Applied Geography 165 (2024) 103237

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Mapping open spaces in Swiss mountain regions through consensus-building and machine learning

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ARTICLE INFO

Handling editor: J Peng

Keywords:
Open spaces
Machine learning
Delphi
Consensus-building
Switzerland

ABSTRACT

The rapid expansion of tourism, transportation, energy, and agricultural infrastructure in mountain areas raises concerns about landscape fragmentation and impacts on aesthetic values. Effective delineation of these areas relies on negotiating various qualities that define them. In our study, we developed a collaborative consensus-building process with experts to map open spaces. Rather than collecting information on the factors characterizing open spaces, we first obtained a consensus on their delineation using a Delphi survey, followed by machine learning to extract variables explaining the spatial extent of the open spaces. Results show that the Delphi survey allowed experts to get a collective understanding on the delineation of open spaces through a process of knowledge (de)construction. By applying machine learning on the consolidated outcomes, we were then able to predict open spaces not only defined by physical aspects, but also characterized by subjective elements related to experts' perceptions of the landscape. Such an approach cannot only serve as a decision-support tool for more sustainable management of mountain areas, but as a tool to produce legitimized maps integrating knowledge and perception of various stakeholders. By incorporating these diverse perspectives, this participative process also fosters understanding and acceptance for future spatial planning decisions.

1. Introduction

Mountain regions are experiencing growing infrastructure development pressure to cover the needs of various sectors from tourism to energy, transportation, and agriculture (Boller et al., 2010; Donázar et al., 2018; Kareiva et al., 2007). Improved connectivity and growing economic interests have transformed these once remote and inaccessible areas into infrastructure-dominated landscapes (Kareiva et al., 2007; Radford et al., 2019; Venter et al., 2016). In particular, the urgent need for a transition to renewable energy sources, driven by the climate and energy dependency crises, has accelerated the installation of renewable energy infrastructures in mountain regions (Job et al., 2021; Kopf et al., 2017; Spielhofer et al., 2023). However, these developments are raising questions about trade-offs with ecological and aesthetic landscape values (Liu et al., 2007; Nischik & Pütz, 2018; Schwick et al., 2018), and have called for actively negotiating conflicting interests to support sustainable development.

Decision-makers have traditionally relied on a variety of maps to facilitate discussions and identify appropriate locations for infrastructure development or nature conservation efforts. Significant progress has been made in developing maps that delineate open spaces in mountain regions (Job et al., 2021; Kopf et al., 2017; Nischik & Pütz, 2018; Plassmann & Coronado, 2021) or other related topics such as wilderness (Radford et al., 2019) or remoteness (Boller et al., 2010). Already during the 1970s, established instruments such as the Bavarian Alpenplan or the Tyrolean Ruhegebiete addressed the need to regulate the different demands in mountain regions by delimiting open spaces using existing and historical land uses, ecological information, as well as future development prospects (Hasslacher et al., 2018; Job et al., 2014). Numerous other studies followed, mostly focusing on land use information and physical landscape attributes and relying on a pre-determined quantification of the impact of infrastructures (Hasslacher et al., 2018). However, recent advancements in machine learning have the potential to facilitate a more explorative approach for assessing the influence of infrastructures in the delineation of open spaces. Indeed, spatial algorithms have demonstrated their effectiveness in mapping complex phenomena in various fields and quantifying unknown relationships and patterns in the data (Casali et al., 2022; Chen, De Hoogh, et al., 2019; Sun et al., 2021; Zuo et al., 2021). However, landscapes cannot only be described by their physical characteristics (Cakci, 2012).

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https://doi.org/10.1016/j.apgeog.2024.103237
Received 7 September 2023; Received in revised form 6 February 2024; Accepted 19 February 2024
Available online 1 March 2024

They are the products of the interplay between natural and anthropogenic factors (European Landscape Convention, 2004) and are subject to varying human perceptions (Hunziker et al., 2008). Mapping open spaces requires considering complex human-nature relationships involving various stakeholders and acknowledging their different views in decision-making processes (Vajjhala, 2006).

Local knowledge and insights from stakeholders as well as experts have been used to varying degrees to improve and refine mapping outcomes (Clavel et al., 2011; Radford et al., 2019; Sadler, 2016). Active, iterative and collaborative processes of creating, sharing and using all forms of knowledge, including experience, values and beliefs, is known to increase the legitimation of knowledge generation (Grêt-Regamey et al., 2013; Jacobs et al., 2015). Guided by digital cartography, such processes have found their ways into geodesign, an interdisciplinary approach that merges geographic information science with design theories to foster more holistic outcomes (Steinitz, 2012). Participatory GIS attempts to achieve this encompassing understanding by engaging communities, stakeholders and experts, and integrate their insights in the mapping and data collection process (Brown & Fagerholm, 2015; Chambers, 2006; Sieber, 2006).

Although the value and benefits of incorporating diverse perspectives and stakeholders are widely acknowledged (Chambers, 2006; Sieber, 2006), unveiling the intricate relationships in complex phenomena often requires expert knowledge (Brown & Fagerholm, 2015). Experts can better understand complex phenomena and unveil intricate relationships, contributing to a more nuanced understanding of the studied phenomenon. Additionally, focusing on expert knowledge helps to strengthen credibility, which supports an effective integration of the outcomes in decision-making (Brown & Fagerholm, 2015; Clavel et al., 2011). In the context of open spaces in mountain regions, a solid background knowledge is essential due to the fuzziness surrounding the concept of open spaces and the required cartographic expertise. Previous research on open spaces has primarily utilized expert knowledge to predetermine the importance of specific factors (Nischik & Pütz, 2018), to validate final mapping results (Kopf et al., 2017), or to analyze and discuss individual case studies (Gurtner et al., 2009). However, expert knowledge has not yet been included as a pivotal element within the spatial modeling process, specifically as part of machine learning algorithms. This combination of advanced extensive expert knowledge and computational capabilities forms a robust foundation for the collaborative design of open spaces in mountainous areas.

The goal of this study is to develop a collaborative consensus-building process among experts to map open spaces as decision-support for steering the development of new infrastructures. By integrating expert knowledge into machine learning algorithms, the study shows how such a process can foster a collaborative consensus-building process that informs the identification of areas that are perceived differently by various stakeholders and thus difficult to delineate in space. The approach is illustrated in Switzerland's mountain regions, which face increasing pressure, particularly from renewable infrastructure development due to climate and energy crises (Spielhofer et al., 2023). After introducing the concept of open spaces, the paper outlines the methodological structure, comprising of a Delphi survey and a machine learning process. The subsequent results section presents the final map of open spaces in mountain regions, the machine learning algorithm used to develop it, as well as the insights of the surveys, highlighting the similarities and differences that emerged between the participants. The paper closes with an in-depth discussion on the relevance of such an approach in addressing the challenges of open spaces management.

2. Background

2.1. Defining open spaces in mountain regions

Open spaces in mountain regions serve multiple purposes, providing essential ecosystem services, supporting ecological connectivity, mitigating landscape fragmentation and biodiversity loss, and preserving cultural values (Job et al., 2022; Nischik & Pütz, 2018). The term "open spaces" encompasses various meanings, including ecological, historical-cultural, economic, social, spatial-structural, and aesthetic aspects. Nevertheless, a clear and universally accepted definition is still lacking (Hartz, 2019). For the purpose of this study, a definition has been adopted based on expert knowledge and existing work such as the project OpenSpaceAlps (Job et al., 2022; Plassmann & Coronado, 2021). The proposed definition serves as a framework to guide the investigation and assessment of open spaces in mountain regions. *Open spaces in mountain regions are characterized as high-altitude, contiguous areas or landscapes that are largely undeveloped and free of technical, spatially impactful infrastructure. These regions can be used for agriculture, forestry, and hunting, and have a high recreational quality due to their acoustic and visual tranquility and closeness to nature.*

2.2. Mapping open spaces in mountain regions

Qualitative mapping is a commonly used approach, in which experts and stakeholders collaborate to produce drawings and discuss possible interpretations of the mapping results. Through this process, a shared vision for the management and sustainable development of mountain landscapes can be developed and refined. Gurtner et al. (2009) show, for example, how participants have engaged in discussions to share their diverse perspectives on mountain regions, as the basis for the analog identification of open spaces. While these projects benefit from robust expert knowledge, the manual classification process confines the study area to limited sample regions, known by the experts.

