The Journal of Transport and Land Use jtlu.org
Vol. 19 No. 1 [2026] pp. 41-58
https://doi.org/10.5198/jtlu.2026.2631

Macroscopic on-street parking inventory modeling: Exploring an open data approach

Matthias Langer, Technical University of Munich, matthias.langer@tum.de
Rolf Moeckel, Technical University of Munich

Abstract: Parking plays a vital role in shaping land use and transport. Despite occupying significant portions of urban space, detailed data on parking locations and capacities are often unavailable. Recognizing the critical significance of such data for comprehensive transportation modeling and sustainable urban planning, this study presents two statistical models designed to predict the available on-street parking length in urban traffic analysis zones. The first model uses OpenStreetMap (OSM) data as its primary input, while the second is based on official parking inventory data from the city of Berlin. Both models are built using multiple linear regression, with land use and built environment characteristics as independent variables. The models are evaluated by applying them to the city of Munich. This research provides new insights into the spatial distribution of urban on-street parking and offers a practical approach for estimating parking supply to support sustainable urban development strategies.

Keywords: Parking inventory, Urban transportation, Land use, OpenStreetMap, Integration of land use and transport

1 Introduction

Studies have shown that an oversupply of inexpensive parking can contribute to economic, environmental, and social challenges (Shoup, 2011). However, despite parking infrastructure covering large portions of urban space, there is a notable lack of comprehensive, publicly available data on its extent, distribution, and usage.

Parking inventory modeling is of great importance, as the availability and accessibility of parking significantly influence travel behavior, mode choice, and urban land use (Weis et al., 2011). Moreover, the information derived from parking inventories plays a crucial role in shaping policy decisions, including pricing strategies, zoning regulations, and demand management approaches. Spatially resolved estimates of parking infrastructure can support research and policy initiatives aimed at reducing car dependency and promoting more sustainable urban systems (Davis et al., 2010).

Recent efforts to model or estimate parking supply have employed a range of data sources, including surveys, field records, remote sensing, and land-use data (Akbari et al., 2003; Davis et al., 2010; Hellekes et al., 2023; Li et al., 2022; Llorca et al., 2022). However, many of these methods are limited in spatial scale, cost-intensive, or not generalizable across different cities. Open data, particularly OpenStreetMap (OSM), could be a promising solution for improving the availability and granularity of parking-related information. OSM provides openly accessible spatial data that can support the identification and estimation of parking infrastructure across regions. This data source is

Received November 29, 2024; Revised November 17, 2025; Accepted December 11, 2025; Available online January 29, 2026

The *Journal of Transport and Land Use* is the official journal of the World Society for Transport and Land Use (WSTLUR) and is published and sponsored by the University of Minnesota Center for Transportation Studies. This paper is also published with additional sponsorship from WSTLUR.

increasingly used in transport research to model urban environments, but it also poses challenges (Briem et al., 2019). One challenge lies in the non-standardized recording of parking lot details in many regions within OSM. As the completeness of the OSM data set varies regionally, applying analyses to different locations requires prior data analysis and pre-processing.

To date, few studies have systematically assessed the feasibility and accuracy of using OSM data to model on-street parking infrastructure at scale. This study addresses this gap using two data sources. First, a model was estimated based solely on OSM data from 14 German cities. Second, official parking inventory data from the city of Berlin were used as blueprint for modeling parking availability in other German cities. The models are then applied to the city of Munich to evaluate their predictive performance and generalizability. By comparing open data-based and official data-based approaches, this study contributes to the growing body of work on large-scale urban data modeling, evaluating their reliability and applicability in cities lacking detailed parking data. This provides insight into the potential of open data for scalable and transferable parking inventory estimation. The findings can inform urban planners, policymakers, and researchers interested in advancing sustainable mobility and land-use planning strategies, particularly as many cities increasingly seek cost-effective, scalable solutions for understanding and managing their parking supply.

This paper builds on previous approaches to estimate parking data within an urban area using open-source data, thereby contributing to parking inventory modeling. These models are helpful in cases where municipalities lack a complete overview of detailed parking data or do not publish it.

2 Literature review

Parking policies significantly shape individual travel behavior, influencing mode choices, trip destinations, and travel times and durations, with parking availability and cost being the main driving factors (Guo, 2013; Weinberger, 2012; Weis et al., 2011; Willson & Shoup, 1990). When parking supply exceeds demand and is affordable, individuals are more likely to rely on personal vehicles. Conversely, limited availability or higher parking fees can lead to shifts in mode choice, such as increased use of public transport, walking, biking, or ridesharing, but also to broader changes in travel behavior (Christiansen et al., 2017). These include reduced trip generation, altered destination choices, changes in time-of-day travel, and even long-term effects on car ownership or household relocation.

Previous studies underscore the importance of considering residential parking infrastructure, revealing that households without off-street parking tend to reduce car usage (Guo, 2013), while guaranteed home parking increases automobile usage (Weinberger, 2012). Employer-paid parking also impacts travel choices (Willson & Shoup, 1990). Further, parking characteristics, such as cost, availability, and convenience, have been shown to influence mode and location choices, as demonstrated by Weis et al. (2011) through a stated preference survey.

The search for on-street parking, commonly referred to as "cruising for parking," can be a time-consuming and sometimes frustrating experience that may contribute to traffic congestion and emissions (Shoup, 2011). While some motorists undertake the search for a free parking spot, others opt to minimize their travel and access time by paying additional fees (Ben Hassine et al., 2022; Chaniotakis & Pel, 2015). However, Arnott and Rowse (2009) found that cheaper on-street options are often preferred to off-street options, contributing to additional congestion.

Parking policies are essential in shaping land-use patterns and destination choices, as widely documented in urban planning and transportation research. Numerous studies have shown that parking supply influences development density, land valuation, and business location decisions (Manville & Shoup, 2005; Merten & Kuhnimhof, 2023; Parmar et al., 2020).

Although many research findings indicate that parking space plays an important role in sustainable urban development, the planning process for this topic has been surprisingly little researched. Shoup (2011) even speaks of “pseudoscience” when referring to isolated planning processes for parking space.

2.1 Estimating parking data

Parking inventory modeling refers to the process of analyzing and estimating the supply and spatial distribution of parking space within a defined area. This often involves integrating various data sources and employing estimation techniques to create a comprehensive picture of parking infrastructure. While using direct measurement of parking inventories through OSM or LiDAR may seem more straightforward, these sources often lack completeness or standardization.

