-scooters and public transport. The sensitivity analysis is implemented with a case study dataset from Stockholm, Sweden.

## 2 Literature review

Previous studies have explored the integration or relationship between shared e-scooters and public transport using different data sources. In the early survey-based studies, the investigations are mainly focused on assessing users' perceptions or willingness to use e-scooters as a solution to the FMLM problem. For instance, Buehler et al. (2021) analyzed the changes in travel behavior and preferences among e-scooter riders and non-riders from pre and post e-scooter system launch surveys, and reported that e-scooters can be a viable travel mode for the first or last mile for public transport. Nikiforiadis et al. (2021) conducted a survey in the city of Thessaloniki, Greece to uncover the user profiles and attitudes towards e-scooter use, and indicated that shared e-scooters mostly replaced walking and public transport trips. Yan et al. (2023) evaluated the potential for shared e-scooters to complement public transit based on a survey in Washington D.C. and Los Angeles. It was found that shared e-scooters as a last-mile feeder mode to transit have been used among the survey participants.

In recent years, vehicle availability data has been available from all micro-mobility operators to the potential users to locate the available e-scooters at a city scale (Zhao et al., 2021). E-scooter trips extracted from such data have gradually become the main data sources to explore the usage patterns of shared e-scooters. A series of recent studies have examined the integration and relationship between shared e-scooters and public transport based on empirical e-scooter trip datasets. For example, Luo et al. (2021) identified the potential impacts of shared e-scooters on the existing bus system at the trip level in Indianapolis City. It was reported that 27% and 29% of e-scooter trips could potentially be competitive and complementary with the bus system respectively. Ziedan et al. (2021) quantified the impact of shared e-scooters on bus ridership with a case study in Louisville, Kentucky. The results suggested that shared e-scooters could potentially complement express bus routes to deal with the FMLM problem. Guo et al. (2023) explored the spatiotemporal variations of the relationships between shared e-scooters and public transport using the e-scooter trip data in Stockholm and Helsinki. It was found that Stockholm displayed more complementary trips than competitive trips while Helsinki showed a reversed pattern. Li et al. (2024) conducted a comprehensive comparative analysis of 124 European cities to investigate the integration between shared e-scooters and public transport.

The above-mentioned studies all recognized the integration between shared e-scooters and public transport by defining a catchment area for each public transport station and examining their spatial relationships with the origins and destinations of the e-scooter trips. We summarized the literature to display the sizes of the predefined transit attachment areas and the selected study areas, as shown in Table 1. Overall, various buffer sizes have been specified for modeling the integration between shared e-scooters and public transport. However, little attention has been paid to uncovering the impact of the size of the transit catchment area on their integration. This study will bridge the gap via a sensitivity analysis.

**Table 1.** The sizes of predefined transit catchment areas in previous e-scooter sharing studies

| Reference | Catchment size | City |
|---|---|---|
| Luo et al. (2021) | 400 m | Indianapolis |
| Yan et al. (2021) | 0.25 mile | Washington, D.C. |
| Ziedan et al. (2021) | 0.1 mile | Louisville |
| Ma et al. (2022) | 300 m | Washington, D.C |
| Guo et al. (2023) | 0.1 mile | Stockholm and Helsinki |
| Li et al. (2024) | 50 m | 124 European cities |

## 3 Methodology

### 3.1 Data and software availability

The data was collected in Stockholm, which is the largest city in Sweden. The trip records of shared e-scooters were collected from a micro-mobility operator from September 1st to September 30th, 2021. The abnormal trips were filtered out firstly based on the criteria of distance (more than 100m and less than 10 km) and duration (more than 1 minute and less than 1.5 hours). After the data preprocessing, the dataset contains 771,296 trip records. Each trip record contains information on the start/end location and time, trip length, and trip duration. In addition, public transport station data was collected from OpenStreetMap (OSM) to measure the integration relationship between shared e-scooters and public transport. Figure 1 shows the study area that covers the active area of shared e-scooters in Stockholm. The red points represent the public transport stations.

The whole study is conducted on a computer with Intel(R) Core(TM) i7-4930K CPU 3.40GHz and 32.0 GB RAM, and the program is coded with Python language. ArcGIS software is also used to generate the kernel density maps.

