AGILE: GIScience Series, 7, 35, 2026. https://doi.org/10.5194/agile-giss-7-35-2026
Proceedings of the 29th AGILE Conference on Geographic Information Science, 16–19 June 2026.
Eds.: Evelyn Uuemaa, Alexander Kmoch, Holger Virro, and Simon Scheider
This contribution underwent peer review based on a full paper submission.

Fuzzy Meta Indices: A Bikeability Case Study in Augsburg

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Abstract. Biking as an active way of travelling has many benefits and many cities try to promote it. The first step to informed decisions that increase the bikeability of a city's street network is to understand where its strengths and weaknesses lie. Therefore one usually creates indices that classify certain aspects of a city's roads into more positive or negative values. We present a methodology to combine multiple such indices into a fuzzy meta index with fuzzy inference systems in a street network. In the case study area of central Augsburg in Germany we present all indices as histograms to make the way these systems work more visible. There we compare the results of different fuzzy inference systems. The best result is then compared with a standard meta index obtained by the weighted mean of the single indices. The results show that the alternations to the fuzzy inference systems allow adjustments to the fuzzy meta index. We conclude that the methodology presented yields an more adaptive alternative to the weighted average for combining sub-indices.

Submission Type: Theory, Analysis, Algorithm, Case Study, Infrastructure

BoK Concepts: [AM] Analytical Methods, [CF] Conceptual Foundations

Keywords. Fuzzylogic, Bikeability, Meta-Index, Augsburg

1 Bikeability is an important but Fuzzy Concept

An increasing number of cities try to facilitate using bicycles as a means of transportation. When we ride bicycles to get from A to B there are not only the benefits of active travel, but also those for the environment (Lee et al., 2023). An important first step for cities to promote cycling is to understand the level of service of its existing infrastructure. The level of service of streets for bicycles is called bikeability. A common way to get an idea thereof is to create an index that summarizes a selection of important factors (Jonietz and Timpf, 2012; Werner et al., 2025; Grisiute and Raubal, 2025). We present a new methodology of calculating such an index using fuzzy inference. With that we want to help cities understand their potential better.

Bikeability is subjective and situational (Löw et al., 2025). A mountain bike rider might look for steep uneven tracks, while a cargo bike rider is interested in flat and even roads. The perfect road is dependent on the situation of the rider. Zadeh (1965) introduces fuzzy logic as a means to address vague or imprecise concepts. Mamdani and Assilian (1975) apply that concept in a way to capture expert knowledge and call it a fuzzy inference system.

We set up multiple different systems with a custom python package[1]. They are then used to create fuzzy bikeability meta indices comprising three different sub indices (elevation-index, comfort-index, accessibility-index). These meta-indices are added to a streetgraph in a case study area in Augsburg. We compare the results of eight different fuzzy inference systems to understand which performs best and compare that with a non-fuzzy meta index.

The research gap we find is that the standard of using the weighted average of sub-indices is often oversimplifying the interactions of the corresponding factors. Further, finding the weights can be difficult and they are not generally applicable (Grisiute and Raubal, 2025; Werner et al., 2025). Therefore, we explore the options fuzzy logic offers addressing the following three questions: 1) How is the fuzzy meta index characterizing the streets of the case study area? 2) Which factors of a fuzzy inference system are important for this characterization? 3) What are the differences between indices from the weighted average and a fuzzy inference system?

1.1 Background of the Bicycle Network

The number of indices that classify streets in terms of their bicycle friendliness increases. Grisiute and Raubal (2025) list accessibility of points of interest, attractiveness of roads, perceived safety and comfort as their top four criterias for highly bikeable roads. Their list of most im-

[1]https://git.rz.uni-augsburg.de/loewpabl/fuzzy_polygons/, last access: April 15, 2026

