Evaluating existing manually constructed natural landscape classification with a machine learning-based approach

Rok Ciglič[1], Erik Štrumbelj[2], Rok Češnovar[2], Mauro Hrvatin[1], and Drago Perko[1]

[1]Research Centre of the Slovenian Academy of Sciences and Arts, Ljubljana, Slovenia
[2]Faculty of Computer and Information Science, University of Ljubljana, Ljubljana, Slovenia

Abstract: Some landscape classifications officially determine financial obligations; thus, they must be objective and precise. We presume it is possible to quantitatively evaluate existing manually constructed classifications and correct them if necessary. One option for achieving this goal is a machine learning method. With (re)modeling of the landscape classification and an explanation of its structure, we can add quantitative proof to its original (qualitative) description. The main objectives of the paper are to evaluate the consistency of the existing manually constructed natural landscape classification with a machine learning-based approach and to test the newly developed general black-box explanation method in order to explain variable importance for the differentiation between natural landscape types. The approach consists of training a model of the existing classification and a general method for explaining variable importance. As an example, we evaluated the existing natural landscape classification of Slovenia from 1998, which is still officially used in the agricultural taxation process. Our results showed that the modeled classification confirms the original with a high rate of agreement—94%. The complementary map of classification uncertainty (entropy) gave us more information on the areas where the classification should be checked, and the analysis of the variable importance provided insight into the differentiation between types. Although the selection of the exclusively climatic variables seemed unusual at first, we were able to understand "the computer's logic" and support geographical explanations for the model. We conclude that the approach can enhance the

explanation and evaluation of natural landscape classifications and can be transparently transferred to other areas.

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1 Introduction

Landscape classifications are part of everyday life in local communities [42,43] because it is natural to seek order in the landscape [20]. Conceptualizations of the natural environment (e.g., perception of landforms) vary in response to the type of landscape that the people live in [56]. There are many landscape classifications available at global and local levels. Some of them, especially older classifications, were produced manually [1,4,39,45,48,53]. These classifications hold a certain level of abstraction; they are mostly subjective and based on expert knowledge [23].

Maps of landscapes are increasingly being used in spatial planning and landscape management [12,27,34,44,52] and are also an integral part of geography education. Thus, most countries have generalized (natural) landscape classifications in geographical textbooks [40]. Some natural landscape classifications are part of official financial and legislative procedures. Slovenian landscape type groups [36] are used for the determination of benefits (si. *bonitete*) from agricultural land [57], a landscape map of Norway is used in policy impact analyses [46], and National Character Areas in England are default spatial frameworks for a wide range of applications [52]. The Map of Biogeographical regions of Europe (its latest version was published by the European Environmental Agency in 2016) is officially used at the European level. The Council of Europe adopted the Pan-European Biological and Landscape Diversity Strategy in 1996 and the European Landscape Convention in 2000. According to the convention, each country should take measures for recognizing and protecting landscapes. Therefore, we agree with Hall et al. [21] that today, it is still important that analysis connected to serious real-life problems must be repeatable and have to provide the argumentation of the decisions made during the analysis.

A production of meaningful and useful natural landscape classification is not an easy task. Namely, several issues with the natural landscape classification process have been noted, especially the transparency of the process [2,17,30,34,35] and an evaluation of the results [11,18,22,31,54]. Authors have used different approaches to cope with the evaluation issue (e.g., comparison of classifications produced by different methods, production of fuzzy maps [14], and (re)modeling of original classifications). Authors have collected and presented some basic methods for accuracy assessment (error matrix, user's and producer's accuracy, and Kappa coefficient) [11], evaluated topographical units with a mean intra-object variance, Moran's I, and an online survey [16], used a neural network to confirm the existing landscape classifications [6], used binary logistic regression to evaluate the existing landscape map of Norway [46], evaluated the Hungarian landscape units delimitation with multidimensional scaling and agglomerative hierarchical clustering [33], and compared automatic classification of landforms with morphographic landform classification mapping in the field [54]. Some authors have used several different methods to evaluate existing classifications [10,41]. A review of the evaluation methods is also available [28].

The development of additional evaluation approaches in landscape classification is reasonable because some old landscape classifications have not been evaluated quantitatively since the time of their publishing. There are new digital data sets and quantitative methods available. They can be used for (re)modeling existing classifications in order to provide quantitative rules and expose potential weaknesses of the delimitations. We are aware that poorly constructed classifications of low quality sometimes cannot be modeled due to a complete absence of logical basis [8]. Additionally, some of the modeling methods do not offer clear modeling structure and are rather complex to interpret (e.g., neural networks and random forests). Therefore, methods for explanation of the models themselves also need to be incorporated in the evaluation process. Such methods have recently been developed at the University of Ljubljana, Faculty of Computer and Information Science [47], and tested in medicine, sport, psychology, and other fields [24].

We propose an evaluation process of existing landscape classifications that includes modeling of the classification, production of an entropy map, and an explanation of the model structure. The latter can bring more detailed information to users, especially due to a growing number of black-box methods for classification (e.g., neural networks) that do not provide insight into the model and are not easy to understand. The following are the objectives of this paper:

- to evaluate the consistency of an existing (20 years old) manually constructed natural landscape classification that is still in official use at the national level with a machine learning approach, and
- to use the general black-box explanation method developed by Štrumbelj and Kononenko [47] that has not been used in landscape classification before in order to contribute to a transparent and quantitative explanation of variable importance.

In this research, we are investigating an example of classifying **natural landscape types**. As a natural landscape type, we consider spatial units (they are not necessarily contiguous) that share similar natural characteristics (bedrock, soil, vegetation, hydrology, climate, and relief). Since we are modeling on the basis of more stable landscape elements, we do not take land use or other anthropogenic elements into consideration. Various names are used for such entities in a literature, e.g., biogeographical regions, ecoregions, bioclimatic zones, and ecological land [1,12].

2   Research area and existing natural landscape classification

Slovenia is a small country with an area of only 20,273 km^2, but only a few, even much larger, countries can compare to its landscape diversity. In this part of Central Europe, four different European natural regions (the Alps, the Dinaric Alps, the Pannonian Basin, and the Mediterranean) meet, as do Slavic, Germanic, Romance, and Hungarian cultural influences. For this reason, Slovenia is renowned for its geographical variety, which is reflected in its natural and cultural diversity. Slovenia has the second-highest biodiversity index in Europe [3]; more than a half of the country lies within ecologically important areas, and according to the European Commission data, more than 37% (approximately 7,700 km^2) of the country is registered as a Natura 2000 site. Therefore, Slovenia can be described as one of the European landscape hotspots [9].

