Machine Learning for the Efficient Prediction of Barrier-Integrated Walk Scores

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Key words: Walkability, Walk Score, Machine Learning, Barriers, Elderly

SUMMARY

Walkability, understood as the extent to which an environment supports walking as a means of transportation in everyday life, is shaped by local, historically grown urban structures and therefore can vary significantly between cities and regions. To systematically record and compare these differences, walkability is typically measured using pedestrian indices and corresponding assessment tools. Composite assessments that calculate distances to multiple amenities simultaneously, such as the Walk Score, may take a relatively long time to process. Against this background, the present study examines a machine learning approach for the efficient estimation of senior-sensitive walkability using Walk Scores. The approach is being evaluated in two German county districts with the goal of reducing processing time while maintaining accurate approximations.

To evaluate the quality of the model and to avoid overfitting, the overall accuracy of the training and the test dataset is compared, supplemented by cross-validation between two study regions, and the performance is evaluated. The results show that the proposed machine learning approach can generate predictions for Walk Scores that are largely accurate and transferable, with significantly lower computational costs.

ZUSAMMENFASSUNG

Die Begehbarkeit (walkability) eines Ortes wird von lokalen, historisch gewachsenen Strukturen geprägt, weshalb Erreichbarkeiten räumlich variieren. Um die Unterschiede systematisch zu erfassen und zu vergleichen, wird die Begehbarkeit in der Regel mit Hilfe von Indizes und entsprechenden Bewertungsinstrumenten gemessen. Zusammengesetzte Indizes, die Distanzen zu mehreren Versorgungseinrichtungen berechnen, wie z. B. der Walk Score, benötigen relativ lange Verarbeitungszeiten für die Berechnung. Vor diesem Hintergrund untersucht die vorliegende Studie, inwiefern ein Ansatz, der auf maschinellem Lernen basiert, zur effizienten Schätzung der seniorenfreundlichen Begehbarkeit mit Walk Scores beitragen kann. Der Ansatz wird in zwei deutschen Landkreisen umgesetzt und hat zum Ziel, die

Rechenanforderungen zu reduzieren sowie dabei ausreichend genaue Näherungswerte zu erreichen.

Um die Modellqualität zu bewerten und Überanpassung (Overfitting) zu vermeiden, wurde die Gesamtgenauigkeit der Trainings- und Testdatensätze verglichen, eine Kreuzvalidierung zwischen den beiden Studienregionen durchgeführt und die Rechenleistung gemessen. Die Ergebnisse zeigen, dass die vorgeschlagene Vorgehensweise mittels Machine Learning weitgehend genaue und übertragbare Vorhersagen von Walk Scores zu wesentlich geringeren Rechenkosten erzielen kann.

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1. INTRODUCTION

Walking is probably the most natural and sustainable form of human mobility**.** It plays a vital role in promoting physical fitness, mental well-being, and social interaction of individuals. As such, walking contributes significantly to health and overall quality of life (see Akhavan & Vecchio 2013, Gatrell 2013, Morales-Flores, & Marmolejo-Duarte 2021). Walking, in addition, supports sustainable urban development by reducing greenhouse gas emissions and encouraging urban forms that can help limit land take (Jeong et al. 2023, Baobeid et a. 2021, Schaffert et al. 2025). These contributions make walking highly relevant to global frameworks such as the United Nations Sustainable Development Goals (SDGs), particularly those related to health (SDG 3), sustainable cities and communities (SDG 11), and climate action (SDG 13) (Bencekri et al. 2023).

A key concept in this context is walkability, which describes the extent to which an environment supports walking as a mode of everyday transport (cf. Warner et al. 2022). Since the ability of cities and municipalities to provide suitable conditions for walking is shaped by local urban structures that developed historically, walkability can vary considerably across regions. To better understand and compare these differences, it makes sense to assess walkability systematically. As a multidimensional concept, walkability is therefore often addressed through the use of certain pedestrian indices and assessment tools (Maghelal & Capp 2011, Fatima et al. 2020). A popular method for assessing walkability in urban settings is the Walk Score (Carr et al. 2010), a widely used metric for evaluating pedestrian friendliness. It is based on a reachability analysis that uses shortest-path routing to determine the distance from a given location to relevant amenities. The number, proximity, and relevance of these amenities are then combined into a single numerical value (a Walk Score) representing overall walkability. The resulting Walk Scores can be aggregated into larger spatial units such as neighborhoods or entire municipalities fostering comparative analyses and spatial planning at multiple spatial scales (Brown et al. 2023).

