ISSN 2336-3193 **Acta Mus. Siles. Sci. Natur., 66: 101-110, 2017**
DOI: 10.1515/cszma-2017-0011 Published: online 30th October 2017, print November 2017

Species distribution models for critically endangered liverworts (Bryophyta) from the Czech Republic: a guide to future survey expeditions.

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Species distribution models for critically endangered liverworts (Bryophyta) from the Czech Republic: a guide to future survey expeditions. – Acta Mus. Siles. Sci. Natur., 66: 101-110, 2017.

Abstract: Using 35 presence-only data samples and five uncorrelated bioclimatic variables, we made species distribution models (SDMs) for 4 species of critically endangered (CR) liverworts from genus Jungermanniales and Marchantiales (*Cephaloziella elegans*, *Leiocolea heterocolpos*, *Lophozia wenzelii* and *Riccia papillosa*) using the maximum entropy modelling method (MaxEnt). Since we were modelling CR species, only one model proved to be strong enough to be used in the field. However, SDMs can serve as effective and fast tools for acceleration of the discovery of the rare and endangered species. The final model presented in this study can serve as a guide to future survey expeditions, the conservation of the target species and also to help understand their ecology.

Key words: Species distribution modelling, MaxEnt, *Cephaloziella elegans*, *Leiocolea heterocolpos*, *Lophozia wenzelii* and *Riccia papillosa*.

Introduction

Species distribution models (SDMs) have emerged as an effective tool in spatial ecology, conservation and land management (Raxworthy et al. 2003, Rushton et al. 2004). They can identify areas of higher probability of occurrence and can guide future survey expeditions for unknown populations of rare and endangered species (Yu et al., 2013). As a relatively simple and effective tool, SDMs could also accelerate the discovery of such species (Raxworthy et al. 2003, Bourg et al. 2005). There are many methods of species distribution modelling (SDM), but many of them require both presence and absence data. The problem is that reliable absence data are rarely available for species that are easily missed during surveys (Pearson et al. 2007), such as bryophytes. The problem is also with their implementation for species with a limited occurrence record. To solve those problems, we chose the maximum entropy modelling method (MaxEnt), which was ranked among the most effective applications under such a scenario (Shcheglovitova et al., 2013).

Studied species

Based on the updated checklist and red list of bryophytes of the Czech Republic (Kučera et al., 2012), we chose four species of liverworts belonging to the critically endangered category (CR). For all species in this category, the lack of data is characteristic. The studied species were considered to be the most appropriate for SDM because the number of unique (unbiased) localities was higher than five. This was the limiting factor for species to be chosen for the application of the SDM. For all SDMs we used literature data only.

The following species were used for the SDM:

Cephaloziella elegans (Heeg) Schiffn. - Jungermanniales, dark green to red-brown, tiny and often disseminated among other mosses. Grows usually in sunny places, on non calcite bare soil and silicate rocks; sometimes also on humus of limestone rocks. Grows from hills to mountains (Duda et al. 2005).

Literature data: Duda et al. (1974), Mikulášková et al. (2007), Marková et al. (2009).

Leiocolea heterocolpos (Thed.) H. Buch - Jungermanniales, green, golden yellow to reddish, rarely brown to reddish plants in loose carpets or usually individual plants disseminated into the cushions of other species of moss. Grows usually on the basis of humus of limestones and dolomite rocks or pillows of calciphyte bryophytes (usually not directly on the rocks) in the highlands and mountains (Atherton et al., 2010).

Literature data: Duda et al. (1989), Kučera et al. (2009), Kuncová et al. (1995), Kučera et al. (2004), Kučera (ed.) (2005).

Lophozia wenzelii (Nees) Steph. - Jungermanniales, green, greenish-brown to reddish plants usually scattered in the cushions of other species, rarely in separate loose carpets. Mostly grows on the mountain bogs, marshy areas; rarely on wet rocks or rock debris (Váňa, 2005a).

Literature data: Duda J. & Váňa J. (1992), Váňa J. (1967), Rivola M. (1971), Kučera J. et al. (2004), Rivola M. (1968), Váňa J. & Soldán Z. (1998), Duda J. et al. (1992), Kučera J. & Váňa (2004).

Riccia papillosa Moris – Marchantiales, dioecious species which usually do not form rosettes, bluish-green plants, sometimes pinkish or purple on the leaf edges. In the Czech Republic found only sterile. Grows on the bare ground between the grass or debris of rocky steppe areas with silicate substrate (Váňa, 2005b).