To address the limitations associated with qualitative approaches, researchers use quantitative mapping techniques to automate the identification of open spaces and extend it to larger areas. In the 1970s, attempts were made to define concepts closely related to the idea of open spaces. The Bavarian Alpenplan, implemented in 1972, regulated the development of transportation infrastructure in the Bavarian Alps with the aim of preventing the overuse of nature and landscapes and reducing the risk of natural hazards. The regional plan divides the area into three institutionally regulated zones, demarcated according to cartographic fieldwork, land use, ecological sensitivity, and future development prospects (Hasslacher et al., 2018; Job et al., 2014, 2020). Between 1972 and 1973, the Austrian region of Tyrol similarly attempted to define so-called quiet areas (i.e., Ruhegebiete), which were characterized by a minimal presence of disturbing infrastructure (Hasslacher et al., 2018; Job et al., 2020). Similar quantitative approaches to open spaces mapping followed, mostly focusing on demarcations based on infrastructure and human presence (Job et al., 2017). The Salzburg state identified alpine quiet areas (i.e., Alpine Ruhezonen) based on the compatibility or incompatibility of land uses and activities. This differentiation adheres to predetermined criteria and is influenced by comparable approaches, including the Alpenplan and the Tyrolean Ruhegebiete (Job et al., 2017). A slightly different approach was introduced by Kopf et al. (2017), who mapped open spaces by identifying relevant infrastructures and then calculating the degree of infrastructure development, i.e., the proportion of the area occupied by infrastructure, at different spatial scales, such as administrative boundaries or hydrological catchments (Job et al., 2022). This approach was later adapted and implemented by Nischik and Pütz (2018), as well as in the context of the OpenSpaceAlps project (Job et al., 2021, 2022; Plassmann & Coronado, 2021). These studies slightly vary in the detailed settings and choices concerning the computation of the impact of infrastructures (e.g., employing different spatial buffers to represent the extent of their influence) as well as in the final spatial aggregation and representation choice. For instance, Nischik and Pütz (2018) decided to group all the obtained watersheds into overarching alpine landscape types based on their level of infrastructural accessibility, while other studies preferred to present the ungrouped outcomes. A thorough and comprehensive examination of the most recent quantitative investigations of open spaces is provided by Job et al. (2022). On a related topic, Boller et al. (2010) have implemented a similar methodology based on the degree of infrastructure development to delimit and define the concept of remoteness. Other studies have combined distance factors and on-site features like land cover or vegetation conditions using weighted and averaged sums for each location. This approach essentially creates a continuous representation rather than discrete, aggregated, statistical results (WWF Austria, 2017). Radford et al. (2019) followed a similar methodology to assess the level of wilderness quality in Switzerland. An expert-weighted overlap of different spatial features influencing wilderness resulted in a spatially explicit wilderness quality index (Radford et al., 2019). These quantitative methods overcome the spatial constraints of qualitative approaches, but expert knowledge is only used to directly assess the importance of specific factors in the aggregation to an index (Job et al., 2022; Nischik & Pütz, 2018) or to validate outcomes (Radford et al., 2019).

Current research reveals a lack of approaches that combine these qualitative and quantitative practices and draw on broader expert knowledge through efficient expert surveys. While qualitative methods provide valuable insights through the integration of expert knowledge, they often suffer from limitations in terms of generalizability and scalability. In contrast, quantitative methods offer the ability to analyze large study areas, automate processes, and ensure statistical consistency, but they lack the nuanced understanding and context provided by qualitative methods (Jacobs et al., 2015; Queirós et al., 2017). To address these limitations and fill the existing research gaps, this study aims to introduce a comprehensive framework for modeling open spaces using machine learning techniques. By iteratively refining their understanding through training procedures, these models can explore and identify unknown interactions within the spatial data and use these insights to predict new information (Casali et al., 2022; Chen, De Hoogh, et al., 2019; Sun et al., 2021; Zuo et al., 2021). This is in contrast with currently employed methods in open spaces mapping which often rely on predefined equations, hypothesis testing, and inferences based on known phenomena to draw conclusions (Job et al., 2022). This study exploits the flexibility of machine learning models to combine quantitative and qualitative information, enabling the integration of expert knowledge alongside the robustness and automated generalization offered by quantitative methods. This methodological approach for effectively combining collaborative, consensus-based knowledge among experts (Bürgi et al., 2022; Burnett, 2023) with the scalability and robustness of quantitative methods is described in detail in the following section.

3. Materials and methods

The map of open spaces in Swiss mountain areas was developed through a consensus-building and machine learning process in which expert knowledge was gathered to determine the location of open spaces in the landscape. In a first part, the Delphi methodology facilitated a consensus-building process by collecting individual views (i.e., drawings of open spaces) and then sharing these views with all participants, while giving them the opportunity to adjust their own initial choices. To achieve this, rather than relying on specialized consensus-building software, we based our approach on a two-tiered online survey developed by our research team using high-quality background maps (swisstopo, 2023c, 2023b). The knowledge gathered through these surveys was then extracted and used as input data for the subsequent modeling procedure. In a second part, we used machine learning techniques to train a spatial model to predict and extrapolate the consensus-based knowledge to the entire assessed mountain regions. Fig. 1 illustrates the central steps of the methodology, emphasizing first the consensus-building process (1st and 2nd survey) and second the subsequent spatial modeling procedure driven by machine learning techniques. The following sections provide a more detailed explanation of these different stages.

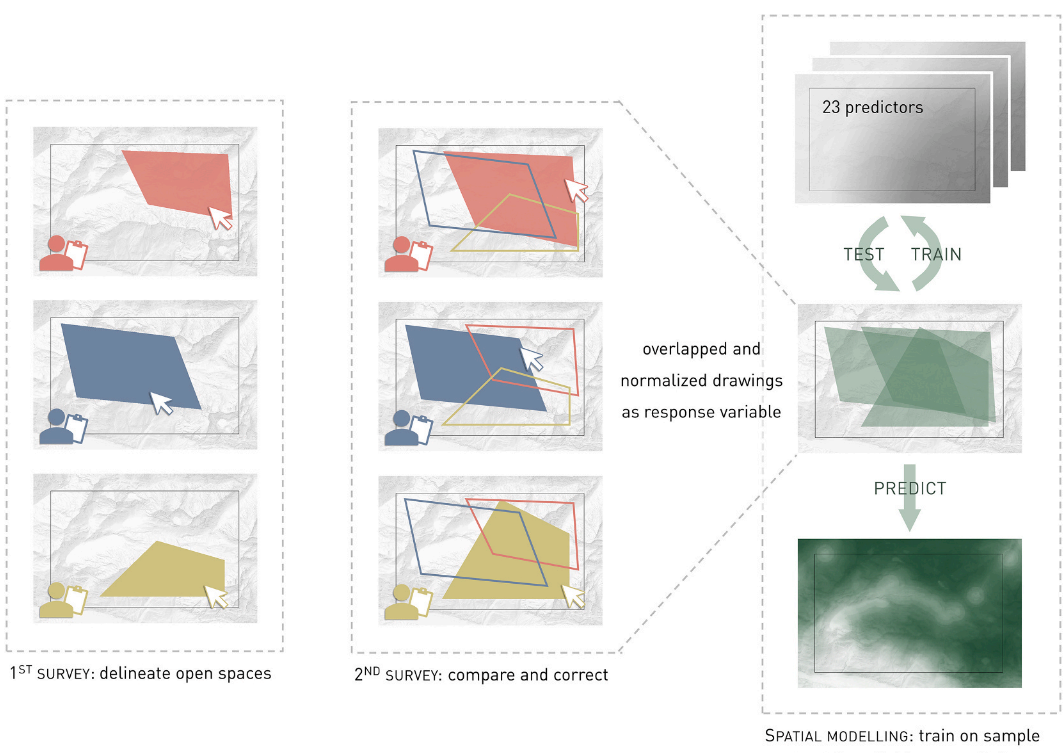

Fig. 1. Graphical summary of the research methodology (own design). The process is divided in three main sections (1st survey, 2nd survey, and spatial modeling), feeding into each other at different points in time during the study.

3.1. Case study and sample regions

This study focuses on the mountainous regions of Switzerland, i.e., the Jura mountains and the Alps. In order to create a comprehensive map encompassing the diversity of the mentioned mountain landscapes in the country, we adopted the delineation outlined by the Swiss Federal Statistical Office (GEOSTAT, 2021). By adopting this classification, the research ensures a comprehensive evaluation of open spaces within the varied mountain landscapes of the country. Due to the impracticality and inefficiency of identifying and delimiting open spaces with experts across the entire case study region, representative sample areas were strategically chosen for conducting the surveys and the subsequent spatial modeling. In an initial step, 80 sample areas were distributed inside mountain regions in Switzerland using a stratified random sampling approach (Howell et al., 2020). This process involved dividing the case study region into three sub-regions (supplementary material A) based on the degree of infrastructure development (Nischik & Pütz, 2018). Subsequently, sample zones were distributed within these sub-regions, assigning fewer samples to regions with extremely low or very high levels of infrastructure development. Conversely, a higher number of sample zones were allocated to the middle sub-region showing a more mixed pattern. Through this stratified sampling approach, the focus was placed on intermediate areas, which could not yet be clearly categorized as either open spaces or highly developed infrastructure regions. The entire procedure was conducted separately for the Alps and the Jura (66 and 14 sample areas respectively), and the resulting sample areas were then merged in a last step. This stratified random sampling approach minimized the occurrence of areas with extremely low or high probabilities of being classified as open spaces, and instead maximized areas where various spatial features interact and contribute to the delimitation of open spaces (supplementary material A).