Natural landscape types	Surface area (km²)	% of surface area	Mean altitude (m)	Mean slope (°)	Predominant rock types (at least 10% of surface)	Predominant vegetation types (at least 10% of surface)
Alpine mountains	3062	15.1	1055.5	26.2	limestone 37.22%; carbonate gravel, rubble, and till 19.67%; dolomite 14.38%	beech 49.42%; dwarf pine and other highland vegetation 12.92%; beech and fir 12.10%; beech and hophornbeam 11.48%
Alpine hills	4660	23.0	582.5	18.9	silicate sandstone and conglomerate 17.26%; metamorphic rocks 16.57%; dolomite 14.87%	beech 41.85%; beech, chestnut, and oaks 31.37%; beech and hophornbeam 12.25%
Alpine plains	819	4.0	373.1	4.6	carbonate gravel, rubble, and till 51.70%; clay and silt 21.62%; carbonate conglomerate 15.40%	hornbeam 65.33%; beech 20.69%; red pine 10.51%
Pannonian low hills	2995	14.8	288.8	10.3	clay and silt 31.10%; marl 29.71%; sand 20.26%	beech, chestnut, and oaks 88.18%
Pannonian plains	1297	6.4	195.6	1.0	silicate gravel 59.62%; clay and silt 20.65%	hornbeam and pedunculate oak 44.44%; hornbeam 24.22%, pedunculated oak 17.4%; beech, chestnut, and oaks 13.23%
Dinaric plateaus	3809	18.8	668.1	15.2	limestone 59.13%; dolomite 24.29%	beech 39.01%; beech and fir 38.65%; beech and hophornbeam 10.02%
Dinaric lowlands	1897	9.4	402.8	7.6	limestone 45.69%; clay and silt 28.29%; dolomite 14.9%	hornbeam and fir 32.42%; beech 28.03%; hornbeam and pedunculate oak 13.65%; beech and fir 11.97%
Mediterranean low hills	1061	5.2	305.1	12.7	flysch 71.56%; clay and silt 13.75%; limestone 10.10%	downy oak 26.45%; beech, chestnut, and oaks 25.66%, sessile oak 20.77%; beech 10.72%
Mediterranean plateaus	673	3.3	425.2	8.9	limestone 82.52%; dolomite 11.22%	downy oak and hophornbeam 69.80%; beech 20.64%
Slovenia	20273	100.0	556.8	14.6	limestone 26.67%; clay and silt 13.13%; dolomite 12.39%	beech 29.53%; beech, chestnut, and oaks 24.94%

Table 1: Some basic characteristics of the Slovenian landscape types.

There were only four attempts to provide a suitable natural landscape classification of the country [32, 36, 38, 45]. In this paper, we focus on the well-established natural landscape classification of Slovenia from 1998 [36], which is still used in the agriculture taxation process. Although the classification was the first partly computer-based natural landscape typology of Slovenia, the borders of landscape types were drawn manually.

Perko defined the core areas of each type by overlapping the digital layers of 7 surface elevation classes, 7 slope classes, 7 rock types, and 7 vegetation types. The slope and elevation data were based on a 100-meter digital elevation model, and the lithology and vegetation data were obtained through digitization of 1:250,000 lithological and vegetation maps and converted to a 100-meter raster grid in order to prepare all the data layer in a raster format. Altogether, 2,401 different combinations were theoretically possible. He filtered the final layer three times using the modus inside of a moving 11 x 11 cell square window, obtaining forty-eight larger and spatially separate homogenous cores with the same combination of elevation, slope, rock, and vegetation. He printed the forty-eight cores on a 1:250,000 scale map and manually drew borders between them, mostly following morphological boundaries and major watercourses. In the end, he combined these forty-eight manually delineated landscape units into nine natural landscape types (these are located in different areas and do not represent unique regions!), which he combined further into four natural landscape type groups (Table 1, Figure 1).
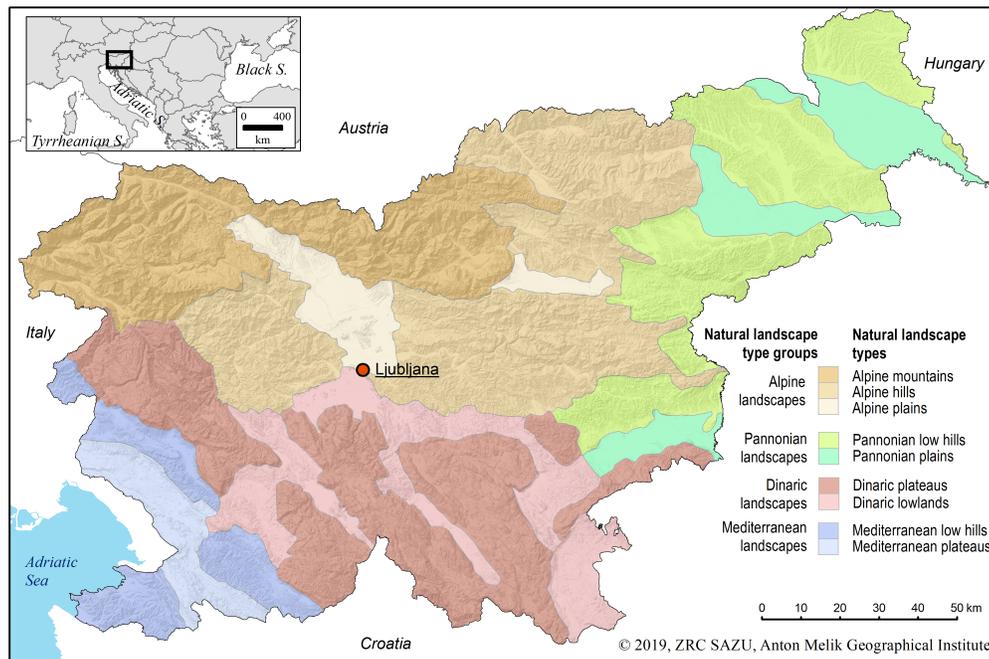

Figure 1: Natural landscape types in Slovenia.

3   Data and methods

We propose a machine learning-based approach for understanding and quantitatively evaluating the existing manually constructed classifications. We evaluated the consistency of Perko's natural landscape classification (in this paper we will use term "original classification") [36] by:

- modeling the original (existing) classification,
- producing a map of entropy (showing areas with high or low classification uncertainty), and
- determining which variables are the most influential (i.e., which natural elements explain the existing classification the best). We achieved the latter by applying a recently developed general black-box explanation method for explaining models' predictions [47]. The method is based on sensitivity analysis—perturbing the inputs and observing variability in the output—and can be applied to any prediction model.

Step 1. We use an automated train-test process to select the best-performing classification method from a set of machine learning and statistical algorithms for the training classification models, that is, the method that produces the models that best generalize the connection between the input variables (data layers) and landscape classification. The best rated method is then used to train a model using only the relevant input variables; that is, variable subset selection is also used (details are described in section 3.2).

Step 2. The model and the uncertainty of its predictions are used to interpret the original classification, primarily by analyzing the disagreements between the model and the original classification but also by the visualization of the entropy. Finally, a general method [47] for explaining how the input variables affect the classification is used on the model to provide more insight into the concepts behind the model and the man-made classification (details are described in Section 3.3).