Literature data: Duda J. (1976), Rivola M. (1957), Váňa J. (1993), Němcová L. (2014).

Material and methods

Studied area

The Czech Republic is a central European country and includes an area of 78,867 km^2, the majority of which is located in the temperate broad-leaved deciduous forest zone (Chytrý 2012; Divíšek et al., 2014). The climate is determined largely by the altitudinal range, which is from 115 to 1602 m, and the mean annual temperature and annual sum of precipitation range from 5.0 to 9.5°C and 320 to 1450 mm (Tolasz et al. 2007). The mean monthly temperature is usually highest in July and lowest in January or February. According to Trnka et al. (2009), the summer season (June–August) is typically characterised as the wettest, with precipitation totals contributing 37% of mean annual totals (ranging from 27% to 43%). In contrast, winter is typically the driest season, accounting for about 18% of the mean annual precipitation total (from 11% to 28%), followed by autumn and spring (Trnka 2015)

Used algorithm

MaxEnt is a machine-learning method (Phillips, 2006; Phillips & Dudík 2008) which calculates a raw probability value for each pixel of the study region. These raw probabilities are scaled to sum to 1 and represent an index of relative suitability (Anderson & Gonzales, 2011), which means they identify regions that have similar environmental conditions to where the species currently maintains populations (Pearson et al., 2007). All models were made using MaxEnt software for species habitat modelling version 3.3.3k (http:// www.cs.princeton.edu/~ schapire/MaxEnt/).

Sampling bias

Sampling bias causes a biased estimation of environmental relationships. The reason for this is that environments that have been sampled more intensively are over-estimated and those surveyed less frequently are under-estimated (Guillera & Arroita, 2015). For this reason, we filtered occurrence records with a linear distance ≤10 km to neighbouring records by using QGIS (QGIS Development Team, 2016). This was the most straightforward means of addressing this problem, since it allowed for the manipulation of the occurrence data by discarding or down-weighting records in over-sampled regions (Phillips et al., 2009). Specifically, we filtered the final dataset to obtain the maximum number of samples that were at least 10 km apart.

After this filtering of occurrence records, we could use a total of 35 samples for SDM (9 *Cephaloziella elegans*, 8 *Leiocolea heterocolpos*, 11 *Lophozia wenzelii*, 7 *Riccia papillosa*)

Environmental variables

WorldClim (http://www.worldclim.org/) (Hijmans et al., 2015) is a set of global climate layers (Bioclim) generated through interpolation of climate data from weather stations. We used all 19 available environmental variable layers in resolution of 30 arc-seconds (ca. 0.9 x 0.6 km resolution in studied region) for our models. All environmental data were acquired using the WGS84 geographical coordinate system (EPSG:4326). In preparation of environmental layers, we used functions from GDAL library (GDAL, 2016).

Because some of the environmental layers were highly correlated, we selected the most meaningful and uncorrelated bioclimatic variables using ENMTools (Warren et al., 2008; Warren et al., 2010) to calculate a Pearson correlation coefficient. We chose only those layers where the correlation coefficient Pearson's r was <0.7 or >-0.7. If variables were correlated between some of the limiting (extreme events) and annual variables, we chose limiting variables for SDMs, because factors like average temperatures and precipitations may have little meaning (Pradhan, 2016) and limiting variables have a higher biological meaning to the distribution of the species (Mbatudde et al., 2012; Pradhan et al., 2012). This resulted in the following 5 bioclimatic variables (Tab. 1).

Tab. 1 List of uncorrelated environmental variables used for SDMs.

Ecological variables used in the analysis	
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO9	Mean Temperature of Driest Quarter
BIO14	Precipitation of Driest Month

Abbreviations: SDMs, species distribution models, BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp), BIO7 = Temperature Annual Range (BIO5-BIO6). The remaining set of variables was used for MaxEnt models and variables with contribution scores < 5% were removed. This process was repeated until a set of un-correlated variables that all had a model contribution > 5% remained.

Background area

We used 25-km circular buffers around presence points for SDMs. The reason for this was that the extent of the geographic region in which background points are taken should be based on dispersal capacity and the history of the species. The chosen size of the buffers seems to be reasonable by not including small areas too close to presence points or large regions that the species does not inhabit. SDMs were then re-projected on the area of the Czech Republic.

Background points

We followed Phillips & Dudik (2008) and included 10,000 random background points to characterise the 'background' of environments available to the species from a background area.

