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Measuring Landmark Salience in Rural Areas: A Comparative Study of Two Models

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Abstract. A number of measures have been developed to formally define the landmark salience of a geographic feature in order to identify landmarks for inclusion in pedestrian navigation systems. However, most of the available research has focused on urban environments. Rural areas differ from urban environments in several ways, such as their level of structure and regularity, and the type and density of landmarks. In this paper, we focus on measures for calculating the landmark salience of geographic features in rural areas. We present results from two models: one explicitly designed to identify landmarks in rural areas, and one originally focused on urban areas. We compare the identified landmarks with those from a survey. The results show that the differences between the models and the survey results are not statistically significant. The results of the two models are marginally statistically significantly different. The first model identifies highly semantically salient geographic features as landmarks, while the second model does not consider semantic salience and prefers natural geographic features. Investigating these facts further may be part of future research.

Submission Type. Theory, Model, Analysis, Dataset, Case study.

BoK Concepts. Geospatial data, Geocomputation.

Keywords. Cognitive science, Landmarks, Computational model, Spatial data modelling, Landmark salience, Rural navigation

1 Introduction

Navigating rural areas presents unique challenges due to the irregular and diverse nature of landmarks in these areas (Snowdon and Kray, 2009). While extensive research has been conducted on the identification and use of landmarks in urban environments (Sorrows and Hirtle, 1999; Raubal and Winter, 2002; Yesiltepe et al., 2021), less attention has been paid to rural areas where landmarks can vary significantly in terms of visibility, permanence, and salience (Kettunen et al., 2013, 2015; Snowdon and Kray, 2009).

There are several examples of navigation in rural areas. People may take a Sunday walk around the fields and meadows near where they live. They might want to take a longer walk, for example around a lake or through woods. Or they might want to spend several days walking, for example in a national park. In all of these examples, people need landmarks to find their way to a particular place in a rural area (perhaps a place to eat or spend the night), to orient themselves, e.g. to find their way back, or to communicate their route to others.

A landmark is traditionally defined as a prominent, easily recognisable feature within an environment that serves as a reference point for orientation and navigation (Lynch, 1960). In this study we define rural landmarks as distinctive geographic features or man-made structures within rural areas that serve as reference points for navigation. Unlike urban landmarks, which are mainly characterised by buildings, signs, or other built elements, rural landmarks can include natural features such as trees, rocks, water elements, or paths, as well as smaller man-made structures such as huts, signs, or fences. These landmarks are often less prominent and more variable due to environmental factors, making their identification and use more complex (Kettunen et al., 2013).

The salience of a landmark refers to the distinctiveness or prominence of a geographic feature in its environment, which makes it stand out and be more easily noticed (Raubal and Winter, 2002). In computational models of landmark selection, salience serves as a critical metric for identifying landmarks. Most existing landmark identification models are primarily designed for urban environments and emphasise man-made and visually distinct landmarks (Raubal and Winter, 2002; Klippel and Winter, 2005; Gedicke et al., 2023). One of the few models that focuses on calculating the overall salience of rural geographic features is proposed by Nuhn et al. (2024). Another model that does not explicitly focus on rural geographic features but includes the attribute "natural" is the model of Binski et al. (2019).

In this paper, we conduct a comparative analysis of the Binski et al. (2019) and Nuhn et al. (2024) models and apply both models to a rural area. The hypothesis is that the models identify landmarks, that correspond to what people would choose. In the following, we give an overview of the related work (Section 2), the constraints for our study (Section 3), the data we used (Section 4), and the results (Section 5). This is followed by a discussion (Section 6) and a conclusion (Section 7).

2 Related Work

This section provides an overview of existing work on the study of landmarks in rural areas (Section 2.1). This is followed by a look at existing models for assessing the salience of landmarks in rural areas (Section 2.2).

2.1 Landmarks in rural areas

Landmarks have been extensively studied and discussed in the wayfinding and navigation literature as essential reference points in different contexts. Most research has focused on landmarks in urban environments (Lynch, 1960; Siegel and White, 1975; Sorrows and Hirtle, 1999; Michon and Denis, 2001; Raubal and Winter, 2002; Tom and Denis, 2003; Yesiltepe et al., 2021). However, wayfinding in rural areas plays an important role, for example in ski touring (Rehrl and Leitinger, 2008), hiking (Kettunen et al., 2013), and mountaineering (Van Damme and Olteanu-Raimond, 2022).

In these scenarios, e.g. ski touring, it is often possible to go anywhere and move freely (e.g. across the field). In this paper we assume that a traveller is closely connected to a network of routes (with roads and paths) and that the traveller uses landmark-based piloting for wayfinding (Allen, 1999). Landmarks can be used for several purposes in wayfinding (Yesiltepe et al., 2021). They are used to find a route to a specific location (Klippel and Winter, 2005; Raubal and Winter, 2002), for orientation purposes (Michon and Denis, 2001; Schwering et al., 2017), and for communication routes (Allen, 1997, 2000).

Routes are typically described using five categories: prescribing action, prescribing action with reference to a landmark, introducing a landmark, describing a landmark, and comments (Denis, 1997). The study of route descriptions in rural areas shows that people refer to two-dimensional landmarks significantly more often in rural areas than in urban ones (Brosset et al., 2008). Most descriptions include actions to which the landmarks refer, followed by non-spatial details to characterise the landmark, highlighting that landmarks in rural areas require more detailed descriptions than urban ones. In rural settings, introducing and describing landmarks are the dominant categories (Sarjakoski et al., 2011), while actions and action-linked landmarks are referenced less frequently than in urban-focused studies.

Analysis of Volunteered Geographic Information (VGI) route directions has identified the types of landmarks and decision points that aid navigation in mountainous regions (Egorova et al., 2015). For landmark descriptions, features such as surface type, landscape colours, and terrain characteristics (e.g., snow) can also function as landmarks in alpine settings (Egorova et al., 2015). Further research has built on these findings by proposing methods for incorporating this information into rescue operations, improving the efficiency and effectiveness of search and rescue efforts in challenging environments (Van Damme and Olteanu-Raimond, 2022). Landmarks are also used to recover from disorientation in the wild (Wattne and Volden, 2024).

Identifying landmarks in rural areas is challenging because many geographic features are subject to change. Landmark permanence refers to the likelihood that a geographic feature is present in form or label (Burnett et al., 2001). Traditional definitions that emphasise static, permanent features (Kettunen, 2014) are less effective in rural areas where elements such as snow or crevasses can shift or become permanent at certain altitudes (Egorova, 2018).