Although OSM provides the possibility to map on-street parking, its completeness and standardization remain inconsistent across cities. Within the “OpenStreetMap Verkehrswende” project (Seidel, 2023), several cities were analyzed for on-street parking completeness in OSM. While in some cities, such as Berlin, plenty of information on parking can be found, other cities only have these information available in parts of some districts or not at all (Seidel, 2023). This inconsistency is partly due to the complexity of the OSM tagging system. Parking may be mapped either as an attribute of a street segment using parking:side=* or as a separate geometry via amenity=parking, with additional optional tags describing physical characteristics, vehicle orientation, fees, time limits, and access restrictions (Openstreetmap, 2025). This flexibility results in inconsistent and often incomplete practices, making their comparison difficult. The “OpenStreetMap Verkehrswende” project explicitly accounted for these variations and controlled for data completeness within each city (Seidel, 2023). It is important to highlight that, in contrast, many other built-environment features, such as road networks, points of interest, or land-use information, are mapped more consistently across cities (Briem et al., 2019).

In contrast to relying solely on OSM-based parking inventories, modeling parking capacity enables more scalable and uniform estimation, particularly in areas where detailed or reliable inventory data are lacking. Yet, the domain remains relatively unexplored. Previous studies, such as Akbari et al. (2003) and Davis et al. (2010), relied predominantly on methods involving labor-intensive steps, such as visual identification or manual surveys, to assess parking.

Moving away from conventional methods, more recent studies have used innovative techniques that take advantage of technological advances. Hellekes et al. (2023) demonstrated the effectiveness of combining remote sensing data with statistical methods and presented a novel approach to parking lot estimation in Braunschweig, Germany. This integration of photogrammetry and statistical analysis accelerates the assessment process and increases the reliability of parking inventory estimations.

Especially in transportation research, considerable effort is invested in land-use data. In an evaluation of the impact of autonomous vehicles on land use, Llorca et al. (2022) contributed by calculating on-street parking based on the length of street links and sub-sample observations for Munich. This approach complements the evolving landscape of automated methods and provides a nuanced understanding of the on-street parking scenario in specific urban environments. Further, Li et al. (2022) followed a bottom-up approach, merging different data sets that include street networks and land-use types.

This comprehensive methodology offers a detailed perspective on the spatial distribution of parking infrastructure, providing researchers and policymakers with nuanced insights into parking allocation in the San Francisco Bay Area.

2.2 Parking space as a political issue and lever

Over the past decades, various policies have been implemented to manage parking effectively, each impacting travel behavior and urban dynamics differently. One of the most common, yet criticized, policies is the requirement for minimum parking spaces in new residential or commercial developments. As highlighted by Shoup (2011) and Weinberger (2012), minimum parking requirements can lead to over-parking and increased car usage. As a result, excessive urban space is used for parking, and the overall efficiency of land use is affected. Occasionally, parking spaces are being repurposed for bike lanes, green areas, or commercial uses. However, established patterns of car use among residents may present challenges to implementing such changes (Schreibmüller et al., 2025).

Addressing the challenge of circling for parking in congested urban areas, real-time information-based technology could be used to implement dynamic pricing and optimize space utilization. Feeney (1989) first observed that the effectiveness of such pricing strategies can vary by location, primarily due to differences in parking price elasticities. More recently, Mackowski et al. (2015) developed a dynamic model to set real-time parking prices that optimize access and space utilization. Using numerical simulations, they demonstrated that their pricing framework has the potential to virtually eliminate vehicles circling for parking. This would lead to a substantial reduction in negative externalities such as traffic congestion and emissions.

Targeting on-street parking specifically for residents, residential parking permits aim to allocate space for residents and reduce the number of visitors by car. However, it can unintentionally foster car usage among the residents themselves (Taylor, 2021).

Originating in the late 1980s, Transit-Oriented Development (TOD) policies encourage the development of dense, mixed-use areas near public transportation. Ibraeva et al. (2020) emphasize that TOD has the potential to significantly reshape parking dynamics by deliberately reducing parking supply in transit-rich areas. This approach not only discourages car ownership but also aligns urban design with broader environmental and mobility goals.

Parking policies should be tailored to specific target groups, aiming to reduce parking space in favor of sustainable transport, while safeguarding access for car-dependent populations and locations. Factors such as location, quantity, associated construction costs, and design considerations contribute to creating a comprehensive and sustainable urban environment.

When examining parking management policies, the effects of these measures often remain uncertain. To address this gap, there is a critical need for methods that first comprehensively map the existing parking landscape. Accurate representation of current parking availability is a prerequisite for studying the potential consequences of alternative parking policies. The following sections outline the formulation and validation of a methodology to quantify parking supply, thereby enhancing our understanding of the complex relationship between parking management, urban dynamics, and travel behavior.

3 Methodology

Drawing from prior research on parking, an approach is introduced to calculate and assess two distinct parking inventory models. The attempt involves two main phases: first, the computation of the parking inventory for each designated zone, estimating two different models, and second, comparing both models. The evaluation framework assesses model accuracy and applicability across varied urban contexts.

3.1 Study area and data sources

This paper explores an attempt to estimate on-street parking inventories in an urban study area. Specifically, the dependent variable is the available parking length by zone. Data should be publicly available to make the attempt reproducible.

The first data source is the data from the German project "OpenStreetMap Verkehrswende" (Seidel, 2023). As a successor of a local, voluntary mapping initiative, this project aimed to deliver precise information on public parking based on OSM data. Within the project, participants focused on deriving detailed information about on-street parking, excluding areas where parking is prohibited or information is not yet mapped. Data are accessible through the project website for parts of the German cities Berlin, Bremen, Dortmund, Hannover, Hamburg, Kiel, Bonn, Bietgheim-Bissingen, Braunschweig, Oldenburg, Wiesbaden, Metzingen, Freiburg im Breisgau, and Magdeburg (see Figure 1). The data set is considered particularly useful in this research, as it controls for variance and incompleteness of the on-street parking tagging practice in OSM (Seidel, 2023). Using the data set requires downloading and aggregating information at the grid cell level, as well as limiting the study area to zones where parking information was available.