Clamping

If we project the model onto the newly projected area, variables are outside of their training range. 'Clamping' shows where the prediction is most affected, so we can determine the effect (if any) that it had on model predictions (Phillips, 2006). Despite addressing all species, the effect of clamping was negligible.

Feature class and regularization

According to the feature types and settings called 'regularization parameters', we can control the complexity of dependencies (Phillips & Dudik, 2008). These parameters are automatically selected in MaxEnt (called 'auto features') and depend on the particular sample size of occurrence records, according to a previous extensive tuning experiment by Phillips and Dudik (2008). In our models, the selection of 'features' was carried out automatically and for regularization multipliers (affects how focused or closely-fitted the output distribution is) we performed a range of β values from 0.5 to 6 in increments of 0.5.

Model evaluation

Because the studied species contains only very few of occurrence records, we followed Pearson et al. (2007) and used an '$n - 1$ jackknife' or 'leave-one-out-jackknife' approach suggested for model evaluation with few samples. To aid model validation and interpretation, the test required the use of a threshold. We used the 'lowest presence threshold' (LPT of Pearson et al., 2007) to convert continuous models to binary predictions for calculating threshold-dependent OR. High-quality models should show zero or low omission (Anderson & Gonzalez, 2011). For validation we also used a receiver operating characteristics curve (ROC) calculating the AUC as the secondary criterion. The AUC calculated with background evaluation data represents a threshold-independent measure of a model’s discriminatory ability (Phillips, 2006). Categories of AUC scores are: invalid (< 0.6), poor (0.6–0.7), fair (0.7–0.8), good (0.8–0.9) or excellent (0.9–1.0) (Swets, 1988). We extracted evaluation OR and AUC values from the MaxEnt output for each jackknife iteration and averaged them to reach the final score. The logistic output was used for all visualizations.

Future field research

As a part of this study, we also provide a conclusion on how to use final outputs in the field research in order to make it clearer and more applicable under real conditions by using QGIS (QGIS Development Team, 2016). Standard MaxEnt output includes a layer with raw probabilities scaled to sum to 1 and represents an index of relative suitability. This output displayed with colour gradient and layer transparency (Fig 1.), or using values 0 to 1 as a scale of transparency, can be combined with topological or other layers, used for orientation in the terrain (Fig 2-6.). In this way, we can get a final map output, which can be used directly in the field.

Maps of this kind can be created with relative ease in QGIS. Freely available data from the OpenStreetMap project (raster tiles or raw vector data (OpenStreetMap contributors 2017), or any data from the local data provider, can be used as a background layer. The greatest benefits of this approach are simple orientation and the possibility to keep information about the real value of relative suitability and complex information in relation to the studied area (Fig 2-6.).

Results

For all species we provide here the number of samples used for the MaxEnt model (sampl.), β values of used regularization multiplier (β), relative per cent contributions of the environmental variables to the final MaxEnt model (contr.) and average OR and AUC values from jackknife iterations (Tab. 2). Here we also provide geographic maps of the models identifying regions that have similar environmental conditions to those in which the species are currently populated (Fig. 1).

Tab. 2 Summarization of results from SDMs for all species with a final AUC score > 0.7.

	*Cepele.	*Leihet.	Lopwen.	*Ricpap.
samples	9	8	11	7
β	0.5	0.5	0.5	0.5
contr. (BIO3)	–	12.5	–	13.2
contr. (BIO5)	100	30.6	59.7	72.5
contr. (BIO6)	–	12.6	5.1	–
contr. (BIO9)	–	44.2	–	14.3
contr. (BIO14)	–	–	35.2	56.9
OR	0.1110	0.2500	0.0909	0.2857
AUC	0.6953	0.4695	0.9361	0.5454

Abbreviations: Cepele - *Cephaloziella elegans*; Leihet - *Leiocolea heterocolpos*; Lopwen - *Lophozia wenzelii*; Ricpap - *Riccia papillosa*; (β) - regularization multiplier; contr. - relative per cent contributions of the environmental variables; AUC - average area under the receiver operating characteristic curve; OR - average omission score. Species with * were not included in the final results and discussion because of the AUC score lower than 0.7 - fair.