To explore the use of rural landmarks in route descriptions, landmarks are categorized into eight landmark groups (Sarjakoski et al., 2013):

1. Structures - constructions made by humans or animals (house, power line, bridge, anthill, bird's nest, etc.)
2. Passages - routes or paths intended for movement (road, path, intersection, etc.)
3. Trees and parts of trees - trees and their components (spruce, stump, wood pile, etc.)
4. Waterways - elements of water systems (lake, ditch, shore, etc.)
5. Landcover - types of vegetation (spruce trees, clearing, marshland, etc.)
6. Rocks - rocky features (stone, rock area, etc.)
7. Signs - human-made markers (guidepost, info board, trail marker, etc.)
8. Landforms - topographic features (incline, hill, depression, etc.)

Structures emerge as the most frequently referenced landmarks in both seasons due to their visibility, while the use of passages decreases in winter due to obscured paths. Conversely, landforms are referenced more often in winter as they become more visible against the snow. Temporary geographic features, such as flowers and tracks, are not included in this analysis (Sarjakoski et al., 2011).

Table 1. Rules for the computation of landmark salience (Taken from Nuhn et al. (2024)).

Dimension	Attribute	Salient	Salience (Attribute)	Salience (Dimension)
Visual	Height V_{h}	If significantly different	$s_{V_{\mathrm{h}}} \in \{0, 20\}$	$s_{\mathrm{Vis}} = s_{V_{\mathrm{h}}} + s_{V_{\mathrm{w}}} + s_{V_{\mathrm{c}}} + s_{V_{\mathrm{s}}} + s_{V_{\mathrm{o}}}$
	Width V_{w}		$s_{V_{\mathrm{w}}} \in \{0, 20\}$	
	Colour V_{c}	Different than the others at the intersection	$s_{V_{\mathrm{c}}} \in \{0, 20\}$	
	SurfaceV_{s}		$s_{V_{\mathrm{s}}} \in \{0, 20\}$	
	Object class V_{o}		$s_{V_{\mathrm{o}}} \in \{0, 20\}$	
Semantic	Cultural and historical importance S_{c}	If *True*	$s_{S_{\mathrm{c}}} \in \{0, 50\}$	$s_{\mathrm{Sem}} = s_{S_{\mathrm{c}}} + s_{S_{\mathrm{e}}}$
	Explicit marks S_{e}		$s_{S_{\mathrm{e}}} \in \{0, 50\}$	
Structural	Location at a Decision Point St_{l}	If *True*	3D: $s_{St_{\mathrm{l}}} \in \{0, 50\}$ 2D: $s_{St_{\mathrm{l}}} \in \{0, 25\}$	3D: $s_{\mathrm{Str}} = s_{St_{\mathrm{l}}} + s_{St_{\mathrm{d}}}$ Intersections: $s_{\mathrm{Str}} = s_{St_{\mathrm{l}}} + s_{St_{\mathrm{d}}} + s_{St_{\mathrm{g}}}$ Routes: $s_{\mathrm{Str}} = s_{St_{\mathrm{l}}} + s_{St_{\mathrm{d}}} + s_{St_{\mathrm{s}}}$
	Distance to the Decision Point St_{d}	If St_{d} = min(St_{d1},...St_{di})	3D: $s_{St_{\mathrm{d}}} \in \{0, 50\}$ 2D: $s_{St_{\mathrm{l}}} \in \{0, 25\}$	
	Degree St_{g}	> 3 branches / > 4 branches	$s_{St_{\mathrm{g}}} \in \{0, 25, 50\}$	
	Slope St_{s}	$\geq 5\%$ / $\geq 10\%$	$s_{St_{\mathrm{s}}} \in \{0, 25, 50\}$	
Temporal	Seasonality T_{s}	If *False*	$s_{\mathrm{Ts}} \in \{0, 50\}$	$s_{\mathrm{Tem}} = s_{T_{\mathrm{s}}} + s_{T_{\mathrm{p}}}$
	Permanence T_{p}	If *True*	$s_{T_{\mathrm{p}}} \in \{0, 50\}$	

2.2 Assessing the salience of landmarks in rural areas

Most existing landmark identification models are primarily designed for urban environments and emphasise man-made and visually distinct landmarks. Here we review one of the rare models for rural areas (Section 2.2.1) and another model that includes a "nature" component (Section 2.2.2).

2.2.1 Model of Nuhn et al. (2024)

The model of Nuhn et al. (2024) is developed for rural areas and is an adaptation of the traditional salience model as introduced by Raubal and Winter (2002). It identifies rural landmarks from a set of geographic features (landmark candidates) at an intersection by considering attributes from several dimensions. The model includes attributes from the visual, semantic, and structural dimensions as the model of Raubal and Winter (2002) and adds a temporal dimension as temporality plays an important role in rural areas (Nuhn et al., 2024). Nuhn et al. (2024) assign salience values to each attribute of the model. Each dimension can reach a total salience of 100, which is distributed across its attributes. For example, the visual dimension has five attributes, and if they are all salient, each attribute receives 20 of the total salience (seeTable1). More details are given below.

Visual Salience: The model of Nuhn et al. (2024) considers five attributes: *height*, *width*, *colour*, *surface*, and *object class*. We implement an analogous version of this model. At each intersection, we calculate the average values for height and width. If a geographic feature's attribute value deviates significantly from these averages, it is assigned a salience value of 20 for both height and width (see Table1, column "Salience (Attribute)"). For the attributes colour, surface, and object class, a geographic feature is considered salient if its value for the corresponding attribute differs from all others at the intersection, in which case it also receives a salience value of 20 (Table 1).

Semantic Salience: Nuhn et al. (2024) include the attributes *Cultural and historical importance* and *explicit marks* in their model. A geographic feature is assigned a salience value of 50 for cultural and historical importance if it holds cultural or historical significance (see Table 1). Similarly, explicit marks are given a 50 salience value when such a mark is present (Table 1).

Structural Salience: For the structural dimension, Nuhn et al. (2024) introduces the structural attributes *location at a decision point* and *distance to the decision point*. As three-dimensional geographic features are only evaluated on the basis of these two attributes, they receive a salience value of 50 if they are salient. For routes and intersections, the model includes two additional attributes, so that two-dimensional landmarks receive a salience value of 25 for each of the two attributes. For the location attribute, the model focuses on local landmarks at intersections, assigning each geographic feature a Boolean value of *True* for this attribute (see Table 1). For the distance to decision point attribute, the geographic feature closest to the intersection is considered to be the most salient and is assigned a salience value for this attribute, while other geographic features are assigned a value of zero. In addition, the model of Nuhn et al. (2024) considers the attribute *slope* for routes and *degree* for intersections. For intersections, degree adds salience based on the number of paths: intersections with four paths receive a salience value of 25, and those with more than four paths receive a value of 50. Routes with an average slope of 5% or more are considered somewhat salient and receive a salience value of 25, while those with a slope of 10 or more receive 50 (Table 1).