The second source of data on on-street parking was an official public data set on the number and area of spaces provided by the City of Berlin (Berlin Open Data, 2022). It offers detailed geospatial information on parking stock within selected areas of the Charlottenburg-Wilmersdorf district. The data are provided at the individual parking location level and includes attributes such as spatial geometry, parking type, and the number of available spaces. These data are used as a blueprint for other German cities, where the official data may not be available at this scale.

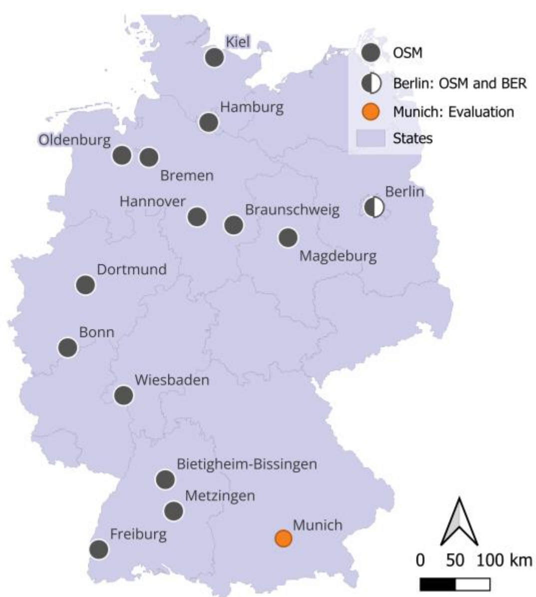

Figure 1. Locations of the model input and the study area for the evaluation

The data sets of the two models are expected to show significant differences. While the OSM data set accumulates voluntarily mapped parking space information from 14 different small, medium-sized, and large cities, the smaller Berlin data set is based on detailed counting by the city administration.

Independent variables include population density, transport, and built environment data. Population data were retrieved from the 2011 German census (Statistisches Bundesamt, 2011), as this was the most recent data available for a considerable period of time. As this data source is already quite old, the data were expanded using local population numbers from 2022. Built environment data were retrieved from OSM only. The data were downloaded using the Overpass API (Overpass, 2023) and the Geofabrik OSM data extracts (Geofabrik, 2024). The built environment data included information on traffic lights, building locations, bus stops, tram stops, street crossings, streetlights, intersections, land use, road types and lengths, pedestrian zones, off-street parking facilities, as well as combined counts for points of interest (POI). For the POI variable, different OSM classifications were grouped into eight groups according to an approach by Abouelela et al. (2024). The groups are described in Table 1.

Table 1. POI classification

Group	OSM classification
Education	kindergarten, library, school, university
Food	bakery, bar, beverages, cafe, fast food, food court, greengrocer, pub, restaurant, supermarket
Health	clinic, dentist, doctors, hospital, optician, pharmacy, veterinary
Leisure	arts centre, cinema, community centre, nightclub, park, picnic site, playground, sports centre, stadium, swimming pool, theatre, zoo, artwork, attraction, guest house, hotel, memorial, monument, museum
Service	atm, bank, beauty, fire station, hairdresser, laundry, police, post office
Shopping	bicycle shop, bookshop, clothes, computer shop, convenience, department store, DIY shop, furniture shop, gift shop, jeweller, mall, market place, mobile phone shop, shoe shop, sports shop, stationery, toy shop

Both estimated models were applied in Munich, and their parking quantity predictions were validated against detailed, location-specific parking data provided by the Munich city administration. The Munich data set covers a large city center area extending over 14 out of 25 municipal districts. It includes the geometry of on-street parking spaces at individual parking locations and attributes such as parking type (Landeshaupstadt München, 2022). The study area is diverse, with a large pedestrian zone in the center, several urban green spaces, scattered commercial zones, and many residential areas. The models can, therefore, be tested for various aspects.

The models were trained on data from multiple German cities, with Munich excluded from training as it was not included in the chosen OSM dataset. Munich was then chosen for validation because, to the authors' knowledge, it is the only city in Germany besides Berlin for which independently verified, high-quality parking data are available. The local distribution of parking space in Munich is shown on the map on the left in Figure 4. The spatial distribution of the cities included in the model estimation, as well as the study area used for evaluation in Munich, is illustrated in Figure 1.

3.2 Model estimation and evaluation

In both models, the dependent variable, parking availability, was measured consistently as the total length of available on-street parking within 100-meter grid cells. The geometries of these grid cells were derived from the census data set used in the models. Independent variables were also collected at the grid cell level. For the OSM-based model, data were available for over 22,000 grid cells across 14 cities. In contrast, the Berlin data set (BER) comprised approximately 1,000 grid cells.

After a preliminary examination of the data, grid cells that were not entirely covered by the parking data sets were excluded. Additionally, extreme deviations in the independent variables, which can be caused by inconsistencies in the OSM data set, such as buildings that were tagged multiple times, were identified. To obtain a more robust model, Z-scores were calculated, which makes it possible to convert various relevant criteria into a single score that can then be used to classify and select data sets (Priebe et al., 2008). Z-scores measure how many standard deviations a data point deviates from the mean of a distribution. For this parking space model attempt, data records with a Z-score of more than three in one of the variables were deleted to remove extreme outliers that could disproportionately influence the model.

To determine a linear relationship between the available parking space and the local environments, multiple linear regressions (MLR) were estimated. MLR is often used in transportation to investigate spatial relationships. For example, Duran-Rodas et al. (2020) used MLR to analyze the spatial characteristics of bike-sharing infrastructures. In this research, MLR were estimated and evaluated in the R statistical software using the “stats” (Bolar, 2019) and the “MASS” (Ripley, 2024) packages. Coefficient of determination, Akaike Information Criteria (AIC), logarithmic likelihood, multicollinearity tests, and p-values of the variables were then used to identify the best model fit. Associations between independent variables and parking length were considered statistically significant, given a p-value below 0.05 (Berkson, 1942), a coefficient of determination higher than 0.3, correlations between predictors below 0.7, a high log-likelihood, and the lowest AIC possible.

After model estimations, goodness-of-fit measures were compared. The final models were then applied to the study area in Munich to evaluate the estimated parking models. Due to the nature of the linear model, some predicted values were negative; these were automatically set to zero.

