Identifying Optimal Locations for Shared e-Scooters Stations in Lexington, Kentucky

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Abstract. In several urban areas, the scarcity of shared micromobility stations to serve first- and last-mile trips coupled with inadequate connections to public transport, limit access to a significant portion of the city's residents. While some dockless schemes are available, these primarily cater to the needs of those in the city center, leaving other areas unserved. This study develops a spatially driven approach to identify suitable areas and optimal locations for deploying first- and last- mile shared micromobility services. The proposed method is applied to the city of Lexington, Kentucky, United States. Initially, a spatial analysis is performed to identify suitable areas for locating shared e-scooter stations. Subsequently, a network analysis is conducted to identify a limited set of optimal station locations within these areas. The outcome of this study is a practical, two-step methodology that does not require large amounts of input data and can be used by micromobility companies and transportation planners when planning and launching new shared micromobility systems.

Keywords: E-scooters · Micromobility · Data-driven · Suitability Index · Optimal Location · Network Analysis

1 Introduction

Over the last years, e-scooter sharing services have expanded rapidly in many cities around the world, primarily to serve first- and last-mile trips. Since 2017, cities across the United States (US) have introduced shared e-scooter sharing programs that often co-exist with docked bikeshare services [1]. This rapid uptake is reflected in usage statistics. In 2018, e-scooters accounted for the highest proportion of micromobility trips in the US, with 38.5 million recorded trips [2, 3]. By 2024, shared e-scooter ridership continued its rapid growth, reaching 85 million trips across North America, a 38% increase from the previous year [4].

Since the use of shared micromobility has been spreading recently all around the world, there are still many open issues in terms of suitable infrastructure, demand analysis

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and safety evaluations [5]. The wide spatiotemporal availability of these services, made possible by mobile applications that easily match real time demand and supply, favors the use of micromobility in combination with other modes of transport, such as fixed and demand-responsive transit. Integrating micromobility with public transport could also enlarge its catchment area, increase its accessibility, and reduce congestion phenomena and pollution, thus making cities more livable [6].

Regarding micromobility infrastructure, the positioning of shared e-scooter stations with respect to suitably aligned criteria is a crucial element in the effectiveness and sustainability of micromobility networks [7]. In this context, the aim of this study is to introduce a methodology for planning first- and last-mile micromobility services by identifying the optimal locations for shared e-scooter stations. The selection process is guided by five spatial criteria: (i) population density, (ii) land-use characteristics, (iii) proximity to bike lanes, (iv) proximity to bust stations, and (v) proximity to major Points of Interest (POIs). According to García-Palomares et al. [8] e-scooter station locations must be related to the proximity of population, activities and the public transport network. The proposed methodology is applied in Lexington – Fayette Urban County, Kentucky (KY) in the US. The results of this study can serve as an effective tool to help urban planners design an equitable and profitable shared docked e-scooter system, since it attempts to pinpoint locations where there is a need for e-scooters, thus maximizing their usage.

2 Literature Review

Shared e-scooter services are a subset of shared micromobility systems. Shared mobility refers to "the shared use of a vehicle, bicycle or other low-speed travel mode" [9] and is often described as a product-service system, as it provides access to a mobility asset (e.g., an e-scooter) without requiring ownership [10]. In the literature, micromobility is defined as the use of micro-vehicles; vehicles with a mass not exceeding 350 kg and a maximum design speed of 45 km/h." [11].

The popularity of micromobility-shared systems has been rising in cities all over the world due to a number of advantages [7]. Especially e-scooters, these include flexibility, quick access to and from public transport stops, energy efficiency, reduced noise levels, minimal parking space requirements and no exhaust pollution [12]. In particular, shared e-scooters offer a convenient solution for short-distance trips and first- and last-mile connections, potentially reducing dependence on private automobiles and alleviating traffic congestion in dense urban environments [13]. As a result, micromobility has been widely discussed as a promising component of more sustainable and efficient urban transport systems [14].

The potential environmental and mobility benefits of micromobility, however, are closely tied to the transport modes it replaces [15]. The findings of previous studies regarding the transport modes that are mainly substituted by micromobility services are contrasting. Studies conducted in European countries indicate that micromobility services often replace walking and, to a lesser extent, public transport trips [16, 17]. Therefore, in many cases the net emission balance is negative and the benefits of micromobility for the environment are questionable. In contrast, mode substitution patterns in

the United States differ, with studies reporting that micromobility services have managed to replace a substantial number of private car trips [13, 18, 19]. Despite the contrasting results, the vast majority of the studies acknowledges that e-scooters' characteristics are well suitable for the first-last mile of any trip chain [20]. Consequently, several studies have examined the integration of micromobility with public transport services and the overall potential of micromobility to enhance multimodality and accessibility [21, 22].

