Vulnerability of natural habitats

Research study

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 THE VULNERABILITY FRAMEWORK

In the assessment of climate change effects the most widely used methodological framework is the Climate Impact and Vulnerability Assessment Scheme (CIVAS) also used by the Intergovernmental Panel on Climate Change (IPCC, PARRY and CARTER 1998, CARTER et al. 2007, IPCC 2007, CLAVIER project). According to this framework, vulnerability to climate change is the degree to which geophysical, biological and socio-economic systems are susceptible to, and unable to cope with the adverse impacts of climate change. The vulnerability of an object is determined by the potential impact of climate change and by the object’s capacity for adaptation (also termed adaptive capacity) to the changing geophysical, biological and socio-economic conditions. Potential impact is further determined by the exposure of the object to climate change, as well as by its sensitivity (Figure 1, Tab 1.). This framework can be applied to any object exposed to climate change. In our case, the objects are natural and semi-natural ecosystems (habitat types), which are self-organizing systems with several relevant physical and biological properties determining their sensitivity, as well as adaptive capacity. These physical dependencies enable us to explore the climatic vulnerability of ecosystems using a modelling approach (CZÚCZ et al. 2009, 2011).

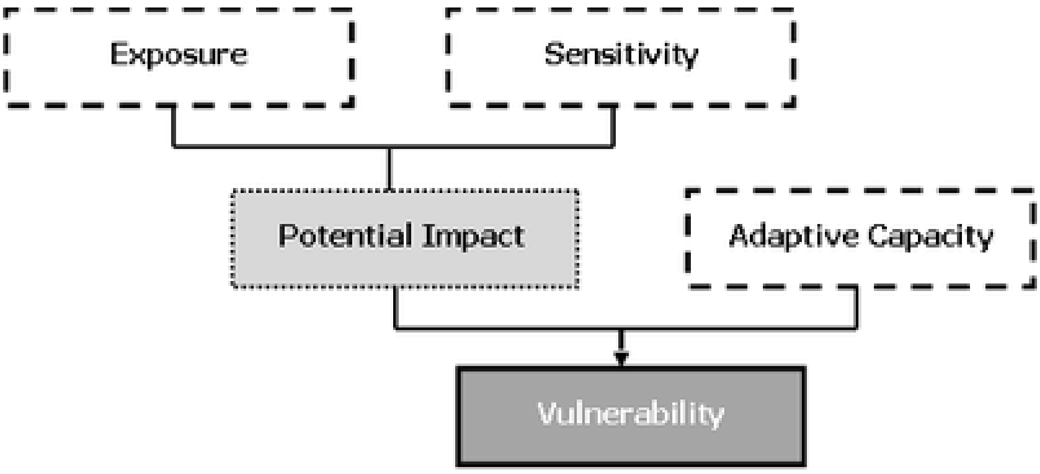

Figure 1. The Climate Impact and Vulnerability Assessment Scheme (CLAVIER project)

Table 1. Key concepts of the Climate Impact and Vulnerability Assessment Scheme and their equivalents in our analysis of climate sensitivity of natural and semi-natural habitats

Concept	IPCC definition	Our customized definition
Exposure, E	"The nature and degree to which a system is exposed to significant climatic variations" (IPCC 2001)	Exposure (of natural habitats to climate) is the projected degree of change in the bioclimatic variables at a given location for a specific time horizon. (multidimensional, depending on location and time horizon)
Sensitivity, S	"Sensitivity is the degree to which a system is affected, either adversely or beneficially, by climate variability or change. The effect may be direct (…) or indirect (…)." (IPCC 2007)	We define climate sensitivity of a habitat as the multidimensional gradient of its modelled "response surface" to the studied bioclimatic factors (with all other abiotic factors held constant). (multidmensional, depending on habitat type)
Potential impact, PI	"All impacts that may occur given a projected change in climate, without considering adaptation" (IPCC 2007)	Potential impact is expressed by the difference of predicted probabilities of presence given the climate of the reference period and under climate change scenarios within current locations of the habitat. (unidimensional, depending on habitat type, location and time horizon)
Adaptive capacity, AC	"The ability of a system to adjust to climate change (including climate variability and extremes) to moderate potential damages, to take advantage of opportunities, or to cope with the consequences" (IPCC 2007)	We define adaptive capacity as the capacity of the location and the landscape context to support successful adaptive processes (local resilience, refuge-based adaptation, migration-based adaptation) for the studied habitat
Vulnerability V	"Vulnerability is the degree to which a system is susceptible to and unable to cope with adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity." (IPCC 2007)	To assess vulnerability we combine the outputs of potential impact and adaptive capacity analyses.

1.2 SCIENTIFIC CONTEXT

Environment based vegetation models have a long history (FRANKLIN 1995). One of the main aims was explaining why certain vegetation types occur where they can be found (e.g. MILLER and FRANKLIN 2002, SOMODI et al. 2010). Predictive models share the basic idea of deducing determinants of the studied phenomenon from existing occurrences, building statistical models on these and being useful for inter- and extrapolation. In principle, this means the formalisation of the requirements of natural vegetation types, which are aggregated here as natural habitats, representing a characteristic functional typology of terrestrial ecosystems. Predictive distribution models for natural habitat types can therefore assist the determination of climate sensitivity (by modelling the dependency of the different habitat types on the various climatic factors) and potential impact (by applying the models to future climate scenarios).

Hungary is in a special position in this aspect, since there is a unique national vegetation map and database, which makes fine scale predictive distribution modelling of the different habitat types feasible. The Landscape Ecological Vegetation Database & Map of Hungary (MÉTA) contains a proportional cover spectrum for each of the main vegetation types per 35 ha units in the country (MOLNÁR et al. 2007, HORVÁTH et al. 2008), which is an ideal base for modelling.

As for the different modelling techniques, tree-based models were found useful in discovering relationships with the phenomenon using many variables, while GLM-based methods were successful in predictive mapping (extra-, interpolation). Nevertheless, GLMs are very restrictive about the data structure (MCCULLAGH and NELDER 1989). Recently, new methods have arisen, which make the previously separate approaches virtually equivalent in statistical characteristics as well: Random Forests (BREIMAN 2001) and Gradient Boosting Models (GBM; FRIEDMAN 2002, ELITH et al. 2008). While random forests are still criticised for their variable selection methods (STROBL et al. 2007), GBM offers cross-validation-based variable selection (ELITH et al. 2008), opposed to the much criticised (e.g. LUKACS et al. 2010) Akaike Information Criterion (AIC) based option of the GLMs. Besides, it also allows a wide range of response curve shapes, which makes it flexible in handling variables from different sources (e.g. soil vs. climatic variables).

1.3 GOALS OF THIS ASSESSMENT

The most important goal of this study was to perform a detailed climatic vulnerability assessment on the most important and climate-sensitive natural and semi-natural habitats of Hungary. Our secondary goal was to provide a good example on how the CIVAS framework can be operationalized in sectoral climate impact studies. Both goals were achieved by determining and quantifying the elements of the CIVAS framework for the climate sensitive natural habitats (CSH) in Hungary.

The first step in this assessment is the determination of climate sensitivity and the selection of the most climate sensitive habitats. We defined climate sensitivity as the degree of dependence on climate-related abiotic factors. Thus the determination of climate sensitivity was carried out through formalisation of the abiotic requirements of natural habitats. Therefore our aim was to construct statistical models for formalisation.

As the planned CIVAS framework is only relevant and applicable for habitat types that are sensitive to climate change, we used the results of this formalization to select those habitat types which are highly sensitive to climate change, which we will work on throughout the CIVAS framework. As a second step, potential impact of climate change was determined for the selected CSH habitat types at their current locations.

To determine the adaptive capacity of the selected CSH we applied the conceptual model described by Czúcz et al. (2011). Accordingly we quantified three indicators for each habitat type and each location:

- The naturalness of the habitat at the current locations
- The diversity of the landscape surrounding the current location
- The landscape pattern of the current stands of the CSHs to estimate adaptation by migration

Finally, we created a demonstrative example for the combination PI and AC to assess the landscape-level aggregated climatic vulnerability of natural ecosystems.

2 METHODS AND APPROACHES

2.1 BIOCLIMATIC MODELLING

Bioclimatic modelling basically relies on finding statistical relationships between vegetation observations and abiotic conditions. Thus, data originates from two sources: vegetation observations and maps of the abiotic background.

Vegetation data in this project originated from the Landscape Ecological Vegetation Database & Map of Hungary (MÉTA; HORVÁTH et al. 2008, MOLNÁR et al. 2007). This database contains field-based cover estimations for 86 main vegetation types in 35 ha hexagonal grid cells covering the entire country (Fig 2). Vegetation is classified in the MÉTA at the habitat level, i.e. at a level coarser than phytosociological plant associations, but finer than formations (A-NER 2003; MOLNÁR et al. 2007, MOLNÁR et al. 2008, BÖLÖNI et al. 2011). Both primary and secondary vegetation is included in the database, as well as seral and climax vegetation types. Since our ultimate current goal is to estimate vulnerability to climate change, we chose habitat types that are considered as stabile under stabile climate conditions, i.e represent climax and subclimax vegetation, rather than transient types in a succession series (Table 2). A few closely related vegetation types were merged, as a posteriori expert evaluation of the mapping found that field mappers were likely not discriminating between them appropriately. For further information on the habitats please consult MOLNÁR et al. (2007) and BÖLÖNI et al. (2011); www.novenyzetiterkep.hu also contains exhaustive information on the field mapping and habitats.

Presence-absence information of the habitat occurrences were used for the modelling purpose. Habitats extremely rare in Hungary (< 100 presences, for example raised bogs) were excluded even if they represent climax stage, since their limited occurrence cannot give sufficient information on their environmental preferences. Since mapping has been carried out with extensive field work, habitat absence information is also reliable. However, current absence of a habitat can be both due to the environment being unsuitable to the habitat (our interest) and due to human activities having removed it. Although, we could not fully eliminate this source of uncertainty, we tried to reduce it by excluding those spatial units from the training data that did not contain any undisturbed vegetation in the MÉTA database. In these hexagons human activities have removed all natural vegetation, thus here absence is clearly not reflecting the requirements of habitats. The MÉTA database contains altogether 267813 hexagons, out of which 87830 have been retained after this screening.