Temporal Salience: Nuhn et al. (2024) extends the traditional model of Raubal and Winter (2002) by including a temporal dimension. The first attribute within this dimension is *seasonality*. If a geographic feature's seasonality value is *False*, it is considered salient and assigned a salience value of 50 (see Table1). The second attribute is *permanence*, where geographic features with a *True* value for permanence are considered salient and given a salience value of 50 (Table 1).

Finally, the overall salience is calculated as the sum of visual, semantic, structural, and temporal salience:

$$S_{rural} = S_{Vis} + S_{Sem} + S_{Str} + S_{Tem} \tag{1}$$

Each of these dimensions can contribute up to 100, meaning the total salience value can reach 400. In the model of Nuhn et al. (2024), the geographic feature with the highest overall salience at an intersection is designated as the landmark.

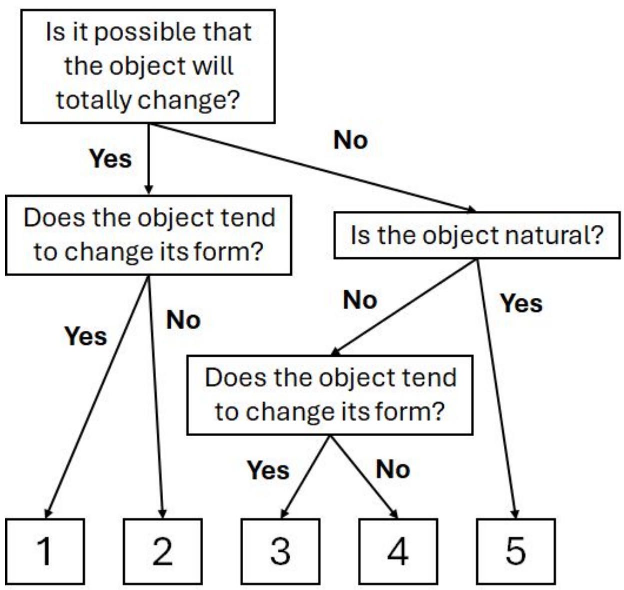

Figure 1. Decision tree 1: Permanence (Taken and adapted from Binski et al. (2019)).

2.2.2 Model of Binski et al. (2019)

The model of Binski et al. (2019) follows a decision tree structure with three separate decision trees for permanence, visibility, and uniqueness. The result of the decision trees is a salience score from 1 to 5.

Permanence (Decision tree 1): For permanence, Binski et al. (2019) first examine whether it is possible for the geographic feature to change completely and become another geographic feature (Figure 1). They give the examples of mountains and airports as permanent geographic features. So we decide regarding the groups of Sarjakoski et al. (2013) that only landforms, waterways, and routes are permanent geographic features and all other geographic features are able to change. Paths can also change as they can disappear under vegetation. Then Binski et al. (2019) examine whether a geographic feature is natural. We consider geographic features from the groups landcover, landform, trees, and waterways as natural geographic features. Next, Binski et al. (2019) evaluates whether a geographic feature tends to change its form in terms of colour, shape, size, and name. We only consider signs to be permanent in form.

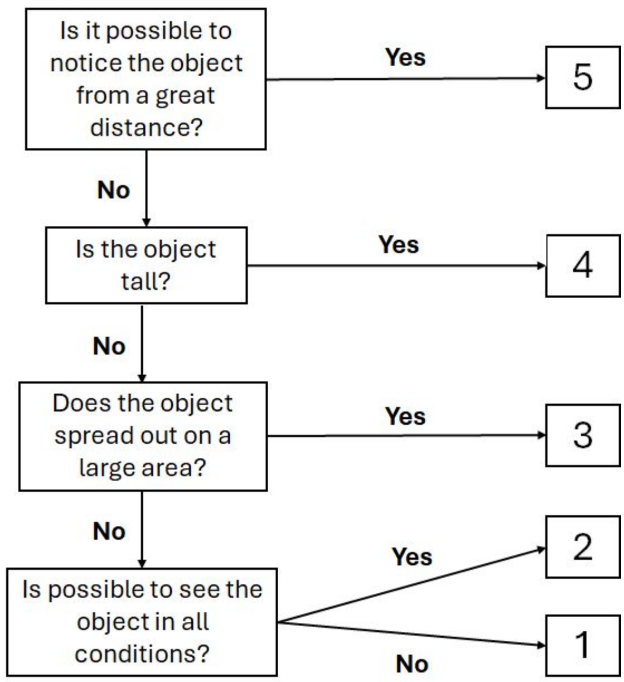

Figure 2. Decision tree 2: Visibility (Taken and adapted from Binski et al. (2019)).

Visibility (Decision tree 2): Binski et al. (2019) examines whether a geographic feature is clearly distinguished from its surroundings and whether it is possible to notice it from a great distance (Figure 2). We confirm that only a few geographic features are visible from a great distance, such as a shed, the lake, the forest, and prominent trees. Next, Binski et al. (2019) evaluates whether a geographic feature is tall. We assume that a geographic feature is tall if it is significantly taller than the other geographic features at an intersection. Furthermore, Binski et al. (2019) examines whether a geographic feature is spread over a large area. We define geographic features of the classes routes, waterways, landforms, and landcover to be spread over a large area. The last leaf of the Binski et al. (2019) decision tree decides whether it is possible to see a geographic feature in all environmental conditions (e.g. light and weather). We find that only routes and signs are visible in all conditions.

Uniqueness (Decision tree 3): For uniqueness, we examine whether a geographic feature is outstanding from its environment (Figure 3). We assume that a geographic feature is outstanding if it has visual salience. Thus, once the visual salience (calculated according to the model of Nuhn et al. (2024)) is greater than 50, we confirm that the geographic feature stands out from its environment. Next, it is examined whether it is possible to find similar geographic features nearby. We define that there should be no geographic feature with the same object class at the intersection. Finally, Binski et al. (2019) examines whether it is easy to mistake the geographic features with other geographic features. Here we define that there should be no geographic features of the same group as those defined by Sarjakoski et al. (2013) at the intersection.