3.2. Delphi method

The Delphi method is an iterative technique that aims to facilitate the transformation of individual opinions into a collective consensus (Turoff & Linstone, 1975). The process involves multiple rounds of survey and feedback, allowing participants to refine and align their views over time. In the initial round, participants provide their individual assessments based on their expertise while in the subsequent rounds, participants review and adjust their responses considering the collective input. Through this iterative process, the Delphi method encourages participants to reconsider their initial positions, contemplate alternative viewpoints, and converge towards a shared consensus (Geist, 2010).

Our Delphi methodology included two online surveys. A total of 117 people participated in the first survey, with 93 of them also completing the second iteration. The 24 participants who did not finish the second survey were excluded from subsequent analyses. These experts were recruited based on expertise or involvement in mountainous landscapes, for recreational or professional purposes. Here, the term expert simply refers to a person with considerable knowledge of mountain regions. Therefore, participants had diverse backgrounds, ranging from mountain guides, scientists, public sector employees to park managers, but with the common characteristic of having extensive knowledge of mountain regions (Fig. 2).

In the first online survey round, experts were instructed to draw polygons representing open spaces in the randomly assigned sample areas based on their knowledge and personal interpretation. They were provided with general guidelines and with the proposed definition to ensure consistency in their assessments. During this mapping process, experts identified open areas by using both the topographic landscape model of Switzerland known as swissTLM3D (swisstopo, 2023c) and SWISSIMAGE, a composition of aerial photographs with resolution between 10 cm and 25 cm (swisstopo, 2023b). These background maps constitute the most reliable dataset in Switzerland and were kept unchanged and consistent for all participants, as well as for the second online survey round. Participants were also given the option to omit drawing polygons in areas where they were unable to identify open spaces according to their considerations. This, combined with the randomized allocation, resulted in different polygon counts across the sample areas. The collective coverage was considered satisfactory for the subsequent machine learning phase.

In addition to mapping open spaces, during the first survey (supplementary material B.1) experts were asked a series of questions to gain further insight into their involvement in open spaces, their area of expertise, and their familiarity with each specific sample area. In addition, participants were asked to evaluate their confidence level in the delineated open spaces. In other words, they were asked to indicate how confident they were about the correctness of their drawings. This provided a deeper understanding of the reliability and subjective interpretations of open spaces, and served as a self-reflection opportunity for the participants, further strengthening the collaborative, consensus-based character of this mapping process. Furthermore, these questions also provided important insights for assessing changes between the responses given after the first and after the second survey. Overall, this initial phase aimed to capture a wide range of ideas, diverse interpretations of the proposed broad definition, and perceptions of open spaces, profiting from the diverse backgrounds and expertise of the participants.

During the second round of the online survey (supplementary material B.2), the primary goal was to reach consensus and refine the mapping of open spaces in the sample regions. To facilitate this process, all experts were given access to the compiled responses from the first round, allowing them to review and compare their own assessments with those of their peers. This encouraged participants to consider different perspectives and integrate new information, allowing them to change their initial responses and align them with a more consensus-oriented view. Experts were asked to re-evaluate their confidence in the delineated open spaces, after having had the opportunity to examine the responses of other participants. Additionally, participants were asked to assess whether viewing other participants' responses improved the quality of their own delineation of open spaces. Incorporating these additional elements into the survey provided a deeper understanding of participants' shifts in perception and of the consensus-building process.

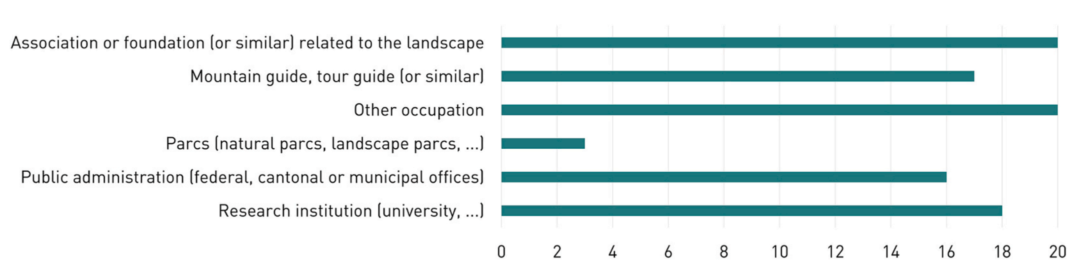

Fig. 2. Background of participants of the two surveys (only participants who completed both surveys are considered). "Other occupation" is a category that includes all non-specified backgrounds that do not fall under the other categories.

3.3. Spatial modeling

Once the surveys were completed, the consensus reached through the Delphi method on the spatial distribution of open spaces in mountain regions was incorporated into the machine learning process. To ensure consistency and comparability, the drawings were merged and the values normalized between 0 and 1 (0 for areas with no identified open spaces, 1 for areas that all experts categorized as open spaces). The resulting normalized values were then used as the dependent variable for the spatial model to learn and understand the relationships between expert survey responses and the predictors (Table 1) selected based on previous studies (Job et al., 2022; Nischik & Pütz, 2018; Plassmann & Coronado, 2021).

Subsampling of input data is necessary to manage computational complexity, improve efficiency and avoid spatial biases (Getis, 2007). In this study, the subsampling process involved generating a point grid, where points were spaced apart by the computed autocorrelation distance threshold of the survey results. Calculating the autocorrelation distance threshold allows to identify the distance at which spatial similarity between data points becomes significant (Getis, 2007). This method guarantees to effectively capture relevant spatial dependencies while managing the data size for more efficient spatial modeling. The resulting data were further divided into training and test sets, with 80% and 20% of the data, respectively. The train set is used to build and train the model by estimating parameters and finding the best fitting function. The test set is a separate subgroup of data that is not used during the training phase and is used to evaluate the performance of the model and its ability to generalize well to unseen data. Additionally, cross-validation was used to further fine-tune the spatial model (Bengio & Grandvalet, 2004; Sun et al., 2021). This statistical technique partitions data into subsets (folds) to improve and evaluate model performance and prevent overfitting. In this study, we used 10-fold cross-validation: the dataset was divided into ten equal folds and the model trained and evaluated ten times, with each fold being used as the validation set once while the other nine folds are used for training. Finally, the performance and findings are averaged across the folds to provide a more robust model.

Spatial modeling was performed using the R programming language (R Core Team, 2023) and the RStudio environment (Posit team, 2023). To account for the non-normal distribution observed in the values extracted from the expert drawings, four non-parametric machine learning models were tested: Multivariate Adaptive Regression Splines (Friedman, 1991), eXtreme Gradient Boosting (T. Chen & Guestrin, 2016), Random Forest (Breiman, 2001), and Generalized Boosted Model (Friedman, 2002). All models were implemented using the caret R package (Kuhn, 2008), which is a comprehensive tool for training and evaluating various machine learning models. The caret package provides a unified interface and streamlined workflows for model training, parameter tuning, cross-validation, and performance evaluation. General performance factors (Mean Absolute Error, Root Mean Square Error, and R squared) were evaluated for each model, and since no single model clearly outperformed the others, an ensemble model was constructed by combining the predictions of all four models (Caruana et al., 2004). This ensemble model exploits the strengths of each model to provide a robust and reliable prediction of open spaces throughout the study area. The resulting maps were produced at 50 m and 100 m resolution. Detailed documentation of the models is provided in the supplementary material, including training parameters and hyperparameters (supplementary material C1), as well as performance metrics (supplementary material C2).

Table 1
Predictors for spatial modeling (based on Job et al., 2022; Nischik & Pütz, 2018; Plassmann & Coronado, 2021).