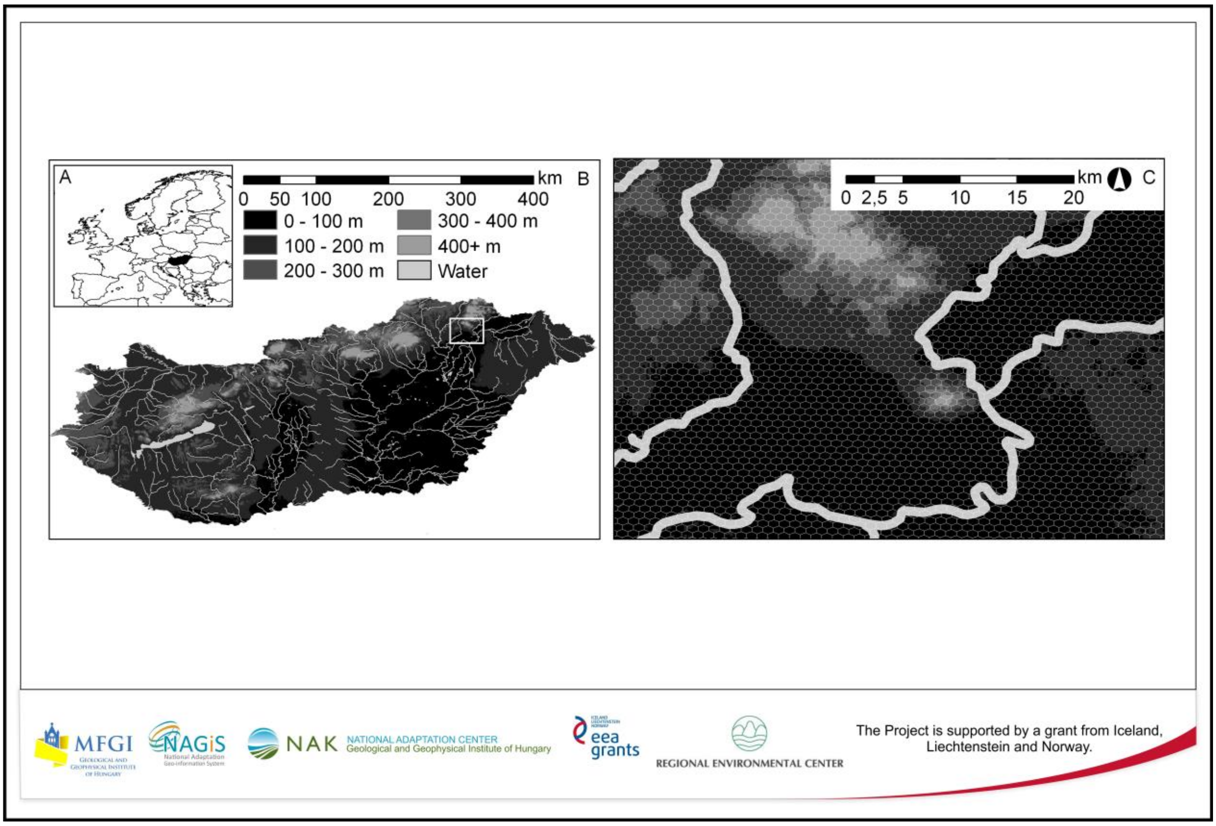

Figure 2. The coverage of Hungary by the MÉTA hexagon lattice. Projection used: World Geodetic System 1984 (WGS 84), the figure was prepared in ArcGIS 10.1

Table 2. Names and abbreviations of the habitats modelled

B1a	Eu- and mesotrophic reed and Typha beds
B1b	Oligotrophic reed and Typha beds of fens, floating fens
B4	Tussock sedge communities
B6	Salt marshes
F1a	Artemisia salt steppes
F2	Salt meadows
F4	Dense and tall Puccinellia swards (alkaline vegetation)
F5	Annual salt pioneer swards of steppes and lakes
G1	Open sand steppes
G2	Calcareous open rocky grasslands
G3	Siliceous open rocky grasslands
H1	Closed rocky grasslands, species rich Bromus pannonicus grasslands
H2	Calcareous rocky steppes
H3a	Slope steppes on stony ground
H4	Forest steppe meadows
H5a	Closed steppes on loess, clay, tufa

Table 2 continued. Names and abbreviations of the habitats modelled

H5b	Closed sand steppes
J1a	Willow mire shrubs
J2	Alder and ash swamp woodlands
J3_J4	Riverine willow shrubs and willow-poplar woodlands
J5	Riverine ash-alder woodlands
J6	Riverine oak-elm-ash woodlands
K1a_K2_K7b	Oak - hornbeam woodlands
K5_K7a	Beech woodlands
L1_M1	Downy oak woodlands
L2a_L2b	Turkey oak woodlands
L2x_M2	Closed mixed steppe oak woodlands on foothills and open steppe oak forests on loess
L4a_L4b	Acidofrequent oak woodlands
L5	Closed lowland steppe oak woodlands
LY1	Forests of ravines (mesic rocky forests rich in *Acer pseudoplatanus*)
LY2	Mixed forests of slopes and screes
LY3	Limestone beech forests
LY4	Mixed relic oak forests on rocks
M3	Open salt steppe oak woodlands with openings
M4	Open sand steppe oak woodlands with openings
M5	Poplar-juniper steppe woodlands
M6	Continental deciduous steppe thickets
M7	Continental deciduous rocky thickets
N13	Acidofrequent coniferous forests

All habitat models were developed using the same set of climatic variables originating from the CarpatClim-Hu database through the NAGiS project (Tab 3). CarpatClim-Hu contains entire Hungary within its domain, otherwise it is similar to the CarpatClim database (Szalai et al. 2013). Climate variables were supplied in ~10 km (0.1°) spatial and daily temporal resolution. The fine temporal resolution was unnecessary for vegetation modelling, therefore daily temperature and precipitation data were aggregated into monthly averages (in case of temperature) and monthly sums (in case of precipitation) over 30-year time periods. This time period was determined by the length of modelled climate data for the future.

Bias correction of predicted future climatic data was done on a monthly base. The difference (in case of temperature) and the quotient (in case of precipitation) of the predicted and observed climate in the period of 1961–1990 was calculated as bias term. Then the predicted future climate was corrected by these bias terms (delta change method). The reference period of the ecological model was set to 1977–2006, so as to fit best the vegetation data, which has been collected between

2004 and 2006. On the other hand, the spatial resolution was too coarse for vegetation modelling, therefore downscaling was applied.

There are two main methods available: statistical and dynamic downscaling. Since dynamic downscaling is highly compute-intensive method and needs a high amount of expert decision, we selected a statistical downscaling (spatial interpolation) approach.

Several methods are developed that are able to achieve statistical downscaling, including basic statistical methods (e.g. General Linear Model (GLM)), deterministic interpolations (e.g. Thin Plate Spline (TPS), Inverse Distance Weighted (IDW), Nearest Neighbour (NN), Voronoi cells or Thiessen polygons), geostatistical methods (kriging), simple and advanced tree-based classification/regression methods (e.g. Random Forest (RF), Gradient Boosting Model (GBM)) and some type of artificial intelligence (AI) methods (e.g. Artificial Neural Networks (ANN)). Detailed enumeration and comparison of the interpolation techniques can be found in HARTKAMP et al. 1999, SLUITER 2008, Li and Heap 2014. In most of the cases of building calibration/evaluation database for ecological models, simple interpolation (e.g. inverse distance weighting, IDW) is done when a finer resolution dataset is needed. Simple interpolators are, however, not able to use auxiliary variables, calculate uncertainty and so on. The precision with which a variable, i.e. climate surface in our case, is estimated may be improved by using auxiliary variables (KNOTTERS et al. 1995).

In our study, regression kriging was used with linear model. Kriging (KRIGE 1966) is widely used for interpolating long-term precipitation and temperature data (e.g. TABIOS and SALAS 1985, HEVESI et al. 1992, HOLDAWAY 1996, DRYAS and USTRNUL 2007). Regression kriging is also widely used in meteorology (GOOVAERTS 1999, 2000, TVEITO et al. 2006, WU and LI 2013).

The spatial interpolation methods differ in their assumptions, local or global perspective, and deterministic or stochastic nature (LAM 1983, LUO et al. 2008). In contrast to deterministic methods, kriging provides a solution to the problem of estimation of the surface by taking account of the spatial correlation (LUO et al. 2008). Kriging is an exact, non-convex, linear, stochastic and local (in some case with global trend) interpolator, that produce a gradual surface (HARTKAMP et al. 1999, LI and HEAP 2014). Although some types of kriging are univariate, regression kriging is multivariate since it uses auxiliary variables (LI and HEAP 2014). Kriging is a stochastic technique similar to IDW in that it uses a linear combination of weights at known points to estimate the value at an unknown point (COLLINS 1995, LUO et al. 2008).

Regression kriging has advantages (can use a known and physically interpretable relationship between the target variable and the auxiliary variable) and disadvantages (assumptions about the error term) as well in contrast to other kriging methods, especially ordinary kriging (Knotters et al. 1995). In case of regression kriging (aka. residual kriging, detrended kriging, kriging with external drift (KED)) the drift or trend is estimated by a regression/detrending function (HOLDAWAY 1996), i.e. linear regression in our study. Although regression kriging and KED are mathematically equivalent to each other, the main difference is that the latter uses secondary variables directly to solve the kriging weights, instead of using simple kriging (SK) on the residuals of a previous regression (HENGL et al. 2007, LI and HEAP 2014)

Three auxiliary variables were used in our study. Linear regression of all of the 5×48 monthly climate data (precipitation, minimum, maximum and mean temperature of the months of the year averaged over the thirty-years periods) was built with altitude, latitude and longitude as covariates. Statistical significance of the covariates and the overall model, and the coefficient of determination of the model were computed. Based on the computed experimental semivariogram an initial semivariogram model was built with fixed sill, nugget and range values. Nugget was adjusted to be 0, partial sill (and sill) is the mean of the semivariance found by the experimental semivariogram, and range was set to be the one eighth of the study window. Then an exponential semivariogram model was fitted with variable sill, nugget and range values.