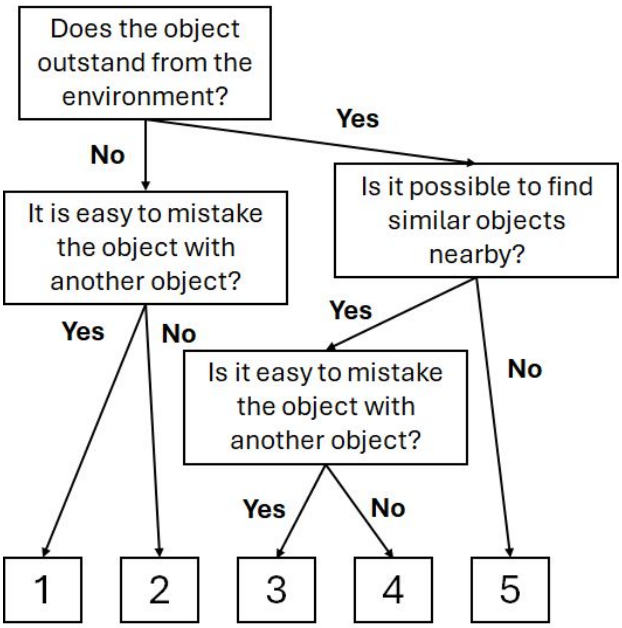

Figure 3. Decision tree 3: Uniqueness (Taken and adapted from Binski et al. (2019)).

The total salience score is calculated as the sum of the scores of the individual decision trees for permanence, visibility, and uniqueness. The total salience score for each geographic feature ranges between 3 and 15. Binski et al. (2019) normalises this score between the values of 1 and 10. Those with values of 6-7 are considered as landmarks (Binski et al., 2019). We establish a geographic feature with a salience equal to or greater than six as a landmark.

3 Constraints for our study

We implement the model of Nuhn et al. (2024) (Section 2.2.1) and the model presented by Binski et al. (2019) (Section 2.2.2). As a basis for the models we make the following assumptions, which are adapted from Nuhn et al. (2024):

- Our focus is on the identification of rural landmarks. A rural area is characterised as an unbuilt area (Nuhn et al., 2024), which can include both man-made structures such as huts, power lines, wayside crosses, and bridges, and animal-made structures such as anthills, bird nests, and beaver dams (Kettunen et al., 2013). In rural areas there are also roads and paths with intersections.
- We restrict our scope to local landmark candidates located at and visible from the centre of intersections, excluding landmarks located between intersections and not visible from them.
- Each intersection contains a set of landmark candidates classified into the landmark groups (Sarjakoski et al., 2013): structures, trees and parts of trees, waterways, landcover, rocks, signs, and landforms. We divide the group passages from Sarjakoski et al. (2013) into *paths and routes*. Routes are larger passages intended for movement and covered with tar or gravel (e.g. Figure 8). Paths are smaller passages covered with gravel, earth, or wood (e.g. Figure 11).
- Intersections can also be landmark candidates. Intersections can look very different, with different structures such as tar, gravel, or soil, making the intersection itself a landmark. They are assigned to either the paths or routes classes.
- Both two-dimensional and three-dimensional landmark candidates are considered. Examples of two-dimensional geographic features are routes and intersections, while examples of three-dimensional geographic features are signs and bridges.
- Landmark candidates are characterised by attributes in the visual, semantic, structural, and temporal dimensions.

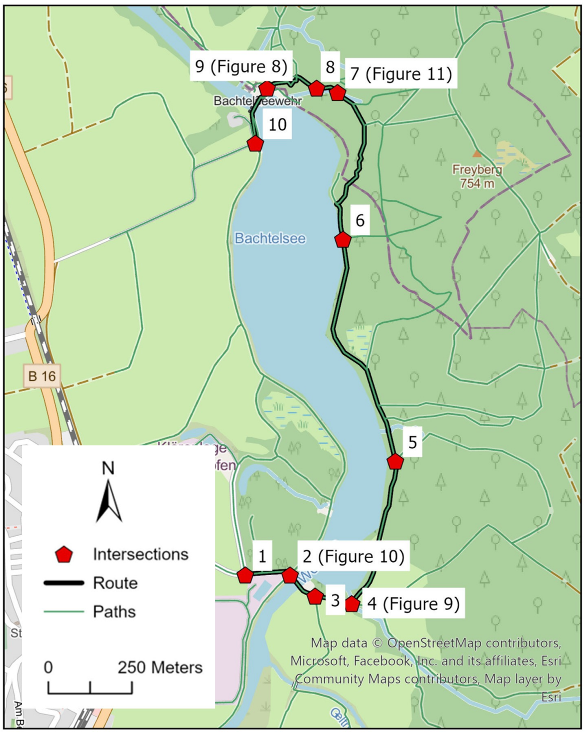

Figure 4. Survey Route with Selected Intersections.

4 Data

We selected a study area in the rural region of Biessenhofen, around Lake Bachtel in Bavaria, Germany (Figure 4). The Bachtel Lake is located in an area characterised by natural landscapes, including forests, hills and water bodies. This setting provides an ideal environment for the study of rural landmarks due to its varied terrain. The study area consists of ten intersections. The first four intersections and the last two intersections contain several man-made structures, while the remaining intersections are deeper in the forest and contain only one man-made geographic feature each (such as a wooden bridge or a sign).

4.1 On-Site Data Collection

We used Esri's Arc-GIS Survey123 (Survey123, 2024) to collect information about geographic features in the study area. Designed primarily for survey design and implementation, this tool has also proved effective for field data collection. We designed a detailed survey form to record the attributes of each potential landmark at the intersections. The attributes were inspired by those outlined by Nuhn et al. (2024), as shown in Table 1. Consequently, we recorded the height, width, colour, surface, and object class of each landmark, as well as its cultural and historical importance, and any explicit markings. Drop-down menus were used for the surface and object class fields. For surface options included coniferous, deciduous, grass, gravel, iron, multistructure, soil, stone, tar, water,

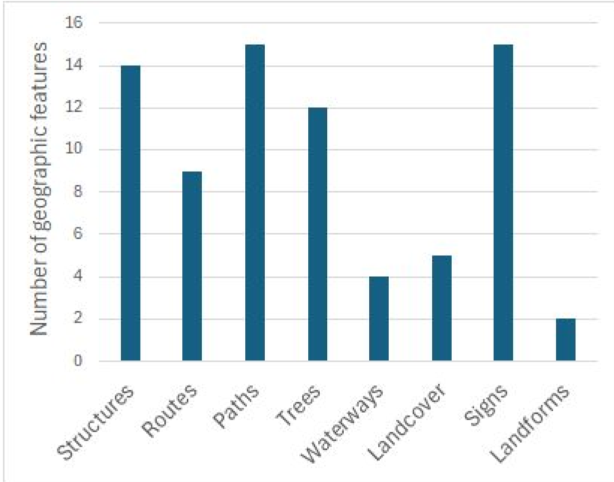

Figure 5. Landmark groups of the geographic features in the study area.

and wood. Object classes were categorised into different classes such as bench, bridge, deadwood, dog waste bin, fence, fish ladder, gully cover, intersection, meadow, path, power pole, ravine, shed, sign, street gutter, tourist info, tree, tree group, tree stump, water, water pipe, wayside cross, wetland, and wood pile. We also recorded the distance of each landmark from the intersection, the number of branches at the intersection (degree), and whether the slope was steep. We also recorded whether the landmark was two or three dimensional, natural, seasonal, or permanent. In addition, a drop-down menu was included to select from the landmark groups (Sarjakoski et al., 2013).