4 Results

4.1 Descriptive analysis

After pre-processing, the final OSM data set consists of 10,983 grid cells within the 14 cities of the OSM parking project. Most records are from the cities of Berlin (n = 8,090), Hannover (n = 721), and Hamburg (n = 697). The final BER data set consists of 948 records within the Charlottenburg-Wilmersdorf district. The data capture the entire on-street parking infrastructure within every grid cell.

The preliminary analysis in Table 2 shows basic statistics for all transportation and built environment variables recorded in the study areas and provides an overview of the urban parameters. In the OSM case, parking lengths range from 0.00 to 412.4 meters per grid cell, with an average of 117.3 meters and a standard deviation of 98.4 meters, indicating considerable variability. Population density spans from 0.00 to 460.0 residents, with a mean of 88.5 and a standard deviation of 111.4. The BER study area, on average, featured slightly longer parking lengths with a lower standard deviation. The population density was also higher on average, almost twice as high, but with greater variation.

In both cases investigated, the POI categories Education, Food, Health, Leisure, Service, and Shopping had between none and 29 occurrences per grid cell. The descriptive statistics for street features, including the number of streetlights, traffic lights, crosswalks, intersections, buildings, and bus stops, provide a differentiated understanding of the urban infrastructure. In the BER case, the lower average building density is noticeable, which may be due to the residential structure of the district studied.

The diversity of the study area is also reflected in the road and land-use characteristics. Regarding the lengths of cycle paths and footpaths, as well as road types, it is noticeable that there are grid cells with minimal transport infrastructure and others with highly developed transport networks. The BER study area had more extended transport networks on average. While some grid cells were entirely occupied by one of the four selected land-use types, others had mixed land uses. The main differences between OSM and BER are the negligible proportion of industrial land in Berlin and the significantly lower proportion of commercial land in the OSM case.

4.2 Model estimation

After several runs of model estimation, best fits were chosen based on the coefficient of determination, p-values, multicollinearity diagnostics, log-likelihood, and AIC. Subsequently, subjective judgment was applied to assess model interpretability, the relevance of included variables, and the overall robustness of the results. This combined approach ensured that the final model selection balanced statistical performance with domain-specific insights. A summary of the linear regression models is presented in Table 3.

The MLR results show significant correlations between various urban characteristics and parking length. While the OSM model included 18 independent variables, the BER model contains only 13. Nevertheless, both models' coefficients of determination (R^2) are similar, explaining approximately 50 to 60 percent of the variation in parking length. Furthermore, both F-statistics are highly significant, confirming the statistical validity of the model and its ability to explain a substantial part of the variance in parking length.

Most of the independent variables of the BER model are also included in the OSM model, showing similar trends. Notably, higher population density, the number of educational POIs, and greater lengths of sidewalks and street networks positively contribute to extended parking spaces. On the contrary, the existence of bus stops and traffic signals leads to shorter parking lengths. While the general length of the road network showed positive effects, this effect is reduced when road types are distinguished. In the OSM model, the parking availability in grid cells with high shares of tertiary roads is higher than in grid cells with secondary roads. Primary and tertiary roads were not included in the BER study area, but for the OSM model, this facility type had a negative impact on parking availability. As residential areas correlated strongly with parking space in the BER case, they were not considered due to redundancies with population density.

The OSM model included further variables that were not part of the BER model. In addition, buildings, tram stops, pedestrian streets, and shares of industrial and pedestrian zones contributed to parking availability. On the other hand, more intersections and extended bicycle networks were found in areas with less parking.

Table 2. Descriptive statistics of parking and spatial data (n_{OSM} = 10,983 | n_{BER} = 948)

Variable	**Min.**		**Mean**		**Max.**		**St. Dev.**	
	OSM	BER	OSM	BER	OSM	BER	OSM	BER
Parking length [m]	0.0	0.2	117.3	193.1	412.4	452.9	98.4	91.7
Population	0.0	0.0	88.5	144.3	460.0	509.0	111.4	124.5
Points of interest								
Education POI	0.0	0.0	0.0	0.1	4.0	3.0	0.2	0.4
Food POI	0.0	0.0	0.4	0.8	15.0	9.0	1.2	1.3
Health POI	0.0	0.0	0.1	0.2	14.0	12.0	0.5	0.9
Leisure POI	0.0	0.0	0.2	0.3	29.0	9.0	0.9	0.8
Service POI	0.0	0.0	0.1	0.2	6.0	4.0	0.4	0.6
Shopping POI	0.0	0.0	0.2	0.3	17.0	11.0	0.8	0.7
Street infrastructure								
Streetlights	0.0	0.0	1.4	3.0	36.0	19.0	2.6	3.4
Traffic signals	0.0	0.0	0.2	0.5	12.0	9.0	0.8	1.2
Crosswalks	0.0	0.0	0.7	1.6	18.0	12.0	1.4	2.0
Intersections	0.0	0.0	0.4	0.6	6.0	6.0	0.7	1.0
Buildings	0.0	0.0	7.2	6.1	49.0	20.0	7.5	4.0
Bus stops	0.0	0.0	0.1	0.2	11.0	4.0	0.5	0.5
Tram stops	0.0	-	0.0	-	3.0	-	0.2	-
Off-Street parking	0.0	0.0	0.0	0.0	4.0	3.0	0.2	0.2
Road type lengths								
Length of cycleway [m]	0.0	0.0	18.5	26.8	458.3	458.3	50.1	62.5
Length of sidewalk [m]	0.0	0.0	178.1	268.3	666.0	627.5	154.5	127.7
Length of roads [m]	0.0	0.0	102.2	140.8	340.0	414.8	73.5	89.3
Primary roads [m]	0.0	0.0	7.8	5.6	283.7	202.5	33.7	29.7
Secondary roads [m]	0.0	0.0	21.7	43.6	338.6	409.3	52.7	81.2
Tertiary roads [m]	0.0	0.0	13.1	22.3	315.1	299.5	36.9	47.7
Residential roads [m]	0.0	0.0	59.6	69.2	255.7	246.9	63.6	63.1
Pedestrian street [m]	0.0	0.0	0.3	0.6	231.9	110.8	6.5	6.5
Land-use type								
Residential area [m²]	0.0	0.0	4,947.5	5,426.6	10,000.0	10,000.0	4,140.9	3289.8
Industrial area [m²]	0.0	0.0	457.1	107.7	10,000.0	9,333.1	2,069.9	773.3
Commercial area [m²]	0.0	0.0	648.0	826.5	10,000.0	10,000.0	1,999.6	2097.5
Retail area [m²]	0.0	0.0	157.4	114.8	10,000.0	9,588.7	817.7	680.3
Pedestrian area [m²]	0.0	0.0	7.7	0.9	5,588.5	248.4	134.8	13.7