Following the preparation of high spatial resolution climate surfaces, seasonal averages of mean temperatures, seasonal sums of precipitation and 19 bioclimatic variables were calculated according to the WORLDCLIM protocol (HIJMANS et al. 2005). Variables describing soil conditions originate from the Digital, Optimized, Soil Related Maps and Information in Hungary (DOSoReMI) (PÁSZTOR et al. 2015). Distances to water bodies refer to the distance of the hexagon centre. Some soil descriptors (Svac, Sac, Sne, Sal, Sval – see Tab 3. for explanation of the abbreviations) were encoded logical (two-state categorical), all other variables are continuous. To assess the variability of the terrain we calculated several topographic indices based on the Digital Terrain Model. In total, 26 soil, 9 hydrological, 6 topographic, and 27 climatic parameters were generated as an initial predictor set.

The explanatory variables used for all models have been selected from the above list. The reduction was based on the inspection of individual variable effects and the correlation structure so as to keep the absolute value of pairwise correlation at maximum 0.8, the total Condition Number (CN) of the predictor set at maximum 30 (DORMANN et al. 2013), and the Variance Inflation Factor (VIF) of the variables at maximum 50. While a stricter condition has been suggested earlier, i.e. setting at maximum 10, see BELSLEY (1991), HAIR et al. (1995), newer literature suggest less strict rules regarding VIF, while keeping CN<30 (O'BRIEN 2007, CHENNAMANENI et al. 2016). Pairwise relationships of the variables were tested with Pearson correlation. The variables remaining after the selection process are listed in detail in Tab 3.

Table 3. Explanatory variables used in the analysis

Variable name	Description	Source/calculations
Bioclimatic variables		
BIO3	Isothermality (Ratio of Mean Diurnal Range and Temperature Annual Range)	CarpatClim-Hu and NAGiS
BIO4	Temperature Seasonality (standard deviation *100)	
BIO5	Max Temperature of Warmest Month	
BIO6	Minimum Temperature of the Coldest Month	
BIO15	Precipitation Seasonality	
BIO18	Precipitation of Warmest Quarter	
BIO19	Precipitation of Coldest Quarter	
Soil characteristics		
Svac	Presence of very acidic (pH < 5.6) soil within a hexagon	DOSoReMI
Sac	Presence of acidic (pH in 5.6–6.6) soil within a hexagon	
Sne	Presence of neutral (pH in 6.6–7.6) soil within a hexagon	
Sal	Presence of alkaline (pH in 7.6–8.6) soil within a hexagon	
Sval	Presence of very alkaline (pH > 8.6) soil within a hexagon	
Ssa	Maximum of sand fraction ratio of the top (0–30 cm) soil layer within a hexagon	
Scl	Maximum of clay fraction ratio of the top (0–30 cm) soil layer within a hexagon	
Soc	Mean organic matter content within a hexagon	
Sda	Mean depth of ground water level within a hexagon	
Srn	Minimum of rooting depth within a hexagon	
Srx	Maximum of rooting depth within a hexagon	
Hydrology		
Dla	Distance to the closest lake	Digitized vector layers
Dri	Distance to the closest river	
Dst	Distance to the closest stream	
Dca	Distance to the closest canal	
Dnw	Distance to the closest non-built (natural) water body of any type (lake, river, stream)	
Dwa	Distance to the closest water body of any type (lake, river, stream, canal)	
Topography		
TPI	Standard deviation of the Topographic Position Index (TPI) within a hexagon	Digital Elevation Model from NAGiS

Presence-absence of each habitat considered was related to the explanatory variables with the help of Gradient Boosting Models (GBMs) in the R statistical environment (R Development Core Team 2013) using the gbm package (Ridgeway 2015). We chose GBMs because they are flexible regarding response curves, decide on explanatory variables retained in the model based on cross-validations rather than the much criticised Akaike Information Criterion (AIC) and proved to be reliable from several aspects in ecological modelling (Bühlmann and Hothorn 2007, Elith et al. 2006).

In our calculations, we followed the analysis sequence described in Elith et al. (2008) and used the code they supplied with their paper with a few changes. One of these was that the high amount of data allowed us to first split the data for each habitat randomly into training and evaluation datasets and build the GBMs using the former only. The splitting was stratified for prevalence; i.e equal presence/absence ratio was insured in the two datasets. Personal experience also made us set two other parameters differently from the original suggestions: the tree complexity to 3 and the bag fraction to 0.5. Since the optimal learning rate (a third parameter to be specified manually for GBMs) depends on prevalence we set this to different levels according to the ratio of presences applying to the different habitats. Thus we selected learning rates between 0.008 and 0.1 automatically based on prevalence – a range appearing also reasonable in Elith et al.'s (2008) experiments, but more importantly this way we achieved a number of trees per model between 1000 and 10 000 (the mean of the number of trees across models was 4800). This also complies with Elith's et al.'s (2008) warning that the number of trees per model should be above 1000. Learning rates were increased/decreased iteratively and the models were rebuilt with new learning rates in case of too high / too low number of trees.

Models were also simplified, i.e. unimportant variables were dropped from the model using methods analogous to backward selection in GLM. Here we also followed Elith et al. (2008). Model performance was assessed by the well-established Area Under the Receiver Operating Characteristic (ROC) Curve (AUC, Swets 1988). The ROC curve relies on the inspection of contingency table of matches between predticted presences and absences vs. observed presences and absences at any possible cutpoints along the probability values of the predictions (Table 4, Figure 3). The higher the curve runs in the coordinate system defined by the True Positive Rate (TP/TP+FP) and 1-False Postivie Rate (1-(FP/(FP+FN)) the better the prediction is. Therefore a higher Area Under the ROC curve (AUC) represent a better prediction and thus a better underlying model.

For climate sensitivity assessment we used both the variable structure directly as well as the relative variable importance supplied by the GBM.

Table 4. Confusion matrix of matches and mismatches of prediction and observations
TPR = TP/(TP+FN); FPR = FP/(FP+FN).

		Prediction	
		1	0
Observation	1	True positive-TP	False Positive- FP
	0	False Negative- FN	True Negative-TN

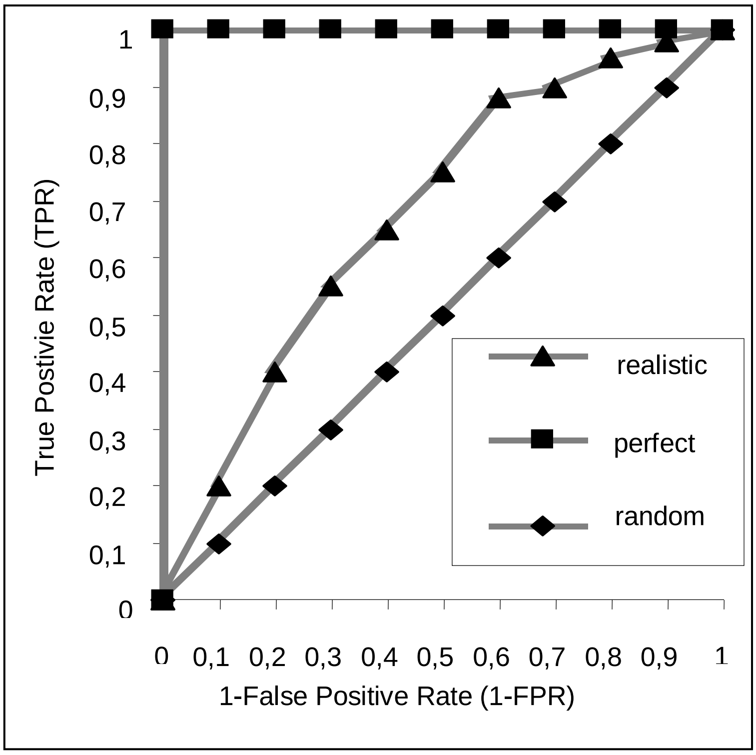

Figure 3. The ROC curve for two extreme and a realistic settings.
"Perfect" – predicted probabilities exactly match orbservations,
"random" – predictions no better than in the random case,
"realistic" – one actual case from the practice. For TPR and FPR consult Table 4

2.2 LANDSCAPE ECOLOGICAL ANALYSIS

The adaptive capacity (AC) of habitats to climate change can be estimated from the landscape structure they are embedded in. Thus the estimation of AC is carried out through landscape ecological analysis. According to the IPCC definition, adaptation is 'the ability of a system to adjust to climate change (including climate variability and extremes) to moderate potential damages, to take advantage of opportunities, or to cope with the consequences' (IPCC 2007, Glossary). In the case of ecosystems, adaptation is predominantly autonomous adaptation, which 'does not constitute a conscious response to climatic stimuli but is triggered by ecological changes' (IPCC 2007, Glossary). Consequently, adaptation includes not only genetic evolutionary adaptation, but also any systemic adjustment processes: local resilience, refugium-based adaptation and migration-based adaptation (CZÚCZ et al. 2011).

Due to the lack of species-level data at such a wide range of habitats as well as due to the theoretical complexity of integrating them (even if they were at hand) at so large numbers as they occur in natural habitats, we excluded the investigation of genetic adaptation capacity. However, we included the other three mechanisms of adaptation.