We collected geographic features and data on their attributes during a field survey on the first of May 2024. We walked along the ten intersections and recorded visible geographic features. We also took photographs of each intersection showing the geographic features.

After data collection, we reviewed each geographic feature and the intersections and decided which ones to include for further investigation. Some geographic features were additionally included by recording their attributes from the photographs taken. We ended up with 76 geographic features at ten intersections in the study area (Figure 4). 46.05% of the collected geographic features are two-dimensional geographic features, i.e., routes or intersections. Nearly 70% of the geographic features are man-made, as both routes and intersections are man-made geographic features.

Figure 5 shows the distribution of geographic features categorised by landmark groups (Sarjakoski et al., 2013). Paths and signs represent the largest groups with 19.74% each, followed by structures with 18.42%, trees account for 15.79%, and routes for 11.84%. The remaining categories are landcover with 6.58%, waterways with 5.26%, and 2.63% of the geographic features fall under landforms. Rocks were not observed and are therefore excluded from further analysis.

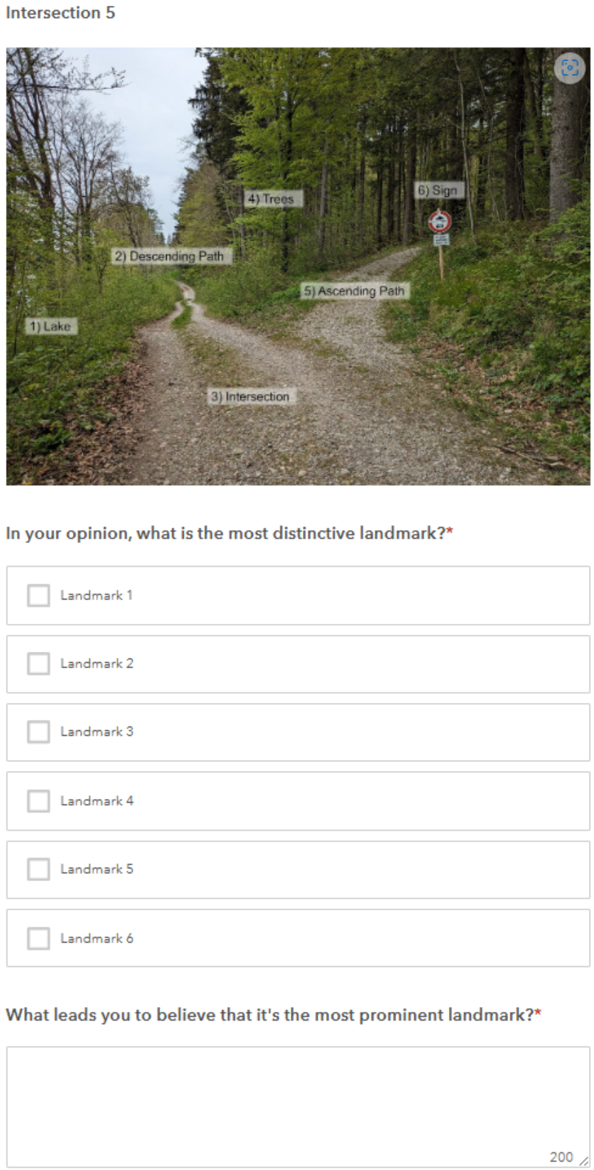

Figure 6. General survey structure illustrated using intersection number 5 as an example.

4.2 Survey

We conducted an online survey using ArcGIS Survey123 to collect landmarks to validate our landmark identification models. The survey consisted of ten photographs of the intersections shown in Figure 4, with two questions for each photograph (Figure 6). The first question asked the participant to select the most distinctive landmark in the photograph, and the second question asked for a free text explanation of the selection. Participants had to answer both questions, with only one selection allowed for the first question.

The survey was shared with family, friends, and acquaintances. As there were no specific criteria for participation in the survey, there was no intentional influence on the composition of the participant group. The survey did not ask for demographic or other personal information. The online survey was open between 21 May 2024 and 04 June 2024. During these two weeks, 25 participants completed the survey. Before starting the survey, participants had to confirm that they agreed to take part in the study and to the processing and storage of the contents of the survey. The survey was approved by the data protection officer of the University.

4.3 Data and Software Availability

The data for the water areas in Figure 4 were downloaded from Geofabrik and the shapefile used was gis_osm_water_a_free_1. The other data in the figure are published in Nuhn (2025), along with the images of the 10 intersections shown to survey participants, the calculations for the Nuhn et al. (2024) and Binski et al. (2019) models, and analysis of the results presented in Section 5.

5 Results

This section presents the landmarks selected by the survey participants (Section 5.1). We examine the model results in detail (Section 5.2) and compare the survey results with the model results (Section 5.3).

5.1 Landmarks selected by survey participants

In order to evaluate our model, we have to divide the geographic features presented in the survey into "Landmark" and "No Landmark". Therefore, we follow the rule introduced by Nuhn et al. (2024) (p.13): "geographic features selected by more than 20% of the survey participants are defined as landmarks". This means that once an item has been selected by at least five survey participants, it becomes a landmark. The number of landmarks at each intersection is not fixed; rather, there are X landmarks at each intersection. The survey resulted in one to three selected landmarks per intersection – a total of 21 landmarks.

Figure 7 shows for each landmark group how many geographic features are selected as landmarks by the survey participants. Most of the selected geographic features are part of the group signs. Trees are the second most selected. Structures such as a wayside cross, a fence, and a shed are selected three times, as are routes and paths. There are also three geographic features from the group waterways (all three times the lake) which are also selected as landmarks. The participants did not choose any landmarks from the groups landcover and landforms.