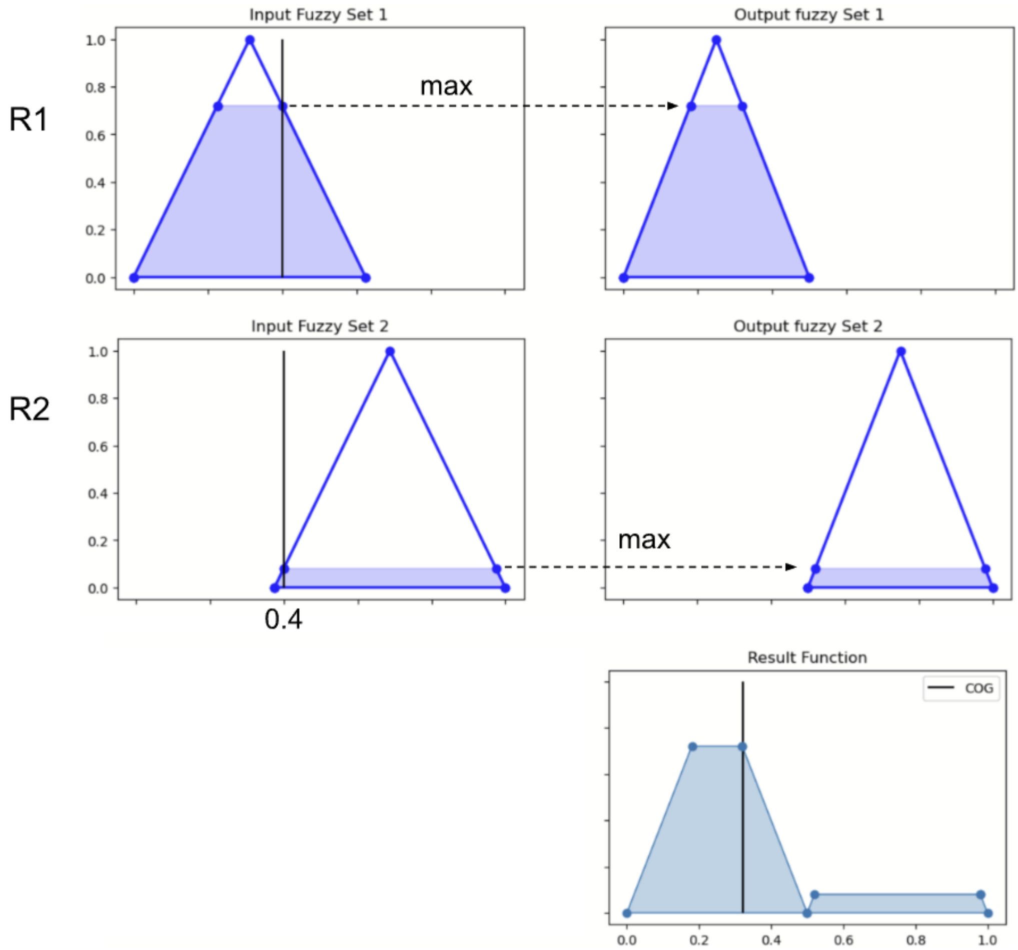

Figure 1. Fuzzy inference example with one input domain (left column) and one output domain (right column). Each domain has two fuzzy sets. Rule 1 (row one) connects Input Fuzzy Set 1 with Output Fuzzy Set 1. Rule 2 has the same structure. The input value is 0.4 (black line) the defuzzified value is 0.333 (Center of gravity).

portant metrics is led by slope. For this study we opt for accessibility, comfort and slope from these two lists, since attractiveness and safety are difficult to parameterize and very subjective (Jonietz and Timpf, 2012). This selection of criterias is also in other bikeability meta indices (Bíl et al., 2015; Werner et al., 2025). We focus on three factors, because it keeps the inference process less complex and better understandable. However, a higher number is possible.

We consider slope in form of an elevation index. It is calculated as the net elevation difference between two nodes connected by an edge (rise-over-run) (Löw et al., 2025). For the remaining two indices we choose proxies that represent the idea of the criterias. The proxy for comfort is a pavement roughness index based on vertical acceleration data of bicycles when riding on a street. There is extensive work on using vertical acceleration measurements of bicycles as a basis for a comfort index. The research agrees that despite minor drawbacks this approach yields reasonable results (Bíl et al., 2015; Löw and Krisp, 2024; Wage et al., 2020) The accessibility index is instantiated with the edge betweenness algorithm that finds those edges that are best connected. It is originally applied in social networks, but works well for all types of networks (Brandes, 2008).

1.2 Applied Fuzzy Logic

Zadeh (1965) puts forward the idea of degrees instead of the binary true and false to address inherent nuances of many concepts such as bikeability. He calls the mathematical framework fuzzy logic that defines fuzzy sets with membership functions. With these functions we can determine to what degree a circumstance belongs to a set and to which it does not (Bezdek, 1993; Yager and Filev, 1994; Zadeh et al., 2016). Mamdani and Assilian (1975) aggregate fuzzy sets to domains and connect them with rules such that it allows to deterministically calculate an output value from multiple inputs. They use these rules to capture expert knowledge and make it applicable for machines. There exist other variants of such systems that differ in how they design the inference (Mitaim and Kosko, 1996; Takagi and Sugeno, 1985). We use a Mamdani style inference system because it is more intuitive and suited for human input.