Local resilience is best estimated by the naturalness of the landscape (COOK 2002, CZÚCZ et al. 2012), from which we choose the Natural Capital Index. Natural Capital Index is expressed as the product of ecosystem quality and quantity (Figure 4)

$$NCI = ecosystem\ quality \times ecosystem\ quantity = q.a$$

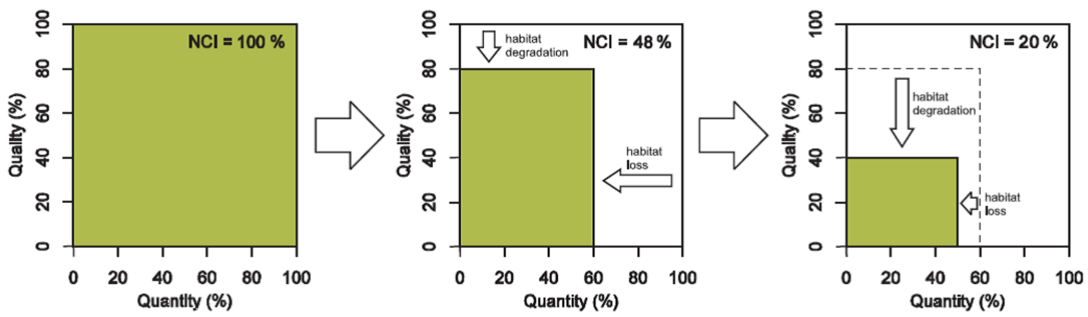

Figure 4. A geometric representation of the Natural Capital Index

Refuge-based adaptation is the more successful the more heterogeneity of the landscape is present, therefore this aspect is quantified by diversity indices (CZÚCZ et al. 2011). We choose the widespread Shannon-diversity to quantify this aspect. Habitat frequencies within a NAGIS square were used as input, thus resulting in an estimate of habitat diversity of the square.

Migration-based adaptation relies on the quantification of the connectivity of the landscape. There is a wide variety of landscape connectivity assessment options. A major dichotomy exists along whether the indices reflect structural or functional features of the landscape. Among the former, several measures are based on the presence of corridors, others on distances, on graph theory also accounting for transversability. There are measures based on the amount of habitat in the landscape, too, which can also be extrapolated towards percolation-related measures. Connectivity indices reflecting functional aspects of the landscape often rely on the probability of moving and use matrix permeability as well (KINDLMANN and BUREL 2008).

As our study involves habitats, rather than individual organisms, functional connectivity indices would not be appropriate. The many constituting species likely have different functional requirements, e.g. matrix permeability. On the other hand the structural aspect of connectivity can be useful because the proximity of similar patches, the presence of corridors and other landscape elements can enhance the migration of various constituent species of the habitat, even if to a different degree per species. Therefore we quantified the migration-based AC by an index based on Euclidean distance (Czúcz et al. 2011) accommodated to presence-absence data.

$$C_i = \sum_{j \mid D_{ij} < D_0} A_j e^{-\alpha D_{ij}}$$

where Ci is the landscape connectivity measured at hexagon i – or, more precisely, the contribution of hexagon i to the overall landscape connectivity, which also reflects the relative position (embeddedness, isolation) of patch I within the landscape network. Ci is measured as the frequency of patches of similar habitat type within the search distance from the focal patch weighted by an exponential distance kernel. Accordingly, D0 is a predetermined search distance, Dij is the distance of the nearby patch j from the focal patch (where Dij<D0). In the original fomrula Aj is the area of the

patch, however, as only use habitat presences this parameter is set to 1 in our case. α is an appropriately chosen dispersal parameter. The indicator can be fine-tuned with the help of this parameter, which should reflect the dispersal ability of the modelled species, or species groups. The search distance should be large enough to contain the bulk of the quickly decaying exponential kernel. Based on CZÚCZ et al. (2011) we set α to 0.5 km-1 and D0 to 1 km.

Each of the three indices were rescaled into a 5-category oridnal scale. The first two were rescaled evenly between the minimum and maximum, the third was rescaled using the boundaries that emerged from the simulations of CZÚCZ et al. (2011). The maximum of these indices was taken as the AC of the habitat in question in a specific spatial unit (NAGIS square or settlement boundary).

2.3 IDENTIFYING CLIMATE SENSITIVE HABITAT TYPES

We used the bioclimatic models for the identification of climate sensitive habitat types. GBM models offer the possibility of automatic variable selection. Boosting makes the model structure equivalent whether it starts on classification and regression trees or generalised linear models. However, during boosting a full model including all the candidate explanatory variables is never built, but short trees/linear models are constructed. The final response curve of the modelled entity is constructed from a large number of such submodels. Variable selection in GBM relies on the frequency of explanatory variables in these trees in an iterative process (cross-validation). GBM provides an estimation of variable importance for variables remaining in the simplified models according to their loadings (i.e. their degree of inclusion into the submodels). This measure helps to assess how influential a variable is. Thus, relative importance can serve as an indicator of climate sensitivity.

2.4 ASSESSING VULNERABILITY

The first step to assess vulnerability is to quantify the potential impact (PI) of climate change on the distribution of the 12 climate sensitive habitats. PI was defined as the difference between the probability of potential presence of the habitat in the future and that in the reference period. To assess PI, the habitat models were applied to the current and future environmental settings given both time periods and climate models separately. Thus PI is available in four combinations for each of the habitats investigated (2 periods × 2 climate models). It ranges from –1 to 1 with –1–0 representing positive impact of climate change on the habitat, while 0-1 represents negative potential impact. This representation was chosen so that the target of this study, the negative climate impact receives large values. PI was first calculated at the MÉTA hexagon level, then estimations were generalised both at the NAGIS pixel level, as well as for each settlement. In the course of generalisation the highest PI value assigned to a hexagon falling within the spatial unit was assigned to the spatial unit (NAGIS pixel or settlement).

Vulnerability (V) depends both on PI and adaptive capacity (AC). The larger the PI is, the more vulnerable the habitat is. This can be mitigated with high AC. During our vulnerability analysis we concentrated on the detrimental effects of climate change only, therefore only positive PIs (high, unfavourable climate impact) were considered. Thus we calculated the vulnerability of a single habitat as

$$V = PI \times (5 - AC)$$

multiplying any positive, but only positive values of PI by the “lack of adaptation capacity” defined as 5–AC, so that high AC appears as 1 and lowest AC appears as 5. This ensured that lower AC leads to higher V. We assessed vulnerability at the spatial unit levels for the NAGIS database (NAGiS square or settlement boundary). For this value we took the highest value of habitat vulnerability within the spatial unit. Values were calculated separately for climate models and periods in the future.

3 RESULTS AND DISCUSSION

3.1 INTERPOLATED CLIMATE SURFACES

The first results are climate surface interpolations (Figures 5–8). In comparison with the original CarpatClim-Hu data the interpolated surfaces are smoother; however some outliers are not captured. Such outliers are more common in the case of temperatures (Figures 5–6) and within that dataset in winter months (e.g. Figure 5). Nonetheless, the interpolation appears successful in general and was therefore further used in the modelling.

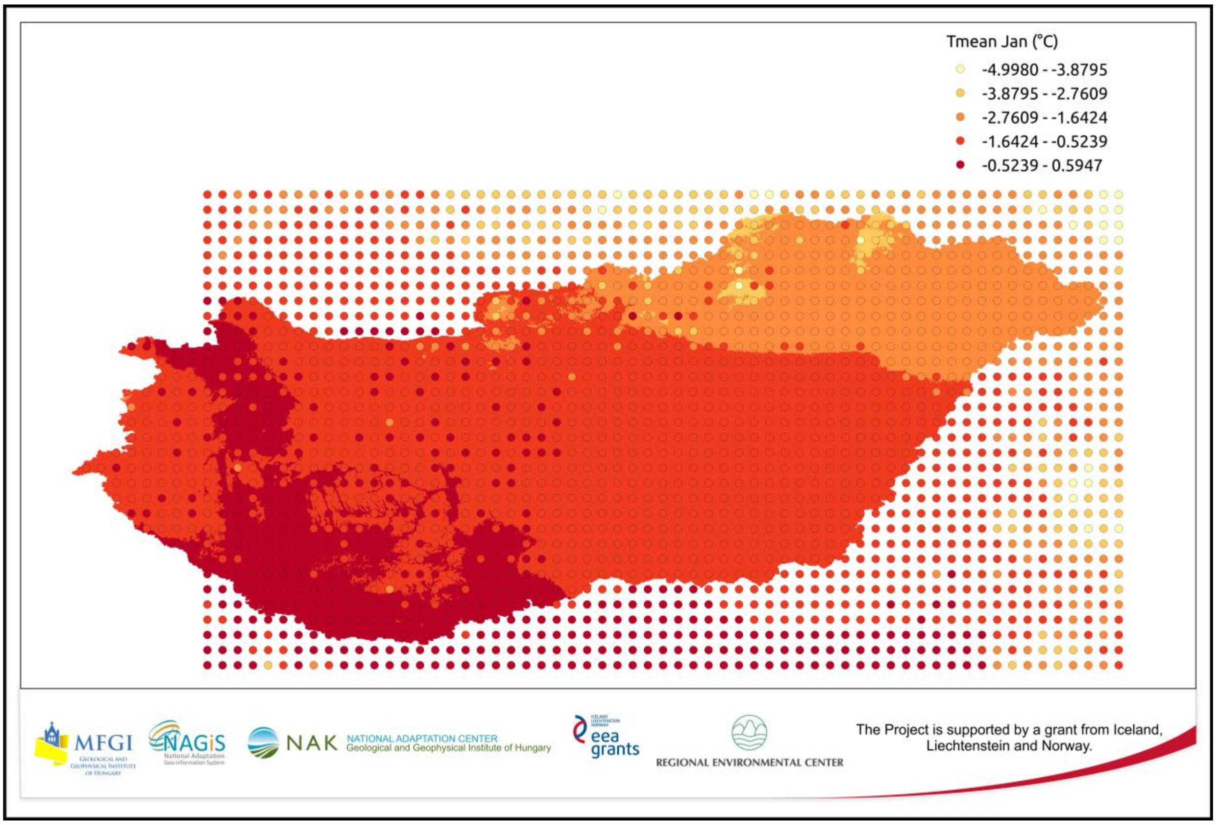

Figure 5. Comparison of CarpatClim-Hu data and interpolation by regression kriging. Average temperature 1977–2006, January. Projection used: World Geodetic System 1984 (WGS 84), the figure was prepared in Quantum GIS 2.10 software