Participants selected mostly three-dimensional geographic features as landmarks (twelve out of 21). Most of these are man-made geographic features, such as signs, a wayside cross, or a shed. Only seven natural geographic features (three times the lake, a tree stump, the start of the forest, a double tree, and an outstanding tree) were selected as landmarks.

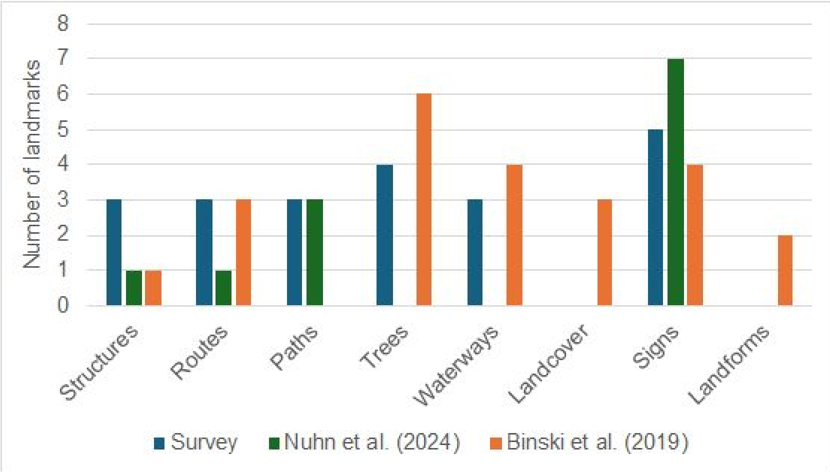

Figure 7. Groups of the landmarks.

5.2 Models results in detail

We identify landmarks with the two models for each survey intersection. The input to the models is the geographic features presented in the survey. The outputs are the identified landmarks. We look first at the results of the model of Nuhn et al. (2024) (Section 5.2.1) and then at the results of the model of Binski et al. (2019) (Section 5.2.2).

5.2.1 Model of Nuhn et al. (2024)

The model of Nuhn et al. (2024) identifies twelve landmarks. Figure 7 shows for each landmark group how many geographic features are identified as landmarks. Seven geographic features are part of the group signs. Paths are the second most selected (with three geographic features). The model identifies one routes geographic feature and one geographic feature of structures (a power pole) as landmarks. The model did not identify any landmarks from the groups trees, waterways, landcover, and landform. The analysis shows that most (eight) of the landmarks are three-dimensional geographic features. All the landmarks are man-made geographic features.

The total salience of the model of Nuhn et al. (2024) can reach a maximum of 400. The mean of the salience values for all objects is 176.84 (standard deviation 53.99). This means that the salience value for all objects is less than half of the possible salience value. This indicates that, on average, the objects in the area only achieve a moderate salience according to the model of Nuhn et al. (2024).

However, there are objects with a high salience value. The highest value is 310 and is reached at intersection 9 for two geographic features - the nature reserve sign and the tourist information (Figure 8). Both have a visual salience of 60 because they are both salient in height and object class. The sign is additionally salient in colour and the tourist information in surface. The highest salience value of 310 is achieved by another geographic feature at intersection 4

Figure 8. Intersection 9 (The colour indicates the number of times the geographical feature was selected as a landmark in the survey: no colour: 0-4 selections and dark green 17-20).

(Figure 9), also a nature reserve sign. It is visually salient in width, surface, and object class. All three geographic features have a semantic salience of 100 and a structural salience of 50 for their location. The temporal salience is 100 for all geographic features because they are permanent and seasonal geographic features.

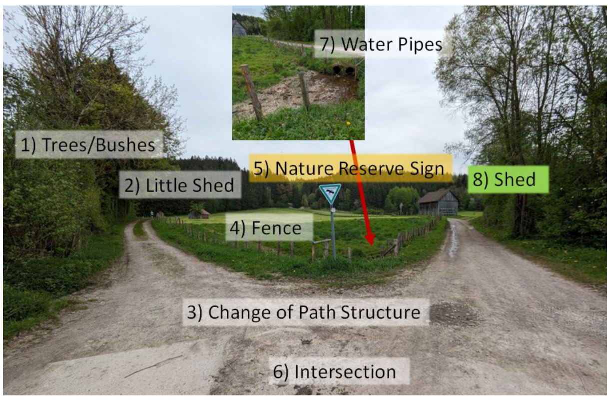

Figure 9. Intersection 4 (The colour indicates the number of times the geographical feature was selected as a landmark in the survey: no colour: 0-4 selections, orange 5-8, and light green 13-16).

There is one geographic feature that received the lowest salience value of 50. This is a tree stump with no visual, semantic, or structural salience. It is only considered to be a permanent geographic feature, which gives it a salience value of 50.

For the twelve geographic features identified as landmarks, the mean is 250.00. After the nature reserve sign and the tourist information with 310, there are seven landmarks with a salience value of over 200. There are two landmarks that only reach a salience value of 190. They have a visual salience of 40 (surface and object class), one of them has a semantic salience of 50, the other one has a structural salience of 50, and both have a temporal salience of 100. Although the total salience is only 190, there is no other geographic feature at this intersection that has a higher salience.

5.2.2 Model of Binski et al. (2019)

The model of Binski et al. (2019) identifies the most landmarks with 23. Figure 7 shows the number of geographic features identified as landmarks by the model for each landmark group. Six geographic features are part of the group trees. Waterways and signs are the second most selected (with four geographic features each). The model identifies three routes and three landcover geographic features, two landform geographic features, and one structures geographic feature (a fence) as landmarks. The model did not identify any landmarks from the group paths. Twelve of the landmarks are two-dimensional geographic features. For this model, the number of natural landmarks is higher (15) than the number of artificial landmarks.

The application of the Binski et al. (2019) model produced salience scores for all geographic features within the expected range of 2 to 10. The mean is 4.46 with a standard deviation of 2.34. There are four landmarks that reach the maximum salience score of 10. Each time it is the lake. It receives for all three decision trees the full salience score, because it is a natural geographic feature that will not totally change (Decision tree 1), it is noticeable from a great distance (Decision tree 2), and it stands out from the environment and it is not possible to find similar geographic features nearby (Decision tree 3).

There are 21 geographic features that received the lowest salience score of 2. These are for example a dog waste bin, a bench, several paths and intersections, tree stumps, a street gutter, a gully cover, a fish ladder, a fence, bridges, and a wood pile. This is because these are not natural geographic features that tend to change its form (Decision tree 1), they are neither visible from a great distance, nor tall, nor spread out on a large area, nor are possibly to be seen in all conditions (Decision tree 2), they do not stand out from the environment and can be easily mistaken with other geographic features (Decision tree 3).