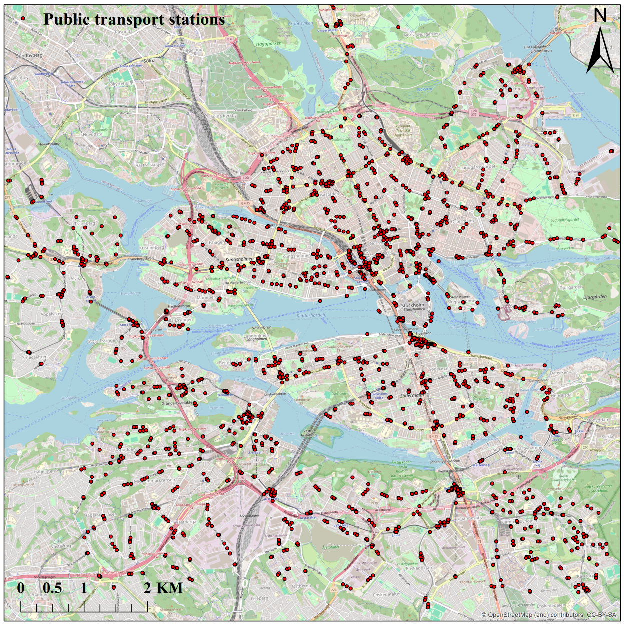



**Figure 1.** Study area.

### 3.2 Model the integration

In this study, we define and model the integration between shared e-scooters and public transport at the trip level based on the method in previous studies (Luo et al., 2021; Guo et al., 2023; Li et al., 2024). This method is straightforward and commonly used, which classifies e-scooter trips into different categories based on the distance between the origin and destination of an e-scooter trip and nearby public transport stations. Each category of e-scooter trips corresponds to one type of integration relationship between shared e-scooters and public transport.

Previous studies have indicated three types of typical relationships between them, including competitive, complementary, and others (Luo et al., 2021). In this paper, we further divide the complementary trips into first-mile (FM) and last-mile (LM) trips. Concretely, one e-scooter trip is considered FM type to support public transport when the destination is within the catchment area of its nearest public transport station, and the origin is not within the catchment area of its nearest public transport station. Conversely, one e-scooter trip is considered LM type to support public transport when the origin is within the catchment area of its nearest public transport station, and the destination is not within the catchment area of its nearest public transport station. If both the origin and destination are within the catchment areas of their nearest public transport stations, the e-scooter trip is regarded as a competitive type. It implies that public transport can satisfy the travel demand of this trip. Otherwise, if both the origin and destination are not within a catchment area of a public transport station, the e-scooter trip is regarded as others.

### 3.3 Explore the effects of catchment size

As described in section 3.2, the defined integration relationships between shared e-scooters and public transport rely heavily on the catchment area size of the public transport station. In this study, we explore the effects of catchment size on the integration by conducting a sensitivity analysis based on the complementary trips.

The modeled integration between shared e-scooters and public transport is measured and described from statistical, temporal, and spatial perspectives. First, statistical analysis is conducted to compare the typical mobility indicators, including trip distance and duration for different catchment sizes. Second, for the temporal analysis, we examine the temporal distribution of frequency of the FM and LM trips for each catchment size on an hourly basis on both weekdays and weekends. The hourly number of trips is averaged by day of the week for the data during one month. Third, we evaluate the spatial distribution of the origins of FM trips and destinations of LM trips respectively for each catchment size using kernel density estimation (KDE). These locations usually represent the places with low public transport accessibility.

## 4 Results

In this experiment, the sensitivity analysis is implemented by specifying a range of transit catchment sizes between 50m and 500m with an interval of 50m.

### 4.1 preliminary analysis of the integration results

We first analyze the proportions of four types of e-scooter trips based on their integration relationships, and how the proportions vary across the different sizes of transit catchment areas, as shown in Figure 2. It can be observed that the proportions of competitive trips are increasing with the increment of the catchment sizes. This is because public transport stations will cover larger areas when the size of transit catchment areas becomes higher, thereby leading to more competitive trips. On the contrary, the proportions of complementary trips do not show a monotonic decreasing trend with the increment of the catchment sizes. The proportion reaches the peak with the catchment size of 100m. Meanwhile, the FM and LM trips present similar proportions for each catchment size. In addition, the trips of 'others' display a decreasing trend. When the catchment size is larger than 300m, the proportions become less than 1%. It implies that users almost can always find a public transport station close to either their origin or destination when they are willing to walk more than 300m. This also reflects the convenience of the public transport system in Stockholm.