Three models did not reach the minimum AUC score of 0,7 (fair), so their evaluation could be misleading. On the other hand, the model for the species *Lophozia wenzelii* reached a very high AUC score of 0,93 (excellent), so we can draw some conclusions. The environmental variable with the highest relative contribution to the MaxEnt model was evaluated as BIO5 (Max Temperature of Warmest Month), but the probability of presence is lower when the temperatures are higher. The second most important environmental layer was evaluated as BIO14 (Precipitation of Driest Month). Specifically, the preference of higher values of preci-

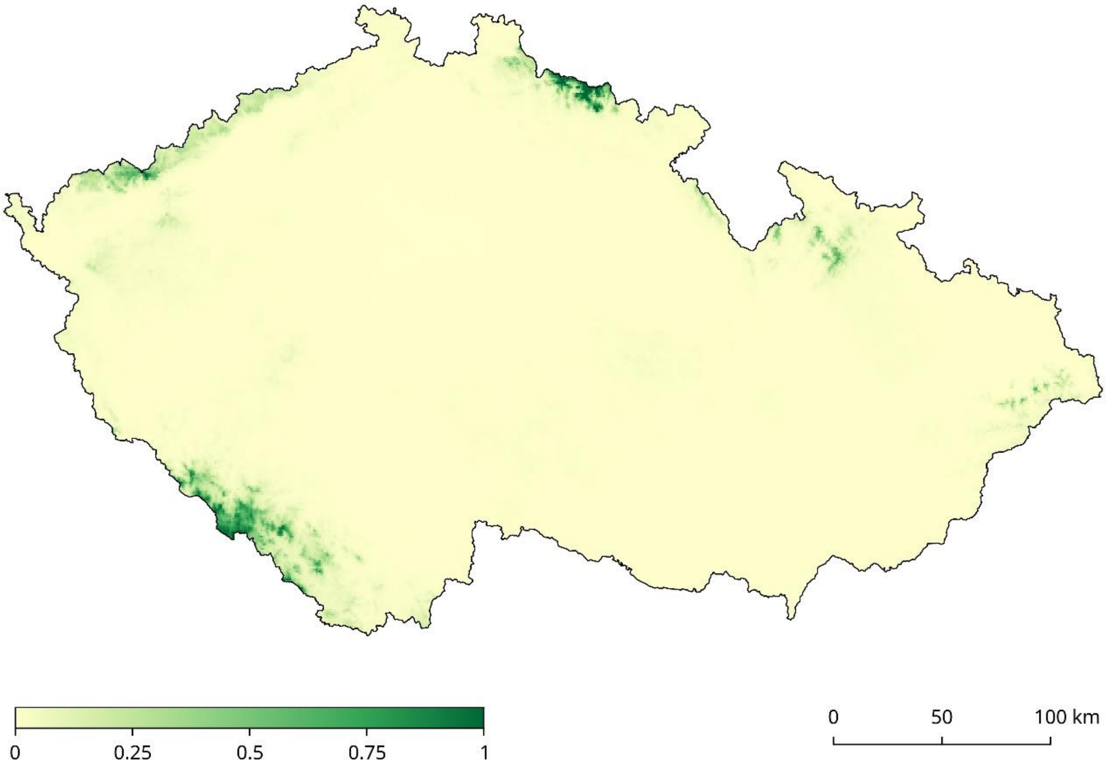

Fig 1: Map identifying regions that have similar environmental conditions to currently found populations of *Lophozia. wenzelii* visualized on a scale from 0 to 1 with displayed 11 collection points.