This applies, for example, to the challenges posed by ageing single-family housing areas, millions of which have been built in Germany since the Second World War (DESTATIS 2023). The owners, who are usually the original builders, tend to remain in their single-family homes after their children move out, with in-migration typically occurring only after the older generation passes away or residents have to move to a nursing home. This results in a comparatively high proportion of elderly residents in single-family housing areas developed, for example, in the 1970s and 1980s (Berndgen-Kaiser 2016; Schaffert & Steensen 2024). In rural areas, where residential estates from these decades are widespread, a multi-scalar approach for measuring walkability is advisable. Such an approach would enable the identification of local walkability, besides demographic issues, of neighborhoods while also capturing service availability and accessibility patterns at higher administrative scales, such as county districts (see e.g. Schaffert et al. 2025). This is reasonable because (rural) housing markets operate regionally (Slocombe 2003; Jones et al. 2011), and resource constraints in rural municipalities often limit local implementation of problem analyses and management. Regional authorities, such as district administrations, therefore, provide more feasible options. However, realistic walkability assessments must also account for barriers such as stairs or steep inclines to meet the needs of seniors living in these ageing housing areas (Horak et al. 2025; Schaffert et al. 2023), who are more likely to face mobility restrictions (Lavery et al. 1996) and wish to age in place independently. Performing calculations at neighborhood-level precision on a street network, while also providing aggregated results for larger spatial units such as counties, increases processing demands and reduces the efficiency of composite measures such as the Walk Score.

These computational challenges open the door for alternative approaches. Machine learning (ML) enables efficient modeling of complex, nonlinear relationships between environmental variables and perceived or objective walkability, without requiring all influencing factors to be predefined. Techniques such as neural networks and dimensionality reduction (e.g. Principal Component Analysis) allow automated selection of relevant features, thereby reducing model complexity and accelerating computations (cf. Delavar et al. 2025; Yang et al., 2024; Zeng et al., 2022). Scalable approaches such as the Active Living Feature Score (ALF-Score) use large-scale geospatial data and user preferences to predict walkability, while avoiding costly route calculations and enabling efficient large-area analyses (Alfosool et al., 2022). Artificial Intelligence (AI) based simulation models further incorporate mobility-specific needs, particularly of older adults, enabling targeted, context-sensitive walkability assessments relevant for supporting ageing in place (Gorrini & Bandini, 2018). Moreover, by integrating big data sources and open geospatial datasets such as OpenStreetMap automated, and cost-efficient updating of walkability analyses are supported (Yang et al., 2024). Complementary studies predict pedestrian activity or reveal dynamic, long-term relationships between urban form, deprivation, and walkability (Cohen et al., 2021; Wang et al., 2024), providing valuable input for refining models and enhancing their practical applicability.

Building on this background, the present study investigates a machine learning–based approach to efficiently estimate senior-sensitive reachability using Walk Scores. We evaluate this approach in two German county districts, with the objective of reducing processing time while preserving accurate approximations of walkability: Landkreis Kaiserslautern in Rhineland-Palatinate and Landkreis Tirschenreuth in Bavaria.

To this means, this study first describes the study areas, data sources, and the methodology for integrating barriers and predicting the Walk Score based on ML. It then presents results on prediction accuracy and computational efficiency. Subsequently, key implications and limitations of the approach are discussed. Finally, the paper summarizes the main findings and outlines potential directions for future research.

2. METHODOLOGY AND STUDY REGION

2.1 Study Region

We examine two case study areas that differ in their spatial and structural characteristics: the district of Kaiserslautern and the district of Tirschenreuth.

The district of Kaiserslautern is located in the federal state of Rhineland-Palatinate, Germany. It extends roughly 40 kilometers from west to east and 30 kilometers from north to south. Elevations range from about 200 meters above sea level near Olsbrücken to over 500 meters in the hilly Palatinate Forest near Johanniskreuz. The district has a population of about 72,000 and surrounds the independent city of Kaiserslautern, which has about 99,000 inhabitants. While not part of the district administratively, the city forms its economic and infrastructural center.

The district of Tirschenreuth lies in northeastern Bavaria, directly at the border to the Czech Republic. It covers an area of about 1,085 square kilometers and has a population of around 72,000. The landscape is characterized by gently rolling hills, reaching over 900 meters in the Steinwald and Upper Palatinate Forest. The settlement structure is predominantly rural, with small towns and villages distributed across the area. The biggest town is Tirschenreuth, with approximately 8,000 residents, so the district lacks a comparably dominant urban center like the city of Kaiserslautern in its surrounding district.

Both study regions are predominantly rural in character but differ in their degree of rurality and socio-economic conditions. According to the classification by the Thünen Institute (Thünen-Institut, 2022), the district of Kaiserslautern is categorized as a type 3 rural area (rather rural with less favorable socio-economic conditions). In contrast, the district of Tirschenreuth is classified as a type 1 rural area (very rural with less favorable socio-economic conditions). These classifications reflect differences in population density, settlement patterns, and socio-economic indicators, to provide a nuanced understanding of the rural contexts. Figure 1 shows the location of both regions in Germany.