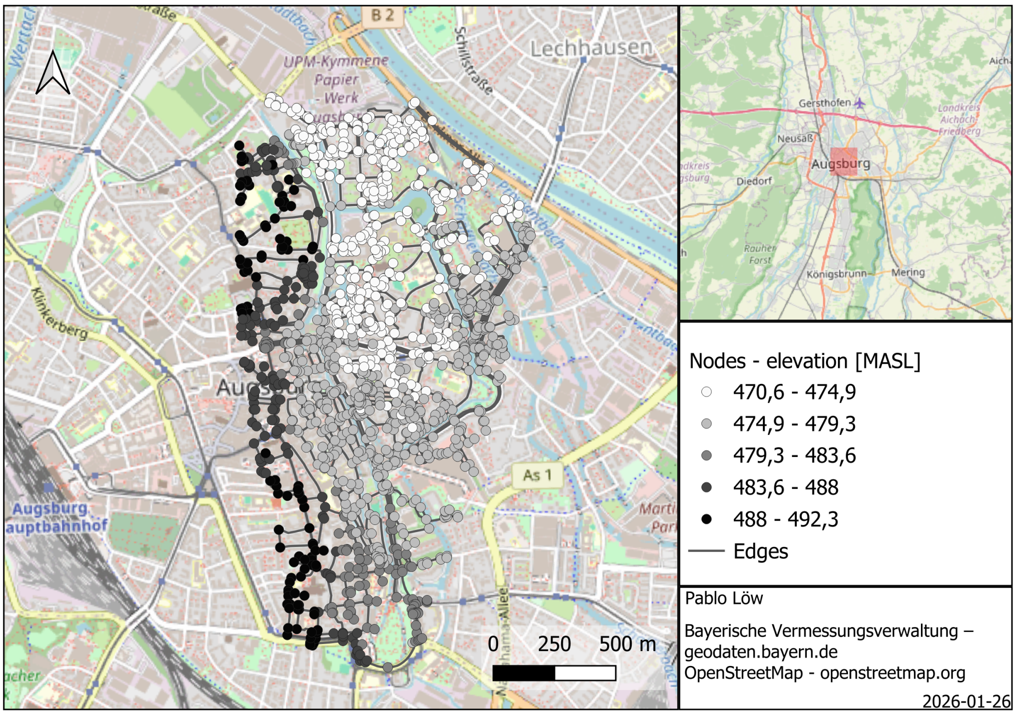

Figure 2. Map of case study area in Augsburg showing the streetgraph with OSMnX. The nodes that represent road intersections are colored according to their elevation showing that the north-east is the lowest and the west the highest part.

The evaluation process of a Mamdani style inference system is exemplary shown in Fig. 1 and can be broken down into three steps: fuzzification, inference, and defuzzification. The first calculates the results of the membership functions for all corresponding fuzzy sets (left column in Fig. 1). The second uses an operator (usually the maximum) per rule to determine the most important fuzzy set of the input domains and its function value (firing strength; arrows in Fig. 1). The last step is optional and uses this firing strength to truncate the membership function of the output fuzzy set. Then a descriptive measure (e.g. center of gravity) is used to analyze these output fuzzy sets (Bellman and Zadeh, 1970). In addition to distribution-based criteria (histograms), we include an external comparison with a linear bikeability index to assess the robustness of the fuzzy approach.

2 Methodology

We select the city of Augsburg in southern Germany as our case study area. The data necessary for our "Comfort Index" is available there. Our goal is to show how to use a fuzzy inference system to create a fuzzy meta index for bikeability. The three sub-indices represent factors that we select as important for bikeability.

We start by computing a street graph for the study area displayed in Fig. 2 with the OSMnX python package (Boeing, 2017). The area is defined by the convex hull of the comfort index data, because that is only available in a limited space. It covers the main part of the inner city of Augsburg. The site is selected due to its wide variety of different street types (e.g. gravel, cobblestones, asphalt) and its vicinity to the University of Augsburg. All indices that we describe in the following sections are aggregated into the edges of this street graph before they are combined with the fuzzy inference system.

Fuzzy inference systems feature many options that change the resulting meta index. Therefore, we create eight different systems and apply each to the same set of input indices and compare the results. Histograms are widely used in scientific data analysis to visualize the distribution of numerical values by grouping observations into bins. They provide an intuitive overview of central tendency, spread, and skewness making them useful for exploratory analysis in various fields. Histograms reduce precision by aggregating values, but they provide a good way of comparing the results (Härdle and Simar, 2007). On that basis we select the best of these eight. The final step is a comparison of its spatial distribution and classification with the linear meta index in form of maps.

2.1 Construction of the Three Bikeability Indices

Fig. 3 shows the sub-indices together with a non-fuzzy combination of them (compare Eq. (1)). A common non-fuzzy way to combine multiple indices is the weighted average (Werner et al., 2025). We call the non-fuzzy meta index calculated this way “linear index”. We set all weights