The two-step approach described above (Figure 2) is general; additional classification methods can be included, and the approach can be applied to any (natural landscape) classification task. Model selection and variable explanation were implemented in R [51].
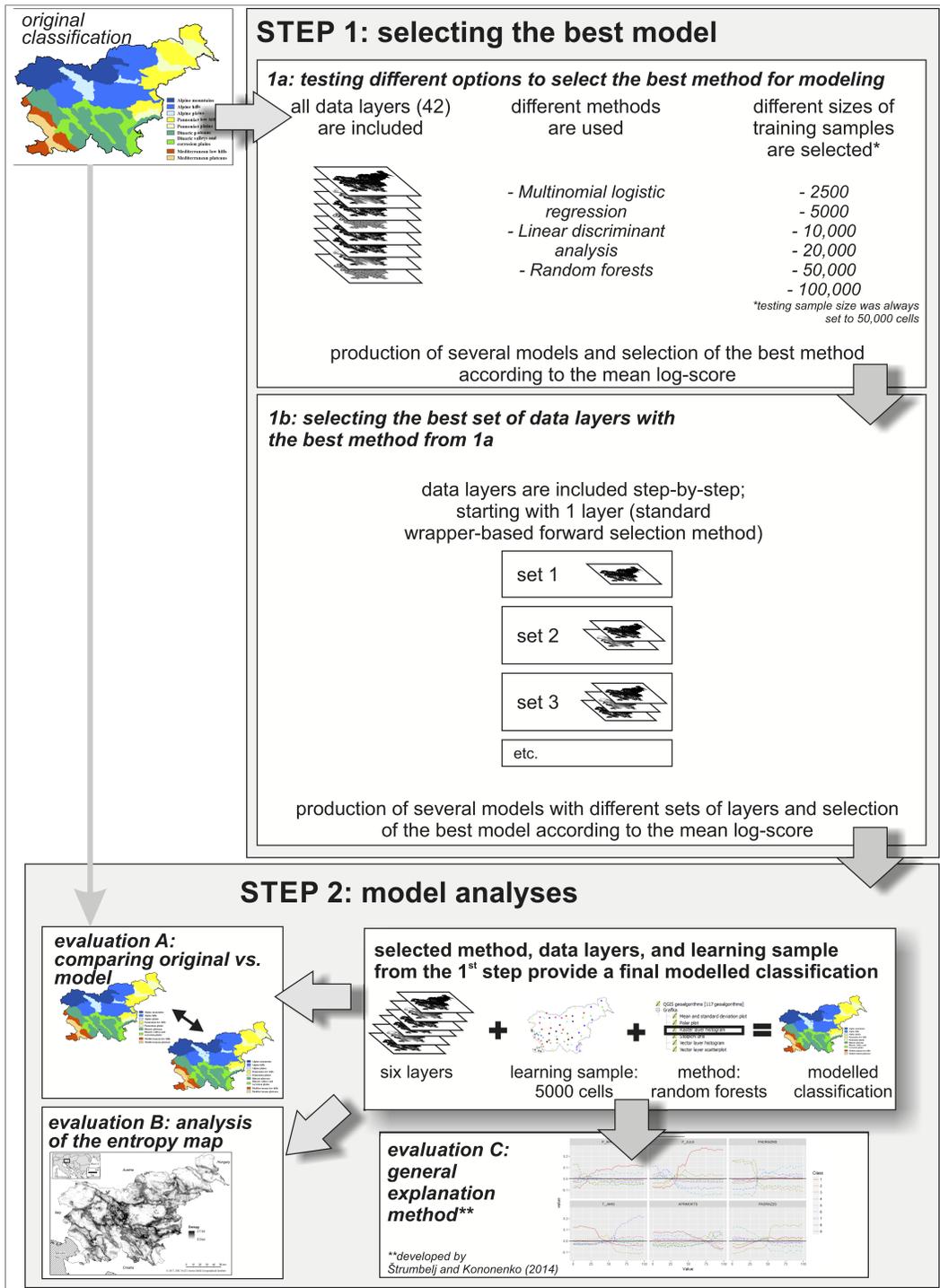
Figure 2: An overview of the methodology.

3.1　Data layers

In order to provide an explanatory model of the Slovenian natural landscape types, we had to take into consideration a set of 42 natural variables (data layers), which are intentionally different from the original Perko's variables, and provide information on various environmental characteristics, such as relief, temperature, precipitation regime, and solar radiation. Original raster data layers were resampled to a cell resolution of 200 m, which was the lowest resolution of all the data layers. That provides 506,450 cells for the entire area. Vector layers were rasterized to the same resolution. All layers were trimmed to match the borders of the research area. The following input variables were included in the analysis:

- Elevation (m),
- Slope (°),
- Aspect (north to south; 0–180°),
- Elevation roughness coefficient (%),
- Slope roughness coefficient (%),
- Aspect roughness coefficient (%),
- Total roughness coefficient (%),
- Texture (share of cells in %),
- Annual temperature difference (°C),
- Average annual temperature (°C),
- Average monthly temperature (January–December, °C),
- Difference between April and October temperatures (°C),
- Average annual precipitation (mm),
- Average monthly precipitation (January–December, mm),
- Precipitation index (ratio between summer and fall precipitation),
- Precipitation index (ratio between summer and winter precipitation),
- Mediterranean precipitation index (difference between quantity of precipitation in October and November and quantity of precipitation in May and June multiplied by 100 and divided by annual quantity of precipitation [25]),
- Solar radiation (MJ/m^2),
- River network density in 0.5 km radius (km/km^2), and
- Bedrock permeability.

Relief data were derived from a digital relief model (provided by The Surveying and Mapping Authority of the Republic of Slovenia), climate data were calculated from data from the Slovenian Environment Agency, solar radiation was prepared by Gabrovec [19], and river network density was calculated from watercourse lines (provided by European Environment Information and Observation Network).

We used a larger number of different variables because we expected the machine-learning algorithms to select the best set. At the time of original classification construction, most of the data layers were not available. However, due to modeling with more stable landscape elements, modeling natural landscape types that were defined 20 years ago with newer data layers does not present an issue.

3.2   Model selection and data layer selection (Step 1)

The first phase of our process is an automatic construction of a model that connects the input variables with the original classification (target variable) using a set of algorithms. In machine learning, this problem is a standard prediction task with a categorical target variable (often referred to as a classification task). In our case, the target variable is a natural landscape type. Numerous different methods for training models exist. However, no method is best for all problems, and it is impossible to determine beforehand which method will train the best model in our geographical setting and whether this might be different for different areas. Therefore, our aim in step 1 is to select the best method automatically from a set of commonly used classification methods.

It is not to be expected that even the best model will perfectly classify every point in every area. Disagreements (misclassifications) will occur for several reasons: the model being unable to model the concepts used in the original classification, areas being objectively difficult to classify into a single type, errors in the original classification, and errors in input variables. Therefore, the goal is to choose the model that has the least misclassifications or the best predictions.

Some methods are able to train very complex models, even up to the point of literally memorizing the classification of every point. This will lead to perfect or near-perfect predictions on the data that were used for training the model, but because the model does not learn the actual concepts, poor predictions on new or unseen data from the same problem may occur. This is known as overfitting, and it is something that we want to avoid. Spatial data are especially problematic because the points are not independent—neighboring points reveal a lot about a point, even if that point is not included in the data that are used for learning.

In light of these facts, the model selection process (Figure 2, part 1A) was as follows. To avoid selecting a model that overfits the data, we used out-of-sample evaluation. To avoid overfitting due to spatial correlation, the data were sub-sampled—only a small percentage of the data points were included to increase the average distance between points. However, results were also reported for other degrees of sub-sampling.