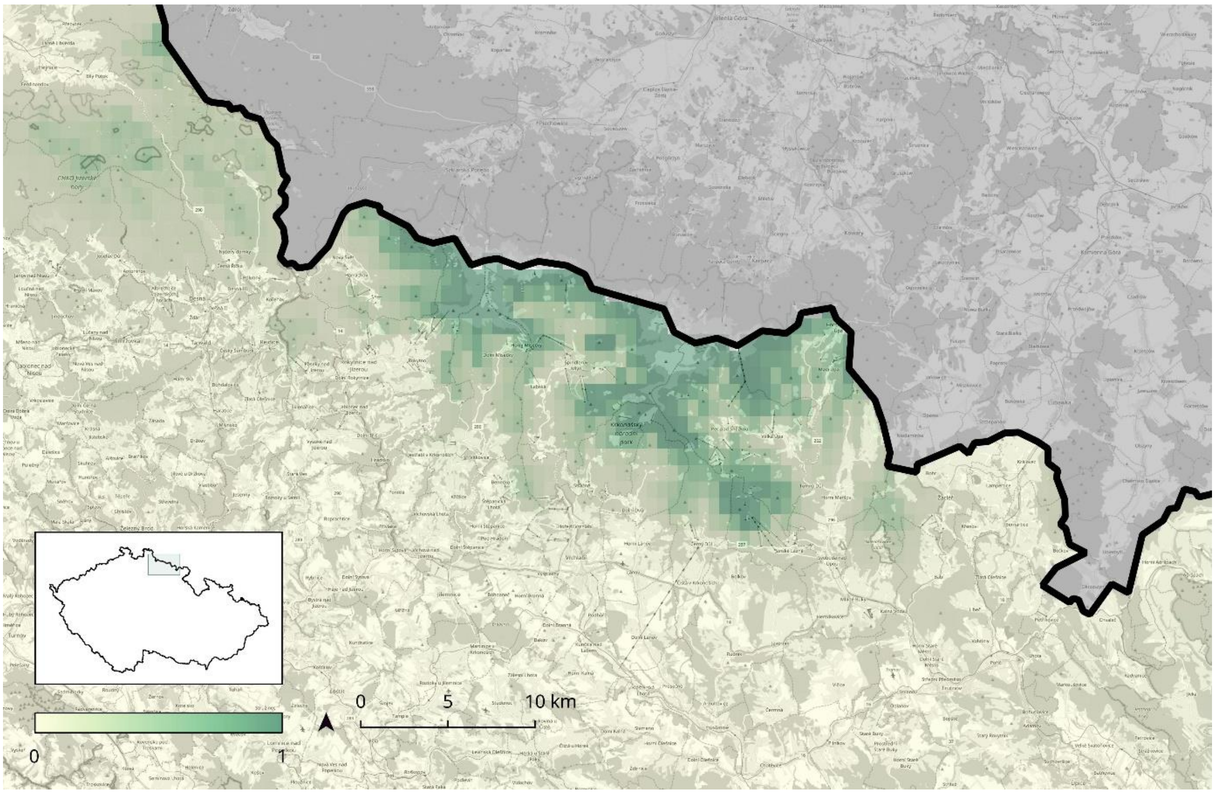

Fig 2: Example of map for further field research, identifying transparent areas on a scale from 0 to 1 (relative probabilities of presence of *Lophozia wenzelii*) on OpenStreetMap background for Krkonoše Mts.