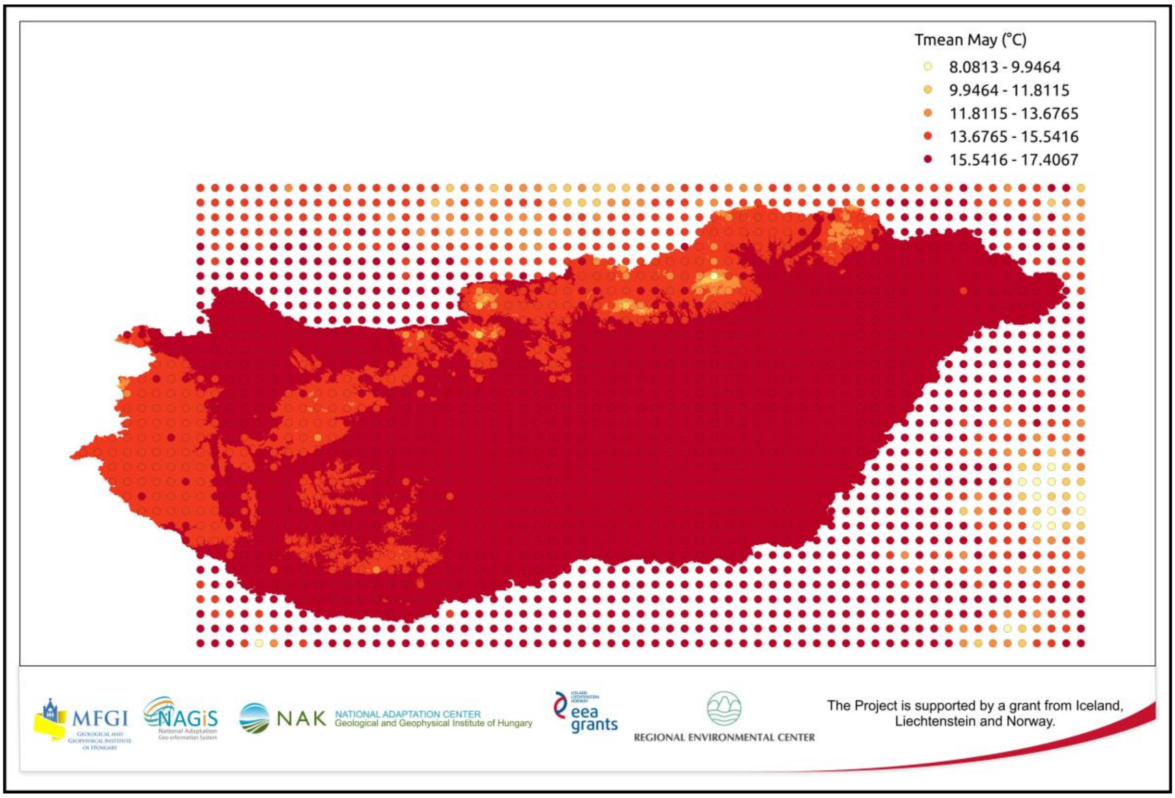

Figure 6. Comparison of CarpatClim-Hu data and interpolation by regression kriging. Average temperature 1977–2006, May. Projection used: World Geodetic System 1984 (WGS 84), the figure was prepared in Quantum GIS 2.10 software

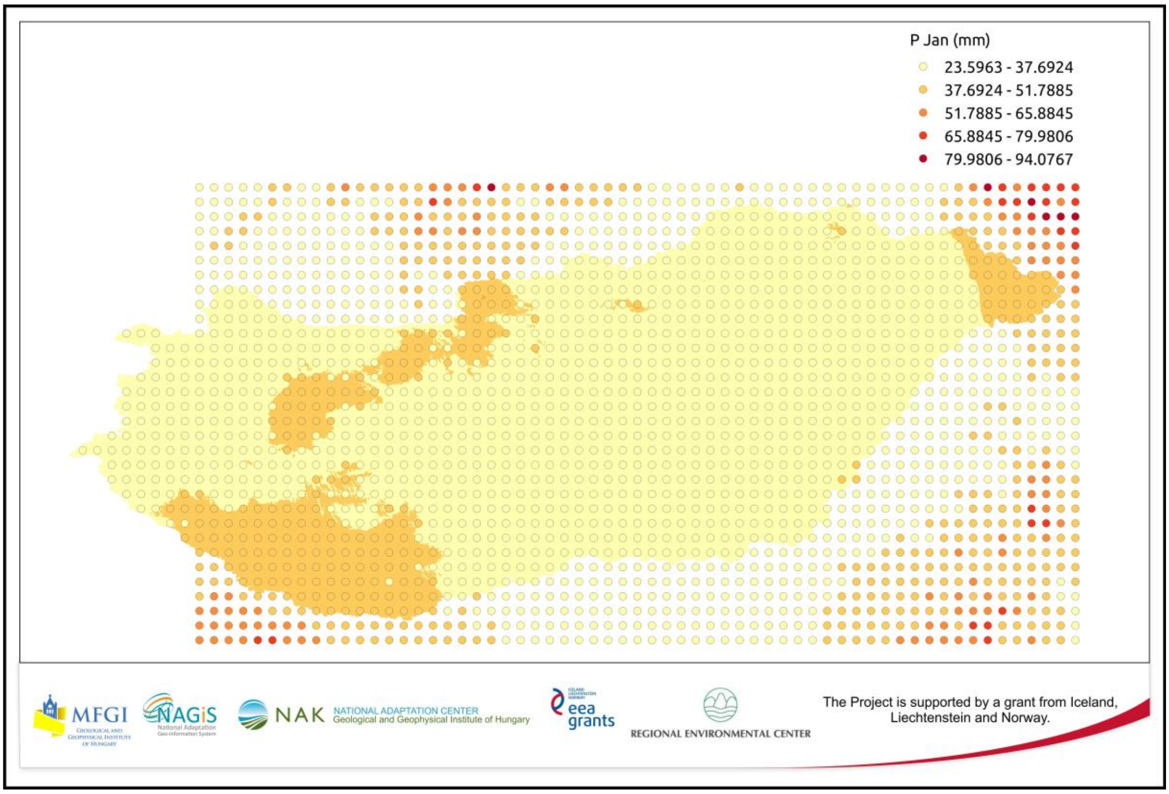

Figure 7. Comparison of CarpatClim-Hu data and interpolation by regression kriging. Mean monthly precipitation 1977–2006, January. Projection used: World Geodetic System 1984 (WGS 84), the figure was prepared in Quantum GIS 2.10 software

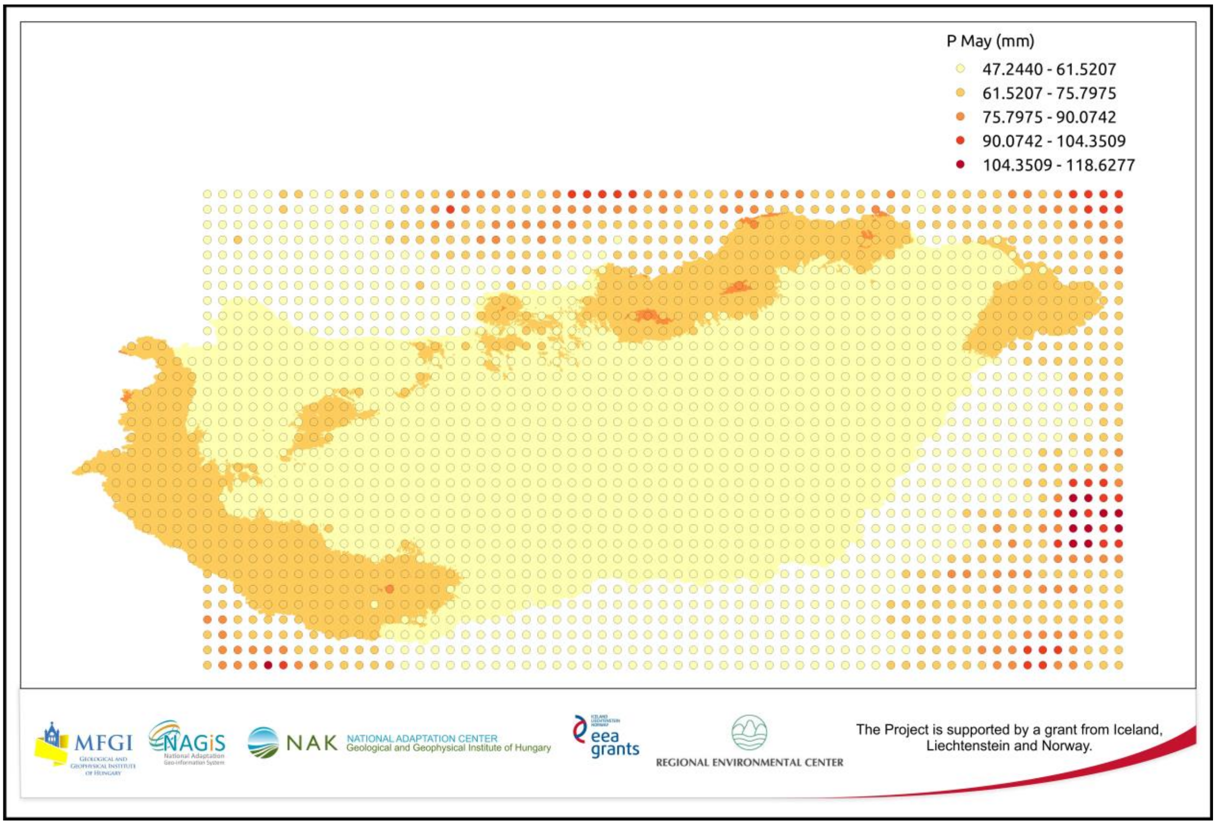

Figure 8. Comparison of CarpatClim-Hu data and interpolation by regression kriging. Mean monthly precipitation 1977–2006, May. Projection used: World Geodetic System 1984 (WGS 84), the figure was prepared in Quantum GIS 2.10 software

3.2 CLIMATE SENSITIVE HABITAT TYPES

According to the AUC measure, our models performed excellent (Tab. 5, see Swets 1988). Only the model of tussock sedge communities (B4; 0.83) and continental deciduous steppe thickets (M6; 0.89) performed lower than 0.9 AUC. The mean AUC was 0.95 across models. Consequently, we can be confident in interpreting our models.