Due to large amounts of data and difficulties of using cross-validation on spatial data due to spatial autocorrelation, we opted to use a train-test split evaluation. We ran the evaluation separately for each of the following numbers of training points: 2,500, 5,000, 10,000, 20,000, 50,000, and 100,000. For each run, the following was repeated 10 times: we selected the training points at random, and, also at random, 50,000 test points (no point was at the same time a test and a training point). For each repetition, the training points were used to train the model and the test points to estimate the classification error of the model. The errors were averaged across 10 repetitions to reduce noise in the error estimates. The criterion used for model selection was the log-score, a proper and local scoring rule, but classification accuracy is also reported. The log-score is defined as the logarithm of the probability that the model assigned to the true class and measures the quality of the predicted probabilities.

The set of machine learning methods that were included in our experiments is summarized in Table 2; however, any other classification method can be added to the methodology. The only restriction is that the method must generate a model that produces probabilistic predictions (that is, output not only the predicted class but also how probable each class value is). This restriction is necessary if we want to be able to quantify the uncertainty associated with each prediction, as described in the section that follows.

Method	Description
Bayesian Multinomial Logistic Regression (MLR)	A Bayesian implementation of standard Multinomial logistics (softmax). The Bayesian approach to statistics has the advantage that the uncertainty due to top data is quantified by the posterior distribution of the predicted probabilities. This would allow for a better quantification of overall uncertainty (see the following section). However, Bayesian inference is computationally intensive, so the GPU-accelerated method was used as implemented in function mlr() in R package *bayesCL* [7].
Linear Discriminant Analysis (LDA)	Standard multiclass LDA with maximum likelihood as implemented in function lda() in R package MASS [50]. LDA is a relatively simple linear but robust statistical model.
Random forests (RF)	Breiman's random forests classifier [5] as implemented in function randomForest() in R package *randomForest* [29]. RF is a complex but still robust non-linear method. Robustness to overfitting is achieved by constructing hundreds of thousands of trees (on randomly re-sampled data and variables) and aggregating their predictions.
Baseline	A basic approach of always predicting the relative frequency of classes as observed in the training data. Only used as a baseline for comparison. No proper method should perform worse than this.

Table 2: A description of the methods for learning classification models that were included in our experiments.

After the most appropriate method is selected and before explaining the model trained by that method, we also perform variable subset selection (Figure 2, part 1B). That is, input variables that do not contribute to the model's predictive quality are removed from the model as part of pre-processing before generating the explanation. The main reason for variable selection is to simplify the explanation—while modern machine learning and statistical models are able to handle a large number of variables, people are still limited by the amount of information they can process.

We use a standard wrapper-based forward selection approach. That is, starting with 0 variables, the variables are added one at a time, at each step adding the variable that most improves the model's predictive quality, to the point where the model's predictive quality is indistinguishable from its predictive quality in the evaluation. As in the evaluation process, the number of test samples was again 50,000 and the number of training samples 5,000, both sets were selected at random, the results were averaged across 10, and the log-score was used to measure prediction quality.

3.3 Model analyses (Step 2)

After the model is trained on the subset of relevant input variables, no further training is done. After the construction of the model classification, we compared it to the original classification (Figure 2, part 2A), and a map showing the uncertainty in the model's classification is produced (Figure 2, part 2B). A misclassification where the model is certain in its prediction indicates an area where the original classification is possibly incorrect, while a misclassification where the model was uncertain indicates an area where the landscape is possibly difficult to classify into a single type.

A single probabilistic prediction in classification is equivalent to assigning a distribution to a categorical random variable. As such, it is straightforward to use information-theoretic entropy as a measure of uncertainty of the model's prediction for some point j (Equation 1):

$$H_j = -\sum_{i=1}^{n} p_{ji} \log p_{ji} \qquad (1)$$

where p_{ji} is the model's predicted probability for class i and n is the number of classes. In this form, entropy is measured in bits. A 100% certain prediction (that is, a prediction where one of the predicted probabilities p_{ji} is 1 and the rest are 0) has 0 entropy, and the maximum entropy can be achieved by predicting uniformly across all classes (that is, $p_{ji} = 1/n$ for all i). A visualization of H_j for all points j is referred to as an entropy map.

Another goal becomes to better understand how this model connects the variables and the original classification. To provide a sensible explanation of the model and its predictions, we post-processed the model using a general black-box explanation method (Figure 2, part 2C) that provides further insight into how the model works. In particular, we use a general black-box explanation method developed by Štrumbelj and Kononenko [47]. It can be applied to any type of prediction model. This method has some other advantages; in particular, it takes into account all possible interactions between input variables as opposed to explaining one variable at a time, as many general black-box explanations do.

The method is based on a sensitivity analysis (changing the inputs and observing changes in the output) and can therefore be applied to a trained model, without any need to re-train the model. The explanations are based on variable contributions (how much variables' values contribute to or against a certain prediction). The explanation of the model (see Figure 5) provides an overview of how values of the input variables influence the model's predictions. It includes, for each variable, a plot of how the importance of that variable varies across its values. Each line represents a class value (in our case landscape type). A positive importance value indicates that the value supports that class value, and a negative value does not support that class value.

Sample size	Baseline	Linear discriminant analysis	Multinomial logistic regression	Random forests
2500	-1.99 (23.1%)	-0.38 (84.9%)	-0.39 (86.4%)	-0.30 (92.0%)
5000	-1.99 (23.1%)	-0.38 (85.0%)	-0.23 (90.8%)	-0.23 (94.0%)
10000	-1.99 (23.1%)	-0.38 (85.1%)	-0.18 (92.4%)	-0.17 (95.5%)
20000	-1.99 (23.0%)	-0.37 (85.1%)	-0.17 (93.0%)	-0.13 (96.6%)
50000	-1.99 (23.0%)	-0.37 (85.3%)	-0.16 (93.3%)	-0.08 (97.8%)
100000	-1.99 (23.1%)	-0.37 (85.3%)	-0.16 (93.4%)	-0.06 (98.3%)

Table 3: Mean log-score (accuracy) for each method and training sample size. Note that all standard errors are less than 0.001 and are not included in the table.

4   Results

4.1   Model selection

Model selection results are shown in Table 3. The random forests method was selected because it outperformed all the other methods for all training sample sizes. All further results were obtained using random forests and the training sample size of 5000 (representing 1% of the total area). The smaller number of training samples was used to prevent overfitting due to the spatial autocorrelation.

4.2   Final variable selection

During variable subset selection, six of 42 variables (data layers) were found to be relevant to the predictions of the random forests method:

- precipitation in April,
- precipitation in July,
- precipitation index (ratio between summer and fall precipitation),
- temperature in January,
- Mediterranean precipitation index (difference between quantity of precipitation in October and November and quantity of precipitation in May and June multiplied by 100 and divided by annual quantity of precipitation [25], and
- difference between April and October temperatures (Figure 3).