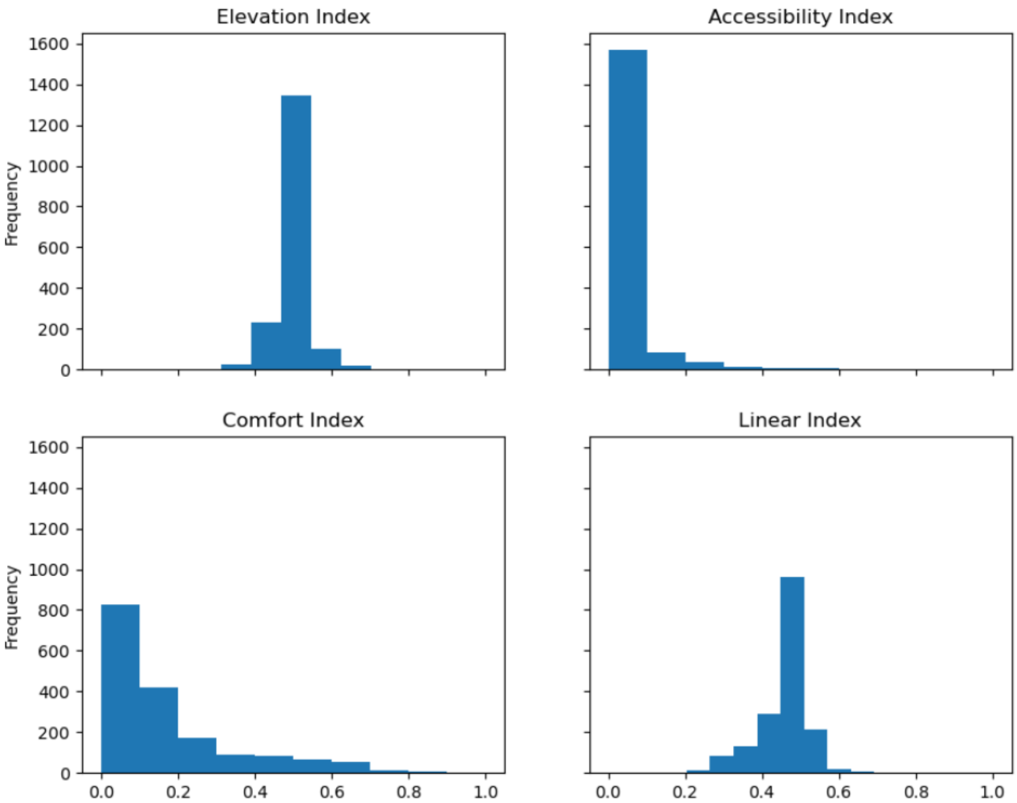

Figure 3. Histograms of the bikeability input indices (Elevation Index, Accessibility Index, Comfort Index) together with the Linear Index (weighted average of the input indices). All indices are between zero and one.

to one since the fuzzy meta index does not include any weighting either.

$$LinearIndex = \frac{CI * w_{CI} + AI * w_{AI} + EI * w_{EI}}{sum(w_{CI}, w_{AI}, w_{EI})} \quad (1)$$

The acceleration- and speed data we use for the comfort index contains 3243381 measurements located throughout the area in Fig. 2. We use smartphones fixed to bicycles with a rubber mounting to collect the data that we store in gitlab (compare link in footnote). The data is filtered to only those measurements that are collected with a speed higher than zero. The comfort index is calculated with the methodology of Löw et al. (2025).

The digital elevation model for the elevation index comes from the Agency for Digitisation, High-Speed Internet and Surveying[2]. It has a resolution of 1x1m and its precision is at best 0.1m according to the agency. We use the methodology of Löw et al. (2025) for the calculation of the elevation index.

The index representing the accessibility in a network relies on the "edge betweenness centrality" algorithm. It quantifies the importance of an edge within a network by measuring the proportion of shortest paths that traverse it. We use edge betweenness centrality in a road network to provide a structural measure of how critical a road segment is for movement across the network (Brandes, 2008).

[2] https://www.ldbv.bayern.de/vermessung/bvv/; last access April 15, 2026

2.2 Design of the Fuzzy Inference Systems

We combine the indices described in the previous sections with eight different fuzzy inference systems. These systems offer many factors to adapt them. For our study we select the following three factors that are most promising: number of fuzzy sets (3 or 5), inference operator (maximum or mean) and number of rules. Table 1 shows all combinations of factors.

Table 1. Fuzzy inference systems used to create fuzzy meta indices of three bikeability sub indices.

	3 Fuzzy Sets per Domain		5 Fuzzy Sets per Domain	
Basic Ruleset	Max	Mean	Max	Mean
Advanced Ruleset	Max	Mean	Max	Mean

A Mamdani style fuzzy inference system that combines three input indices needs at least four domains. Three are used to fuzzify the input values and one to calculate a crisp output value with a defuzzification method (most commonly the center of gravity). We realize the different number of fuzzy sets per domain with two template domains (compare Fig. 4). With these template domains we create either a fuzzy inference system that has three fuzzy sets per domain for all domains or five.