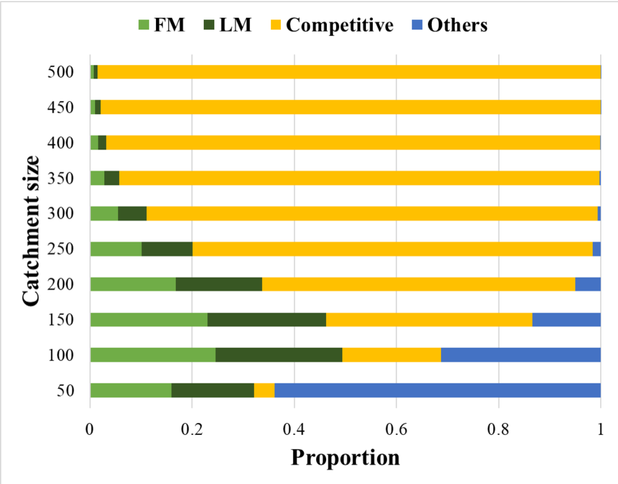



**Figure 2.** Proportions of different types of e-scooter trips.

### 4.2 Statistical analysis

In this section, the statistical distributions of trip distance and duration are compared between different sizes of transit catchment areas, as shown in Figure 3. It can be observed that the catchment size has similar influences on the two indicators. With regards to trip distance, the minimum normal values and median values are around 100m and 1 km respectively for all the catchment sizes, while the maximum normal values increase from 3.4 km (catchment size of 50 m) to 4.9 km (catchment size of 500 m). The changes become remarkable when the transit catchment size exceeds 300m. Similarly, the minimum normal values and median values of trip duration are around 1 minute and 7 minutes respectively for all the catchment sizes, while the maximum normal values increase from 24 minutes (catchment size of 50 m) to 31 minutes (catchment size of 500 m).

### 4.3 Temporal analysis

In this section, we examine the hourly variations of the average number of trips for FM and LM categories on weekdays and weekends. To save space, only the catchment sizes of 100m, 200m, 300m, 400m, and 500m are compared in this analysis, as shown in Figure 4. It can be observed that the variations in the average number of FM and LM trips display the same patterns on workdays and weekends. The plot by the time of workday displays that the average numbers of FM and LM trips present two obvious peaks during the morning (i.e. 8:00–9:00) and evening (i.e. 17:00–18:00), which corresponds to the two commuting peaks. Note that the evening peak is higher than the morning peak indicating more usage of e-scooters after work to solve the first-mile-last-mile problem. On the contrary, the long time period (i.e. 14:00-17:00) in the afternoon becomes the peak on weekends.

We further explore the effects of catchment size on the temporal patterns by visual comparison. It can be observed that the impact of the transit catchment size on the temporal patterns becomes larger when the catchment size exceeds 300m.

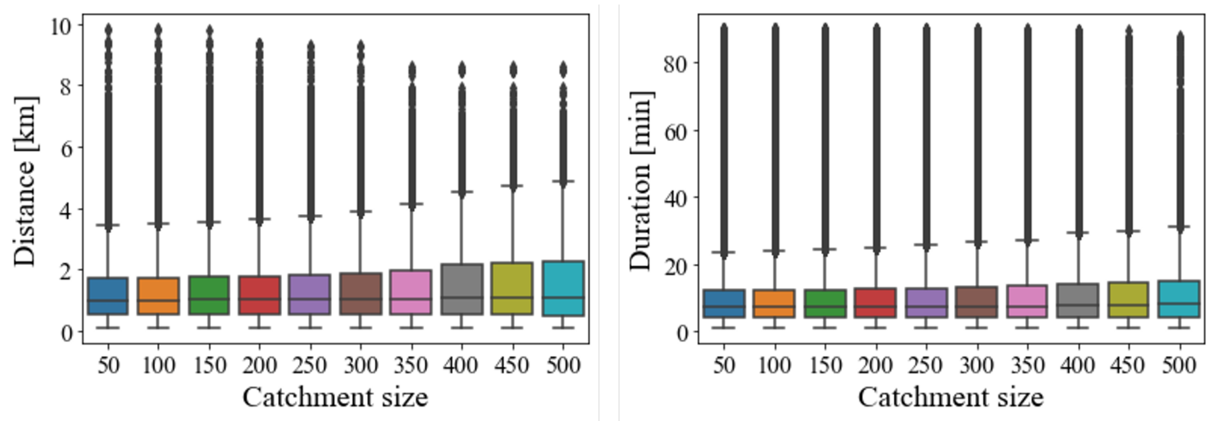
### 4.4 Spatial analysis

In this section, how the transit catchment size influences the spatial patterns of FM and LM trips is further explored. Figure 5 displays the spatial distributions on the origins of FM trips and the destinations of LM trips across different catchment sizes using kernel density maps. The red color represents high density while the green color represents low density. To avoid the kernel density maps occupying too much space, we only compare the maps calculated from the FM and LM trips with the catchment sizes of 100m, 300m, and 500m.