From an infrastructure planning perspective, the spatial configuration of shared micromobility systems plays a critical role in their performance. Most shared micromobility systems in the United States operate as docked systems, in which stations are located in places designated by local authorities [7, 23]. Compared to dockless or free-floating systems, docked e-scooter systems are more oriented toward regular and commuter-oriented travel patterns [23]. Each of these systems requires specific stations where the vehicles will be securely locked. Decisions regarding the initial placement and size of these stations, as well as strategies for expanding the system by adding new stations or reorganizing existing ones, are critical [7]. Prior studies emphasize that establishing a successful shared service network requires careful consideration of station locations relative to POIs, public transportation, and overall user accessibility [24, 25]. Empirical evidence from Washington D.C., for example, indicates that higher population density and greater concentrations of POIs are associated with increased e-scooter usage [26]. Consequently, a quantitative site suitability analysis for shared e-scooter services is essential.

As a result, the identification of optimal locations for shared micromobility infrastructure in urban environments has become an active area of research. Existing studies address both dockless and docked micromobility systems, often with the objective of maximizing system usage while minimizing operational costs and maintaining high service quality [27]. Methodologically, the literature identifies that the use of spatial models for the prediction of the optimal location of facilities has the ability to overcome the weaknesses of linear regression models, as they better account for spatial autocorrelation (i.e., the correlation between two different points in space) and non-stationarity [28].

A portion of the literature focuses on data-intensive, demand-driven approaches. For instance, Sandoval et al. [29] proposed a data-driven method to identify parking locations for shared dockless e-scooters based on the potential demand by clustering historical trip data. Likewise, Zakhem and Smith-Colin [30] used trip clustering method to identify parking zones for dockless e-scooters. Colovic et al. [31] developed a Multi-objective Micromobility Maximal Coverage Parking Location (M-MCPL) model that returns the optimal shared e-scooter parking locations. This model is based on the following objective functions: (i) the maximization of the population coverage; (ii) the maximization of multimodal accessibility coverage (i.e., bus, railway, and metro modes); (iii) the maximization of the attraction coverage considering the most relevant points of interest for each corresponding zone in large urban areas. Similarly, Deveci et al. [32] used a hybrid fuzzy Multi – Criteria Decision Making (MCDM) model considering 12 criteria, concerning users, public authority, service operator, and urban livability. Finally, Ayfantopoulou et al. [33] conducted a data-driven analysis using the K-Means algorithm to

select suitable locations for docked scooter-sharing service stations, based on trip data, road geometric characteristics, and station capacity.

A smaller body of research employs GIS-based analyses to identify optimal facility locations. Roslan and Naharudin [7], for example, developed a GIS-based MCDM approach to optimally positioning rental stations of docked e-scooter shared services in respect to prospective consistent criteria. They used eight criteria, including population density and proximity to significant locations, to perform a suitability analysis in Shah Alam city in Malaysia. Likewise, Kabak et al. [34] deployed a similar approach to locate bike-sharing station sites in Karsiyaka, Izmir, Turkey. While these studies highlight the value of spatially explicit, criteria-driven methods, they often depend on extensive datasets or context-specific assumptions that may constrain their transferability.

Overall, the literature demonstrates that while shared e-scooter systems offer meaningful mobility and sustainability benefits, their effectiveness depends heavily on the spatial configuration of the supporting infrastructure. Prior research highlights the importance of station placement for ensuring accessibility, encouraging multimodal integration, and maximizing system usage. A wide range of methodological approaches has been explored, from demand-driven clustering techniques to multi-criteria decision-making models. Yet most studies require extensive and context-specific datasets. In contrast, comparatively few studies develop GIS-based frameworks tailored specifically to shared micromobility systems. This gap underscores the need for practical, transferable methods that can guide early-stage planning in data-constrained environments. Responding to this need, the present study proposes a GIS-based approach that integrates area-level suitability analysis with network-based location optimization, using a limited but meaningful set of criteria derived from the existing literature to support planners and operators in the strategic deployment of docked e-scooter infrastructure.