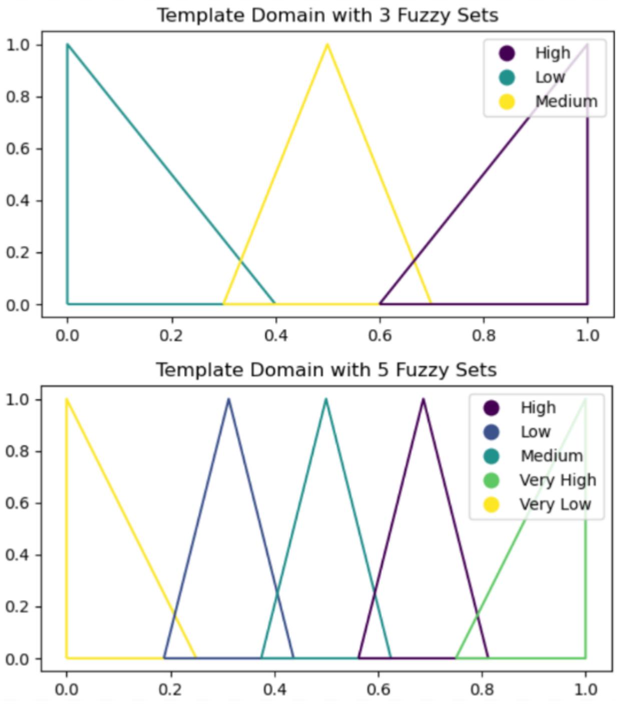

Figure 4. Template Domains with 3 and 5 Fuzzy Sets respectively. Each featuring only triangles and an overlap of 25%.

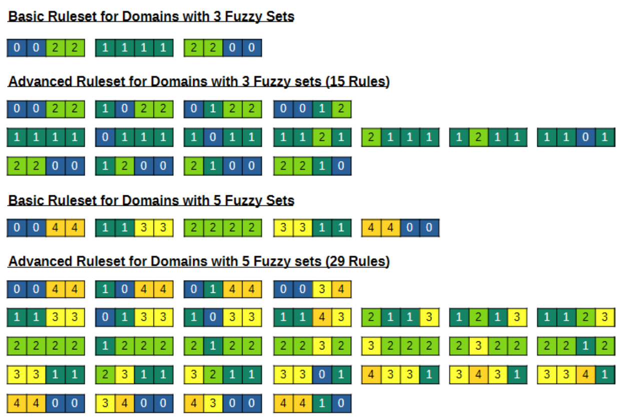

Figure 5. Four rule sets of the fuzzy inference systems. Each combination of four digits are one rule. Each digit stands for one fuzzy set of the domain in this order: Comfort Index, Elevation Index, Accessibility Index and Street Quality Index. The fuzzy sets are numbered from 0:low to 3:high in case of three fuzzy sets. For domains with five fuzzy sets it goes from 0:very low to 5:very high. The colors are according to the numbers.

The upper template in Fig. 4 has three and the bottom five fuzzy sets. Each fuzzy set is defined by triangle shaped membership functions with an overlap of 25%, since a linear increase of membership is appropriate for indices. For each template the triangle membership functions cover the exact same range (left 0.4, and right 0.25) and peak in the middle of their respective ranges. Only the membership functions on each end of the range [0, 1] are adapted such that the left peaks at zero and the right at one. That is necessary to increase the potential of the center of gravity method to reach the ends of the range.

The next factor that we alternate is the operator. This operator is used to determine the contribution of a rule to the final defuzzification method. The standard for fuzzy inference systems is to use the maximum (max). We additionally execute each fuzzy inference system with the mean, since that yields good distributions. The operator combines all fuzzified values connected by a rule.

The last factor that we use to create different fuzzy meta indices is the rule set. It can be used to incorporate the preferences of users and comprises any number of rules. The maximum possible number of reasonable rules is dependent on the number of fuzzy sets and domains in a fuzzy inference system. We opt to create a basic rule set with less rules and a more advanced rule set with more rules. Fig. 5 shows for each fuzzy inference system both versions. The number of rules for the fuzzy inference system with five fuzzy sets per domain is naturally higher than that with three, if all fuzzy sets are used at least once. For the advanced rule set we allow exactly one exception for the input domains to include a fuzzy set of one rule above or below.

We apply each of the eight fuzzy inference systems edgewise to create one fuzzy meta index per street direction. These are then presented in histograms to find the most promising configuration for the fuzzy inference system. The graph with the best fuzzy meta index is then compared with the linear index.

2.3 Data and Software Availability Section

The vertical acceleration data is not made publicly available for license reasons. We provide the graph with the aggregated comfort index in a gitlab repository[3]. The code in the jupyter notebook starts with loading all necessary python packages except for the custom fuzzy logic package that can only be accessed via a request. It recreates all figures and results provided throughout this paper.