Based on the relative importance of climate related variables compared to other variables retained in the simplified models (Table 6), the twelve most climate sensitive habitats (CSH) are mixed coniferous forests (N13), mixed forests of slopes and screes (LY2), annual salt pioneer swards of steppes and lakes (F5), beech woodlands (K5_K7a), oligotrophic reed and Typha beds of fens & floating fens (B1b), closed lowland steppe oak woodlands (L5), closed steppes on loess, clay, tufa (H5a), steppe oak woodlands on foothills and on loess (L2x_M2), Turkey oak woodlands (L2a_L2b), forest steppe meadows (H4), willow mire shrubs (J1a), and oak-hornbeam woodlands (K1a_K2_K7b). In all of these, the relative importance of climate variables were at least 55% of all variable importance (100%). We conduct the further analysis using these habitats. All further figures have been plotted in the R statistical environment using the Hungarian Unified National Projection (EOV; EPSG Spatial Reference System Identifier: 23700).

Table 5. Model performance according to the Area Under the ROC Curve (AUC) measure (see also Figure 2)

Habitats	AUC
B1a	0.908655
B1b	0.957458
B4	0.825739
B6	0.951257
F1a	0.975977
F2	0.976988
F4	0.961804
F5	0.954928
G1	0.978997
G2	0.97248
G3	0.955517
H1	0.933013
H2	0.977884
H3a	0.953303
H4	0.932601
H5a	0.930552
H5b	0.973943
J1a	0.918826
J2	0.920672
J5	0.948344
J6	0.964838
L5	0.978275
LY1	0.949829
LY2	0.953719
LY3	0.981422
LY4	0.972972
M3	0.956832
M4	0.942875
M5	0.979099
M6	0.888373
M7	0.946805
N13	0.993994
J3_J4	0.986159
K1a_K2_K7b	0.951151
K2_K7b	0.959395
K5_K7a	0.972385
L1_M1	0.962648
L2a_L2b	0.950084
L2x_M2	0.954412
L4a_L4b	0.953398

Table 6. Modelled habitats ordered according to the relative importance of climate predictors in their models. Number and relative frequency of climate predictors are also shown. Habitats selected for further analysis are typed bold

Habitat codes	No. of climate variables	Frequency of climate variables	Relative importance of climate variables
N13	**2**	**1**	**1**
LY2	**2**	**0.67**	**0.75**
F5	**4**	**0.67**	**0.67**
K5_K7a	**7**	**0.44**	**0.62**
B1b	**6**	**0.6**	**0.61**
L5	**7**	**0.5**	**0.6**
H5a	**7**	**0.41**	**0.6**
L2x_M2	**7**	**0.47**	**0.6**
L2a_L2b	**7**	**0.44**	**0.59**
H4	**7**	**0.47**	**0.58**
J1a	**6**	**0.46**	**0.58**
K1a_K2_K7b	**7**	**0.47**	**0.55**
J6	7	0.58	0.54
M7	1	0.5	0.53
LY4	6	0.5	0.53
F2	6	0.46	0.52
F1a	5	0.5	0.52
J5	7	0.5	0.52
B6	6	0.4	0.52
F4	5	0.5	0.52
J2	6	0.5	0.51
M6	4	0.44	0.5
B4	3	0.43	0.49
H2	6	0.4	0.47
LY3	4	0.5	0.46
K2_K7b	7	0.41	0.42
G2	3	0.38	0.42
L1_M1	7	0.47	0.41
L4a_L4b	5	0.38	0.39
H3a	5	0.42	0.39
G3	3	0.43	0.37
M5	3	0.38	0.34
B1a	6	0.33	0.31
H5b	6	0.43	0.31
J3_J4	7	0.5	0.3
LY1	2	0.4	0.29
G1	6	0.43	0.28
M3	1	0.14	0.17
H1	0	0	0
M4	0	0	0

All 7 climate predictors were included in the final models of K5_K7a, L5, H5a, L2x_M2, L2a_L2b, H4, and K1a_K2_K7b. The model of B1b and J1a lacks one climate predictor only: isothermality and precipitation of the coldest quarter, respectively. F5 has four climate predictors, while N13 and LY2 have 2 climate predictors. The model of LY2 includes one non-climatic predictor only (TPI), while the model of N13 is completely climate dependent. Both of the latter models include the “precipitation of coldest quarter” variable. Table 7 provides the relative importance of explanatory variables for the habitats selected for further analyses.

Table 7. Predictor structure and relative importance of explanatory variables in models of the most climate sensitive habitats

Habitat codes	N13	LY2	F5	K5_K7a	B1b	L5	H5a	L2x_M2	L2a_L2b	H4	J1a	K1a_K2_K7b
Svac												
Sac												
Sne												
Sal												
Sval												
Scl				1.3	7.7	5.8	5.4		2	6.4	4.9	
Ssa				2		4.5	5		4.7	4	8.8	3.1
Soc				2.1	14.3		5.9	4.2	2.7		7.2	1.6
Srn			24.5	0.8		5.5	3.1	3.5	3.2	6	4.8	2.5
Srx				1.2		7.7	2.7	3.1	3.9	4.3	3.8	3.5
Sda				1.1		5.5	4.4	5.9	12	8.1		2.4
Dca				2.1	7.5		3.1	8.4	5	5		2.5
Dri			8.8	1.3			4.1				8.7	2.2
Dst							3					
Dla					9.1			3.1			4.1	
Dnw						2.9						
Dwa								5.7	2.6	3.4		
TPI		24.9		25.7		7.6	2.8	6.3	5.2	4.6		26.9
BIO3				2.3		13.2	3.9	8.5	3.9	6.5	8.8	2.9
BIO4			15.3	26.4	10.8	8.9	13	14.8	11.9	7.7	9.7	11.6
BIO5		53	18.5	26	7.1	3.8	22.8	6.3	21.2	6.3	7.3	9.4
BIO6			17.6	1.7	15.1	10.6	6.6	6.4	4.3	5.9	16.9	3.7
BIO15			15.3	2.2	9.1	10.3	4.3	7	5.3	13.7	7.7	4.4
BIO18	37.6			2	11.5	4.3	5.5	12.1	8.6	11.9	7.4	20.6
BIO19	62.4	22.1		2.1	7.7	9.4	4.4	4.6	3.4	6.2		2.7

3.3 POTENTIAL IMPACT

As expected the potential impact is predominantly negative on CSHs (Table 8). Forest types identified as CSHs are likely to be negatively affected (Figure 9). The exception is L5, where climate models highly disagree regarding the outcome. A similar pattern emerged for forest steppe meadows (H4). Results for these two habitats have to be handled with care therefore. The two wetland types are likely to benefit at least partially from climate change. The most likely reason for this is an increased winter precipitation with climate change. Loess steppes (H5a) also have the potential to benefit from climate change. A benefit is especially striking for annual saline vegetation (F5), which is in good accordance with its adaptation to soil salinity, typical for arid climates (Figure 10).

PI estimations have been produced both for the NAGIS grid and settlements (for an example see Figure 11). The former have been delivered to the online system, the latter is given in Appendix 1.

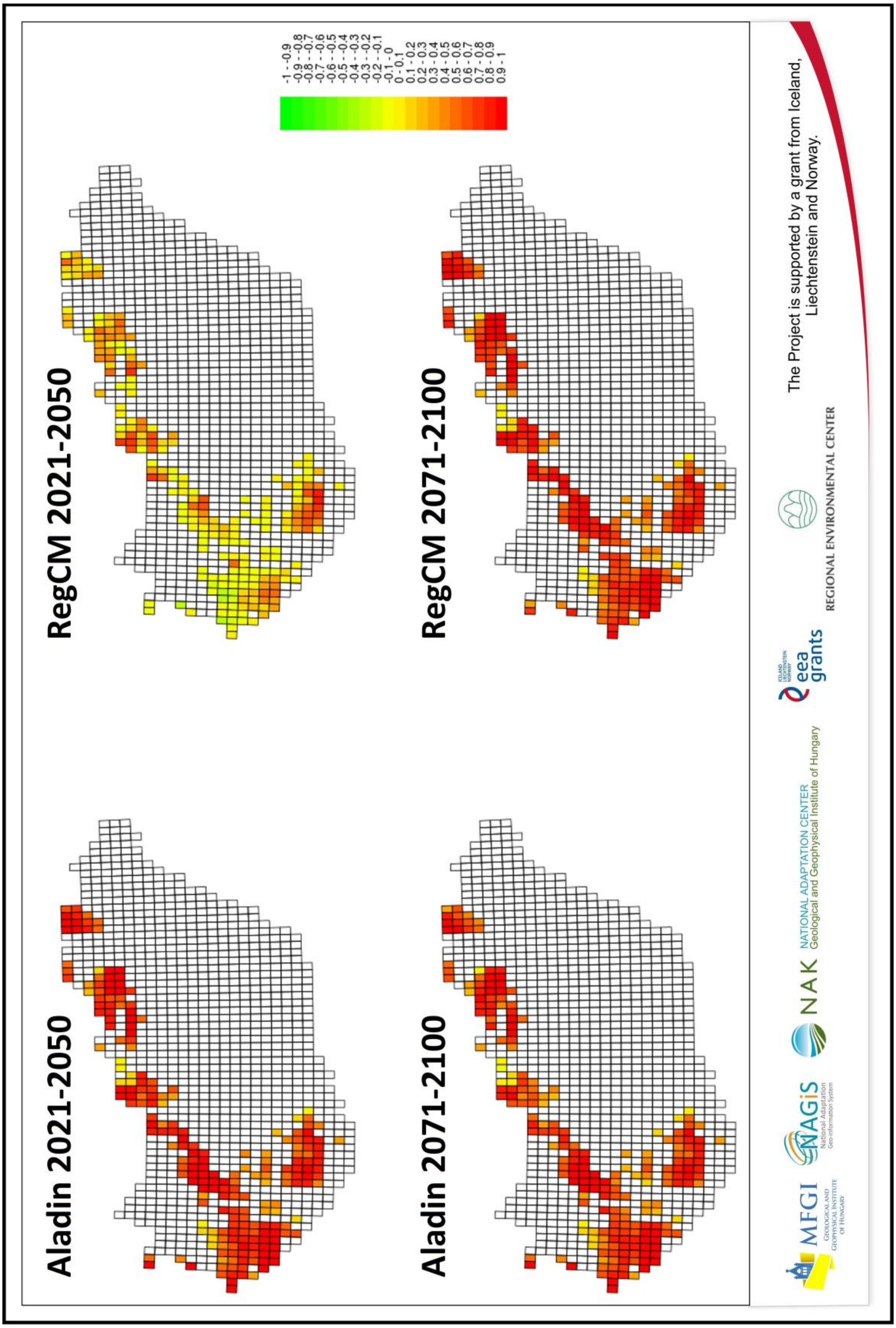

Figure 9. Potential impact (PI) of climate change to existing stands of beech forests (K5_K7a) – aggregated for NAGIS squares. Subfigure titles refer to the climate model and the future period in relation to which PI was examined. Unfavourability of PI increases from green to red