As shown in Figure 5, it can be observed that the transit catchment size has a remarkable influence on the spatial distributions. For the kernel density maps with a catchment size of 100m, the hot spots are mainly concentrated in the downtown area, such as Stockholm Central Station, Hamngatan (shopping street), Skeppsbron (one of the main traffic routes in Old Town, and also the oldest wharf in Stockholm, Götgatan (one of the three classic entry and exit routes to and from Stockholm). For the kernel density maps with a catchment size of 300m, the hot spots gradually spread outside, and the number of hot spots also becomes lower. As can be seen from the kernel density maps with a catchment size of 500m, all the hot spots in the city center disappeared. The high-density areas are all distributed outside the E4/E20 Motorways. Another interesting finding is that the origins of FM trips and the destinations of LM trips present similar spatial distribution given a certain size of the transit catchment area. This reflects a regular human mobility pattern within a city. The origins of FM trips and the destinations of LM trips represent the locations where public transport accessibility is low.

## 5 Conclusion

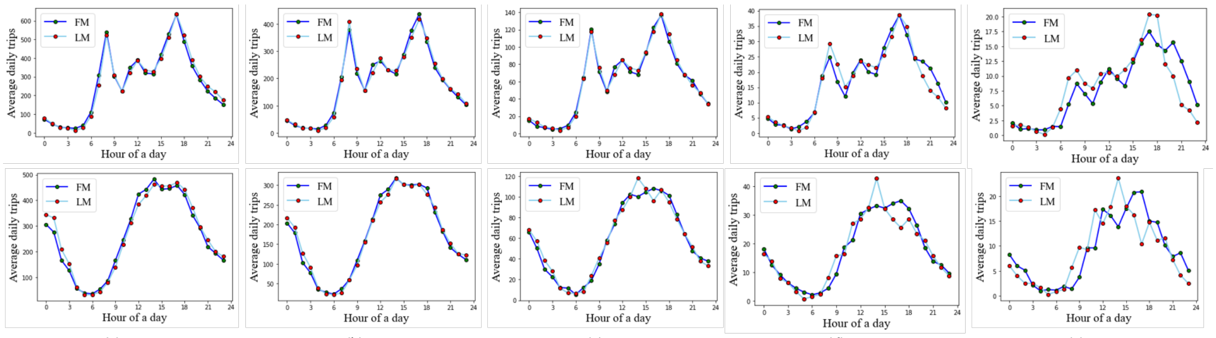
Shared e-scooters have been widely used for people's short- and medium-distance travel to solve the first-mile and last-mile problems in public transport. One common approach to modeling the integration between shared e-scooters and public transport is to identify the spatial relationships between the origins and destinations of e-scooter trips and catchment areas of public transport stations. However, there is no study to systematically quantify the impact of the transit catchment size on the integration of shared e-scooters in the public transport system at a fine spatial and temporal scale. In this paper, we explore the impact of the transit catchment size on their integration at the trip level from statistical, temporal, and spatial per-




(a) Trip distance

(b) Trip duration

**Figure 3.** Basic statistics of trip distance and duration.




(a) 100m (b) 200m (c) 300m (d) 400m (e) 500m

**Figure 4.** Temporary analysis of trip frequency on weekdays and weekends across different catchment sizes. The first row is for weekdays, and the second row is for weekends.

spectives by taking Stockholm as a case study. The main findings of this study are summarized as follows.