3 Comparison of the Indices

We present the results of the different fuzzy inference systems used to combine the three indices into one fuzzy meta index for each edge in the street graph of our study area. From those versions we select the one with the best distribution and compare it with with the linear index of Fig. 3. Thereby we consider “best” as the index that is A) cen-

[3]https://git.rz.uni-augsburg.de/geoinf-gig/fis_metaindex

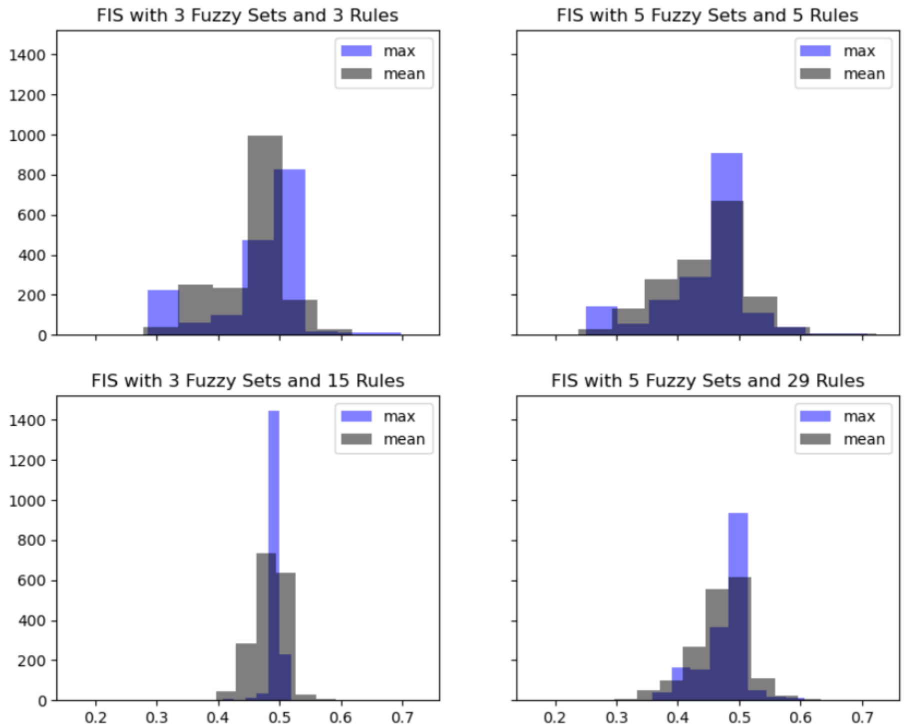

Figure 6. Distributions of the fuzzy meta indices created with different fuzzy inference systems (FIS).