4.3   Model analyses—discrepancies and uncertainties

As already mentioned, 94% of the original classification was confirmed by modeling with the random forests method. However, visual presentation of the classification entropy (Figure 4) gave us precise information about the spatial arrangement of the landscape classification uncertainty according to the model. The map presents areas (cells) that are harder to classify as a specific natural landscape type. Higher entropy means higher classification uncertainty. Smaller random areas (or individual cells) with high entropy might be a consequence of a data error, but larger areas with high entropy might need corrections in the original classification.
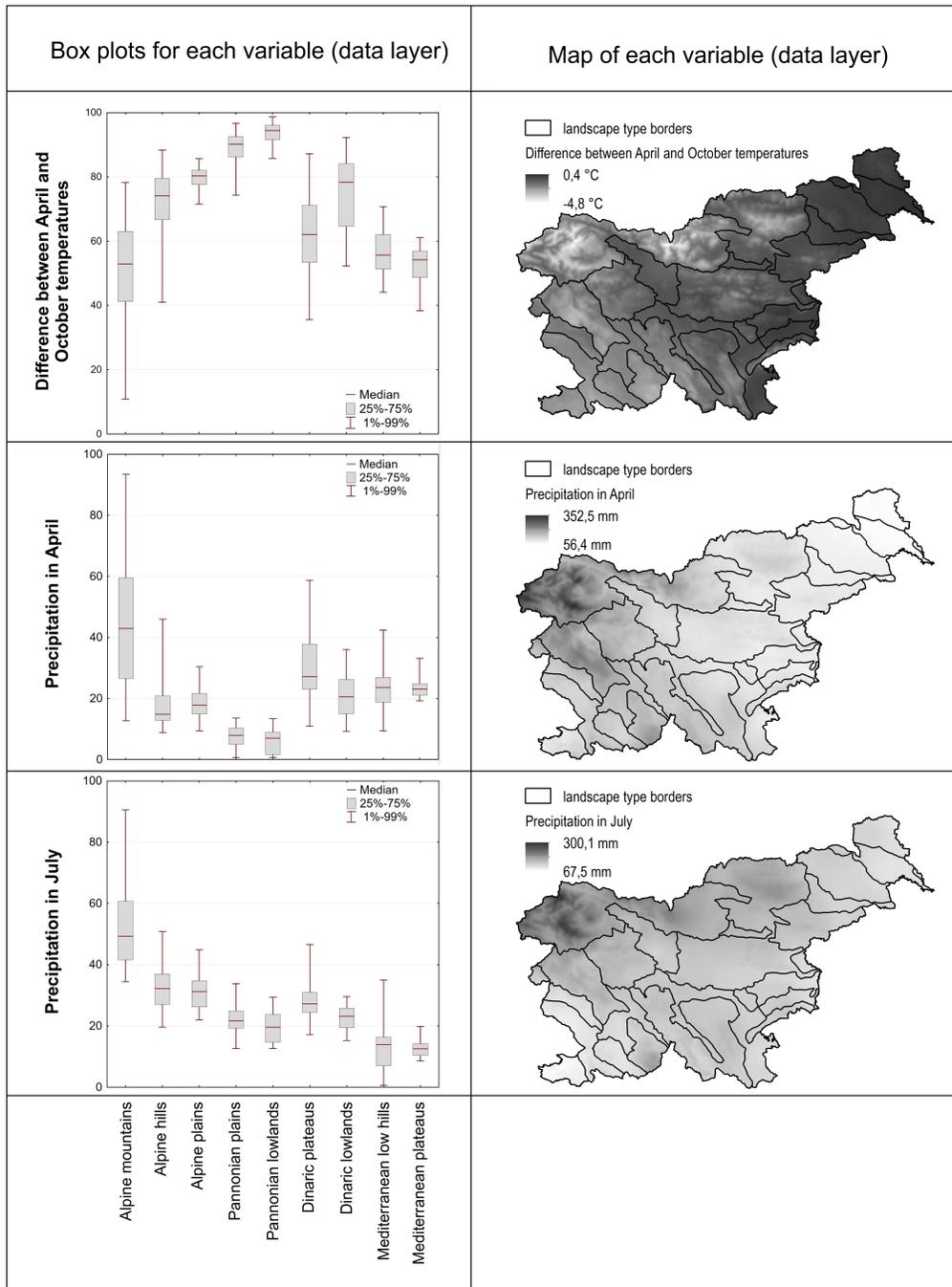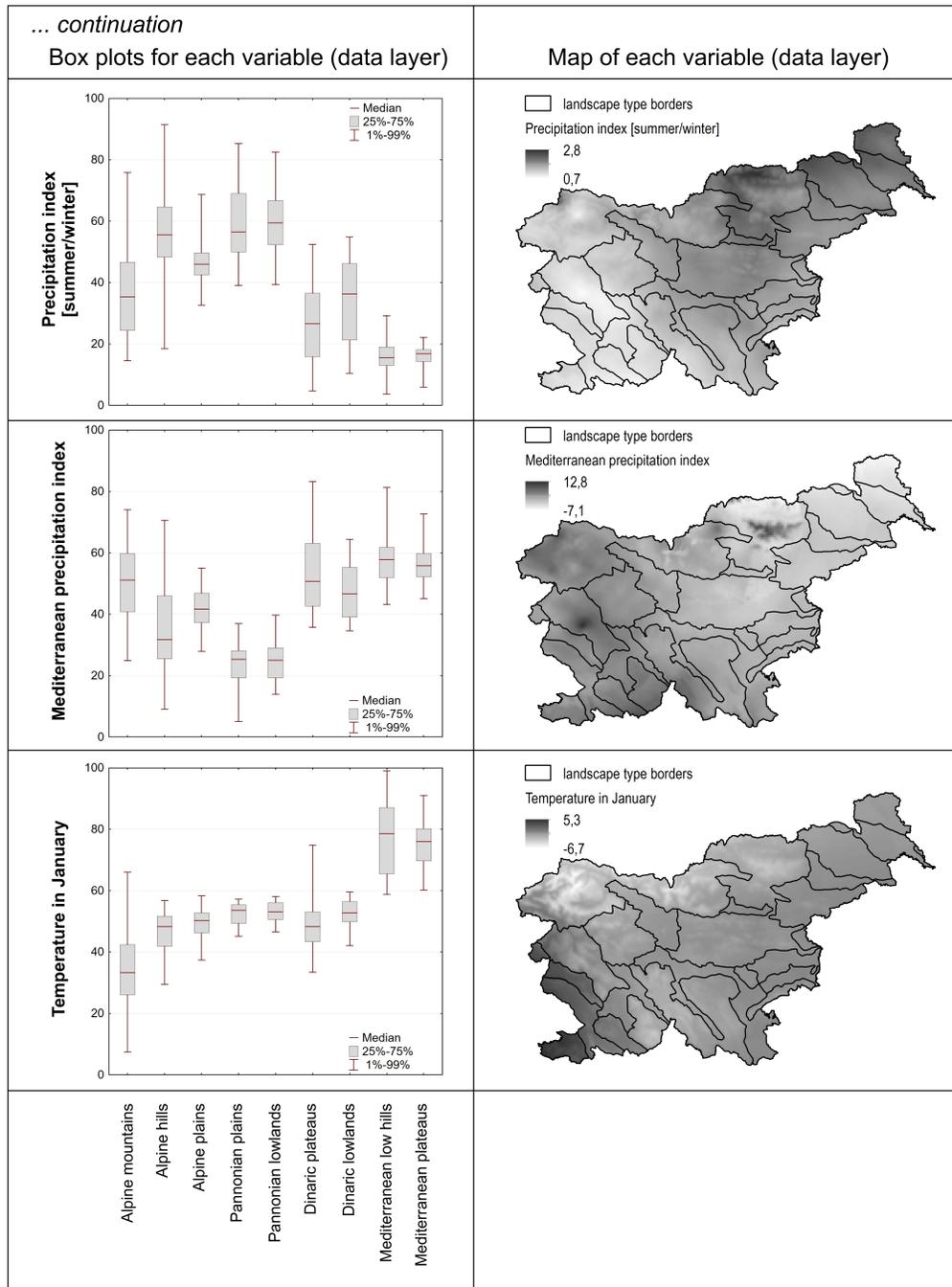
Figure 3: Box plots (standardized values to scale 0–100; left column) and maps for selected explanatory variables (real values; right column). Maps also include borders between natural landscape types. For specific natural landscape types on the map, see also Figure 1. Names of natural landscape types (x-axis) in box plots are located at the bottom.
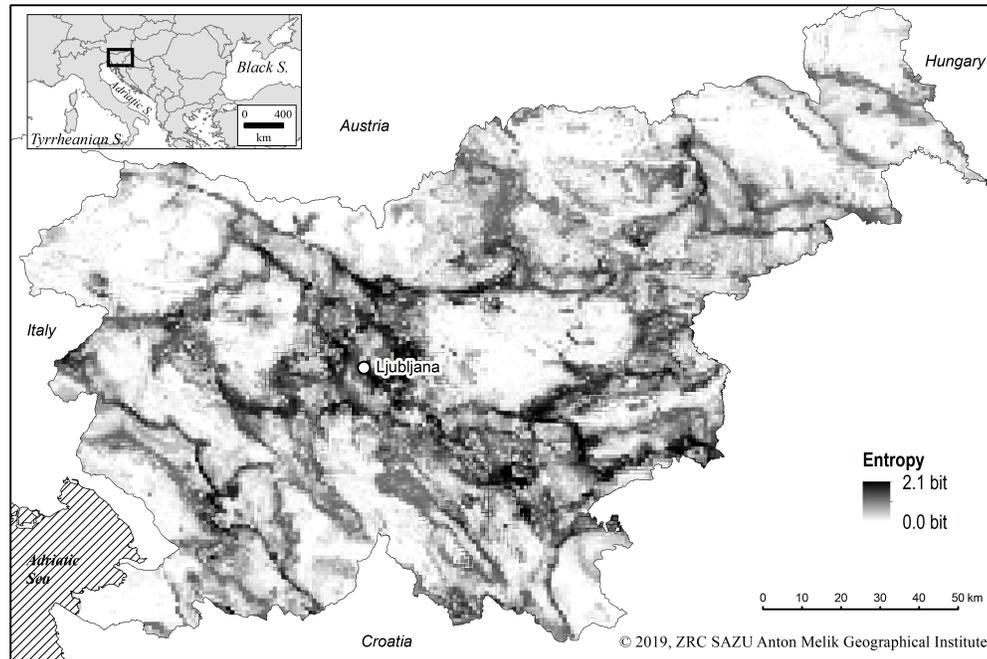
Figure 4: A map of entropy (in bits). Darker areas represent areas where there is more uncertainty in the model's classifications.