Category	Subgroup	Data source	Predictor
Transportation	Roads and paths *(no tunnels)*	swisstopo (2023c)	distance to large roads [m] distance to medium roads [m] distance to small roads [m] distance to large paths [m] distance to small paths [m]
	Railways *(no tunnels)*	swisstopo (2023c)	distance to all railways [m]
	Cable cars, lifts	swisstopo (2023c)	distance to person cable cars [m] distance to material cable cars [m]
	Airports	FOCA (2023a)	distance to airports [m]
	Helicopter landing sites	FOCA (2023a, 2023b)	distance to heliports [m]
	Public transport stops	swisstopo (2023c)	distance to transport stops [m]
Settlement	Building footprint *(filtered)*	swisstopo (2023c)	distance to buildings [m]
	Leisure facilities	swisstopo (2023c)	distance to leisure facilities [m]
	Industrial facilities	swisstopo (2023c)	distance to industrial facilities [m]
Utilities	Reservoirs, dams	swisstopo (2023c)	distance to water infrastructure [m]
	Natural hazards protections	swisstopo (2023c)	distance to protection infr. [m]
	High-voltage lines	swisstopo (2023c)	distance to high-voltage lines [m]
	Communication antennas	swisstopo (2023c)	distance to antennas [m]
	Single features *(fountain, …)*	swisstopo (2023c)	distance to single objects [m]
Environment	Naturalness	Price et al. (2021)	naturalness [index]
	Digital elevation model	swisstopo (2023a)	slope [degree] ruggedness [index] elevation [m]

4. Results

4.1. Open spaces in Swiss mountain regions

The open spaces map (Fig. 3) classifies locations along a continuous spectrum ranging from "not open spaces" (represented as white) to "open spaces" (depicted as dark green). The distribution of open spaces in Swiss mountain regions is highly heterogeneous with large, unfragmented open spaces present mainly in the Alps at high elevation, while the Prealps and the Jura mostly entail larger, more isolated open spaces areas of medium value (light green). In the Jura we find only around 3 km^2 of areas with values above 0.8, while in the Alps and Prealps around 7′000 km^2. Over the whole study area, valley bottoms are distinctly recognizable as non-open spaces, featuring a combination of buildings, transportation networks and various other infrastructures. This general trend is consistent with experts gathered comments (supplementary material D).

A closer look reveals interesting findings about the impact of specific infrastructure, particularly in regions of medium to high open spaces values (supplementary material E). Specifically, roads have a substantial impact on the configuration of open spaces, while smaller paths have a more limited influence. This phenomenon is particularly noticeable in open spaces configuration of the Pre-Alps and the Jura, where the trails network predominantly consists of wide, drivable paths. In contrast, the alpine area encompasses numerous narrower trails, which, due to their relatively minor impact, contribute to elevated open spaces values and larger unfragmented areas. Cable cars and lifts, whether utilized for the transportation of materials or individuals, constitute another important aspect for the delineation of open spaces. Their influence is particularly

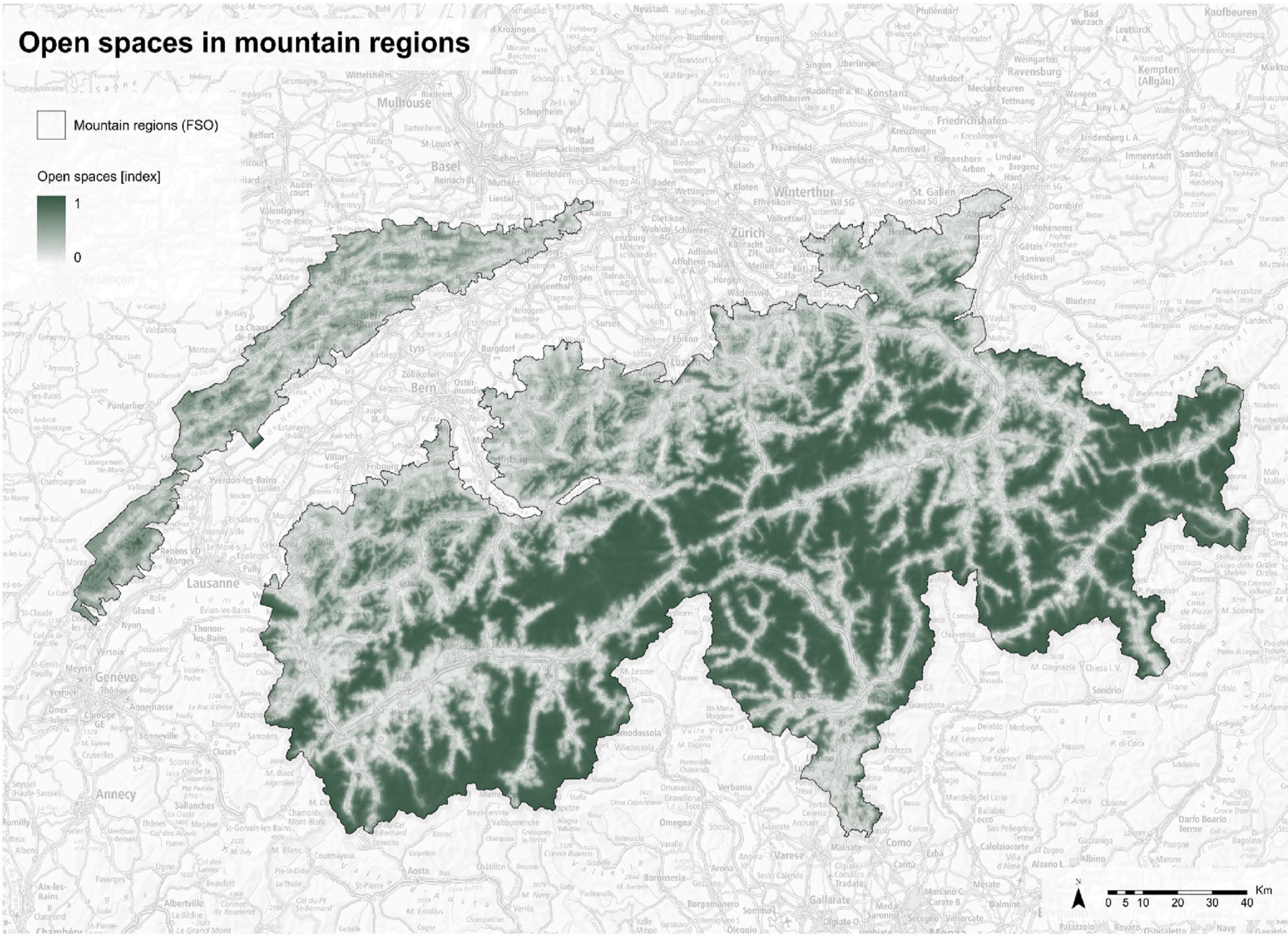

Fig. 3. Final modeling result showing open spaces in mountain regions in Switzerland displayed as a continuous index with values ranging from 0 (not open spaces at all) to 1 (clearly open spaces), at 50-m resolution.

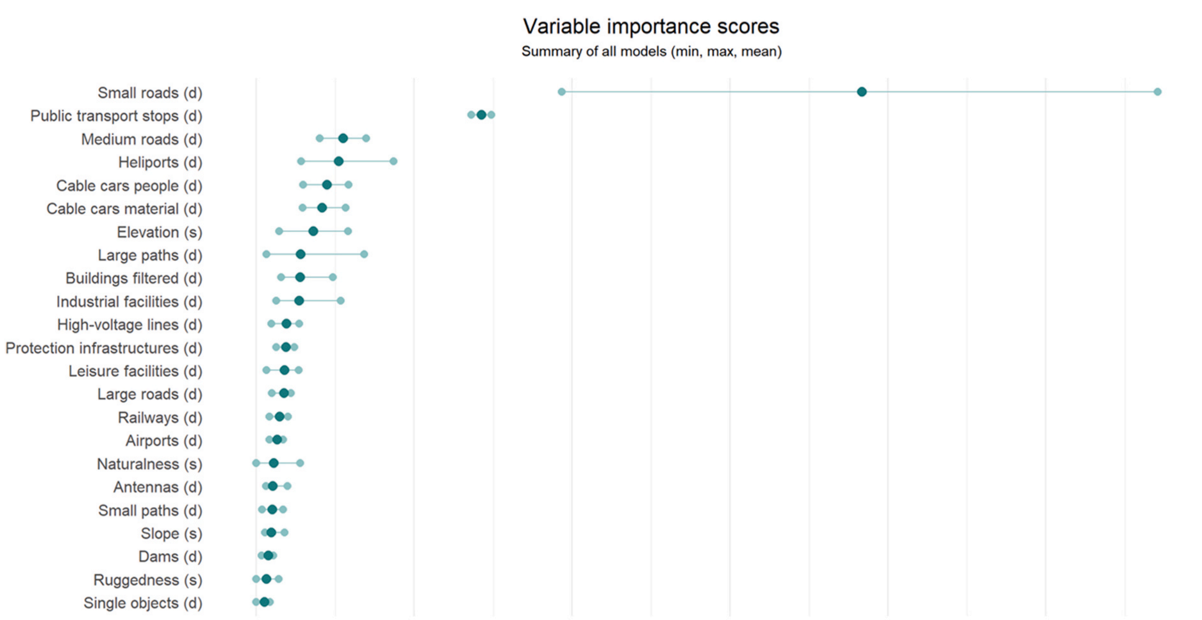

Fig. 4. Relative variable importance in modeling open spaces in mountain regions. For each predictor the minimum, maximum and mean importance scores derived from the four tested models and the ensemble model are displayed. Annotation: d = variable represents the Euclidean distance to the corresponding infrastructure, s = variable represents the feature on site.

noticeable when grouped together, as in ski and tourist resorts.