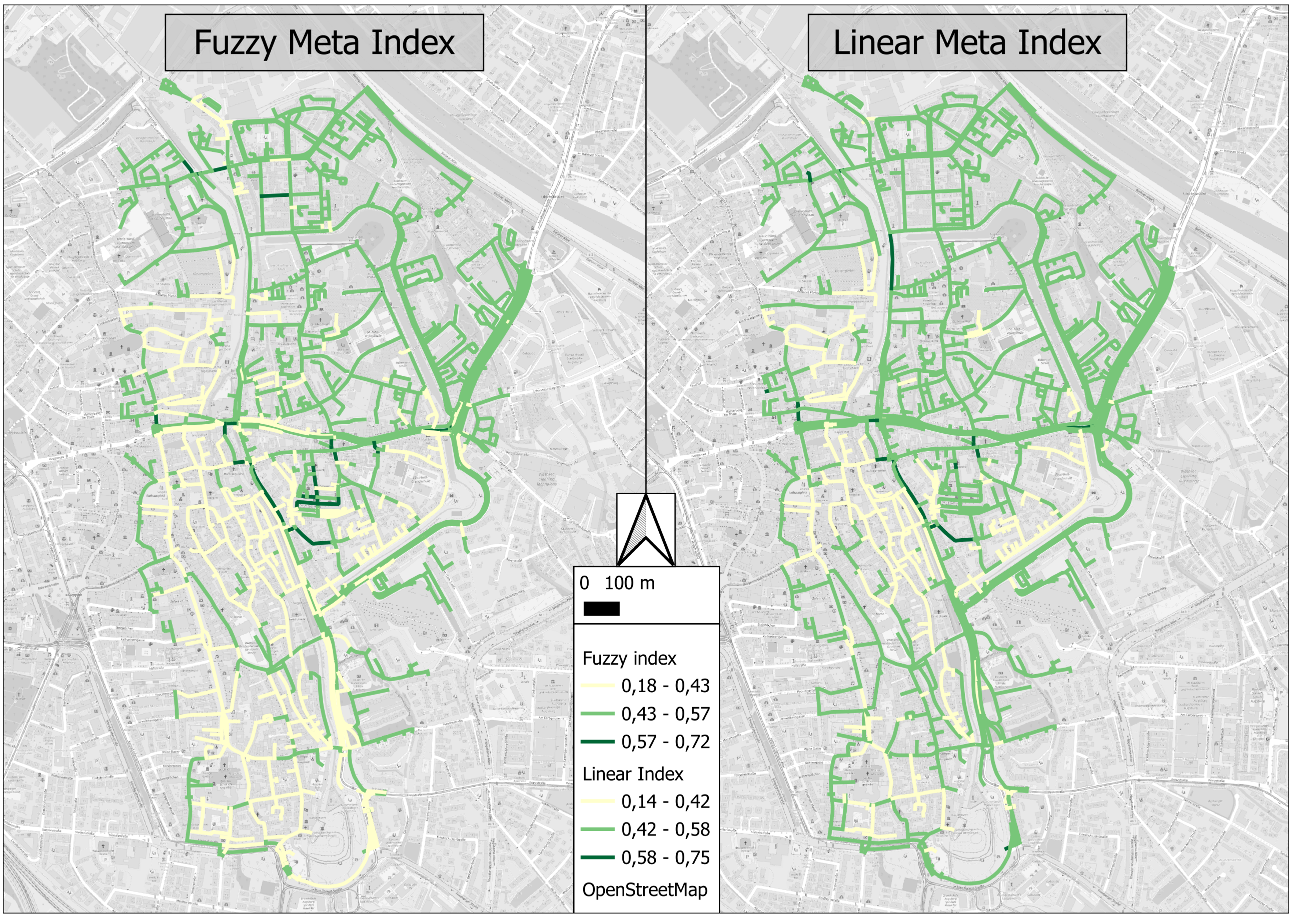

Figure 7. Comparison of the two different indices in the street network. The left map shows the index from the fuzzy inference system and the right the linear one.

tered around the middle of the target range (0.5) and B) is close to a normal distribution.

Fig. 6 shows the distribution of the eight fuzzy meta indices. In each of the four sectors we have the same fuzzy inference system using a different operator. From top left to bottom right the number of rules increases and the number of fuzzy sets per domain from left to right. Fig. 6 shows the trend that using more rules leads to finer resolutions indicated by thinner bins. The impact of the maximum operator is in all cases except the top left one a higher focus. The mean operator creates a broader distribution. All indices are positioned close to 0.5, but slightly skewed towards the lower end of the range. The higher end is underrepresented by all indices. The version with three fuzzy sets and 15 rules is the worst in regards of its distribution. Both histograms in the top row have an elevated bar at around 0.3 for the max operator. We use the fuzzy inference system with five fuzzy sets, five rules and the mean operator for the comparison with the non fuzzy meta index since it fits our two criterias best.

Fig. 7 shows the indices in the streetgraph next to each other. Overall many roads especially in the north-east are classified similarly. From the center to the west and to the south there are streets that are differently classified by the two indices. When we compare that with Fig. 2 we assume that both indices react differently to the ascension there. If that is the case the fuzzy meta index emphasizes elevation. To confirm that further research is necessary. No roads are considered by one index to be in the low class that the other puts into the high class, or vice versa. The only contradictions are to adjacent classes.

4 Discussion and Outlook

We use mamdani style fuzzy inference systems to create bikeability meta indices from different sub indices. Each of these sub indices represents one or more factors that play a role in the bikeability of streets. However, there are many more important factors that influence bikeability. We select three exemplary variables, to demonstrate the methodology, while maintaining comprehensibility. Elevation and pavement roughness are well established and already used in other studies. Applying "edge betweenness centrality" is more experimental.

The results show that fuzzy inference systems offer many options to adapt the meta index to varying situations and exigencies. In this study we explore the impact of the number of fuzzy sets per domain, number of rules and two operators (maximum and minimum) on the final index. We are aware that there are many more options a fuzzy inference system offers, but we opt for this selection because they all have profound impact. The differences in the results presented in section three are proof of that.

According to the results some variations of the fuzzy inference system affect the indices in different ways (research question 2). The number of fuzzy sets per domain and the mean-operator tend to provide a wider spread of the values and the number of rules alters the resolution. We opt for the fuzzy meta index with the lower resolution and widest spread to cover a broader spectrum of values. Yet all tested versions of fuzzy inference systems do not cover nearly the entire target range [0,1]. That can not be achieved despite changing the first and last fuzzy membership function of each domain to peak at zero and respective one. We expect this change to nudge the resulting range towards the end of the spectrum, because the center of gravity is influenced by the area. That area is potentially spread wider when the functions focus on zero and one. The drawback of using the center of gravity is that the results tend towards the middle. But neither does the non-fuzzy meta index cover the whole range. If covering the whole range is a requirement we suggest applying a min-max stretching to the results. Future work will be on developing a method that circumvents this drawback of the center of gravity to allow a regular setup of the fuzzy sets.

The design of the rule set is very important and difficult to optimise. Conceptually, it is the part of the fuzzy inference system that can store user preferences. However, these are case specific and require a user study that is beyond the capacity of this short paper. But we can prove that adapting the rule set is profoundly impacting the fuzzy meta index. Further research can tackle remaining options to adapt them (e.g. different designs for the membership functions), test how they perform when more sub-indices are combined, or different types of fuzzy inference systems. Another important factor that is ignored in this paper is a deeper spatial analysis of the results which we leave to later research.

Summarizing the results we conclude that a fuzzy approach to creating a meta index allows a finer level of adaption to varying scenarios. The fuzzy meta index characterizes the streets similar to the linear index but with a different weighting (research question 1).