3 Methodology

3.1 Study Area and Data Collection

The proposed methodology is applied to the case study of Lexington – Fayette Urban County, KY. Lexington is the second largest city in the state, with a population of nearly 320,000 residents [35]. Most people in Lexington commute to work with car, pickup truck, or van (86.1%), while only 1.8% use public transportation in 2020 according to the US Census Bureau [35]. This strong reliance on private vehicles highlights the need for alternative mobility options that can enhance first- and last-mile connectivity, particularly in conjunction with public transit.

Public transportation in Lexington is provided by Lextran, which operates a fleet of 65 buses along a network of 22 bus routes [36]. The bus network follows a hub-and-spoke configuration, with routes primarily oriented towards downtown Lexington as a central hub and extending outward in a radial pattern. While this configuration supports downtown access, it limits cross-town connectivity and reduces transit accessibility for areas located farther from the central core.

At present, shared micromobility services in Lexington consist exclusively of dockless e-scooters. The absence of docked e-scooter and bike-share stations, combined with inadequate integration between micromobility services and the existing public transport network, constrains the potential of e-scooters to effectively serve first- and last-mile trips. This limit access to a significant portion of the city's residents.

Data used in this study refer to the Lexington – Fayette Urban County and were collected from various publicly available sources. First, the census block groups boundaries coupled with population totals from the 2020 census are acquired from the ESRI Data Hub [37]. Additional spatial datasets utilized in this study include land cover data [38], bicycle and pedestrian facilities (BKPD) [39], and the location of bus stops and POIs, both sourced from OpenStreetMap (OSM) [40]. Population data refer to 2022 measurements, land cover data are from 2021, the BKPD was produced in 2019 and OSM data reflect the most recent updates available in 2024. The use of these widely accessible datasets aligns with the study's goal of developing a transferable methodology that does not rely on extensive data sources.

All spatial analyses were conducted using ArcGIS Pro version 3.1.0. Three main extensions were employed: Spatial Analyst, Geoprocessing Tools and Network Analyst. Data preprocessing steps included clipping all datasets to the study area boundary and ensuring a consistent projected coordinate system across layers. Figure 1 presents the spatial distribution of population and population density at the census block group level, highlighting a clear core-periphery pattern in Lexington–Fayette Urban County, with higher population counts and especially higher population densities concentrated in the urban core and surrounding inner neighborhoods, while outer and peripheral block groups exhibit lower densities despite sometimes containing larger total populations. Figure 2 illustrates land cover patterns across the study area, emphasizing the strong contrast between the densely developed urban core – dominated by medium- and high-intensity developed land – and the surrounding peripheral areas, which are largely characterized by agricultural land uses (hay/pasture and cultivated crops) interspersed with forested patches and limited low-intensity development.

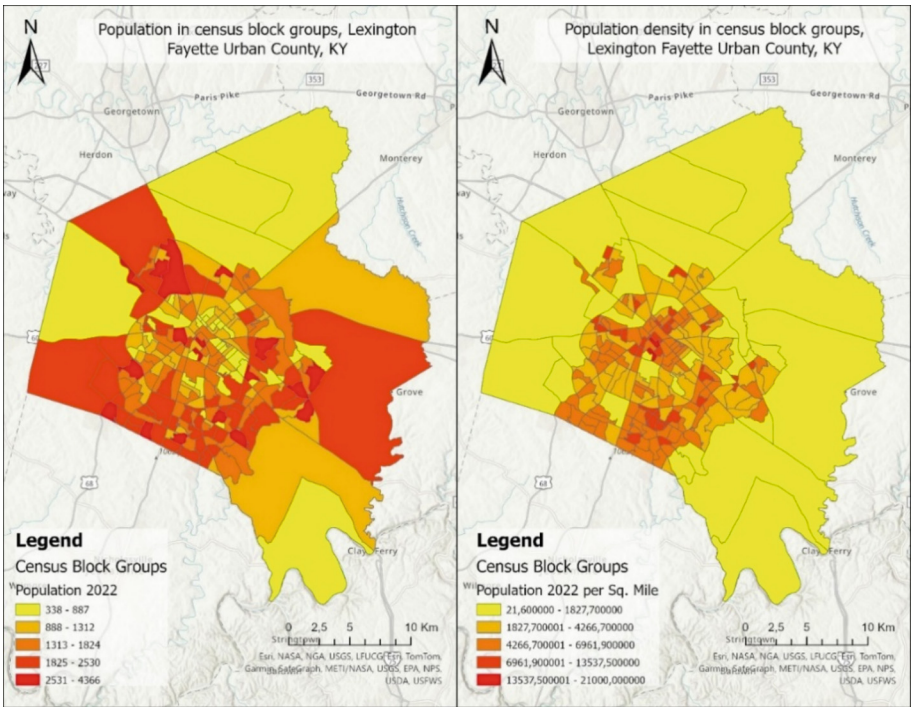

Fig. 1. Population and Population Density in census block groups, Lexington Fayette Urban County, KY (Data source: [37], Maps created by the authors)