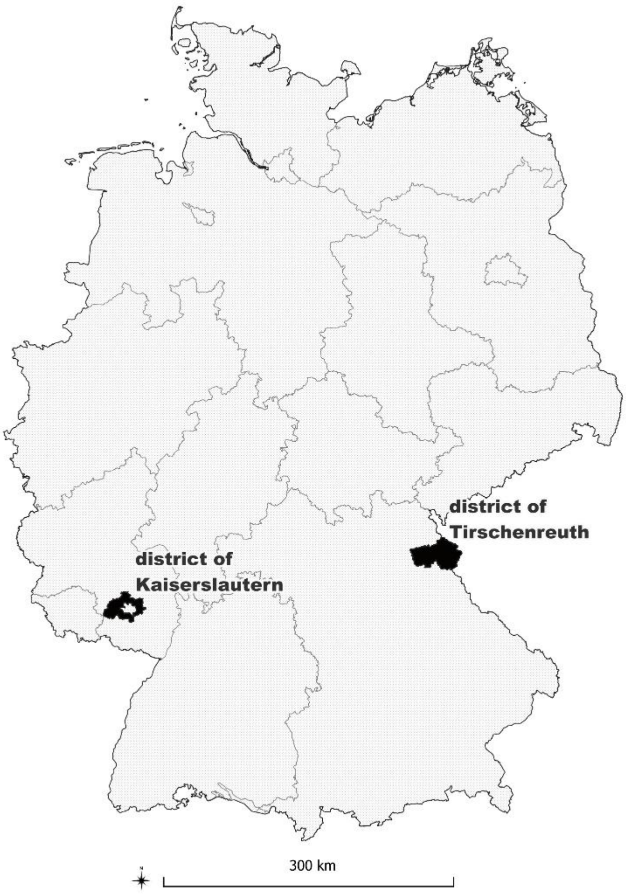

Figure 1: The country districts of Kaiserslautern and Tirschenreuth within Germany and its Federal states.

2.2 Walk Score

The Walk Score is an accessibility index based on routing algorithms. It is calculated through a network-based analysis that determines the distance from a given starting point to relevant amenities such as grocery stores, restaurants, parks, schools, and health centers. The index increases with the number and importance of reachable amenities, taking into account both the distance and the time it takes to reach them on foot. Results are expressed on a scale that ranges from 0 to 100, with higher values indicating better pedestrian accessibility (Carr et al. 2010). Scores between 90 and 100 ("Walker's Paradise") indicate that daily activities can easily be carried out without a car; 70–89 ("Very Walkable") means most activities are reachable on foot; 50–69 ("Somewhat Walkable") indicates limited walkable destinations. 25–49 ("Car Dependent") means most trips require a car, and 0–24 ("Highly Car Dependent") indicates that a car is essential. Figure 2 shows exemplary results from a Walk Score computation, aggregated on a grid.

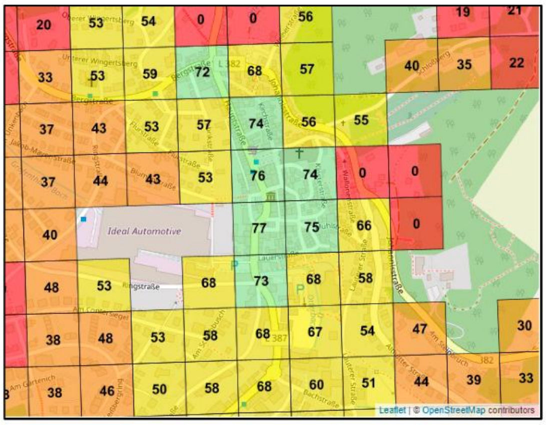

Figure 2: Example of a Walk Score map illustrating walkability values assigned to each individual grid cell (Schaffert et al. 2025).

With a focus on senior-sensitive walkability, this study draws on a Walk Score–based application that specifically considers the needs of older citizen by integrating barriers into the assessment (cf. Müller et al. 2024, Kim & Jin 2023, Schaffert et al. 2023; cf. Towne et al. 2016).

2.3 Machine Learning, Data and Processing

ML is a subfield of AI that enables algorithms to learn from examples rather than relying solely on predefined rules. While rule-based programming requires developers to specify every instruction, ML systems identify patterns in data and use these patterns to make predictions or decisions. This ability enables them to handle complex tasks such as forecasting of trends, grouping similar items, or recognizing unusual behavior in a variety of application areas (Shailaja et al. 2018).

In order to train a ML model, the truth of the target variable (in this case the Walk Score) is required. The data we use therefore contains true Walk Scores for routes in the both investigated county districts within a 100m x 100m grid. In terms of input features for the ML model, we use data from the OpenStreetMap project (https://www.openstreetmap.org). These include barrier points, barrier lines and points of interest. Barriers, for example, are stairs, which are more difficult to overcome and therefore influence the walking time. Case studies in the context indicate that between one-third and one-half of seniors aged 65 or older report difficulties walking or climbing stairs (Webber et al. 2010), with more than half identifying staircases as their main mobility barrier (Mou et al. 2024). Following the Walk Score methodology, points of interest encompass all relevant amenities across the following categories: coffee shops, bookshops, banks, shops, schools, restaurants, parks, grocery stores, and entertainment facilities.