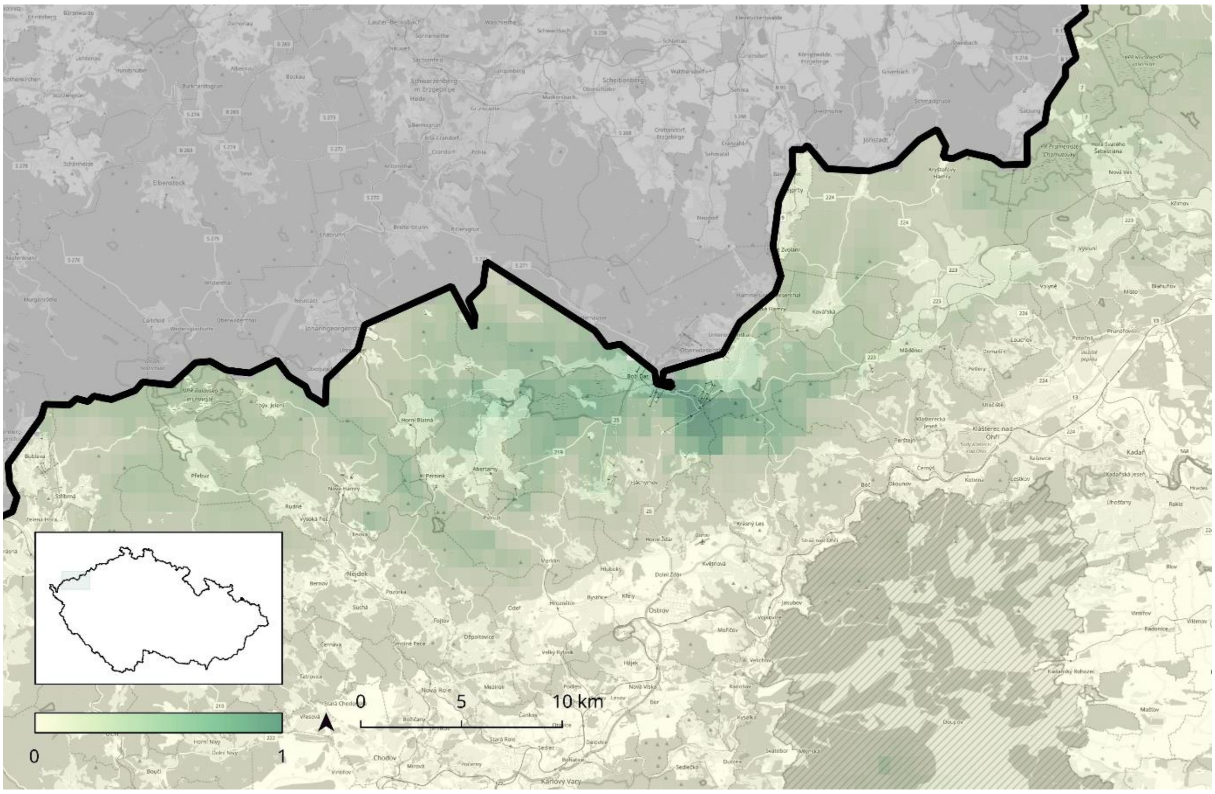

Fig 3: Example of map for further field research, identifying transparent areas on a scale from 0 to 1 (relative probabilities of presence of *Lophozia wenzelii*) on OpenStreetMap background for Krušné hory Mts.

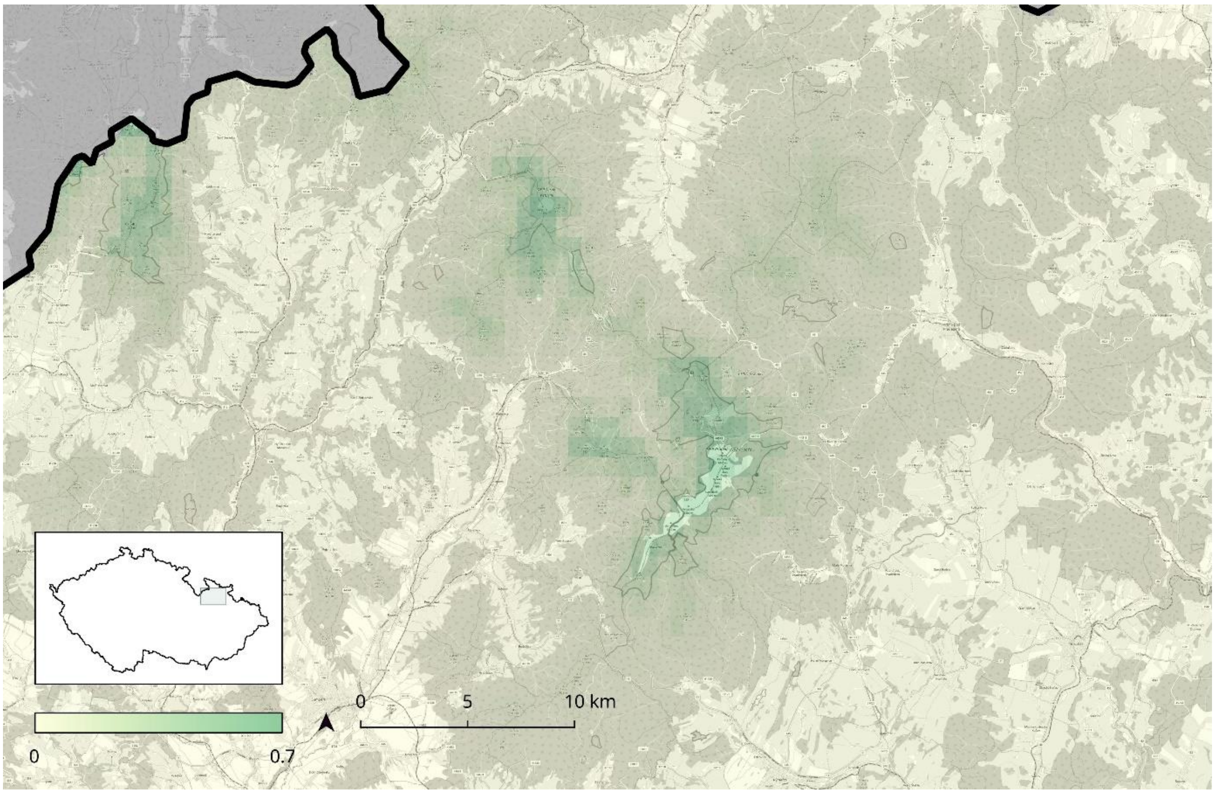

Fig 4: Example of map for further field research, identifying transparent areas on a scale from 0 to 0.7 (relative probabilities of presence of *Lophozia wenzelii*) on OpenStreetMap background for Jeseníky Mts.