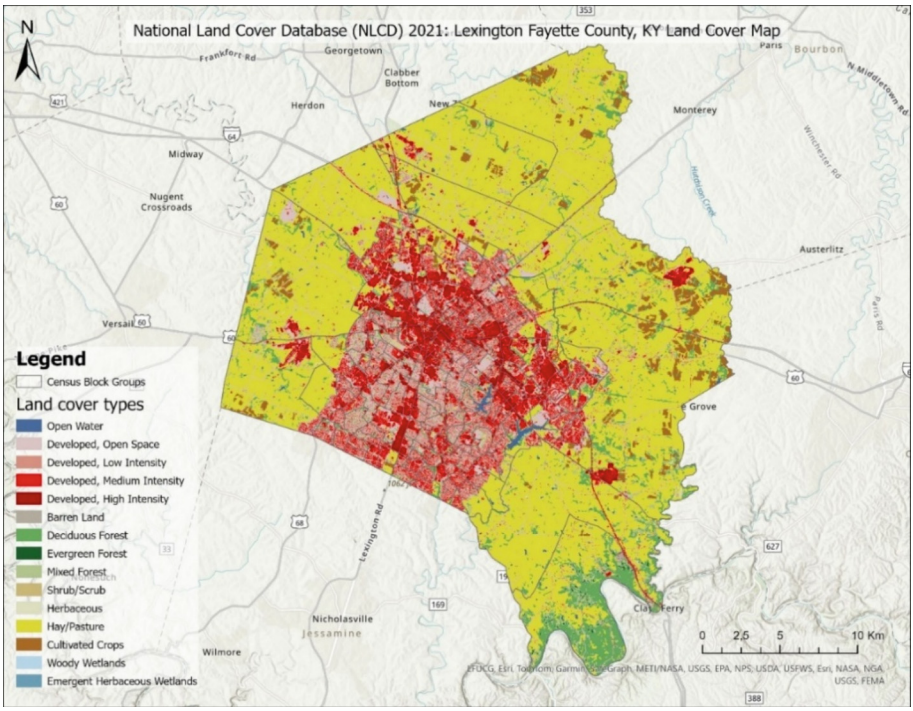

Fig. 2. Land cover in Lexington Fayette Urban County, KY (Data source: [38], Map created by the authors)

3.2 Suitability Analysis

The first objective of this study is to identify suitable areas within Lexington where shared e-scooter stations can be located, with the aim of maximizing potential usage. This is achieved through a suitability analysis, a spatial decision-support process in which multiple criteria are evaluated and combined to identify locations that best satisfy predefined objectives. The selection and weighting of criteria are critical steps in such analyses, as different factors may contribute unequally to overall suitability.

In the literature, several techniques have been proposed to determine the relative importance (weights) of suitability criteria, including the Analytic Hierarchy Process (AHP) and other multi-criteria decision-making approaches [41]. In this study, however, all selected criteria are assigned equal weights. This choice is made deliberately to maintain methodological simplicity, and to avoid introducing subjective bias in the absence of stakeholder-specific preferences. The focus of the analysis is therefore placed on the spatial interaction of the criteria rather than on weight calibration.

The suitability analysis is modelled by using a Weighted Overlay Analysis (WOA) in which several rasters are overlayed by using a common measurement scale and each one is weighted according to its importance. Based on the literature review, five criteria are selected to spatially define the suitable areas for shared e-scooter station deployment: (i) population density, (ii) land use, (iii) proximity to bike lanes, (iv) proximity to bus stations, and (v) proximity to POIs. For population density, areas with higher densities are

assumed to be more suitable, reflecting higher potential demand. For land use, the highest suitability score is assigned to "Developed, High Intensity" areas, as these locations typically exhibit concentrated activities and trip generation.

The remaining three criteria are proximity-based and are calculated using Euclidean distance analysis. This method computes the distance from each raster cell to the nearest relevant feature (bike lanes, bus stations, or POIs). In all cases, shorter distances are considered more favorable, as closer proximity enhances accessibility and the likelihood of e-scooter usage.