4.2. Machine learning model

The relative variable importance scores (Fig. 4) offer further valuable insights into the variables' predictive power in identifying and determining open spaces in mountain regions. The utilized variables are ranked in descending order of importance, with distance to small roads emerging as the most influential predictor, followed by the distance to public transport stops, medium roads, heliports, cable cars, and elevation. The distance to single objects and the ruggedness index displayed lower importance values. The variation in importance scores across the models used to build the ensemble model (min, mean and max values in Fig. 4) did not change the overall ranking of the variables. This suggests that the ensemble model demonstrated stability and robustness, as the selection of different models for the ensemble did not result in substantial fluctuations in the rankings of variable importance. The most notable fluctuation was observed in the "small roads" variable, which consistently had the highest score across all models but showed high variability. This can be explained by the varied methodologies used by the models in computing variable importance scores (Grömping, 2015). In fact, while the caret R package (Kuhn, 2008) provided a unified interface for the machine learning models used, it still retained the inherent characteristics of each algorithm when it came to calculating variable importance. In Generalized Boosted Model (Friedman, 2002) and eXtreme Gradient Boosting (T. Chen & Guestrin, 2016), trees are constructed based on the strengths and weaknesses of the different variables identified in previous iterations, which in our study led to a more frequent inclusion of the variable "small roads" and thus to very high importance scores for this variable. Conversely, the Random Forest model (Breiman, 2001), with its randomized selection approach for testing variable importance, led to lower importance scores for the variable "small roads".

As previously mentioned, given that none of the selected models outperformed the others, an ensemble model was generated (Caruana et al., 2004). This final model displays sound performance metrics, with a Mean Absolute Error (MAE) of 0.14 and a Root Mean Square Error (RMSE) of 0.18. These values suggest that, on average, the model's predictions are within a reasonably small margin of error from the actual values. Indeed, values of MAE and RMSE closer to 0 are indicative of better predictive accuracy. Regarding the R-squared (R^2) value, the model demonstrates a strong ability to explain the variance in the training data, with an R^2 of 0.75. This indicates that the ensemble model captures a substantial portion of the underlying patterns. The ensemble model holds a stable R^2 value of 0.67 also when assessing its performance on the test dataset. This signifies that the model's predictive power extends to previously unseen data, explaining approximately 67% of the variations.

The reliable performance of the machine learning model is attributed, partly, to the quality of the underlying data, specifically the response variable derived from the survey responses. Fig. 5 shows a sample of the polygons drawn by the experts during the second round of the survey – employed in generating the mentioned response variable. The random assignment of sample areas to survey participants resulted in an average of 9 expert responses per area, with some sample areas having as many as 13 responses and others having as few as 5. These

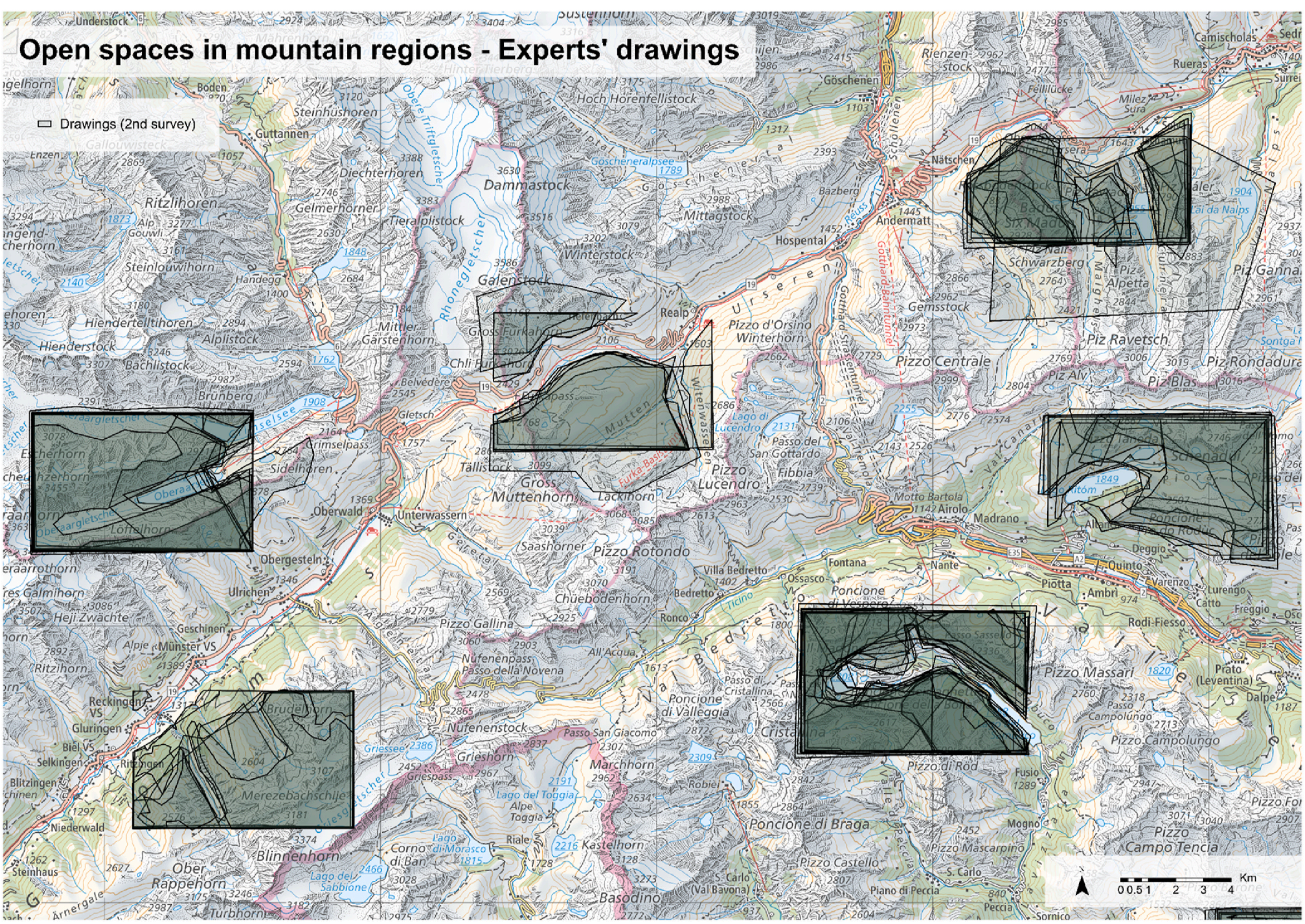

Fig. 5. Extract of polygons sketched in the second survey. Drawings are overlapped, not yet masked nor normalized.

polygons depict how various experts have interpreted the proposed definition, especially regarding the understanding of terms like "*largely undeveloped*" and "*free of technical, spatially impactful infrastructure*". Across all sampled areas, a consensus among experts emerges in identifying at least one region as falling under the classification of open spaces (dark green shade), while certain parts of the landscape are unanimously deemed as entirely non-open spaces (white areas without polygons). Nonetheless, a closer examination shows that differences occur, as certain experts demarcated broader and more generalized open spaces, while others opted for more precise differentiations guided by specific infrastructural elements identified on the map.