Table 3. Model fit

	OSM Model			BER Model		
Variable	**Beta**	**Std. Error**	**Sign.**	**Beta**	**Std. Error**	**Sign.**
(Intercept)	1.321	1.517		27.071	6.391	***
Population	0.175	0.007	***	0.125	0.018	***
Education POI	8.956	2.416	***	8.306	5.638	
Leisure POI	-	-		-4.352	2.675	
Service POI	-	-		-8.189	3.493	*
Streetlights	-	-		3.325	0.668	***
Traffic signals	-12.872	0.944	***	-14.046	2.216	***
Intersections	-11.004	1.137	***	-19.272	3.156	***
Buildings	0.412	0.097	***	-	-	
Bus stops	-11.526	1.358	***	-16.831	4.418	***
Tram Stops	-9.486	3.761	*	-	-	
Length of cycleway [m]	-0.050	0.013	***	0.067	0.036	.
Length of sidewalk [m]	0.065	0.004	***	0.181	0.019	***
Length of roads [m]	1.043	0.013	***	0.905	0.042	***
Primary roads	-0.889	0.021	***	-	-	
Secondary roads	-0.733	0.015	***	-0.426	0.037	***
Tertiary roads	-0.503	0.018	***	-	-	
Pedestrian street [m]	-0.266	0.091	**	-	-	
Residential area [m²]	0.002	0.000	***	-	-	
Industrial area share [m²]	0.006	0.000	***	-	-	
Commercial area share [m²]	0.004	0.000	***	0.004	0.001	***
Pedestrian area [m²]	-0.010	0.004	*	-	-	
Residual standard error	61.67 on 10,964 degrees of freedom			62.94 on 934 degrees of freedom		
Multiple R^2	0.608			0.535		
Adjusted R^2	0.607			0.529		
F-statistic	944.7 on 18 and 10,964 DF			82.78 on 13 and 934 DF		
p-value	< 2.2e-16			< 2.2e-16		

*Significance codes: '***' p < 0.001, '**' p < 0.01, '*' p < 0.05, '.' p < 0.1*

4.3 Model evaluation

Using the previously estimated models and OSM data, the availability of parking lengths was estimated for parts of the city of Munich. The results were then compared with each other and with aggregated official parking counts. Table 4 presents descriptive statistics for the observed parking lengths and those predicted by both models in the study area, along with their deviations. The "difference" rows quantify the percentage deviation between observed and predicted parking availability across the specified statistical measures. Figures 2 and 3 show a visual comparison of these values. The scatter plots on the left contain a trend line and the corresponding confidence intervals. Histograms on the right summarize the deviations between the actual and modeled values.

The OSM model, on average, overestimates the observed parking length by just eight percent. While in grid cells with low parking availability, the length is overestimated, this negative bias decreases with increasing parking length. The parking space tends to be underestimated when the availability is more than 250 meters per grid cell. Apart from the minimum parking availability, differences between observed and predicted values range between 4 and 22 percent. The deviation distribution in Figure 2 shows a reasonably normal distribution curve. In most cases, the modeled value deviates slightly from the observed value. However, extreme overestimates of over 100 percent occur frequently.

The BER model exhibits the same trend, with overestimated parking spaces for grid cells with low availability and underestimated values beyond the third quantile of available parking spaces. Nevertheless, the mean estimate deviates by 20 percent. The trend toward overestimation is also evident in Figure 3. Overestimates of the available parking space occur primarily in grid cells with a short available parking length, while underestimates dominate from a length of around 250 meters. The histogram shows a high proportion of overestimates exceeding 100 percent. In addition, negative deviations of around 20 to 40 percent, as well as estimates that hardly deviate from the actual values, occur most frequently.

Table 4. Descriptive statistics of the model evaluation

Variable	Min	Q1	Mean	Q3	Max.	St. Dev.
Munich – Observed	**0.1**	**85.5**	**157.9**	**223.2**	**476.3**	**90.6**
OSM model	0.0	111.3	170.7	227.9	396.0	78.7
Difference	*-100%*	*+30%*	*+8%*	*+2%*	*-17%*	*-13%*
BER model	0.0	142.8	179.8	218.9	372.5	60.1
Difference	*-100%*	*+67%*	*+14%*	*-2%*	*-22%*	*-34%*

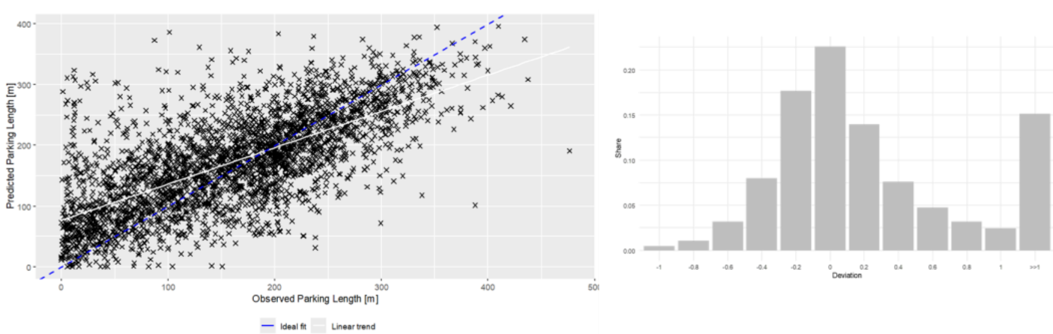

Figure 2. OSM model: Observed vs. predicted parking length (left) and deviations (right)