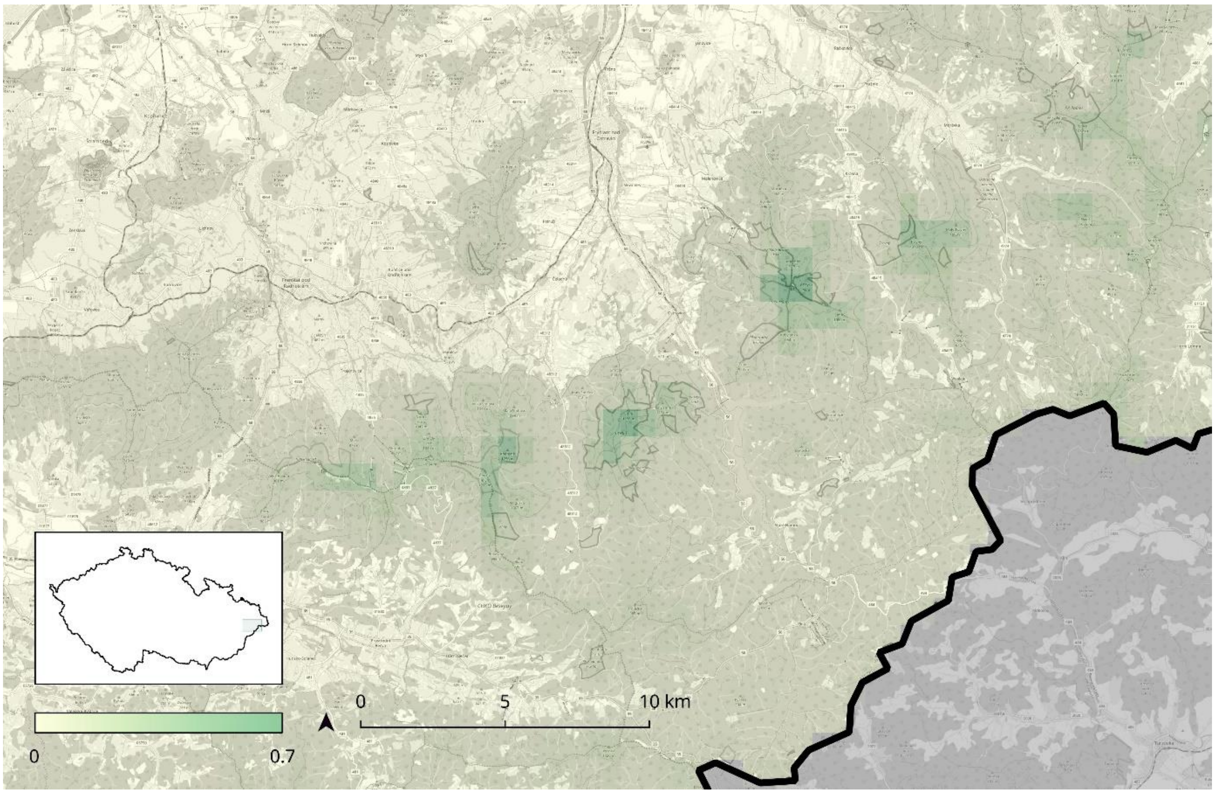

Fig 5: Example of map for further field research, identifying transparent areas on a scale from 0 to 0.7 (relative probabilities of presence of *Lophozia wenzelii*) on OpenStreetMap background for Beskydy Mts.