The overall suitability modeling framework is illustrated in Fig. 3 and consists of several sequential steps: rasterization of each vector layer, calculation of distance measurements where applicable, and reclassification of each criterion. The reclassification of each feature involves the rating of each cell from score 0 (not suitable) to score 10 (most suitable) in six classes. The five criteria, reclassified and rated, are presented in Fig. 4.

For the land-use criterion, certain land cover classes are treated as exclusionary variables. Specifically, land cover types deemed unsuitable for station placement (e.g., water bodies or undeveloped natural areas) are assigned a "NoData" value during reclassification. This operation removes these cells from subsequent calculations, ensuring that they do not contribute to the final suitability index.

Following reclassification, the five standardized, unitless raster layers are combined using the WOA to produce a composite suitability index for the study area. The resulting suitability index for the area, shown in Fig. 5, represents the spatial distribution of suitability for shared e-scooter station deployment across Lexington and serves as the basis for the subsequent network-based location optimization.

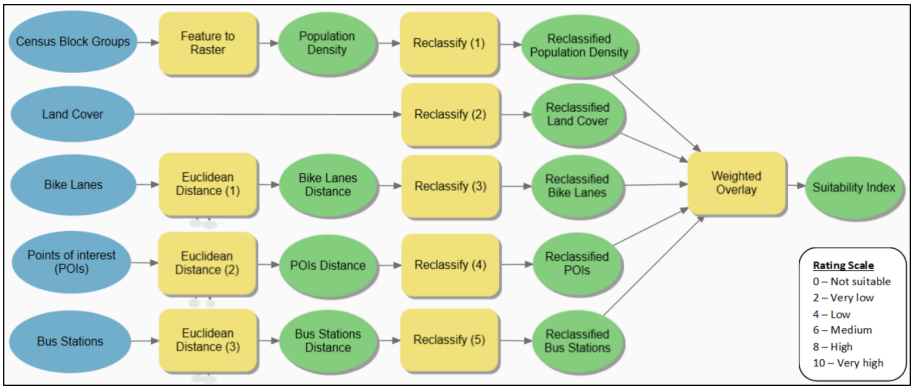

Fig. 3. Suitability modeling workflow

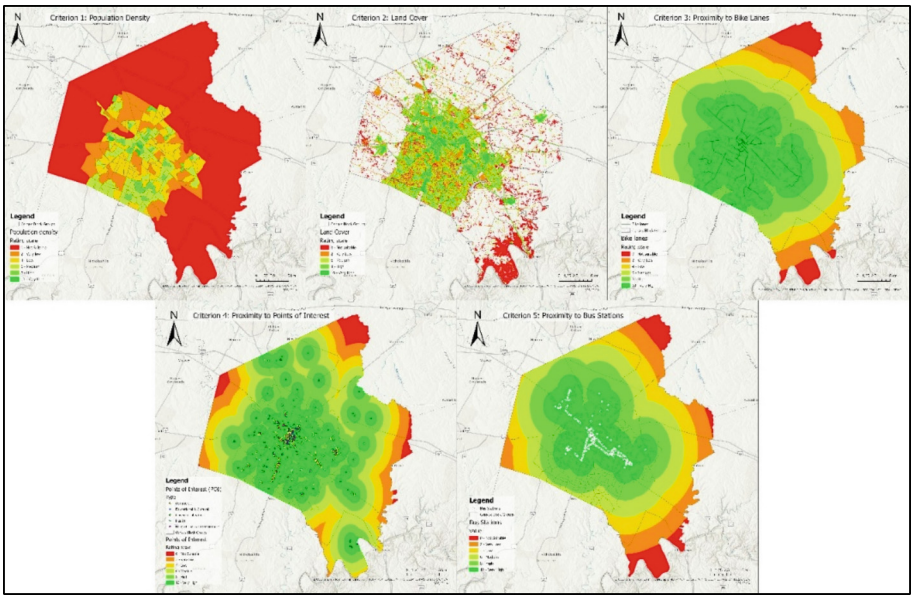

Fig. 4. The five (5) criteria for the suitability analysis (after reclassification)

3.3 Network Analysis

The second objective of this study is to identify the optimal point locations for the shared e-scooter stations within Lexington Fayette Urban County, KY. For that purpose, a network-based location-allocation analysis is employed. Location-allocation models are used in transportation and facility planning to determine the best locations for a predefined number of facilities while allocating demand in a way that optimizes a specific objective function [42].