The idea behind creating a dataset of input features is to apply a buffer to each parcel and count the number of barriers and points of interest. Figure 3 shows the steps of this process in the software QGIS (https://qgis.org/, accessed 09. December 2025). For each raster cell of the 100m x 100 m grid, we take the center point as the point object and create a buffer around it. We then count the number of objects for each feature within the buffer and assign them as columns to the raster centroid. This process allows testing different buffer distances, as the model's performance may vary with wider or narrower ranges.

We also consider the total length of all barrier lines in each raster, as this could impact the ML model. For example, one raster might have five barrier lines, while another has just one. However, the five barrier lines may be very short and not significant to the Walk Score, whereas the single barrier line may be long. This information needs to be integrated into the data. Table 1 shows exemplary a data point from the final data set. It illustrates the number of barriers that are located in one of the defined buffers around a grid cell and have entered the calculation.

Table 1: Exemplary data point of the final dataset
(w = Walk Score; n = number in total; m = meters).

	Feature	**Data**
Output	Walk Score [0 < w < 100]	37.47
Input	Barrier points [n]	22
	Barrier lines [n]	7
	Length of barrier lines [m]	151.03
	Coffee [n]	1
	Books [n]	1
	Banks [n]	2
	Shopping [n]	31
	Schools [n]	2
	Restaurants [n]	2
	Parks [n]	2
	Grocery [n]	4
	Entertainment [n]	0
Coordinates for visualization	Longitude [°]	7.64236925
	Latitude [°]	49.4793501