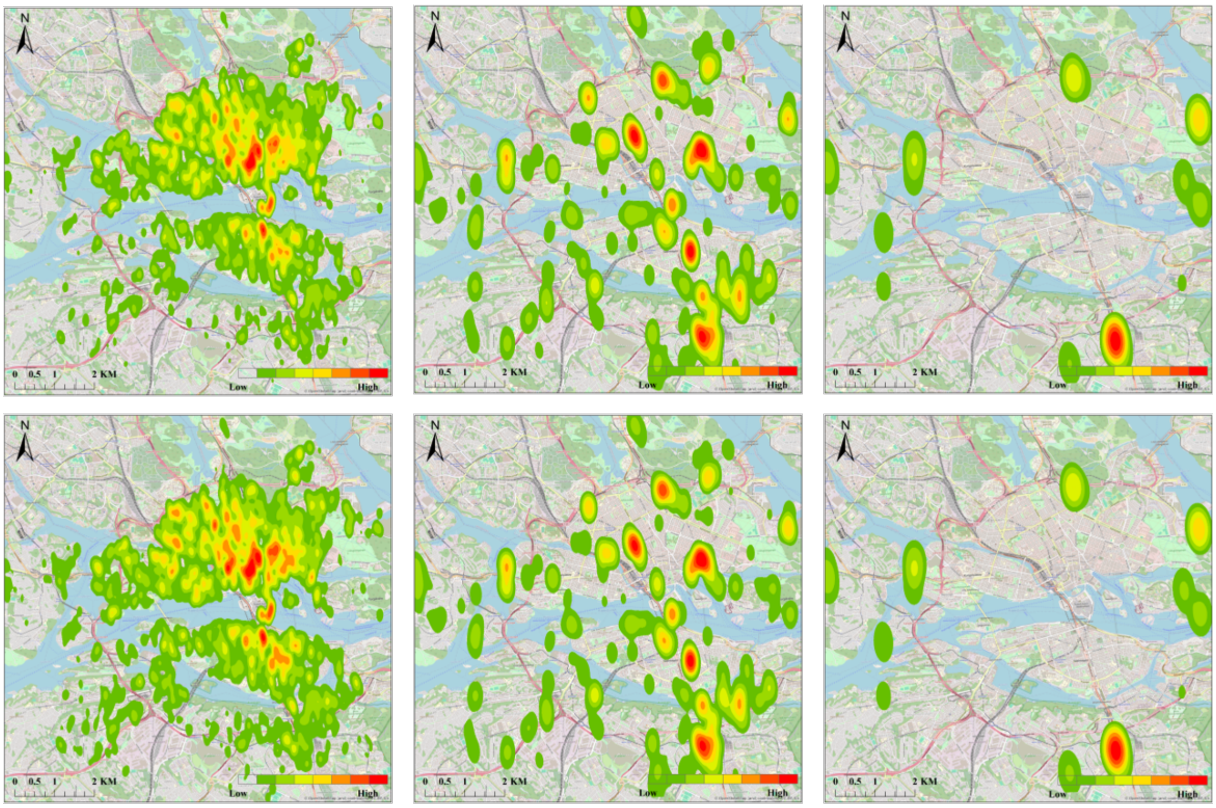
First, the preliminary analysis results indicate that the transit catchment size has a remarkable influence on the different types of integration relationships. The competitive trips and the trips of 'others' show increasing and decreasing trends respectively with the increment of catchment size. In addition, the FM and LM trips present similar proportions for each catchment size. Their proportions are the highest with a catchment size of 100m.

Second, the results of the statistical analysis on trip distance and duration with box-plot reveal that the maximum normal value and the height of the box become higher with the increment of catchment size, especially when the size is larger than 300m. On the contrary, the minimum normal values and medians are generally stable across the catchment sizes.

Third, from the temporal analysis results, it can be observed that the FM and LM trips present similar and typical patterns on weekdays (one morning peak and one evening peak) and weekends (one afternoon peak). It further demonstrates some use of shared e-scooters to connect public transport for commuting trips. The results are consistent with the findings in the study by (Yin et al., 2024). Besides, when the catchment size exceeds 300m, it shows an obvious influence on the temporal patterns.

Lastly, the spatial analysis results further uncover the remarkable effects of the transit catchment size on the spatial hot spots of FM and LM trips. When the size of the catchment area is small (e.g., 100m), the hot spots are mainly concentrated in the downtown area, such as Stockholm Central Station. With the catchment size becoming larger, the hot spots are shifted gradually towards the outskirts of the city. This also reflects the good coverage of the public transport system in Stockholm.

Despite a thorough investigation, some open questions could be further investigated in future work. First, the transit catchment areas are generated based on Euclidean distance in this study. It makes more sense to generate them based on network distance. Second, it would be interesting to explore the catchment size effects in some other cities. This research calls for more attention to consider these catchment size effects while modeling the integration between shared e-scooters and public transport.



(a) 100m (b) 300m (c) 500m

**Figure 5.** Kennel density maps on the origins of FM trips and the destinations of LM trips across different catchment sizes.


## 6 Acknowledgments

This research has been supported by the Young Scientists Fund of the National Natural Science Foundation of China (52202389), and a grant administered through K2 - The Swedish Knowledge Centre for Public Transport (grant number 2023001).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