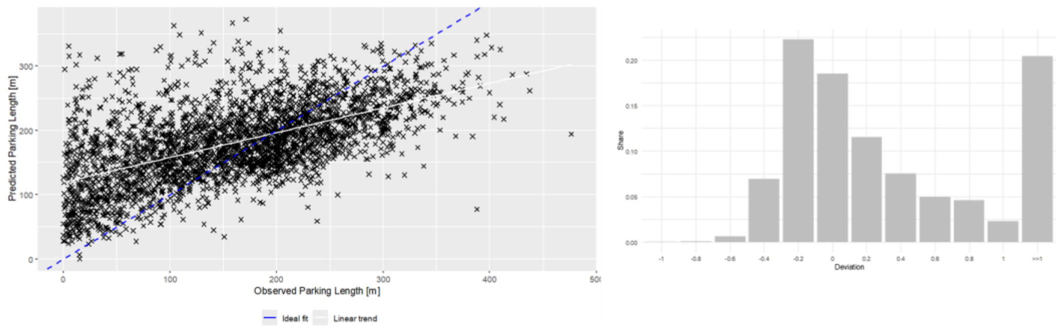

Figure 3. Berlin model: Observed vs. predicted parking length (left) and deviations (right)

While the OSM and BER models show reasonable regression results and similar trends of overestimating parking spaces in grid cells with low availability and underestimating values after a certain parking length, the OSM model demonstrates superior performance. The OSM model, on average, only overestimates observed parking length by eight percent, compared to the BER model, which deviates by 20 percent on average. Furthermore, the deviation distribution of the OSM model exhibits a reasonably normal curve, with most modeled values showing only slight deviations from observed values. In contrast, the BER model's histogram indicates a much higher proportion of extreme overestimates.

After comparing the two estimated models, the OSM model was chosen for further spatial analysis. The spatial distribution of modeled parking length deviations is visually presented on the right-hand map in Figure 4, allowing for a direct comparison with the observed parking length displayed on the left side.

Notable clusters of high positive deviations are evident in Munich's city center, where parking is often prohibited or restricted, and in the northern part of the study area. Both areas are characterized by relatively scarce on-street parking space. Conversely, many locations with little deviation between modeled and observed lengths have high parking availability, indicating better model performance in areas with abundant available parking.

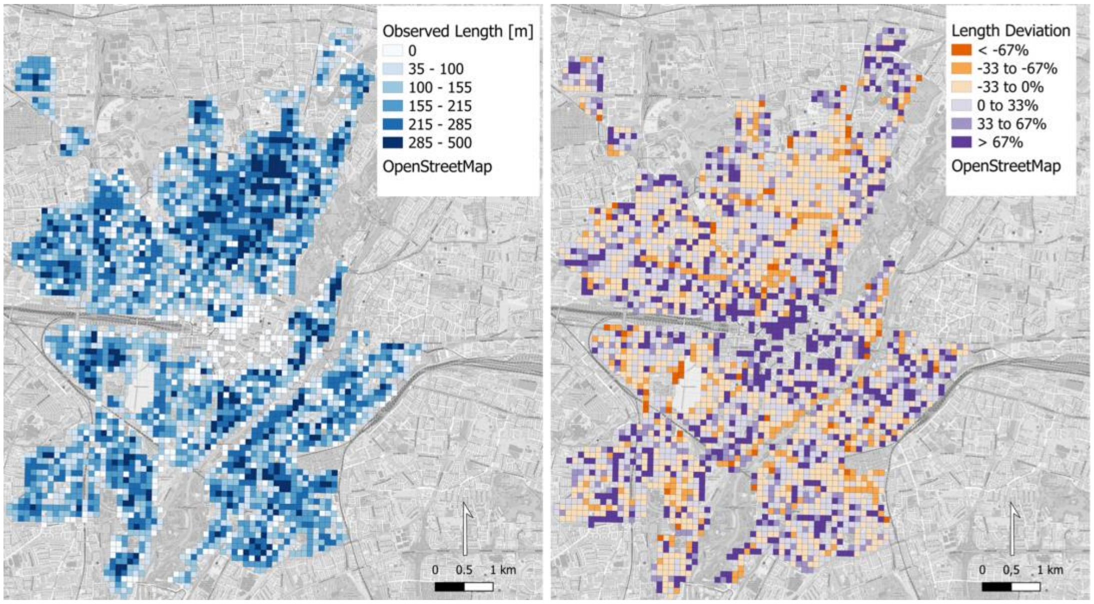

Figure 4. Observed parking length in Munich (left) and modeled length deviation (right)

5 Discussion

Examining two models for parking management, based on OSM and official data by the Berlin city administration, provides insights into the structure of parking supply in urban areas. Both models are conceptually sound and are based on the logic that increasing population density and urban development contribute to an increased supply of parking spaces. In contrast, the availability of parking spaces is restricted by space-consuming infrastructure elements such as intersections or bus stops, which compete for limited urban space. Understanding how these factors interact is crucial for effective urban planning and parking management strategies as cities evolve and face growing pressures of urbanization. By acknowledging the interplay between demographic and urban features, the models describe parking supply patterns influenced by the constraints of essential urban infrastructure.

The OSM model, incorporating data from 14 German cities of varying sizes and characteristics, provides a multi-site perspective, capturing a range of parking schemes and benefiting from a substantial sample size. While acknowledging known challenges with OSM data quality, the OSM model's approach signifies a comprehensive and broader understanding of parking dynamics across various urban settings. On the other hand, the BER model, derived from reliable, official parking counts in a specific district in Berlin, provides a smaller sample size and a relatively homogeneous parking situation.

Both models are evaluated using official parking data from Munich, a city not included in the model estimation, to assess their performance. This allows comparison to determine if modeling parking space supply in a large city can rely on distribution patterns from another large city or if seeking uniformity across various study areas is more appropriate. The OSM model demonstrates lower average deviations and a reduced occurrence of exceptionally high deviations.

While better results in the OSM model may be expected due to cross-city training, the additional insight lies in demonstrating the model’s transferability and generalizability across urban contexts, supporting its practical application in cities lacking detailed parking data.

Modeling parking inventories is particularly relevant for travel demand modeling. Parking is often considered one of the driving factors in destination and mode choice (Christiansen et al., 2017; Weis et al., 2011). Yet, most travel demand models ignore parking due to limited data availability. In an era where parking policies aimed at reducing car-oriented developments are promoted, proper consideration within transportation models is desirable. Emerging trends, such as the expansion of electric vehicle charging infrastructure or autonomous vehicles, highlight the importance of accurately representing parking in contemporary models.