For 23 geographic features identified as landmarks, the mean salience score is 7.45. The lake is the landmark the most outstanding since the next salience score is only 8.7 (the ravine). There are also six landmarks that reaches a salience score of 7.3 (three times an intersection, the start of the forest, a sign, and a tourist information board). There are five landmarks that only reach the threshold of 6, such as three times meadow and two signs.

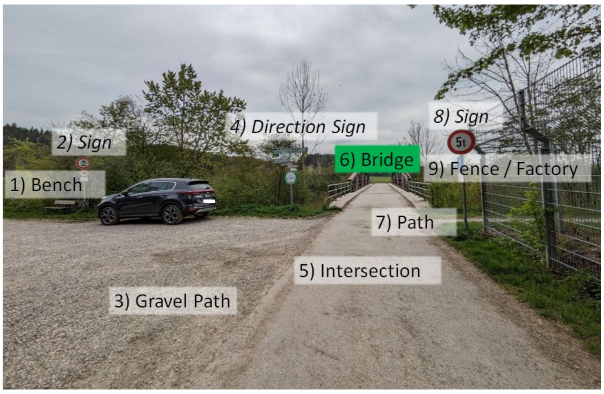

Figure 10. Intersection 2 (The colour indicates the number of times the geographical feature was selected as a landmark in the survey: no colour: 0-4 selections and dark green 17-20).

For eight of the ten intersections the model found more than one landmark. For intersection 1 for example four landmarks are identified (the meadow, trees, the intersection, and a fence). The intersection itself is the most salient with a score of 7.3. An intersection with three identified landmarks is intersection 8. Here a double tree, the ravine, and the lake are identified as landmarks. There are two intersections with only one identified landmark. At Intersection 2 (Figure 10), only the intersection itself is identified as a landmark, although at first glance other geographic features (e.g. the bridge) could also be identified as landmarks. The reason for this can be found in the fact that there are no natural geographic features at the intersection that would receive a high score for decision tree 1. The intersection extends over a large area and therefore receives a score of three for decision tree 2. Although there is the fence, which ranks higher as an intersection for decision tree 2 because it is tall, it does not qualify as a landmark as it gets the lowest score for decision tree 1 and decision tree 3. The intersection is outstanding from the environment and it is not possible to find similar geographic features nearby, so it gets a score of five for decision tree 3. Most of the other geographic features at the intersection get a score of one because they are not outstanding and are easily confused with other geographic features at the intersection. This is also true for the bridge. We assume that a geographic feature is salient if it has visual salience (Section 2.2.2). However, the bridge has a lower visual salience than the intersection because it differs in surface. For the surface attribute, a geographic feature is considered salient if its value differs from all other geographic features at the intersection. Since there is another wooden geographic feature (a bench) at the intersection, the bridge has a lower visual salience than the intersection, which is the only geographic feature made of tar at the intersection.

The other intersection with only one landmark is intersection 7 (Figure 11). Here a ravine is identified as a landmark. It is the only geographic feature at the intersection that cannot change completely and it is a natural geographic feature (Decision tree 1). Furthermore, it is one of the geographic features at intersection 7 that is spread over a large area (Decision tree 2) and it stands out from the environment (Decision tree 3) as it has a visual salience of 80. This is because it is salient in terms of (negative) height, colour, surface, and object class.

5.3 Comparison of Survey and Model Results

The evaluation of the results of the survey and the two models reveal notable differences in the identification of the most salient landmark, as the landmarks identified at each intersection vary across the three methods. The survey resulted in one to three landmarks per intersection, while the Binski et al. (2019) model identifies one to four, and the model of Nuhn et al. (2024) one and for two intersections two. At only two intersections – number 4 and 9 – the models and the survey agree on a single landmark: a nature reserve sign (Figure 9) and a tourist information board (Figure 8).

We apply McNemar's test to compare the landmarks identified by the model with those selected in the survey (McNemar, 1947). This test is based on a contingency table combining the results of the model and the survey (Table 2). The null hypothesis is that the number of landmarks identified by the model but not the survey is equal to the number identified by the survey but not the model. A significance level of $\alpha = 0.05$ is used. If the p-value calculated by McNemar's test exceeds α, the null hypothesis is accepted, indicating that there is no significant difference between the model and survey results.

The two-tailed p-value for comparing the survey results with the model of Binski et al. (2019) is 0.838, which is not statistically significant according to conventional criteria (Table 2). Similarly, when comparing the survey results with the model of Nuhn et al. (2024), the p-value is lower at 0.124, but still indicates no significant difference between the model and survey results.

Table 2 shows that the models are in better agreement with the survey about which geographical features are not landmarks than about what is a landmark. The model from Nuhn et al. (2024) agrees 46 times with the survey that a geographical feature is not a landmark. The model of Binski et al. (2019) has 42 agreements with the model of Nuhn et al. (2024) about what is not a landmark.

6 Discussion

The evaluation of the models in Section 5 shows that the differences between the two models and the survey results are not statistically significant. However, for this study (Section 3) certain constraints are made which could affect the results.

We collected the data in a rural region around a lake. In general, the choice of study area influences the evaluation of the model. The model of Nuhn et al. (2024) has already been tested in another rural area. In both cases, the model produced results that were not statistically significantly different from the selection of survey participants. We can therefore assume that the model is suitable for rural areas. As for the Binski et al. (2019) model, this is the first study to test it in rural areas. This means that it is unclear whether it would be able to identify landmarks in other rural areas.

The results of the two models are only marginally statistically significant (p=0.046). These differences can be explained by the different attributes which are taken into account by the two models. Firstly, Binski et al. (2019) does not take semantic salience into account, unlike the model of Nuhn et al. (2024). Here, objects with semantic salience are given a high value, i.e. a higher chance of being identified as a landmark. This also results in a different distribution of identified two- and three-dimensional landmarks. In the original implementation of Nuhn et al. (2024) 86% of the identified landmarks are three-dimensional. In our implementation, 67% are three-dimensional geographic features. In Nuhn et al. (2024), most of the identified landmarks are signs that are classified as three-dimensional. Thus, Nuhn et al. (2024) [p. 18] assumes "that as soon as a sign is present and visible (this may depend on the season and vegetation), we can use it as a landmark". However, only 48% of the landmarks identified by the Binski et al. (2019) model are three-dimensional and only four out of 23 are signs. The reason why more signs are not identified as landmarks can be found in decision tree 3, where visual salience is used to assess whether a geographic feature stands out from its environment. Visual salience is a relative attribute, as it is highly dependent on the other geographic features at an intersection. Thus, if a geographic feature does not stand out from the others at the intersection, it will receive a lower salience in decision tree 3.