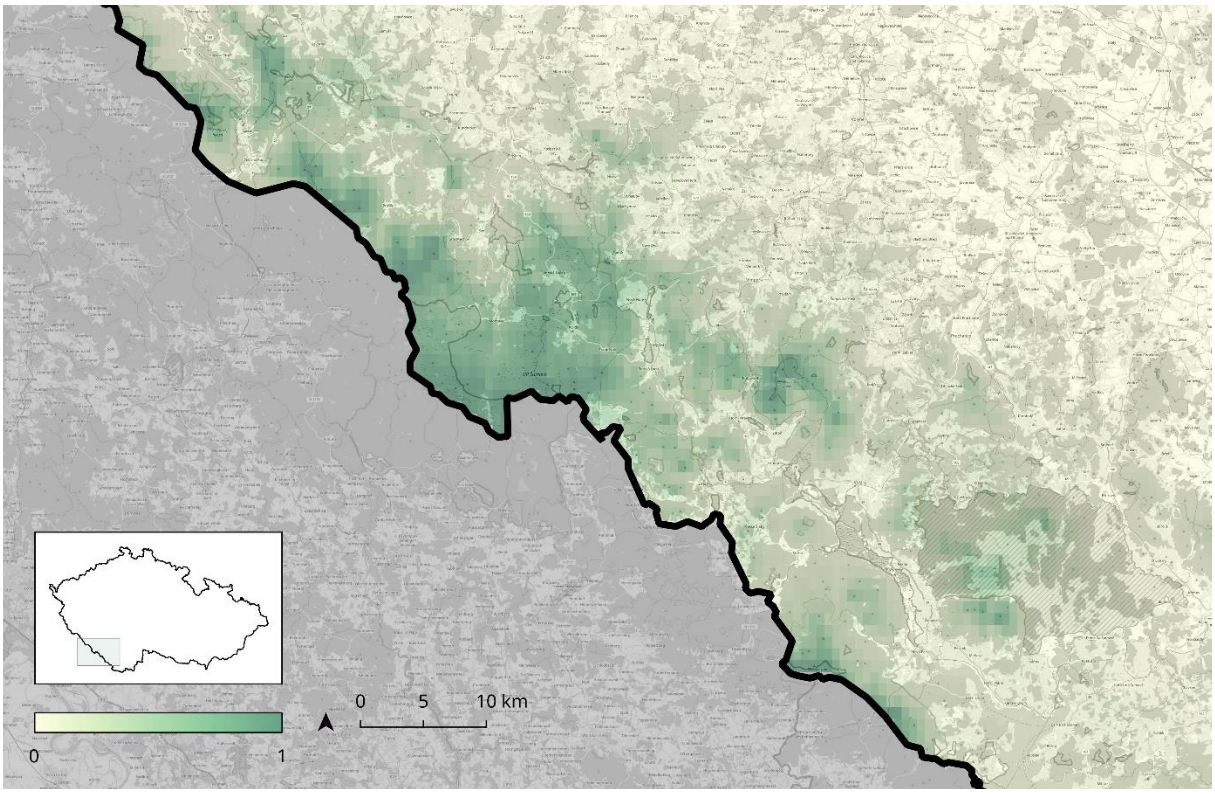

Fig 6: Example of map for further field research, identifying transparent areas on a scale from 0 to 1 (relative probabilities of presence of *Lophozia wenzelii*) on OpenStreetMap background for Šumava Forest.

pitation occurred as a result of the fact that most precipitation falls in the Czech Republic in June or July, and the least amount of rainfall in January or February (Tolasz et al. 2007). Therefore, BIO14 indicates a higher probability of presence with higher precipitation in winter. Also BIO6 (Min Temperature of Coldest Month) is included in the model, but the contribution of this variable is negligible.

As a result, a map identifying regions that have similar environmental conditions to currently found populations was made. From this map we can observe five regions with higher similarity, specifically: the Beskydy mts., the Jeseníky mts., the Krkonoše mts., the Krušné hory mts. and the Šumava mts, with concentration of the suitable localities in higher parts of the mountains. The regions with highest similarity were evaluated as the Krkonoše mts. and the Šumava mts, but model also predicted regions in the Beskydy mts. and the Jeseníky mts. as the new potential regions for studied species (Fig. 1).

For the purposes of future research, we provide here detailed maps focusing on regions chosen by MaxEnt as most suitable for the presence of studied species. These maps can serve as guides for field research which could lead to verification of the presented model.

Discussion

Microclimatic changes are very important for bryophytes (Benítez, 2015), and ecological conditions needed for most mosses are likely to be micro-environmental (Bates, 2004), but macro-climatic conditions on coarser spatial and temporal scales are crucial to the composition of epiphytic communities (Bates, 2004; Marini, 2011).

We can assume that our model reflects the real situation, but it would be appropriate to test the model directly in the field, because such research could improve the validity and precision of area prediction. Until then, our model can serve as a guide to future survey expeditions, to understanding of ecology and an aid in the conservation of the *L. wenzelii*.

Results of this study are also in agreement with Číhal et al. (2017), who found out that snow can function as isolation from the surrounding environment, and thus makes these species more resistant to temperature ranges. In this case we can also see that the studied species is sensitive also to higher temperatures and thus is making it vulnerable to environmental conditions connected with temperature. Such a low thermal resistance can be possibly also the reason of their belonging to the critically endangered category (CR), but further research focused on this theme has to be made.

As a part of this article we also present a suitable method on how to use prediction maps in field research, which can simplify the process and make it more applicable under real conditions.

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