4.4 Model analyses—explanation of how the input variables affect the model's predictions

The general black-box explanation method for explaining variable importance provided variable importance plots (Figure 5). The plots explained the variable importance of each variable according to its values for the determination of each specific natural landscape type. The output makes it possible to interpret the existing landscape classifications in greater detail.

5 Discussion

5.1 Possibilities of spatial evaluation of the natural landscape classification

The evaluation of the original classification will be discussed first. After modeling with the random forests method, we compared the modeled classification with the original classification in order to see the rate of agreement and the areas of major discrepancies. Modeling with 5,000 training cells and 6 variables achieved a high level of agreement (94%), which was more than expected. Similar modeling with four pre-selected variables and
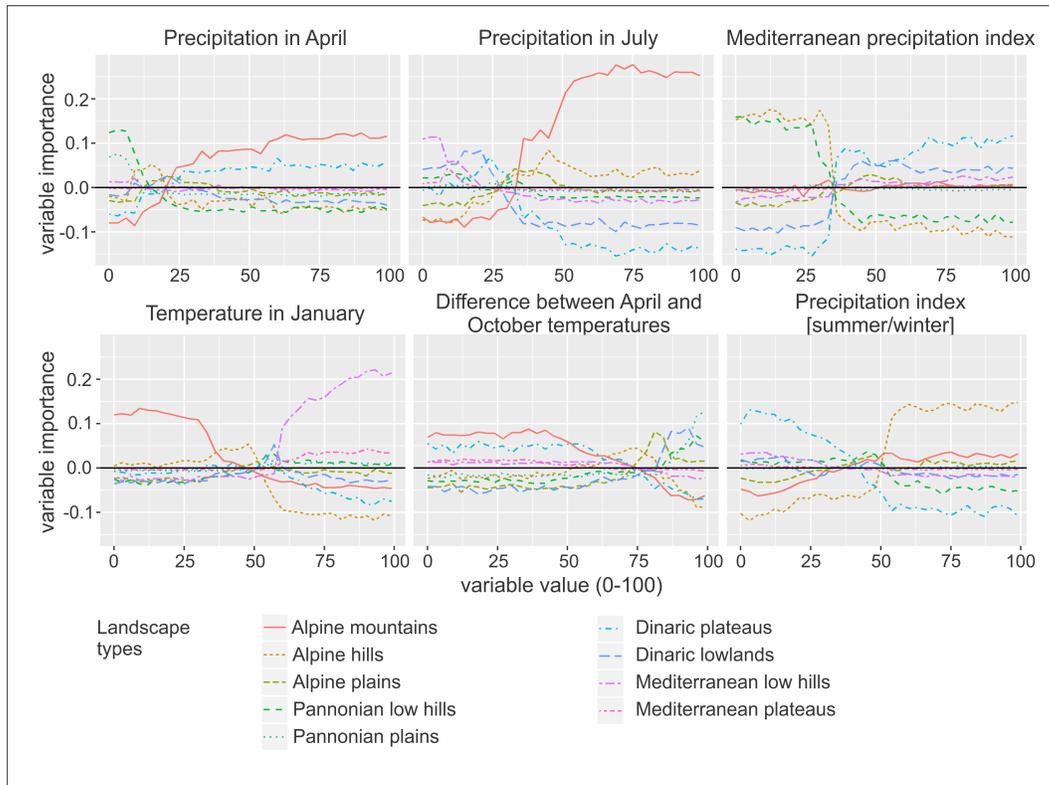
Figure 5: The general method for explaining variable importance provides insight into the connection between the input variables and the predicted probability of a particular natural landscape type. The graphs provide an overview of how values of the input variables influence the model's predictions. The explanation includes, for each variable, a plot of how the importance of that variable differs across its values. Each line represents a class value (in our case natural landscape type). A positive importance value indicates that the value supports that class value, and a negative value indicates that it does not support that class value. For instance, let us demonstrate how variable temperature in January (bottom left graph) helps to classify the Alpine mountains (red line). We can see that low temperature values in January (x-axis: values that are lower than 50) have positive variable importance for the determination of the Alpine mountains. This means that low temperatures speaks in favor of the Alpine mountains.

other methods (statistical models and decision trees) were less successful—with up to 75% agreement [9]. This can be explained by a larger number of variables used and a more complex model (random forests).