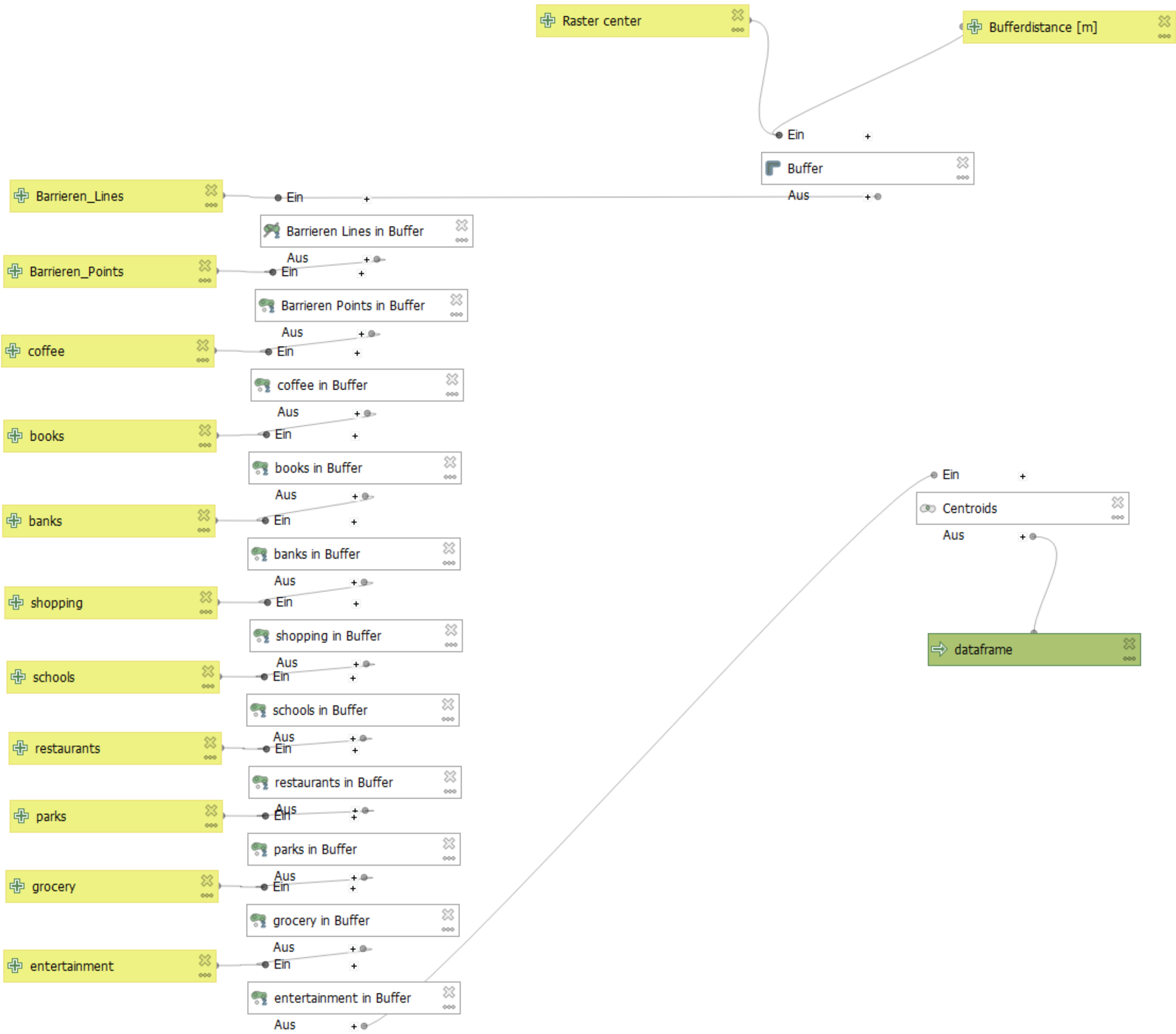

Figure 3: QGIS Model Workflow to Create the ML Dataset.

To train the ML model, we split the dataset into training (area 1) and testing (area 2), using the two different regions to account for spatial dependencies. This ensures that the model is tested on completely unknown data. To check for further differences in geospatial behavior, we also reverse the training and testing area for a second assessment of model quality. To evaluate the quality of the ML model, we consider the overall accuracy (OA) of the training and test sets, as well as the root mean squared error (RMSE), since these are common metrics for regression problems. The RMSE shows the average difference between predicted and actual values.

The true Walk Score is 0 for many raster cells. This can cause problems for ML algorithms trying to model the output using the input features. To address this, we opted to train a zero-inflated regression model (ZIR, cf. Richardson et al. 2017). A ZIR is a combination of a classifier and a regressor. The classifier classifies all data points where the target feature is zero. The regressor models the target variable using all the other data points (Figure 4). The benefit of two-part models such as the ZIR therefore becomes apparent when dealing with datasets with excess zeros (Lee et al. 2006). As our dataset contains many instances, where the Walk score is zero, we decided to use this type of machine learning model.

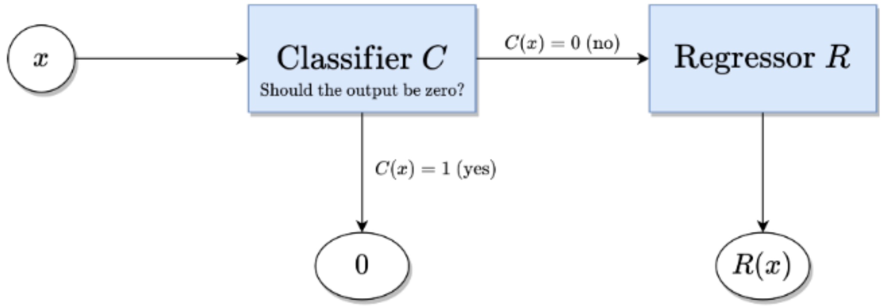

Figure 4: General Methodology of a Zero-Inflated Regression (Kübler 2021).

An example of the benefit of a ZIR can be seen in Figure 5. Had a linear regression been used for the displayed data, the linear model would also have considered the zeros, increasing the error margin for the other data points.

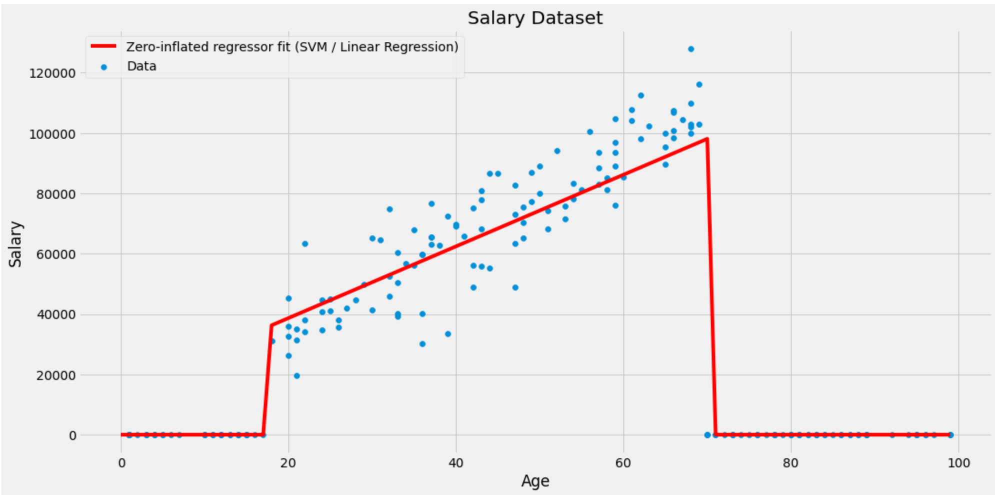

Figure 5: Example of a Zero-Inflated Regression (Kübler 2021).