Declaration of Generative AI in writing

The authors declare that they have used Generative AI tools for language editing to improve readability, but not for generating scientific content, research data, or substantive conclusions. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

References

Bellman, R. E. and Zadeh, L. A.: Decision-making in a fuzzy environment, Nordic Journal of Surveying and Real Estate Research, 1970.

Bezdek, J. C.: Fuzzy models—What are they, and why? [Editorial], IEEE Transactions on Fuzzy Systems, 1, 1–

6, https://doi.org/10.1109/TFUZZ.1993.6027269, conference Name: IEEE Transactions on Fuzzy Systems, 1993.

Boeing, G.: OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks, Computers, Environment and Urban Systems, 65, 126–139, https://doi.org/10.1016/j.compenvurbsys.2017.05.004, 2017.

Brandes, U.: On variants of shortest-path betweenness centrality and their generic computation, Social Networks, 30, 136–145, https://doi.org/10.1016/j.socnet.2007.11.001, 2008.

Bíl, M., Andrášik, R., and Kubeček, J.: How comfortable are your cycling tracks? A new method for objective bicycle vibration measurement, Transportation Research Part C: Emerging Technologies, 56, 415–425, https://doi.org/10.1016/j.trc.2015.05.007, 2015.

Grisiute, A. and Raubal, M.: Rethinking Bikeability Indexes: Fusing Knowledge Graph and MCDA Technique for Multicriteria Bike Network Evaluations, AGILE: GIScience Series, 6, 1–8, https://doi.org/10.5194/agile-giss-6-25-2025, 2025.

Härdle, W. and Simar, L.: Applied Multivariate Statistical Analysis, Springer Berlin Heidelberg, Berlin, Heidelberg, 2. 2nd ed. 2007 edn., https://doi.org/10.1007/978-3-540-72244-1, 2007.

Jonietz, D. and Timpf, S.: Entwicklung eines GIS-basierten Bikeablity-Index am Beispiel der Stadt Augsburg, Geoinformatik; Shaker: Aachen, Germany, pp. 83–90, 2012.

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barret, K., and others: IPCC, 2023: Climate Change 2023: Synthesis Report, Summary for Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland., 2023.

Löw, P. and Krisp, J.: Smoothing the Ride: A Surface Roughness-Centric Approach to Bicycle Routing, AGILE: GIScience Series, 5, 1–6, https://doi.org/10.5194/agile-giss-5-39-2024, 2024.

Löw, P. S., Krisp, J. M., and Keler, A.: Enhancing Bicycle Route Selection with Fuzzy Logic: A Case Study in Augsburg, KN - Journal of Cartography and Geographic Information, https://doi.org/10.1007/s42489-025-00202-3, 2025.

Mamdani, E. H. and Assilian, S.: An experiment in linguistic synthesis with a fuzzy logic controller, International Journal of Man-Machine Studies, 7, 1–13, https://doi.org/10.1016/S0020-7373(75)80002-2, 1975.

Mitaim, S. and Kosko, B.: What is the best shape for a fuzzy set in function approximation?, in: Proceedings of IEEE 5th International Fuzzy Systems, vol. 2, pp. 1237–1243 vol.2, https://doi.org/10.1109/FUZZY.1996.552354, 1996.

Takagi, T. and Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control, IEEE Transactions on Systems, Man, and Cybernetics, SMC-15, 116–132, https://doi.org/10.1109/TSMC.1985.6313399, conference Name: IEEE Transactions on Systems, Man, and Cybernetics, 1985.

Wage, O., Feuerhake, U., Koetsier, C., Ponick, A., Schild, N., Beening, T., and Dare, S.: RIDE VIBRATIONS: TOWARDS COMFORT-BASED BICYCLE NAVIGATION, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B4-2020, 367–373, https://doi.org/10.5194/isprs-archives-XLIII-B4-2020-367-2020, 2020.

Werner, C., Wendel, R., Kaziyeva, D., Stutz, P., van der Meer, L., Effertz, L., Zagel, B., and Loidl, M.: NetAScore: An open and extendible software for segment-scale bikeability and walkability, Environment and Planning B: Urban Analytics and City Science, 52, 265–274, https://doi.org/10.1177/23998083241293177, 2025.

Yager, R. R. and Filev, D. P.: Essentials of fuzzy modeling and control, New York, 388, 22–23, https://www.academia.edu/download/46574024/Essentials_of_fuzzy_modeling_and_control20160617-22779-1b9663x.pdf, 1994.

Zadeh, L. A.: Fuzzy sets, Information and Control, https://doi.org/https://doi.org/10.1016/S0019-9958(65)90241-X, 1965.

Zadeh, L. A., Abbasov, A. M., and Shahbazova, S. N.: Fuzzy-Based Techniques in Human-Like Processing of Social Network Data, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, https://doi.org/10.1142/S0218488515400012, 2016.