The areas of high uncertainty are located on the border areas of the landscape types, especially on the contacts between flat and hilly types, e.g., in the surroundings of the Ljubljana basin (Figure 4). However, a few other areas of high uncertainty formed, for example border zones between the Dinaric plateaus and the Mediterranean low hills and border zones between the Dinaric plateaus and the Pannonian plains. Dinaric plateaus

differ from those low-hill and plain areas in vicinity due to their higher altitude and their climate characteristics (higher rate of precipitation, lower temperature). Due to quite distinct differences, high uncertainty has its origin in actual mistakes made during the manual creation of the original classification. On the other hand, the Dinaric plateaus are very similar to the Dinaric lowlands. The latter have similar precipitation regimes and similar amount of precipitation. Therefore, these uncertainties are more a result of a true similarity of the two natural landscape types.

We also visually checked box-plots of entropy for each natural landscape type (Figure 6) in order to find the most complex type. Surprisingly, Alpine plains have the highest entropy on average. One of the main reasons is that these landscape types are located in two separate areas, which have a different value of the precipitation index. High entropy is also a consequence of some hilly areas inside the type. Similarly, Pannonian plains also have high entropy (3rd highest average entropy). Dinaric lowlands are the 2nd hardest to classify. This is due to the facts that the type is quite diverse and that includes Ljubljana moor, karst poljes, karst plains, and some lower parts of karst hills. Additionally, the landscape type is also diverse from the climatic point of view. It spreads from the west towards the east, and it represents a transitional area between the Mediterranean and Continental climate, making classification even more difficult (see also Figure 1).
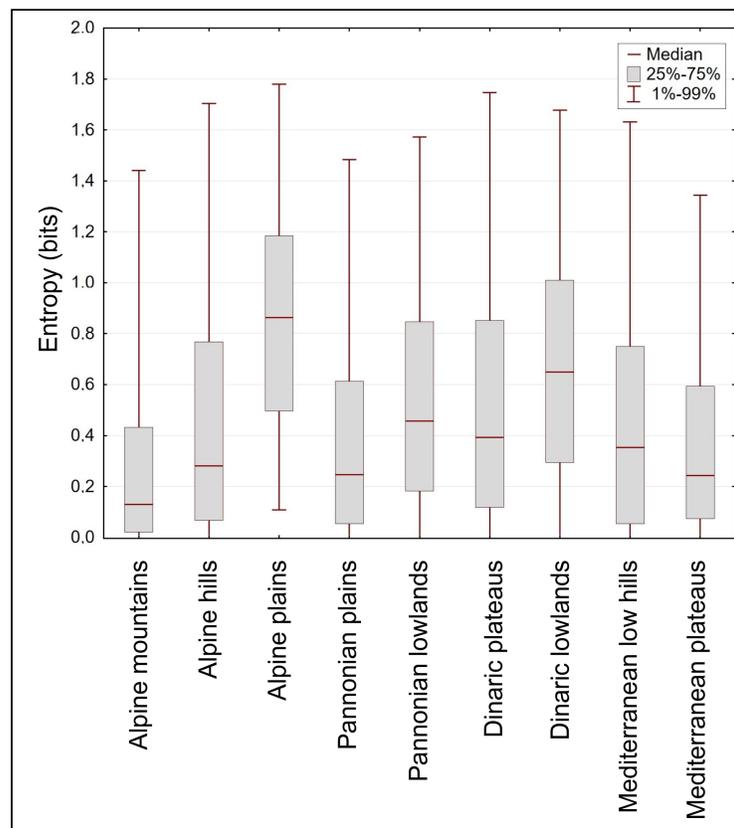

Figure 6: Box plots for entropy grouped by original landscape types.

Most of the mistakes are related to similar landscape types (Table 4). For example, Dinaric plateaus and Dinaric lowlands have very rough terrain with numerous dolines and an absence of a surface fluvial system. Therefore, it is harder to differentiate between larger landforms there than in fluvial landscapes with distinct valleys and ridges.

		Original landscape types								
		Alpine mountains	Alpine hills	Alpine plains	Pannonian low hills	Pannonian plains	Dinaric plateaus	Dinaric lowlands	Mediterranean low hills	Mediterranean plateaus
Predicted landscape types	Alpine mountains	14.5	0.2	0.1	0.0	0.0	0.1	0.0	0.0	0.0
	Alpine hills	0.5	21.8	0.2	0.4	0.0	0.1	0.1	0.0	0.0
	Alpine plains	0.0	0.2	3.6	0.0	0.0	0.0	0.0	0.0	0.0
	Pannonian low hills	0.0	0.3	0.0	14.0	0.5	0.1	0.0	0.0	0.0
	Pannonian plains	0.0	0.0	0.0	0.3	5.8	0.0	0.0	0.0	0.0
	Dinaric plateaus	0.1	0.2	0.1	0.0	0.0	17.8	0.7	0.1	0.0
	Dinaric lowlands	0.0	0.2	0.0	0.0	0.0	0.7	8.4	0.0	0.0
	Mediterranean low hills	0.0	0.0	0.0	0.0	0.0	0.1	0.1	4.8	0.1
	Mediterranean plateaus	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	3.2

Table 4: Confusion matrix (%) for landscape type classification shows the most frequent pairs of misclassification.

One of the most important parts of our research is the explanation of the variable selection (Figure 5). At the time of constructing the original natural landscape classification, the following elements that influenced the formation of types were elevation, slope, rocks, and vegetation. Our analysis did not take into account any other knowledge or perception about the country and focused purely on digital values of the data layers. At first, the list of selected explanatory variables (see Section 4.2) for modeling was surprising. Namely, a lot of geographical research regarding natural landscape classification is tightly connected to landforms (geomorphology), including elevation and slope.

Random forests modeling and further explanation of variable importance, in our case, partially disproved the importance of most of geomorphological data layers at this level of natural landscape classification, at least directly. Six data layers (precipitation in April, precipitation in July, precipitation index, temperature in January, Mediterranean precipitation index and the difference between April and October temperatures) were used to train the classification model. All layers are climate variables. The original climate layers were interpolated from ground meteorological stations [15] and thus provided a gentler (not noisy) surface.

Indeed, climate data seems more appropriate for delimitation of landscape types because the natural landscape types are much larger in comparison to individual landforms. Therefore, exclusion of slope is reasonable, although slope is often regarded as one of the main geomorphological components. However, elevation was indirectly involved because

it was also used in the modeling of temperature and precipitation maps [15]. Therefore, the elevation layer is highly correlated with the difference between April and October temperatures and also temperature in January.

These findings are also supported by other analysis [10]. According to their research on scale, climatic variables and elevation were classified in the same group of variables, which are more appropriate for classification at the national scale (Slovenia covers approximately 20,000 km^2). On the other hand, geomorphological properties (e.g., slope) were defined as more appropriate on a larger scale covering smaller, local area.

Therefore, we confirm that climate variables can sufficiently represent the original natural landscape classification and that surface configuration is less important, with an exception of elevation, which has an indirect influence.

Graphical and statistical revision of the data layers included in the model (Figure 3) and their importance (Figure 5) revealed that we can define distinct rules for the definition of groups of natural landscape types and most individual natural landscape types. The Alpine mountains are determined by high April and July precipitation values and also low January temperature values. The Pannonian landscapes stand out due to the low April precipitation values and high difference between April and October temperatures. The Mediterranean landscapes have low July precipitation values and high January temperatures. There are some situations that cannot be easily described. These are differentiations between the following:

- Mediterranean low hills and Mediterranean plateaus,
- Pannonian low hills and Pannonian plains, and
- Dinaric plateaus and Dinaric lowlands.