In our case, we use a logistic regression classifier and a linear regression regressor for the ZIR. Logistic regression models ‘are used to study effects of predictor variables on categorical outcomes. Normally, the outcome is binary, such as presence or absence of disease’ (Nick and

Campbell 2007). In our case, the logistic regression therefore classifies whether or not there is a zero.

A ‘multiple linear regression model is the most commonly applied statistical technique for relating a set of two or more variables ‘ (Jobson 1991, p. 219). Mathematically it can be displayed as:

$$\hat{y}_i = b_o + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots b_n x_n \quad (1)$$

where $\hat{y}_i$ is the target of our model, in our case the Walk score, and x_n are the input features. The model then finds the coefficients b_n to model $\hat{y}_i$. These coefficients can later be interpreted as feature importances, making the model transparent and interpretable.

3. RESULTS

In our data generation process, we tested different buffer sizes. The best model performance was achieved with a buffer size of 1000m instead of 500m, 2000m or 3000m. We checked for overfitting by looking at the OA of the training and test sets. If the accuracy of the two test sets differs, overfitting can be assumed. Overfitting means that the model is too closely adapted to the training data and makes inaccurate predictions on new data. Otherwise, the model shows good generalization on unseen data, what indicates that it has learned the underlying relationships and also makes good predictions on new data. To respect geospatial dependencies, we trained the model twice: First, we trained the model on the data from area 1 (district of Kaiserslautern) and test it on the data from area 2 (district of Tirschenreuth). Then, we reversed the process and train the model on the data from area 1 and test it on the data from area 2. We then consider the RMSE. Furthermore, we include a time measurement to predict each instance in the data. The prediction with the time measurement is done on a Windows 11 system with a 1st Gen Intel® Core™ i7-1185G7 processor, 32 GB of RAM and a 64-bit operating system. The following Table 2 shows the ML results.

Table 2: ML model results.

Area	ML purpose	Instances	OA	RMSE	Time [millisec]
1	Training	7564	0.586	12.808	2
2	Test	5699	0.545	10.133	3
2	Training	5699	0.736	7.713	3
1	Test	7564	-0.647	25.549	2
Mixed	Training	9947	0.644	11.233	2
Mixed	Test	3316	0.628	10.832	1

Training the model on the data for area 1 and testing it on the data for area 2 produced results showing no overfitting and good generalization. However, when the training and testing data were reversed, the ML algorithm failed to model the Walk Score, as evidenced by the significant difference in quality measures between training and testing. This may be due to the smaller number of training samples (5699 instead of 7564 from before). To investigate this further, we trained the model a third time, combining both regions and splitting the shuffled data into 75% for training and 25% for testing in order to increase the number of samples used to train the model. These results again demonstrate better generalization and improved performance. However, combining data from different geospatial contexts is not recommended. The model evaluation is not performed on data that may contain unseen geospatial structures. This shows, however, that the model might need more data to be trained adequately.

Figures 6 and 7 show an example of the true and predicted result. As can be seen, the model recognizes that the Walk Score tends to increase (green color) in the city center, where there are more amenities or services, and decrease (red color) on the city borders. The vast majority (78.14 percent) of all grid cells in the test area have a deviation of up to 10 Walk Scores. Essential spatial patterns are also preserved, such as a high Walk Score in the well-served center of towns, which decreases towards the outskirts.

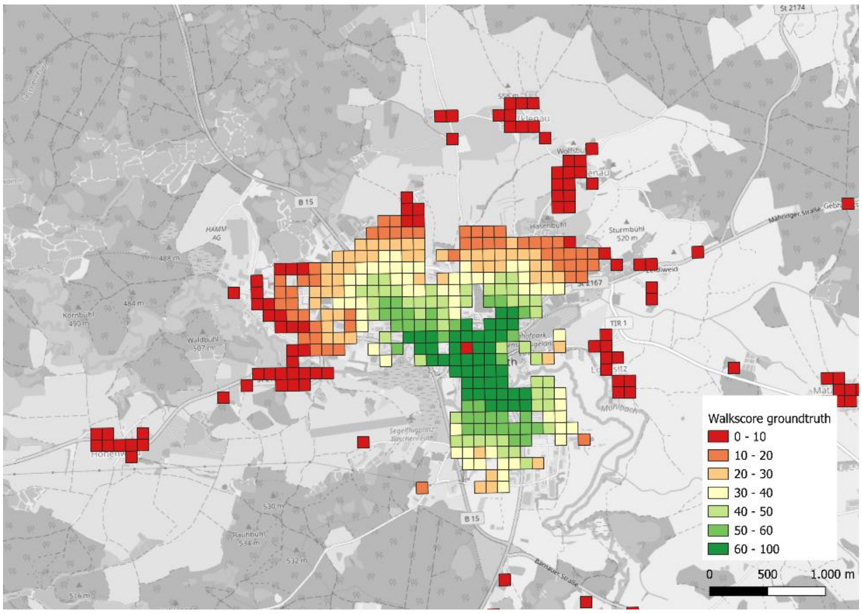

Figure 6: True Walk Score for the city of Tirschenreuth. (Map orientation: North)