4.3. Qualitative survey questions

Interesting findings also arise from the qualitative questions. Outcomes from both surveys reveal a significant decrease in experts' confidence scores regarding their delineation of open spaces (Fig. 6, above). In the first survey, 61% of participants expressed a high level of confidence in their drawings (ranging from "moderately confident" to "very much confident"), while the remaining 39% expressed low level of confidence (from "only slightly confident" to "not confident at all"). The second survey yielded opposing results: 59% of the participants indicated a low confidence level, while 41% reported a high confidence level. Interestingly, despite this decline in self-assessed confidence, participants perceived an improvement in their drawings through the process of comparing their views with those of their peers (Fig. 6, below). Indeed, in the second survey, most participants (68%) reported that their evaluations of their own drawings had improved significantly (ranging from "moderately improved" to "very much improved"). This development of the experts' judgements on the delineation of open spaces could be summarized in three steps: construction, deconstruction, and consolidation. In the first survey, participants drew open spaces and on average they expressed a high level of confidence in their drawings – the construction phase. In the second survey, after having had the possibility to adapt their drawings by comparing them with the ones of their peers, the confidence scores of the participants significantly decreased – the deconstruction phase. However, this decrease in confidence was accompanied by a perceived improvement in the participants' drawings thanks to the possibility of observing those of their peers. The stage of critical examination and deconstruction was thus followed by a period of reconstruction and consolidation, which contributed to an overall improved delineation of open spaces.

After each individual mapping task, participants were asked to evaluate their knowledge of the assessed sample area. 53% of the time, participants were already familiar with the given location (either familiar or had already visited the region), while the other 47% of the time the mapping exercise was completed with no explicitly good knowledge of the sample area. For the confidence scores, participants with no location-knowledge did not substantially vary their self-assessments between the first and the second survey (Fig. 6, above). In this case, the previously discussed process sees a two parts development with the construction phase directly followed by the consolidation. Participants without place knowledge were already more open to questioning their delineation of open spaces – based solely on the mapping exercise. Their confidence scores were relatively low already in the first survey and hence they experienced only a minimal adjustment. On the contrary, experts with location knowledge had to reconsider their personal interpretation to adapt to the more generalized understanding of open spaces. Their initial very high confidence scores were driven both by the understanding of landscape characteristics on the map as well as by individual experiences. The latter were very valuable insights which led to diversified delineation of open spaces that underwent a deconstruction phase before consolidating in a final, consensus-based outcome. In terms of perceived improvement following the second survey, no significant differences were observed between participants with and without location knowledge (Fig. 6, below), hinting to a successful and effective consolidation phase across all experts.

The distribution of the normalized response values across sample areas between the first and second surveys shows increased polarization and more homogeneous outcomes, suggesting an enhanced agreement among experts (Fig. 7, left). In fact, the analysis of all overlapped polygons shows more areas with values close to 0 or 1, meaning that participants were more inclined to agree on (not) defining a specific area as open spaces, while there are fewer mountain regions where the open spaces drawings of experts do not match. This difference in values distribution between the two surveys is statistically significant (p-value

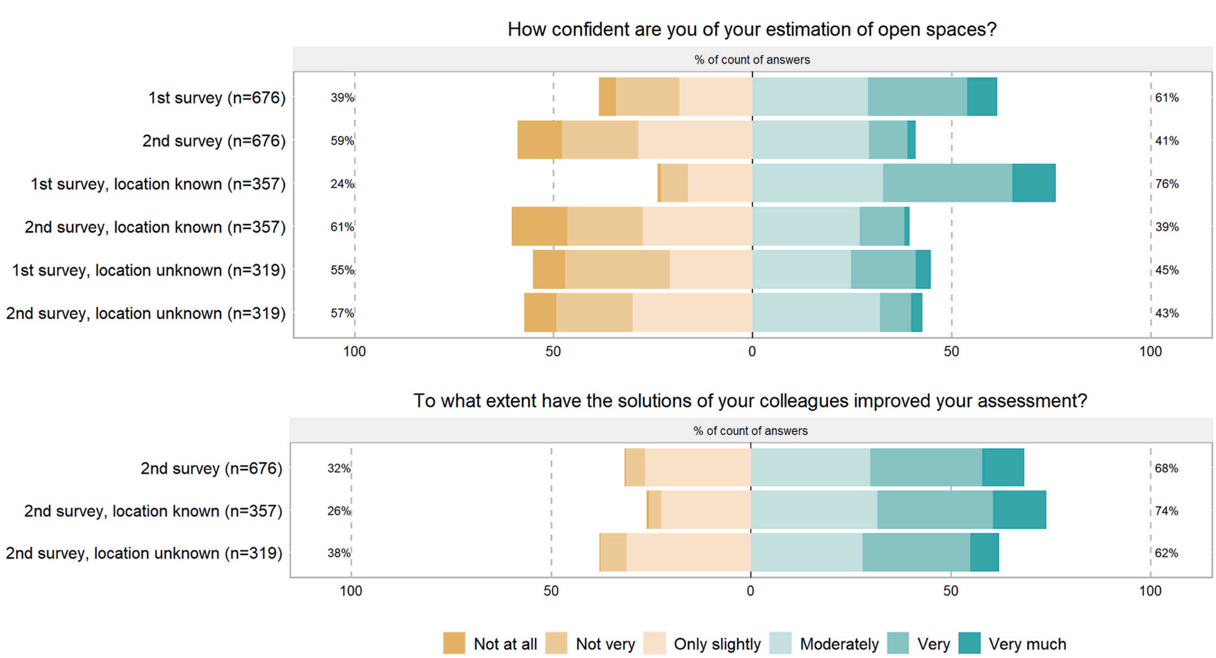

Fig. 6. Perceived confidence in own drawings for the first survey and the second survey (above) and perceived improvement of own drawings after the revision possibility in the second survey (below). The results shown are grouped according to location knowledge as well as for whole surveys. Each observation (n) is a unique answer to a mapping of a sample area.

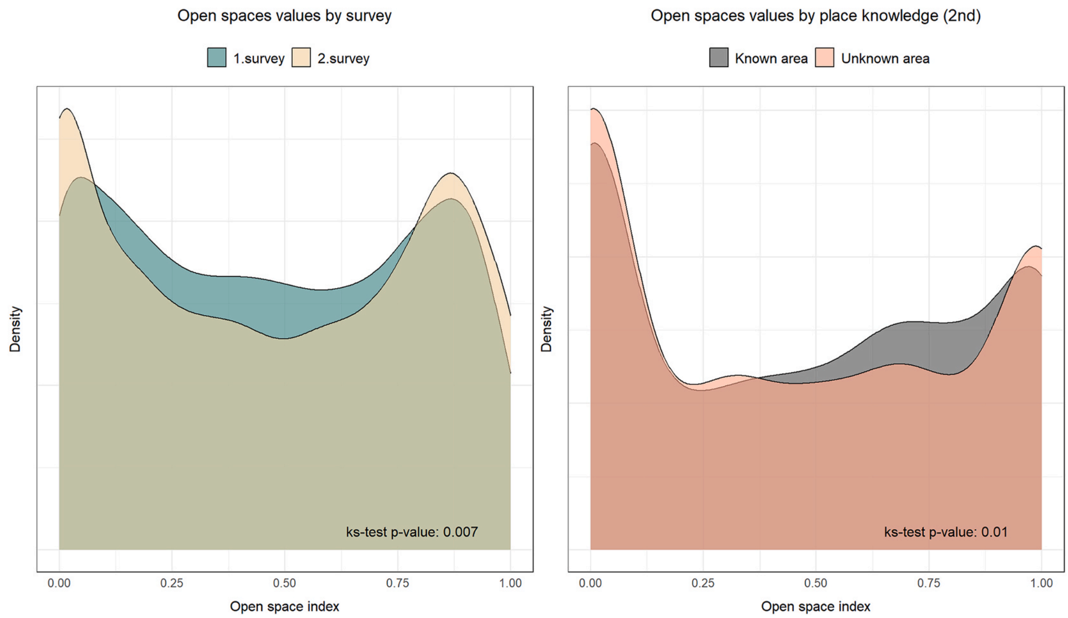

Fig. 7. Density plots of open spaces values extracted from participants' drawings and normalized (0–1). The two plots represent open spaces values difference between the first and second survey (left), and open spaces values from the second survey according to knowledge of the sample area (right).

$\leq$0.01) and supports the machine learning process by providing clearer information to be used as response variable for the model. A further interesting distinction in normalized open spaces values emerges when comparing responses based on location-knowledge (Fig. 7, right). There is a statistically significant difference in the distribution (p-value $\leq$0.01) between participants that knew the assessed sample area and participants that had no previous knowledge of the region. The formers show a more heterogenous pattern, while experts that did not have specific knowledge about the assessed area have a more polarized understanding of open spaces in mountain regions. This suggests that, when possible, experts tend to include their personal interpretation in the definition of open spaces, leading to a more faceted result.