The analysis builds directly on the results of the suitability assessment. The first step involves extracting the areas identified as highly suitable from the suitability analysis, having a score of 10. Subsequently, this raster layer is converted into polygon features, and then into point features, which serve as potential or candidate facility locations for shared e-scooter stations. These candidate points represent locations that satisfy all suitability criteria and are therefore eligible for final selection.

Demand points are represented by the centroids of census block groups, weighted by population density. This reflects the assumption that areas with higher population concentrations generate greater potential demand for shared e-scooter services. The walking time is adopted as the impedance (cost) metric and the maximum walking time of 10 min is set as the service cutoff. This value is consistent with commonly accepted thresholds for first- and last-mile access to transit and micromobility services [43].

This location-allocation model is configured to select ten facility locations, employing the "Maximize Coverage" approach. This number was chosen to represent a feasible initial deployment scenario for a docked e-scooter system in Lexington. It should be noted that the proposed methodology is scalable, and the number of facilities can be adjusted to reflect alternative planning scenarios. The maximal coverage location problem, originally formulated by Church & Velle [44], seeks to locate a fixed number of facilities so as to maximize the total demand covered within a specified service distance or time [45, 46]. In this context, coverage is defined as the population-weighted demand that can reach a selected e-scooter station within the 10-min walking threshold. The result of this model is presented in Fig. 7, in results section.

4 Results

The suitability index for identifying optimal areas for shared e-scooter stations within Lexington Fayette Urban County, KY is presented in Fig. 5. This index emerged from the WOA with equal weights assigned to each of the five criteria: population density, land use, proximity to bicycle infrastructure, proximity to bus stops, and proximity to POIs. The resulting map illustrates the spatial distribution of suitability areas across the county, with darker green areas indicating higher suitability scores.

High-suitability areas are primarily concentrated in downtown Lexington and in the vicinity of the University of Kentucky. This spatial pattern can be attributed to the convergence of several favorable conditions in these areas, including high population density, mixed and high-intensity land uses, dense concentrations of POIs, and strong proximity to both public transport stops and bicycle infrastructure.

Areas with a suitability score of 0 represent areas that do not meet the minimum criteria for station placement and are therefore correctly identified as not suitable. Regarding a red-colored area in the west of the downtown core between suitable areas, it is deemed unsuitable because the population density in this area is extremely low as it is an industrial area.

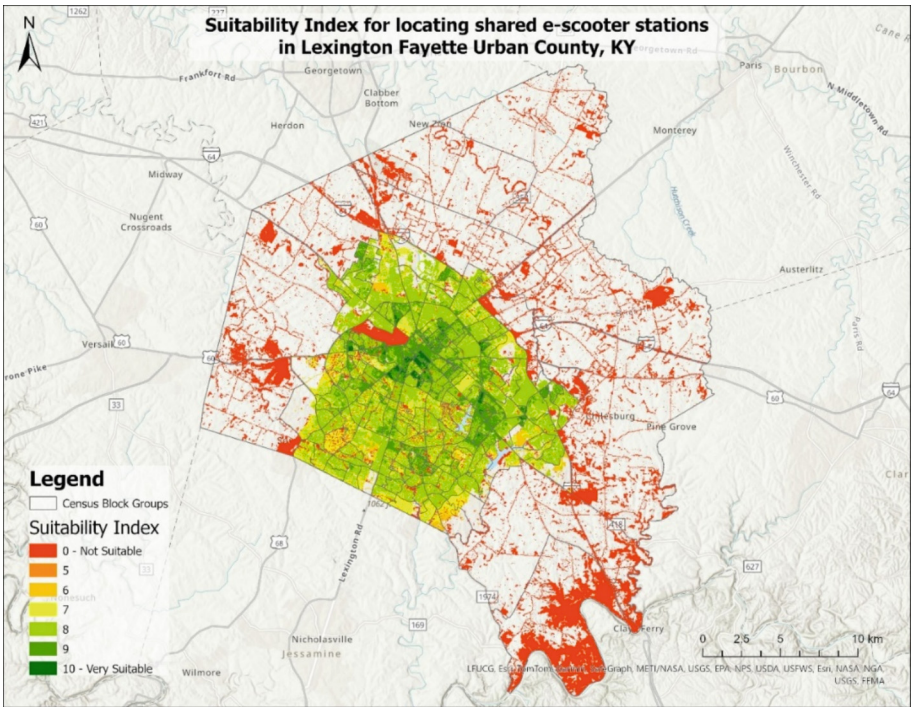

Fig. 5. Suitability index for locating shared e-scooter stations in Lexington Fayette Urban County, KY (WOA with equal weights)

To better understand the model results, a suitability index with unequal weights (Table 1) is also calculated and presented in Fig. 6. In this case, population density and proximity to bike lanes criteria have higher weights. As can be observed from the map in Fig. 6, the unequal weights lead to slightly different results. Specifically, the most suitable areas are fewer and there are more areas rated with the score of 9 out of 10.