Because officially recorded, detailed on-street parking data are rarely available, the use of an inventory model, as presented in this paper, provides a practical way to address data gaps. When applied within agent-based transport models, inventory models can further expand the ability to model and assess urban travel behavior. As cities continue to grow and face urbanization challenges, understanding and modeling parking behavior becomes indispensable for effective urban planning and the formulation of sustainable mobility strategies.

6 Conclusions

This study presented a macroscopic open-data approach to model the length of available urban on-street parking. Two models using OSM and official count data were estimated, compared, and later evaluated against observed parking availability in Munich, Germany.

The study acknowledges several limitations that offer opportunities for future research and model refinement. With parking length chosen as the dependent variable, it is essential to distinguish between parking length and parking capacity. Future research should focus on estimating parking capacity, which requires more sophisticated data sets and a better understanding of spatial and contextual factors, such as the orientation of on-street parking. While MLR served as the main method, future research should explore nonlinear models, such as hurdle models (Hellekes et al., 2023) and interactions between variables to improve both the model performance and its interpretability.

A comparison of the two models showed that both have reasonable coefficients of determination and significance levels. Both models identified the same factors for changes in parking space availability, including the length of multimodal networks, the presence of intersections and bus stops, and population density. Differences could be due to the varying quality and completeness of the data sets. Possible uncertainties must be considered, especially when using OSM data.

The high share of large deviations is acknowledged. The presented models result from multiple iterations aimed at developing a transferable model based on readily available data. The results in Figure 2 illustrate that the most significant deviations occur in cases of small observed parking lengths, suggesting that while the model may not perfectly replicate reality, major patterns are adequately captured. Ultimately, the model's suitability for specific applications will depend on the judgment of the final user.

Efforts should be made to improve data quality and availability, which depends mainly on the supporting community in the case of OSM. Additionally, consideration must be given to the fact that the data used are not raw OSM data but data from the OSM project by Seidel (2023), which is not regularly updated.

Another limitation of the current methodology concerns the spatial scale of the analysis. A grid-based approach was chosen here for computational efficiency and alignment with conventional traffic analysis zones (TAZs) in conventional travel demand models. The chosen grids were particularly useful as they matched the provided model data. Further elaborations could focus on different zoning or levels of detail. While this approach captures broad patterns, it may not fully represent differences between individual street links. Future analysis can focus on link-based modeling, potential computational constraints, and benefits over zone-based models.

Despite these limitations, our approach offers simplicity and flexibility, facilitating iterative improvements. The model's adaptability enables easy modifications and adjustments, laying the groundwork for future enhancements.

Moving forward, the research agenda prioritizes several key areas. First, efforts will focus on model improvement and exploring advanced methodologies. Extending the study to rural areas will provide valuable insights into the generalizability of our findings. Spatial analyses of the model results will help to improve the understanding of the model's performance in different landscapes and highlight areas where further refinement could be beneficial.

Future iterations can benefit from including complex parking details, such as residential parking schemes or parking spaces for electric vehicles. Including further potential parking facilities, such as public or private off-street parking, freight loading bays, or dedicated parking for people with disabilities, is a desirable extension. This approach contributes to a more comprehensive understanding of traffic and parking dynamics, thereby facilitating urban development modeling. Such insights are essential for designing effective planning strategies and promoting sustainable traffic management.

Acknowledgments

Rolf Moeckel participated in the initial conceptualization, design of the methodology, and early drafting of the manuscript. He passed away on 4 February 2025, prior to the final submission and acceptance of the paper. The remaining author acknowledges and deeply appreciates his contributions to this work.

This research was supported in part by the German Research Foundation under the grant agreement MO 1420/2-2.

For this paper, DeepL and Grammarly were used to assist with individual translations. All text and content were produced and reviewed by the authors, who take full responsibility for the manuscript.

Author contribution

The authors confirm their contribution to the paper as follows: conceptualization and methodology: M. Langer and R. Moeckel; investigation, visualization, and writing: M. Langer; supervision and first draft review: R. Moeckel.

References

Abouelela, M., Durán-Rodas, D., & Antoniou, C. (2024). Do we all need shared E-scooters? An accessibility-centered spatial equity evaluation approach. *Transportation Research Part A: Policy and Practice, 181*, 103985. https://doi.org/10.1016/j.tra.2024.103985

Akbari, H., Shea Rose, L., & Taha, H. (2003). Analyzing the land cover of an urban environment using high-resolution orthophotos. *Landscape and Urban Planning, 63*(1), 1–14. https://doi.org/10.1016/S0169-2046(02)00165-2

Arnott, R., & Rowse, J. (2009). Downtown parking in auto city. *Regional Science and Urban Economics, 39*(1), 1–14. https://doi.org/10.1016/j.regsciurbeco.2008.08.001

Ben Hassine, S., Mraihi, R., Lachiheb, A., & Kooli, E. (2022). Modelling parking type choice behavior. *International Journal of Transportation Science and Technology, 11*(3), 653–664. https://doi.org/10.1016/j.ijtst.2021.09.002

Berkson, J. (1942). Tests of significance considered as evidence. *Journal of the American Statistical Association, 37*(219), 325–335. https://doi.org/10.1080/01621459.1942.10501760

Berlin Open Data. (2022). *Parkraumbestand in teilen Charlottenburg-Wilmersdorfs* [Parking space inventory in parts of Charlottenburg-Wilmersdorf]. Offene Daten Berlin [Open Data Berlin]. Data license Germany – attribution – Version 2.0. https://daten.berlin.de/datensaetze/parkraumbestand-teilen-charlottenburg-wilmersdorfs

Bolar, K. (2019, April 1). The STAT package. Comprehensive R Archive Network (CRAN). https://cran.r-project.org/web/packages/STAT/index.html

Briem, L., Heilig, M., Klinkhardt, C., & Vortisch, P. (2019). Analyzing OpenStreetMap as data source for travel demand models: A case study in Karlsruhe. *Transportation Research Procedia, 41*, 104–112. https://doi.org/10.1016/j.trpro.2019.09.021

Chaniotakis, E., & Pel, A. J. (2015). Drivers' parking location choice under uncertain parking availability and search times: A stated preference experiment. *Transportation Research Part A: Policy and Practice, 82*, 228–239. https://doi.org/10.1016/J.TRA.2015.10.004