5. Discussion

5.1. Distribution of open spaces in the landscape

Landscapes can be delineated based on both objective features and subjective factors such as aesthetic, cultural, and emotional values (Cakci, 2012). However, previous efforts to delineate open spaces have mostly focused on investigating the spatially disruptive impacts of selected infrastructure (Job et al., 2022; Nischik & Pütz, 2018), without accounting for the diverse interpretations of individuals. This research has shown how to address this methodological gap by incorporating expert views directly into the spatial modeling process. We adopted a collaborative consensus-building approach among experts to explore both qualitative and quantitative factors that influence open spaces in mountain regions. A Delphi survey (Turoff & Linstone, 1975) was used to elicit, discuss, and ultimately refine expert perspectives towards a consensus-based delineation of open spaces. The revised expert opinions were then integrated into a machine learning model and used to produce a more holistic and legitimized open spaces map.

The distribution of open spaces on the map shows significant differences both between and within the different mountain regions. In general, the findings are consistent with previous studies (Job et al., 2022; Nischik & Pütz, 2018; Plassmann & Coronado, 2021), indicating a higher concentration of open spaces at higher altitudes and in remote alpine regions, and a lower concentration in fragmented landscapes such as the Prealps or the Jura. The definition of open spaces adopted for mountain regions and presented to the survey participants, though hinting to a high-altitude character, could potentially contribute to creating this dichotomy. Nonetheless, while acknowledging this contrast is essential for depicting open spaces in mountain regions, smaller or lower-valued open spaces are also of considerable importance, depending on their location. Previous studies have revealed limitations in providing such precise information at regional and local scales, mainly due to the inconsistent availability of data (Job et al., 2022; Plassmann & Coronado, 2021) or conceptual preferences for other mapping methods (Kopf et al., 2017; Nischik & Pütz, 2018). In contrast, our novel map accounts for a detailed delineation by showing a continuous open spaces index without aggregating the information into larger areas. As depicted in Fig. 8, Nischik and Pütz (2018) delineated water catchment zones to offer a comprehensible summary of how open spaces are distributed on a larger scale, but this aggregation conceals information at the local level. In contrast, our map of open spaces clearly displays this information, allowing us to investigate not only prominent open spaces regions, but also local or regional differences. The absence of clear boundaries could improve interpretation and understanding on a small scale but it could also hinder seamless integration into spatial planning tools. Nonetheless, it is crucial to recognize that the Swiss federal structure requires a comprehensive understanding across scales - from the local plot owner to national policies and strategies. In this context, the map of open spaces acts as a dataset for supporting decisions, with the potential for later aggregation at various spatial levels.

5.2. Factors shaping open spaces delineation

The obtained detailed visualization also supports the understanding of the underlying effects of different infrastructures on open spaces delineation. This visual interpretation is also facilitated by the machine learning model, which summarizes these findings in variable importance scores (Kuhn, 2008). Importance scores are indicative of the assessments made by experts involved in the collaborative consensus-building process. Therefore, exploring the diverse meanings assigned to different features provides insights into the opinions of these experts (Wei et al., 2015), and this understanding can improve the interpretation of identified open spaces. Transportation infrastructure such as small and medium sized roads, public transportation stops, and large trails show high importance scores. This reinforces the findings of previous studies showing that transportation networks have a strong

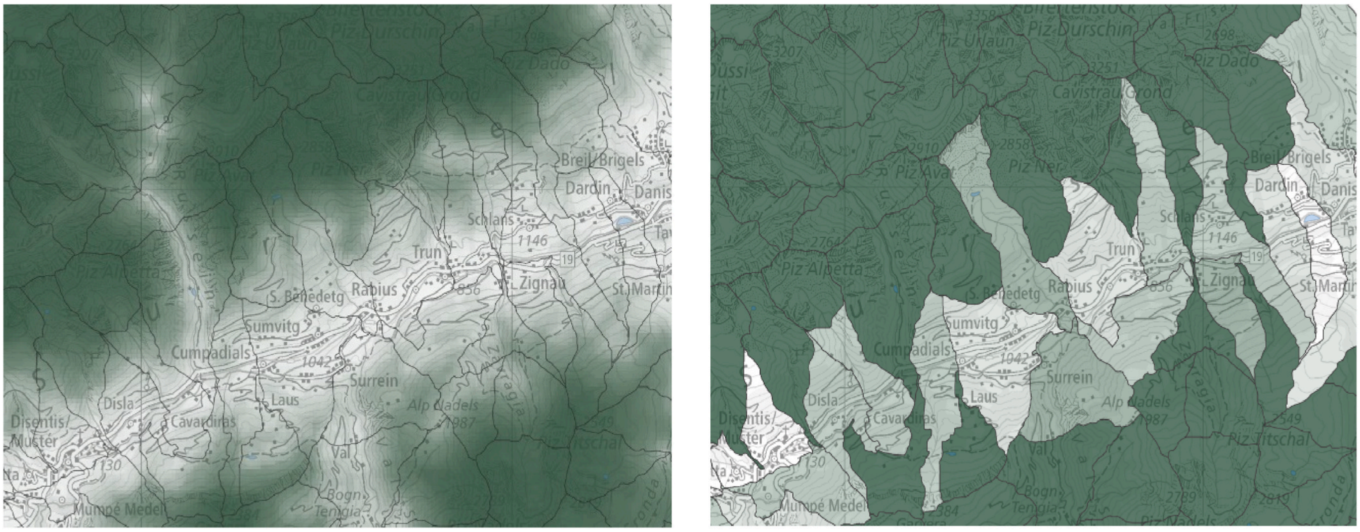

Fig. 8. Extract of (left) our open spaces map with water catchments and (right) map of Nischik and Pütz (2018).

influence on landscape conditions (Balkenhol & Waits, 2009; Doyle & Havlick, 2009; Van Der Ree et al., 2011). In line with previous studies, cable cars for material and people also show relatively high importance scores in determining the location and distribution of open spaces (Job et al., 2022; Plassmann & Coronado, 2021). Especially for groups of cable cars, such as those found in ski resorts, the visual prominence as man-made landscape features likely contribute to the high importance scores (Hedblom et al., 2020). As already suggested by Radford et al. (2019) while assessing wilderness quality, elevation is an important proxy for the open spaces index due to the fact that it is highly correlated with many causal factors. Other predictors based on on-site characteristics, such as naturalness, slope, and ruggedness, have lower importance scores. Contrary to elevation, these factors are simply less visually recognizable on the map, thus explaining the lower importance scores. Similarly, single objects and small paths have low importance scores due to their reduced impact on the assessment of open spaces (Nischik & Pütz, 2018). Dams or antennas also have lower importance scores, but their importance in the model could be low not because of actual lack of impact – these features arguably have a significant visual influence in the landscape (Ioannidis et al., 2022) – but because roads and other predictors already partially capture and explain some of their effects (Kutner, 2005). Thus, while these features still contribute to the final predictions of the model, they have a less decisive impact on the open spaces delineations made by experts during the surveys. In general, this distribution of importance scores is also affected by the methodology of the study. During the mapping exercise, experts delineated open spaces using topographic maps or satellite imagery. This data basis remained consistent across all participants and across both surveys, but the quality and level of detail of the background map might have impacted the obtained importance scores. Easily recognizable transportation infrastructure – visual clues to landscape fragmentation – could have influenced experts' perceptions in their assessment (Cakci, 2012). On the contrary, features that were less distinguishable on these background maps (e.g., steepness, naturalness, individual human-made elements) did not receive the same level of attention from experts delineating open spaces. As a result, their importance in influencing the final model was relatively lower. Nonetheless, it is crucial to highlight that regardless of their importance scores, all predictors provide valuable information about their contribution to the model's estimates and offer insights into the underlying phenomenon. The importance of a predictor should be viewed in relation to others incorporated into the model, rather than as an absolute measure (Wei et al., 2015).

5.3. Multifaceted influence of expert knowledge

The use of expert knowledge is fundamental to scientific inquiry in various fields, as it promotes evidence-based decision-making and improves the accuracy and reliability of models and assessments (Drescher et al., 2013; Jacobs et al., 2015; O'Hagan, 2019). Elicitation procedures play a crucial role in gathering and transferring expert knowledge into quantitative information for model integration and decision-making (Drescher et al., 2013; Martin et al., 2012). Rigorous methods are required in collecting and incorporating expert knowledge into decision-making processes, which ultimately enhances the validity of the outcomes (Drescher et al., 2013; Jacobs et al., 2015). Our study proposes such a structured integration by incorporating expert representations of open spaces as response variables into the modeling process. This allows the machine learning algorithm not only to use, but to directly reproduce expert knowledge, providing a simple, efficient, and transparent way to openly account for expert understanding. By exploiting the insights and awareness of experts, the model can help discover intricate patterns that may be difficult to identify when analyzing the underlying data alone (O'Hagan, 2019). Stakeholders can follow and interpret the reasoning behind the map, namely that the model simply replicates the experts' drawings of open spaces. This stringent use of expert knowledge increases transparency and interpretability (Drescher et al., 2013), providing more accurate and contextually relevant results, and making the map a valuable tool for open spaces management. Yet, the direct incorporation of expert knowledge into machine learning algorithms poses a potential bias risk, as experts introduce subjective perspectives that clearly influence the results (Jacobs et al., 2015). In this research, experts were encouraged to express their perspectives, confront them with those of their peers, and ultimately arrive at a consensual result. This redefinition, facilitated by Delphi methodological approach, homogenizes the opinions of the experts, thus reducing potential subjective bias (Beiderbeck et al., 2021; Geist, 2010). However, group biases or overconfidence (Martin et al., 2012) may persist and would require further investigation.