Table 1. Criteria weights value

Criteria	Weights
Population Density	0.30
Land cover	0.10
Proximity to bike lanes	0.30
Proximity to POIs	0.10
Proximity to bus stations	0.20
Sum	1

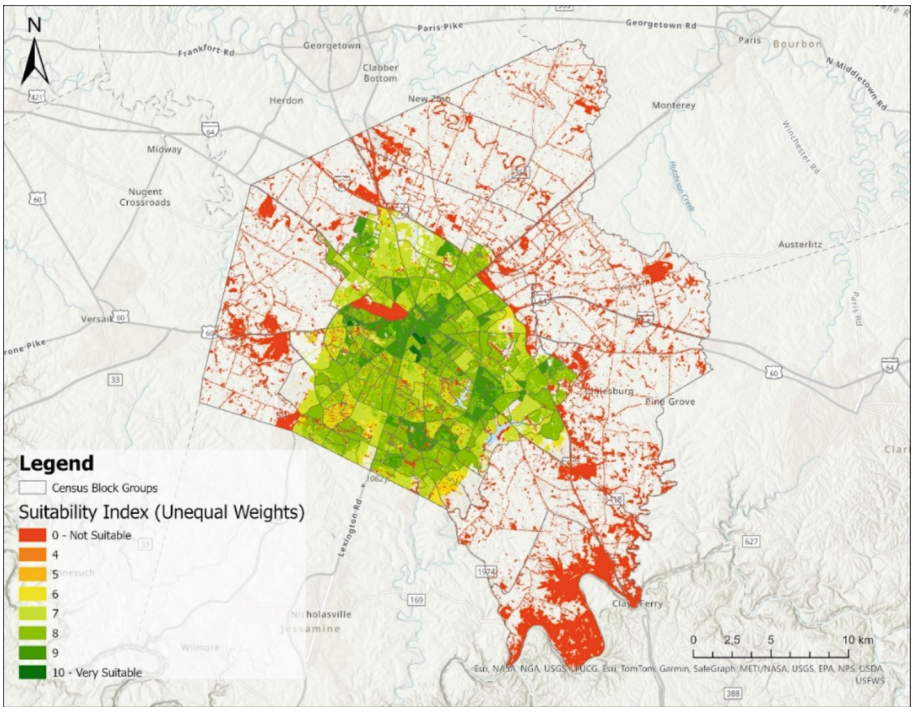

Fig. 6. Suitability index for locating shared e-scooter stations in Lexington Fayette Urban County, KY (WOA with unequal weights)

Figure 7 shows the ten optimal locations, in terms of points, within the suitable areas that are the chosen facilities from the potential ones after the location-allocation model. These locations are optimal, since they are accessible from a high proportion of commuters (maximization of coverage). It is noted that suitable areas are the areas with score ten in suitability analysis with equal weights.

The ten points are indeed in areas with high expected demand, as indicated by high population density, proximity to major points of interest, and accessibility to public transportation and bicycle infrastructure. Notably, one of the points is located within the University of Kentucky, a significant hub of demand in Lexington, with two additional points located in proximity.