Another difference is that the model of Binski et al. (2019) assigns a salience score of 5 to decision tree 1 once a geographic feature is natural. This leads to the high number of natural landmarks identified. The model of Binski et al. (2019) was developed for urban environments. In rural areas, artificial geographic features are generally more salient. Future work could investigate whether giving artificial geographic features a higher score would lead to better results.

We have taken the rules for calculating landmark salience from Nuhn et al. (2024) (Table 1). They present - as we do

Table 2. McNemar's contingency table.

		Survey		Mc Nemar
		Landmark	No Landmark	
Model Nuhn et al. (2024)	Landmark	3	18	p = 0.124
	No Landmark	9	46	
Model Binski et al. (2019)	Landmark	10	11	p = 0.838
	No Landmark	13	42	

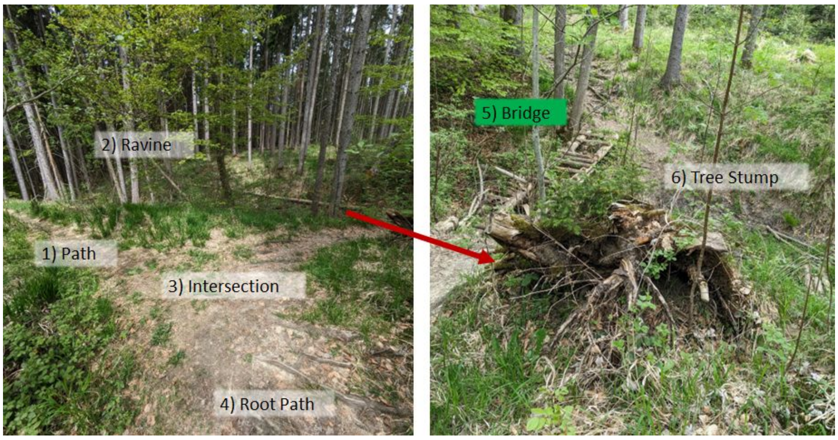

Figure 11. Intersection 7 (The colour indicates the number of times the geographical feature was selected as a landmark in the survey: no colour: 0-4 selections and dark green 17-20).

in this paper - their salience measures without any empirical evidence that they lead to better results compared to other salience measures. Thus, the salience measures and the conditions that must be fulfilled for the attributes to be considered salient are based on many assumptions. These assumptions could be validated in a future empirical study.

As mentioned by Nuhn et al. (2024), visibility depends on the season and vegetation. The visibility of certain landmarks, such as lakes, can change dramatically with the seasons. For example, during the summer months, increased vegetation can obscure landmarks such as lakes, making them harder to recognise. A total of 29 geographic features are classified as seasonal. Eight of these were selected as landmarks by survey participants. These were trees, tree stumps, and a group of trees. The lake was also a seasonal landmark chosen by the participants. It can change its appearance during the seasons, for example it can look like a meadow in winter when it is covered with snow. Unlike the study in Nuhn et al. (2024), we only include one non-permanent geographic feature in our study, a pile of wood. This geographic feature was only selected twice by survey participants, so it did not reach the threshold to be classified as a landmark. Nuhn et al. (2024) concludes that non-permanent, salient geographic features can be included in route descriptions. However, as we only considered one non-permanent geographic feature, we recommend further research into the permanence factor.

Similar to Nuhn et al. (2024), we conducted an online survey to evaluate our model. This approach has some drawbacks compared to on-site surveys. The images are centred, which can unintentionally draw attention to specific geographic features. Participants are limited to one view of the decision point, whereas in realistic conditions they would be able to move their head/eyes to look around. In future studies, a virtual environment such as Street View might provide more realistic conditions for such a survey.

Additionally, labelling geographic features may enhance the salience of certain landmarks by making them stand out more in the images. The number of selectable landmarks and geographic features is also limited. Participants had to choose one landmark, the most prominent one. However, sometimes there could be several salient landmarks in each image, or even the opposite case, no landmark at all. Furthermore, there is no such restriction in landmark salience models, as there may be no landmark at all or several. Therefore, in future studies, it should be possible to choose no landmark, one landmark, or several landmarks.

Furthermore, some features may be less visible in the images; for example, the slope of routes is difficult to discern (Pingel, 2010). Other factors, such as lighting conditions, shadows, and camera height, may have further influenced the perceived prominence of geographic features.

7 Conclusion

In this study, we conducted a comparative analysis of two rural landmark identification models: the Binski et al. (2019) and the Nuhn et al. (2024) models. Through both model application and a participant survey, we assessed how effectively these models identified landmarks in rural areas.

Our hypothesis was that the models would identify landmarks that correspond to what people would choose. We show that the differences between the models and the survey results are not statistically significant. However, looking at the results, Table 2 shows that the models are in better agreement with the survey about which geographical features are not landmarks than about what is a landmark.

We have identified open questions for future research, both in the development of the models for the identification of landmarks in rural areas and in the investigation of the survey results. The model of Nuhn et al. (2024) has now been tested in two rural areas and produced results that were not statistically significantly different from the selection of survey participants. We can therefore assume that the model is suitable for rural areas. As far as the Binski et al. (2019) model is concerned, this is the first time that it has been tested in rural areas. The model should be applied in other study areas to test its functionality for other landscapes and geographic features.

The results of the two models are statistically significantly different. Currently, the model of Binski et al. (2019) does not take semantic salience into account and prefers natural geographic features. In contrast, the model of Nuhn et al. (2024) identifies highly semantically salient geographic features as landmarks. Investigating these facts further may be part of future research.

We only considered permanent geographic features, with the exception of a pile of wood. We recommend further research to investigate how people select landmarks depending on their permanence. We are also interested in understanding the role of seasonal changes in landmark selection and whether significantly different landmarks are selected in winter compared to summer.

In rural areas, navigation systems based on landmarks could significantly improve wayfinding. However, a key challenge in developing such systems is the limited data available for natural areas. 22 of the geographic features used in this study can be found in a topographic map and 44 in OpenStreetMap. However, they do not come with all the visual, semantic, and structural data needed for the models. This study's data was collected through a field study - a method that, while effective, is typically time-consuming and complex, making it impractical for large-scale landmark identification in applied systems. A potential focus of future work could be to use crowdsourced data to explore its viability as a resource for collecting attributes essential for identifying rural landmarks.

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Declaration of Generative AI in writing

The authors declare that they have used Generative AI tools in the preparation of this manuscript. Specifically, the AI tools were utilized for language editing, improving grammar, and sentence structure, 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.

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