Delphi surveys require the involvement of experts for their domain-specific expertise and perceptive insights (Beiderbeck et al., 2021; Geist, 2010). Formulating reasoned results is made possible by their deep understanding of trends and underlying mechanisms. Our study places a particular value on expert guidance because, while the concept of open spaces has clear boundaries, it also provides room for diverse interpretations. It is essential for participants in our Delphi study to have a strong common base of understanding (Hasson et al., 2000). This shared baseline is key to facilitating an unbiased approach to exploring and debating different interpretations of the issue, whether to build consensus or highlight differences (Beiderbeck et al., 2021; Geist, 2010; Hussler et al., 2011). Our study showed that using the Delphi method to guide a collaborative consensus-building process among experts led to a convergence of opinions on the definition of open spaces. Specifically, there was a higher level of consensus between the first and second survey rounds as to whether an area was classified as open spaces or not, resulting in a generally accepted outcome. These evaluations rely on expert knowledge, but like all forms of knowledge, they inherently carry a certain level of uncertainty (Martin et al., 2012). This uncertainty can be mitigated through the acquisition of additional information. Therefore, it is crucial not only to determine the consensus among participants but also to inspect the level of confidence they have in their responses (Rowe et al., 2005; Turoff & Linstone, 1975). Our study demonstrated an overall decline in confidence regarding experts' definition of open spaces. However, lower confidence does not necessarily indicate concerning outcomes, as experts who change their answers are more likely to then make accurate predictions (Rowe et al., 2005). Our study confirms this observation by demonstrating a perceived improvement in the experts' answers after the Delphi survey. The observed changes along the process of construction, deconstruction, and consolidation of knowledge highlight a transformative experience for participants in which their initial beliefs and confidence in their delineation of open spaces were challenged, and through the exchange of diverse perspectives, they ultimately achieved improved results with higher consensus among experts. The consensus achieved reflects a wide range of values shared by the experts, thus validating and legitimizing the findings to support the development of a well-considered and collaborative strategy for decision-makers (Dell'Ovo et al., 2020).

This study further revealed significant differences in the drawings of open spaces and confidence measures between experts familiar with the sample area being evaluated and those without this location knowledge. Our findings indicate that experts with location knowledge experienced a greater adjustment in confidence in their open spaces drawings. This pattern is supported by the so-called confirmation bias, a cognitive predisposition that occurs when people tend to search for, interpret, and remember information in a way that confirms their preexisting beliefs (Nickerson, 1998). In our case, experts who were familiar with the assessed region were possibly biased by this prior location knowledge. They then had to reassess their beliefs, which resulted in a significant decrease in their previously high confidence level. However, this adjustment did not affect their results, which were still perceived to have improved in response to their peers' feedback. Despite this realignment process, experts with location knowledge still tend to provide more varied and multifaceted results while identifying open spaces.

A variety of experts, including scientists, mountain guides, public sector employees and park managers, participated in this research's Delphi survey. No notable distinctions in the delineation of open spaces nor in their self-assessment could be observed among these various groups. Although investigating intergroup disparities was not the central focus of this research, it is important to acknowledge that the lack of variability observed can only be partially explained by actual uniformity. The uneven distribution of participants across expert groups or a lack of difference-oriented questions might have contributed to the absence of significant differences between the experts' groups. Therefore, there is a need to broaden the scope of this research to explore the complex interactions between different mountain experts and to expand the investigation to include experts from other disciplines and landscapes. Notably, as already mentioned above, this study did not delve deeply into the spatial-functional dynamics between mountain regions and valley bottoms. Various aspects, such as tourism, agriculture, or land requirements for renewable energy, have influenced the distribution of open spaces in the past and could further drive future developments (Meyer et al., 2022). This research is limited and focused on the delineation of open spaces in mountain regions. Future efforts must combine this renewed and collaborative knowledge on open spaces with other demands on land to manage the resulting trade-offs, which are essential when discussing sectoral and spatial planning strategies aimed at the sustainable development of these ecologically sensitive regions. In this regard, the collaborative methodology used in this research has the potential to facilitate a harmonious connection between highlands and lowlands, contributing to a more comprehensive and nuanced understanding of open spaces and their interactions with the surrounding environment. Additionally, efforts to democratize planning processes would further benefit from the inclusion of laypeople. Indeed, an additional limitation of this study is that it focuses solely on experts, even though the management solutions implemented must be comprehended and approved by a range of other stakeholders (Dell'Ovo et al., 2020) who may not have this level of expertise. Comparing the delineation of open spaces in mountain areas between experts and non-experts therefore has the potential to provide interesting new insights and offers the opportunity to identify limitations and gaps within the reached expert consensus and to stimulate inventive ideas for managing these areas (Hussler et al., 2011).

6. Conclusion

In this study, we developed a collaborative consensus-building process for integrating expert knowledge into machine learning algorithms to map open spaces and provide decision support for new infrastructure development in mountain regions. The Delphi approach used in the study favored the alignment of perspectives on the definition and delineation of open spaces. Initially, in a construction phase, participants drew open spaces and generally expressed a high level of confidence in their drawings. Then, in a deconstruction phase, experts experienced a decrease in confidence as a result of comparing their interpretations with those of their peers. This confidence loss was accompanied by a perceived improvement in the quality of the experts' drawings, indicating a final phase of reconstruction and consolidation. The survey also revealed that experts familiar with the sample area being evaluated provided more diverse and varied results. These are also the experts who experienced the greater adjustment in confidence level throughout the surveys, but this adjustment did not affect the quality of their results, which were still perceived to have improved in response to their peers' feedback. The results of the surveys proved to be suitable and effective for guiding the machine learning process to finally map open spaces in Swiss mountain regions. The resulting open spaces map provides a detailed and continuous index that allows the study of large open spaces regions as well as the exploration of local or regional differences. In addition, we were able to demonstrate the impact of different infrastructures on the distribution of open spaces, providing insights into landscape elements that exhibited a stronger or weaker influence.

In summary, this study presents a legitimized open spaces map to support decision-makers in managing open spaces in mountain regions. This approach can specifically assit in identifying areas that are perceived differently by different stakeholders and are therefore difficult to delineate. Landscape fragmentation and loss of aesthetic values are critical developments that spatial planning needs to address. This novel map does not provide a ready-to-use solution, but rather an instrument to guide practitioners in tackling these pressing issues. It also provides a way to discuss and potentially mitigate issues that require consideration and realignment of different and possibly competing stakeholder perspectives, offering an effective and valuable process for collaborative consensus-building that can foster acceptance of future planning decisions and collaboration with decision-makers.

Fundings

This work was supported by the alliance formed of Swiss Alpine Club SAC, Stiftung Landschaftsschutz Schweiz, and Mountain Wilderness Switzerland. Funding sources participated in discussing and reviewing

the preliminary study design and in the data collection process, but had no role in the analysis, interpretation, nor in the writing of this article.

Data availability

The results, processed data and scripts have been made available alongside this publication (https://doi.org/10.5281/zenodo.10143639).

CRediT authorship contribution statement

Matteo Riva: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Felix Kienast:** Writing – review & editing, Supervision, Conceptualization. **Adrienne Grêt-Regamey:** Writing – review & editing, Supervision, Conceptualization.

Acknowledgements

We would like to thank Sebastian Moos (Mountain Wilderness Switzerland), Stephan Schneider (Stiftung Landschaftsschutz Schweiz) and Philippe Wäger (Swiss Alpine Club SAC) for their motivation and initial request to map open spaces in Switzerland, and for their valuable discussions and collaborative efforts throughout the project. We would also like to extend our sincere thanks to Orencio Robaina Martinez de Salinas for his invaluable contribution in setting up the website used for the Delphi survey. His technical expertise and dedication were pivotal in creating a user-friendly platform that facilitated our research and engagement with participants.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2024.103237.

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