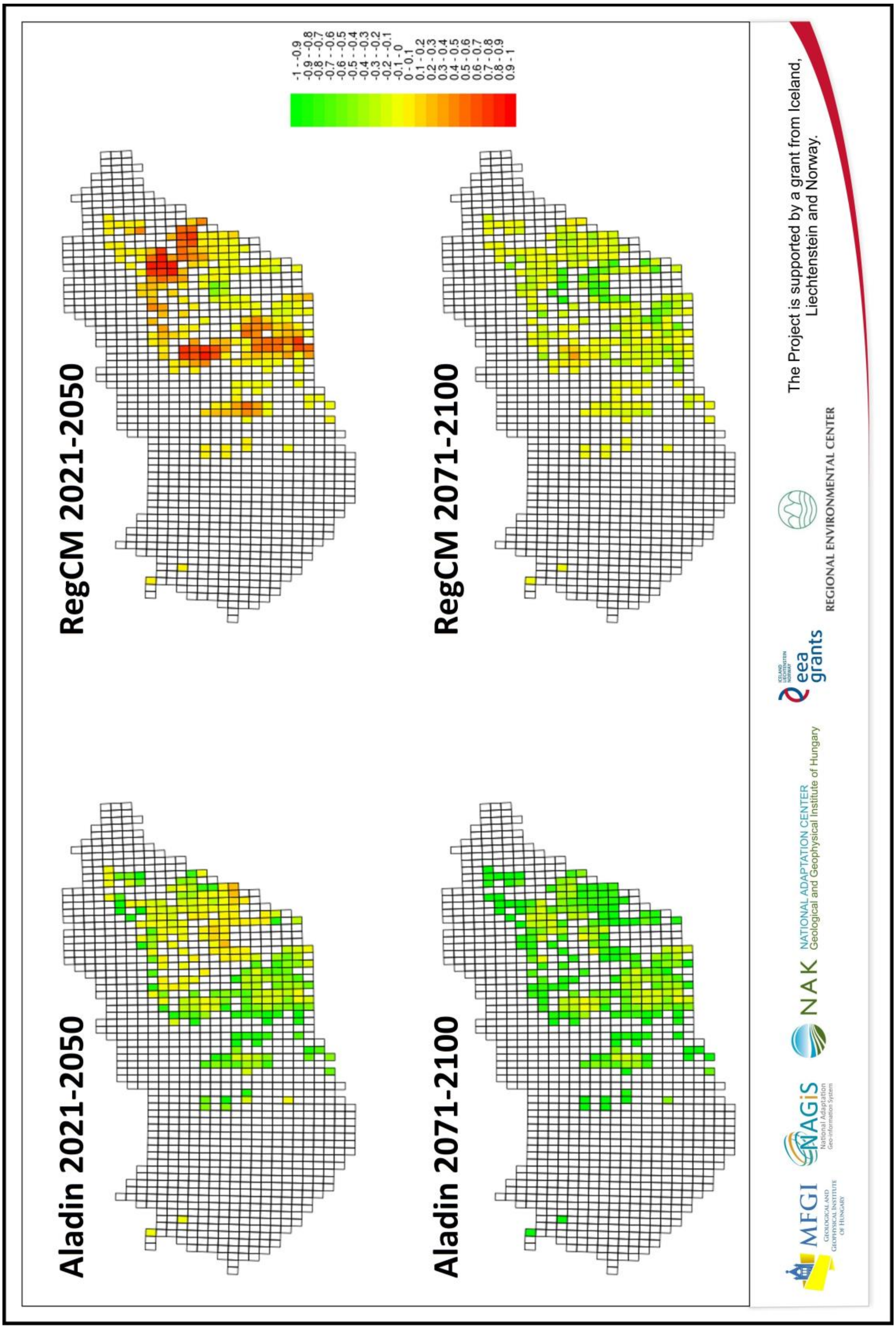

Figure 10. Potential impact (PI) of climate change to existing stands of annual salt pioneer swards of steppes and lakes (F5) – aggregated for NAGIS squares. Subfigure titles refer to the climate model and the future period in relation to which PI was examined. Unfavourability of PI increases from green to red

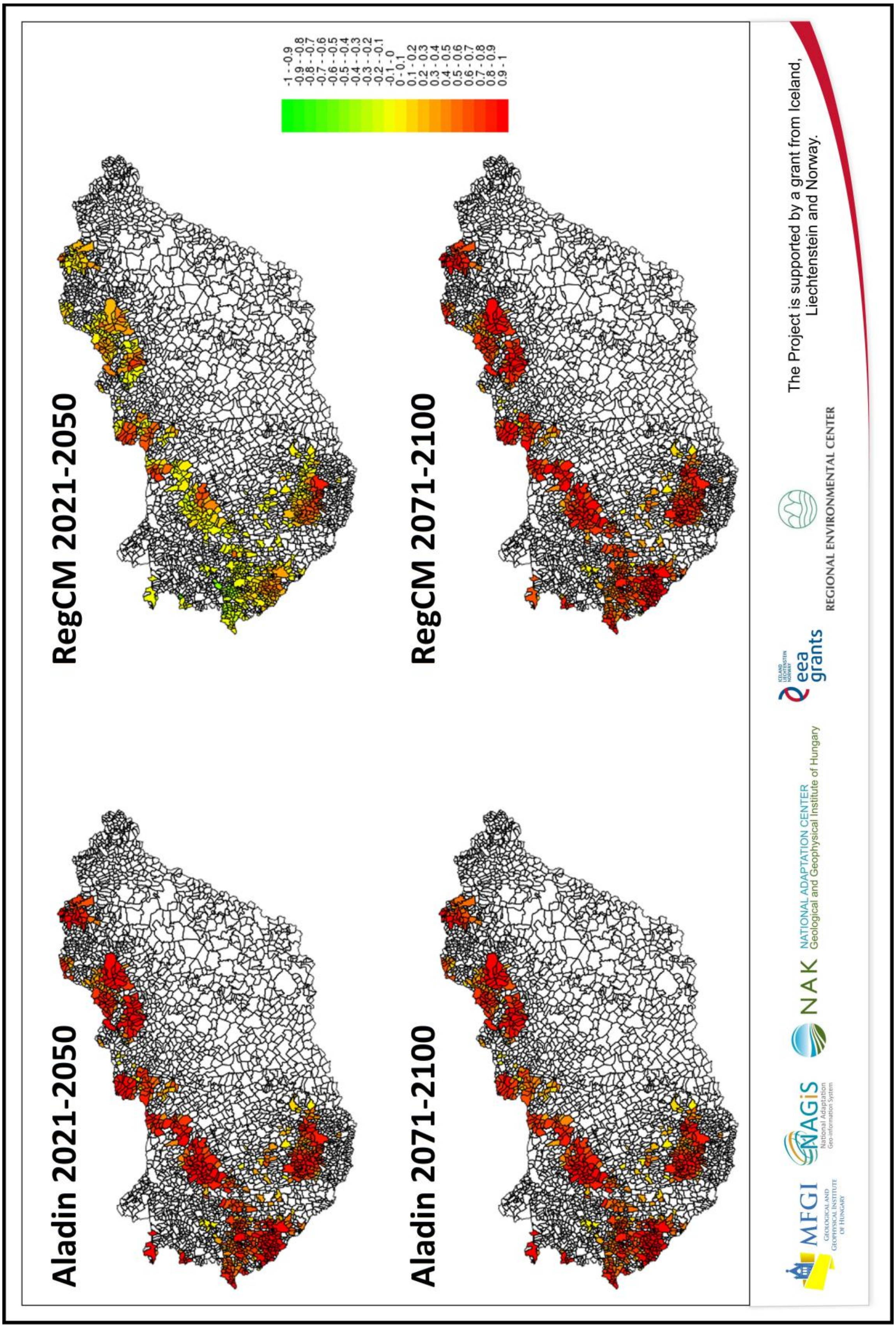

Figure 11. Potential impact (PI) of climate change to existing stand of beech forests K5_K7a – aggregated for settlement boundaries. Subfigure titles refer to the climate model and the future period in relation to which PI was examined

Table 8. Potential impact (PI) of climate change on the most climate sensitive habitats. The table summarizes the spatial pattern of potential impact within the country. We also indicate if any conflict between predictions of climate models has been identified and if a change in trends was discernible between the two periods

Period	21–50		71–50			
Climate model	ALADIN-Climate	RegCM	ALADIN-Climate	RegCM	Conflict	Trend change
N13	Negative				No	No
LY2	Negative				No	No
F5	positive or neutral	mostly positive, sometimes negative	positive or neutral		No	No
K5_K7a	Negative				No	No
B1b	negative at the edges, positive in the centre		negative in the West, positive elsewhere		No	Yes
L5	Neutral or positive in the East, negative in the West	Negative	neutral, sometimes positive	neutral or negative	Yes	Incon-sistent
H5a	Variable, but positive in the East	Variable, but negative in the East	positive or neutral		Yes	Incon-sistent
L2x_M2	Negative				No	No
L2a_L2b	Negative, neutral in the South				No	No
H4	neutral or negative	positive	Positive in Central Hungary, neutral or negative elsewhere	Variable, negative in Eastern Hungary	Yes	Yes
J1a	Negative in the East, neutral or positive in the centre		positive or neutral		No	Yes
K1a_K2_K7b	Negative				No	No