In general, modeling produced reasonable results that are highly similar to the original classification, and most of the explanations of the natural landscape types also have a logical geographical background.

5.2 An assessment of the method and its capabilities

The classification phase of the presented machine learning-based approach did not have any issues or limitations in this geographical setting. The models were able to achieve high classification accuracy and quality of probabilistic predictions. Random forests were the best, and it is reasonable to assume that will often be the case in this setting, even if other areas or classifications are evaluated. However, even if this is not the case, any other classifier can be used in this phase, due to the generality of the general black-box explanation method in the second phase of the process.

The general black-box explanation method used in the second phase of the process has two general limitations, both of which become more apparent as the number of variables in the model increases. The first is computation time, and the second is clarity of explanation (that is, it becomes increasingly difficult to interpret when the number of variables exceeds a few dozen). Fortunately, this geographical setting is such that relatively few (six) variables are important. Therefore, the limitations of the general black-box explanation method were not an issue and would only become an issue if hundreds of data layers were used. It is understandable that so few variables are important in this setting, especially for the existing manually created classifications, which cannot be based on many variables

purely because humans are also limited in how many variables they can take into account. Therefore, the general black-box explanation method is suitable for this setting.

We were able to confirm most of the computer explanation and understand the main reasons for divisions between the natural landscape types; however, some pairs of natural landscape types were hard to easily differentiate (see Section 5.1). The data also possess a certain degree of noise (e.g., due to the interpolation of climate data). Also note that the general black-box explanation method, while taking into account all interactions between input variables when determining their importance, reports only one variable importance number per variable (layer). While the method itself can easily be generalized to report importance for each pairwise interaction (or higher level interactions), these can quickly become difficult or even impossible for the user to interpret. Random forests tend to have many higher level interactions, which could explain why for certain cases a reasonable geographical explanation was not possible. It is in the structure of decision-tree based models that every node depends on all the prior tree splits on the path from the root to the node, which results in interactions.

5.3   Broader implications of the results and relation to previous results

The main challenge was to explain the existing natural landscape classification of Slovenia, as other authors did for Norway and Hungary [33, 46]. For one part of Slovenia, a similar evaluation with machine learning modeling was done for "Karst landscape of the interior of Slovenia" [6] and for the entire country [9], but these analyses have not explained variable importance of the selected variables. Since the selection of variables is important [55], our paper brought a deeper understanding of Slovenian natural landscape types that also includes model explanation.

The evaluation of the classification confirmed several previous findings and addressed some issues. Previous studies [13, 44, 46] have already noted that the spatial changes are not sharp, and our results support this kind of perception. The map of entropy (one of the outputs of the modeling) exposed the areas that have mixed characteristics and cannot be 100% classified as one type. Since the highest levels of entropy were located close to the type borders, we confirmed that boundaries are usually created subjectively, as mentioned by previous discussions [18, 36]. Manual drawing of boundaries involves mistakes that are consequences of data quality and resolution, digitization, scale etc. and cannot be avoided.

We gain insight into a complex system of variables' importance by using the general black-box explanation method. As previous papers argue [2, 17, 34], transparency is also very important to clearly present the methodology behind studies. Our methodology can be easily replicated, and the method for explaining variable importance provides insight into the variables' influences on a classification of a specific natural landscape type. Both steps bring new possibilities for explaining classifications. An evaluation is especially important because a general approach does not exist [31], and one might get different results for the same area. In our case, climatic variables were selected for modeling, and surprisingly, no exact geomorphological variables were included. Namely, landform is one of the most important shaping factor [49]. This opened up more ideas for further investigations, e.g., lowering the resolution (low filtering) of input geomorphological data layers in order to get more "gentle" shapes and larger types at the national level. Another option for evaluation of the manually created natural landscape classification is also a usage of unsupervised classification methods. In our case, a production of nine clusters would provide

"completely objective" classes. A similar study was done for the climate classification of Slovenia [26]. The results of an unsupervised classification were similar to some of the older climatic classifications. Therefore, a similar approach has also been tested for the natural landscape classification [37]. The comparison between modeled classifications and the original have shown that models, according to the unsupervised classification methods, achieved lower rates of agreement, which was expected. However, this also means that unsupervised classifications revealed the fact that the original classification could also be designed in a different way.

5.4   Practical application

In our research, modeling confirmed that existing natural landscape classification is made with great sense. The classification can mostly be described with logical statements, although the original classification was determined on the basis of other data mainly with manual delimitation. In the case that the original classification was irrational, the models would not be able to form [8]! Our results also provided information on areas with high entropy. Those areas can be further investigated (also in the field) in order to correct the original classification.

Since the classification we analyzed is also used for official purposes of agricultural land taxation [57], our results can be useful for improving classification (e.g., for correction of the borders between plain and hilly landscape types) by repeating the process at a higher resolution (e.g., 25 m, in case all the data layers are available at such resolution). Another option is to produce a detailed landform classification first and then use it as a starting point for subsequent classification of complex land surface features [14], especially if adding data on other landscape elements. However, using such methods for providing corrections would contribute to a better and more effective distribution of taxes and subsidies and thus to a fairer society.

6   Conclusion

Natural landscape classifications are important for a suitable understanding of the environment. Therefore, they must be prepared with great care, especially if they have a direct impact on official regulations and policy. Therefore, the main aim of the paper was to introduce and test new approaches for natural landscape classification evaluation using machine learning. By modeling existing classifications with random forests and with the general black-box explanation method for explaining variable importance, we were able to analyze how the existing manually defined natural landscape classification can be (re)produced and explained with machine learning algorithms. The new approach was tested for the case of Perko's [36] natural landscape classification of Slovenia, which is used in the official taxation process.

After the comparison of the modeled and the original classification, we found that most of the original was confirmed by the modeling. The automated modeling achieved a high rate of success (original and modeled classifications agreed in 94% of the cases) even with a small training sample (1%). However, with the production of the entropy map, we were also able to find areas with high rates of uncertainty. These areas should be more carefully examined in order to slightly correct the borders between the natural landscape types.

The analysis with the general black-box explanation method provided insight into how different variables influence the classification of natural landscape types. Most of the automated explanation was logical and was confirmed by the analysis of the geographical characteristics of the research area. Therefore, a selection of variables proved to be reasonable, although a set of exclusively climatic variables was not expected. Namely, many landscape researchers usually give most attention to geomorphological variables. The selection of variables for modeling at the national level was eventually proved to be correct; climate variables are more general than geomorphological variables, and some of them are also correlated with elevation; thus, elevation was not included as an independent variable. However, the detailed evaluation of variables revealed differences between natural landscape types, which were reasonable and in most cases easy to explain. The method did not provide clear explanations for some differentiations between landscape types with very similar characteristics.

The process of modeling and evaluating that we propose addresses important natural landscape classification issues, especially transparency and evaluation. The process can evaluate different numeric models and is reproducible. The results can show the classification probability and what affects it. They can also explain the influence of specific characteristics (variables) of a natural landscape classification. Finally, the discrepancies between an original and a model and also areas with high entropy can also help us to improve classification and to diminish subjectivity. Therefore, the methodology could become a useful tool for natural landscape classification evaluation. Lastly, the use of the approach is an example of how modern methods in landscape ecology, geography and related sciences can improve landscape management and increase financial fairness.

Acknowledgments

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