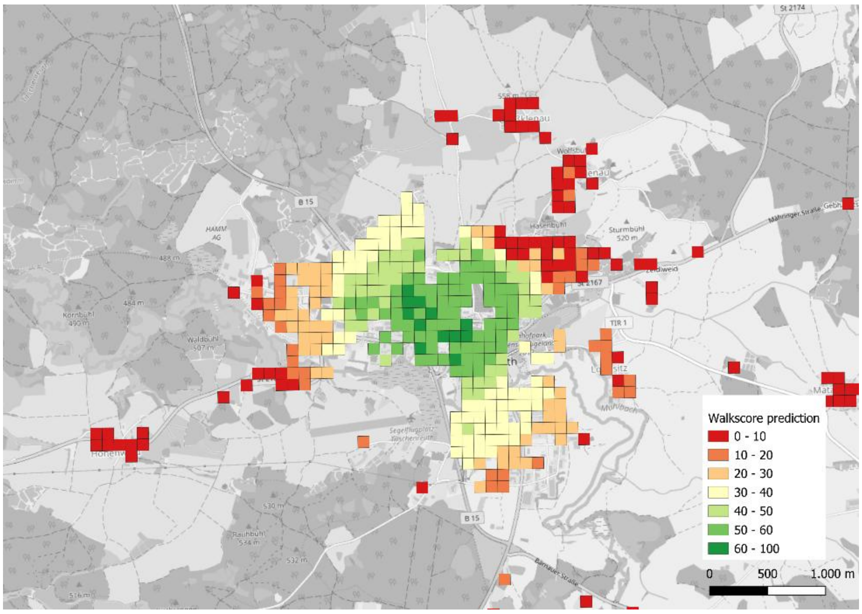

Figure 7: Predicted Walk Score for the city of Tirschenreuth. (Map orientation: North)

While calculating a district using the conventional method took us around half an hour, the ML-calculated values are computed in only 1-3 milliseconds. This demonstrates the potential of using ML to compute Walk Scores, particularly for larger areas and higher numbers.

4. DISCUSSION

In small villages where there are few amenities or services, barriers and a low Walk Score, the zero-inflated regression classification shows good results. Larger errors appear in larger villages. Figure 8 shows the true Walk Score values (red = low Walk Score; green = high Walk Score) and Figure 9 shows the error from the prediction on the right (white = low error; red = high error). The ground truth values show that the Walk Score increases in the center of the village and decreases towards the edges. This can be explained by the greater number of Points of Interest (POIs) in the center. However, there are a few raster cells where the Walk Score is 0 (red color), which could indicate the presence of unbreachable barriers leading to a very low Walk Score. The highest errors in the prediction are found in these raster cells. The model predicted a high value because many POIs can be found around the raster center. However, the model does not calculate walking routes. This means it cannot identify these special raster cells in the same way that the normal calculation process for Walk Score would.

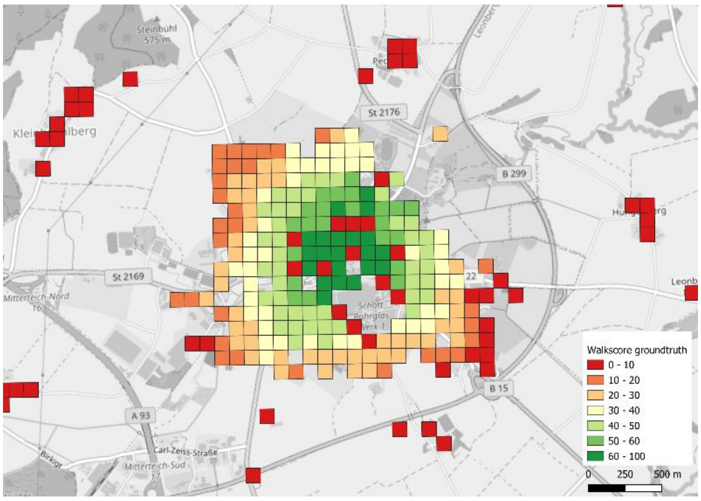

Figure 8: True Walk Score for the city of Mitterteich (district of Tirschenreuth). (Map orientation: North)