Christiansen, P., Engebretsen, Ø., Fearnley, N., & Usterud Hanssen, J. (2017). Parking facilities and the built environment: Impacts on travel behaviour. *Transportation Research Part A: Policy and Practice, 95*, 198–206. https://doi.org/10.1016/j.tra.2016.10.025

Davis, A. Y., Pijanowski, B. C., Robinson, K., & Engel, B. (2010). The environmental and economic costs of sprawling parking lots in the United States. *Land Use Policy, 27*(2), 255–261. https://doi.org/10.1016/j.landusepol.2009.03.002

Duran-Rodas, D., Villeneuve, D., Pereira, F. C., & Wulfhorst, G. (2020). How fair is the allocation of bike-sharing infrastructure? Framework for a qualitative and quantitative spatial fairness assessment. *Transportation Research Part A: Policy and Practice, 140*, 299–319. https://doi.org/10.1016/j.tra.2020.08.007

Feeney, B. P. (1989). A review of the impact of parking policy measures on travel demand. *Transportation Planning and Technology, 13*(4), 229–244. https://doi.org/10.1080/03081068908717403

Geofabrik. (2024). Geofabrik download server. http://download.geofabrik.de/

Guo, Z. (2013). Home parking convenience, household car usage, and implications to residential parking policies. *Transport Policy, 29*, 97–106. https://doi.org/10.1016/j.tranpol.2013.04.005

Hellekes, J., Kehlbacher, A., Díaz, M. L., Merkle, N., Henry, C., Kurz, F., & Heinrichs, M. (2023). Parking space inventory from above: Detection on aerial images and estimation for unobserved regions. *IET Intelligent Transport Systems, 17*(5), 1009–1021. https://doi.org/10.1049/itr2.12322

Ibraeva, A., de Almeida Correia, G. H., Silva, C., & Antunes, A. P. (2020). Transit-oriented development: A review of research achievements and challenges. *Transportation Research Part A: Policy and Practice, 132*, 110–130. https://doi.org/10.1016/j.tra.2019.10.018

Landeshaupstadt München. (2022). Open geodata: Parkseiten. https://geoportal.muenchen.de/portal/opendata/#LayerInfoDataDownload

Li, R., Helmrich, A., & Chester, M. (2022). Parking by the bay: The supply and implications of parking infrastructure in the San Francisco Bay Area. *Journal of Transport and Land Use, 15*(1), 527–545. https://doi.org/10.5198/jtlu.2022.2123

Llorca, C., Moreno, A., Ammar, G., & Moeckel, R. (2022). Impact of autonomous vehicles on household relocation: An agent-based simulation. *Cities, 126*, 103692. https://doi.org/10.1016/j.cities.2022.103692

Mackowski, D., Bai, Y., & Ouyang, Y. (2015). Parking space management via dynamic performance-based pricing. *Transportation Research Procedia, 7*, 170–191. https://doi.org/10.1016/j.trpro.2015.06.010

Manville, M., & Shoup, D. (2005). Parking, people, and cities. *Journal of Urban Planning and Development, 131*(4), 233–245. https://doi.org/10.1061/(ASCE)0733-9488(2005)131:4(233)

Merten, L., & Kuhnimhof, T. (2023). Impacts of parking and accessibility on retail-oriented city centres. *Journal of Transport Geography, 113*, 103733. https://doi.org/10.1016/j.jtrangeo.2023.103733

Openstreetmap. (2025, August 21). Street parking. https://wiki.openstreetmap.org/wiki/Street_parking

Overpass. (2023). Overpass turbo. https://overpass-turbo.eu/

Parmar, J., Das, P., & Dave, S. M. (2020). Study on demand and characteristics of parking system in urban areas: A review. *Journal of Traffic and Transportation Engineering, 7*(1), 111–124. https://doi.org/10.1016/j.jtte.2019.09.003

Priebe, S., Saidi, M., Kennedy, J., & Glover, G. (2008). How to select representative geographical areas in mental health service research: A method to combine different selection criteria. *Social Psychiatry and Psychiatric Epidemiology, 43*(12), 1004–1007. https://doi.org/10.1007/s00127-008-0383-4

Ripley, B. (2024). Support functions and datasets for venables and Ripley's MASS [R package MASS version 7.3-60.0.1]. Comprehensive R Archive Network (CRAN). https://cran.r-project.org/web/packages/MASS/index.html

Schreibmüller, J., Aumann, S., Preiß, S., & Kinigadner, J. (2025). From car-dependent to public space enthusiast: How can a typology of attitudes help to understand social acceptance of street space reallocation projects? *Transportation Research Interdisciplinary Perspectives, 30*, 101370. https://doi.org/10.1016/j.trip.2025.101370

Seidel, A. (2023). *Parkraumanalyse für den Berliner Ortsteil Neukölln – Methoden- und Ergebnisbericht* [Parking analysis for the Berlin district of Neukölln – Methods and results report]. OpenStreetMap Parkraum Projekt [Parking Project]. https://parkraum.osm-verkehrswende.org/project-prototype-neukoelln/report/

Shoup, D. C. (2011). *The high cost of free parking* (Updated ed.). American Planning Association.

Statistisches Bundesamt. (2011). Gitterzellenbasierte ergebnisse des zensus [Grid cell-based census results]. https://www.zensus2022.de/DE/Was-ist-der-Zensus/gitterzellenbasierte_Ergebnisse_Zensus2011.html

Taylor, E. (2021). Free parking for free people: German road laws and rights as constraints on local car parking management. *Transport Policy, 101*, 23–33. https://doi.org/10.1016/j.tranpol.2020.11.013

Weinberger, R. (2012). Death by a thousand curb-cuts: Evidence on the effect of minimum parking requirements on the choice to drive. *Transport Policy, 20*, 93–102. https://doi.org/10.1016/j.tranpol.2011.08.002

Weis, C., Vrtic, M., Widmer, P., & Axhausen, K. W. (2011). Influence of parking on location and mode choice: A stated choice survey. *Arbeitsberichte Verkehrs- und Raumplanung*. https://doi.org/10.3929/ethz-a-006543999

Willson, R. W., & Shoup, D. C. (1990). Parking subsidies and travel choices: Assessing the evidence. *Transportation, 17*(2), 141–157. https://doi.org/10.1007/BF02125333