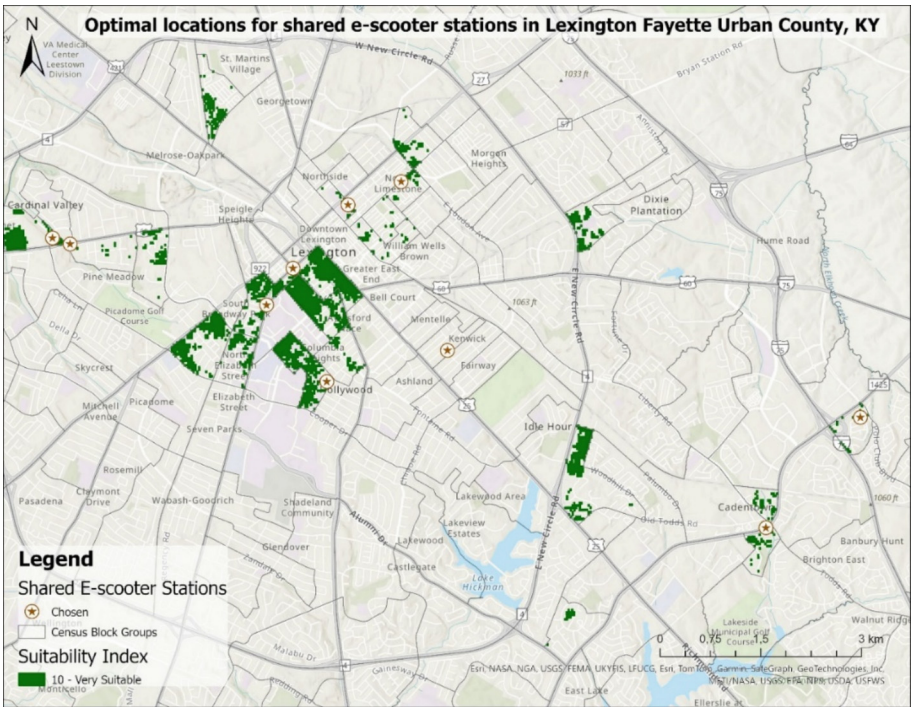

Fig. 7. Optimal locations for shared e-scooter stations in Lexington Fayette Urban County, KY

5 Conclusions

This study presents a comprehensive, two-stage methodology for identifying both suitable areas and optimal point locations for shared e-scooter stations. The methodology is applied to Lexington-Fayette Urban County, KY, a city where docked shared micromobility services are currently absent, and reliance on private vehicles is high. The framework is designed to support planners and micromobility operators in developing data-informed strategies for first- and last-mile mobility solutions.

In the first stage, a WOA is used to generate a suitability index based on five key criteria: population density, land use, proximity to bike lanes, proximity to bus stops, and proximity to POIs. Areas with high suitability scores correspond to locations with high population concentrations, accessible infrastructure, and significant trip-generating activities. This index provides insights into where demand for shared e-scooters is likely to be highest, offering a practical tool for identifying priority areas for system deployment. Users of this methodology have the option to conclude their analysis at this stage. However, for those seeking to identify optimal points rather than areas, the second part of the methodology offers a solution.

The second stage of the methodology applies a location-allocation model to the candidate areas derived from the suitability analysis. Using a maximize coverage approach, the model identifies ten optimal locations for docked e-scooter stations, ensuring that the largest proportion of population-weighted demand is within a 10-min walking distance.

The selection of ten stations represents a feasible initial deployment scenario. Notably, the identified locations correspond to areas with high population density, proximity to major activity hubs such as the University of Kentucky, and convenient access to public transport and bicycle infrastructure.

Although this methodology offers significant utility, several limitations should be acknowledged. The analysis currently relies on a fixed set of five criteria with equal weighting and does not explicitly account for sociodemographic characteristics such as age, gender, or car ownership, which could influence demand patterns. Similarly, detailed travel demand data could further refine the location-allocation results [8]. In addition, the framework combines established methods (weighted overlay analysis and maximize-coverage location-allocation) and does not benchmark its performance against more advanced approaches, such as demand clustering or stakeholder-driven multi-criteria decision-making models. The proposed station locations are also not empirically validated against observed micromobility usage patterns, expert judgement, or alternative parameter settings beyond a limited sensitivity test, as docked systems are not currently implemented in the study area. Furthermore, demand is primarily approximated through population density and accessibility variables, without explicit equity metrics or demographic segmentation.

Future research could expand the set of criteria, incorporate stakeholder preferences for weighting, and conduct broader sensitivity and benchmarking analyses across alternative modeling approaches. The integration of observed or proxy demand data (e.g., from dockless systems or travel surveys) would enable empirical validation of the results, while the inclusion of equity indicators and demographic segmentation could support more inclusive planning. Finally, evaluating alternative numbers of stations through sensitivity analyses would improve the proposed framework by optimizing coverage and operational efficiency.

Overall, this study contributes a scalable, data-light, and transferable framework for planning shared e-scooter facilities in urban environments. It combines geospatial suitability analysis and optimization to provide both planners and mobility operators with a structured approach to identify priority areas and specific locations that maximize service accessibility, connectivity, and potential usage.

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