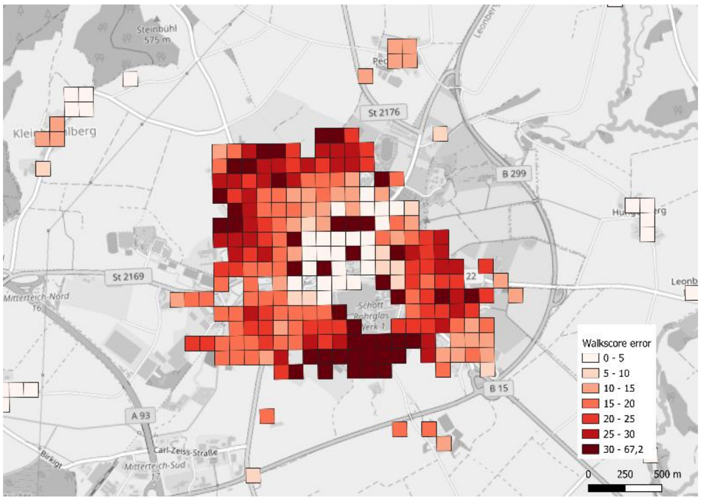

Figure 9: Deviation from the prediction to ground truth. (Map orientation: North)

Table 3: Feature importances (coefficients) of the Zero-inflated regression.

feature	coefficient
Barrier points	4.12
Barrier lines	3.22
Length of barrier lines [m]	-6.88
Coffee	-3.26
Books	5.55
Banks	4.58
Shopping	-16.22
Schools	4.58
Restaurants	4.11
Parks	0.42
Grocery	12.27
Entertainment	-0.54

Another issue becomes apparent in the feature importances. Table 3 shows the coefficients of the linear regression in the zero-inflated regression, and therefore the feature importances.

A high positive feature importance indicates that the value of the modeled feature (Walk Score) increases when the feature value increases. A negative feature importance indicates the opposite. The Walk Score decreases when the feature value increases. Table 2 shows three problematic feature importances marked in orange and two in green. The first two orange features are the number of barrier lines and the number of barrier points. Both of these coefficients (3.22 and 4.12) are positive. This means that the higher the number of barriers around the considered point, the higher the Walk Score. However, this is illogical as the barriers should reduce the Walk Score and have a negative coefficient, like the first green feature, the length of barriers (-6.88). The same issue arises for the 'shopping' feature, which has a high negative coefficient (-16.22). However, the importance of POIs should be positive, as with the grocery category (12.27), since the Walk Score normally increases with more reachable POIs. Taking into account the importance of the features and the issue in Figure 8 and 9 above, the model predictions cannot be fully trusted. Further investigation also shows problematic parts in the prediction.

Another point of discussion concerns the data used in our approach: We relied on street data from the OpenStreetMap (OSM) project, which is also utilized in many current walkability studies (Horak et al. 2022, Otsuka et al. 2021). While, unlike official geodata in Germany, OSM operates without mandatory regulations for data quality assurance, instead relying on recommendations, the quality of street data has improved to a level that can be considered as sufficiently reliable for our application (Zhang and Malczewski 2017). However, unlike network-related data, senior-specific Points of Interest (PoI), such as pharmacies or physiotherapy facilities, do not fall under OSM's core data categories. Therefore, the quality of these PoI data can vary significantly, depending on the contributions from the OSM community (Brückner et al., 2021). Our primary goal was to present a methodological approach to calculate the Walk Score using machine learning, rather than providing an exact real-world representation. Thus, we used OSM data to successfully demonstrate how this approach can be applied within the constraints of open, publicly available data, while acknowledging the limitations in PoI data accuracy.

5. CONCLUSION AND FUTURE WORK

The goal of this study was to reduce computational effort while maintaining meaningful approximations of walkability applying the Walk Score. The approach was conducted through Machine Learning and tested in two German county districts: Landkreis Kaiserslautern in Rhineland-Palatinate and Landkreis Tirschenreuth in Bavaria. The results show that the ML-based Walk Score calculation leads to a significant increase in efficiency in our study areas, while the loss of accuracy is not too large.
This represents a significant improvement over traditional, computationally intensive methods. It opens up new applications for urban and spatial planners, as it will enable real-time calculations of complex Walk Scores and scenarios (e.g., the closure of a shop) in the future. In future research, more data from other regions in Germany should be included to identify, if the mentioned problems reappear and how the model can be improved. In addition, planning experts should be consulted to verify whether the variations in Walk Scores are acceptable for their specific purposes. Our results show, at least, that it may be worth taking this next step.

Furthermore, explainability with a focus on geospatial explainable AI (Roussel & Böhm 2025) and user-friendliness remain key to making results accessible to diverse stakeholders. While ML enables faster predictions, barrier-integrated calculations remain essential for explicitly revealing the factors behind high or low Walk Scores. Complementary work (Schaffert et al. 2025) indicates that explainability can be enhanced through advanced visualization components, such as 3D terrain views and the display of individual routes, adding further dimensions of accessibility. A GIS-based viewing component could integrate multiple layers, for example: dynamically generated ML results for scenario simulations (e.g., facility closures), a pre-processed Walk Score as ground truth for a given date, and the locations of relevant amenities. This layered approach would allow users to change perspectives and detail levels, strengthening both interpretability and practical applicability.

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