3.4 *ADAPTIVE CAPACITY*

Many of the CSHs are zonal and widespread types and thus have relatively high AC, which has the potential to greatly mitigate the PI (Tab 9). Most widespread zonal habitats, such as oak-hornbeam woodlands (K1a_K2_K7b), beech woodlands (K5_K7a; Figure 12), and others which form larger blocks in the current landscape have high AC in the centre of the blocks, which decreases towards the edges and reaches low AC values. Turkey oak woodlands (L2a_L2b), however, are so widespread that this pattern does not apply to it and has high AC even at the edges of its current patches, which ensures the best AC among the CSHs (Figure 13). There are habitats with variable pattern, but typically medium to high AC: B1b, L5, H5a, H4, LY2. An important aspect of the AC of loess steppes (H5a) is that there is a high AC area in the South-east of Hungary, while its AC is low in the South-west (Fig

14). It is also worth to note that relatively lower AC areas of LY2 appear aggregated North to Lake Balaton and in the Mecsek Mountains, which points out areas likely to become vulnerable. In this analysis J1a appears to be one of the types that has the lowest AC overall, which coincides with its ecology. Willow shrubs typically appear in small depressions in the landscape surrounded by other vegetation or even agricultural land. So neither its connectivity nor characteristics of its surroundings (diversity, natural capital) predestine for high AC. L5 also has low AC values, which can be attributed to the fragmentedness of this type. Opposed to J1a, L5 would not be fragmented under natural conditions, but as it is a habitat of the lowlands it became a frequent victim of human landscape transformation.

PI estimations have been produced both for the NAGIS grid and settlements (for an example see Fig. 15). The former have been delivered to the online system, the latter is given in Appendix 1.

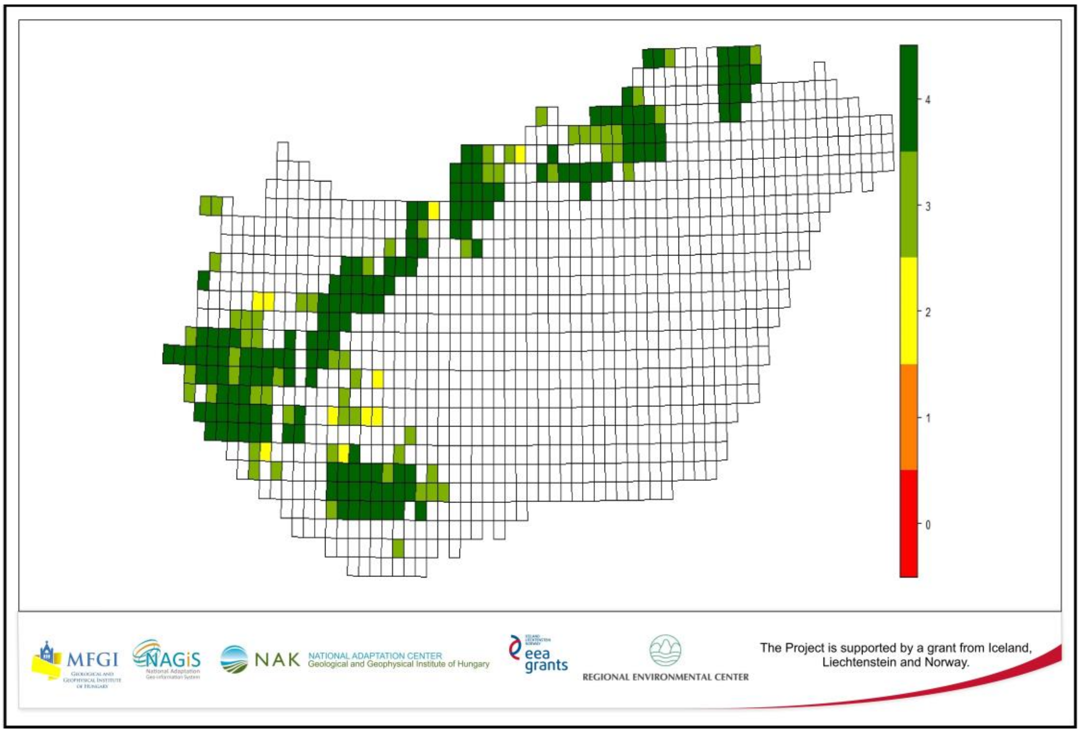

Figure 12. Adaptive Capacity (AC) of beech forests (K5_K7a) – aggregated for NAGIS squares. AC increases from 0 to 4 (red to green).

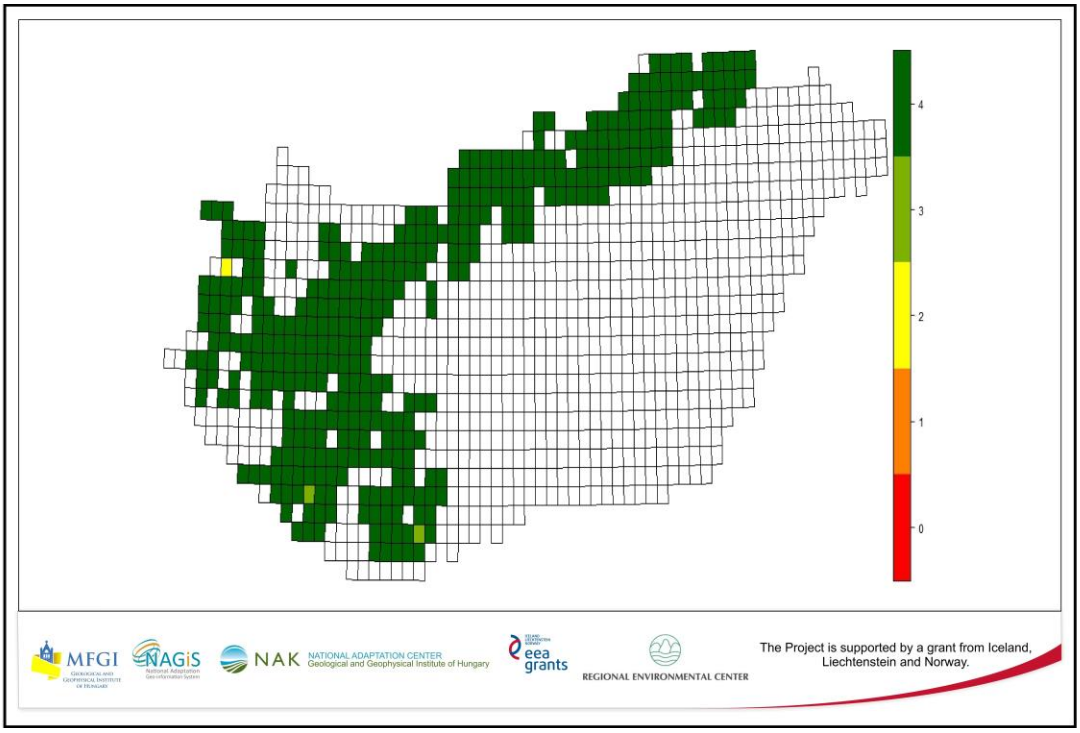

Figure 13. Adaptive Capacity (AC) of turkey oak woodlands (L2a_L2b)– aggregated for NAGIS squares. AC increases from 0 to 4 (red to green)

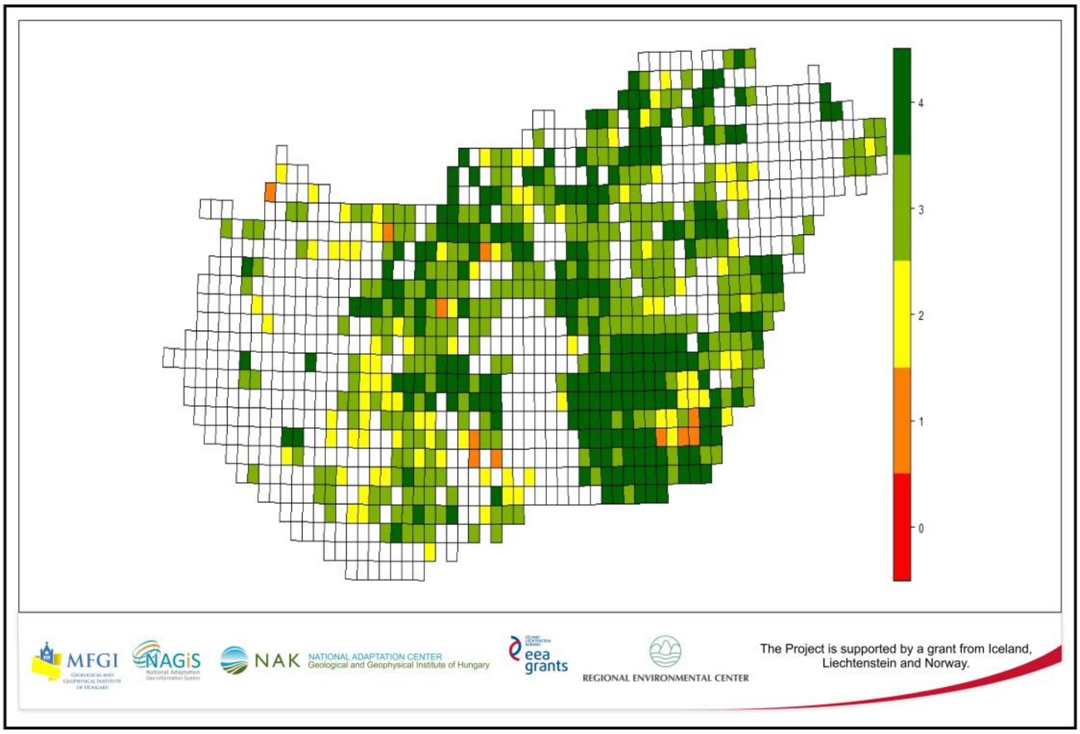

Figure 14. Adaptive Capacity (AC) of loess steppes (H5a) – aggregated for NAGIS squares. AC increases from 0 to 4 (red to green).

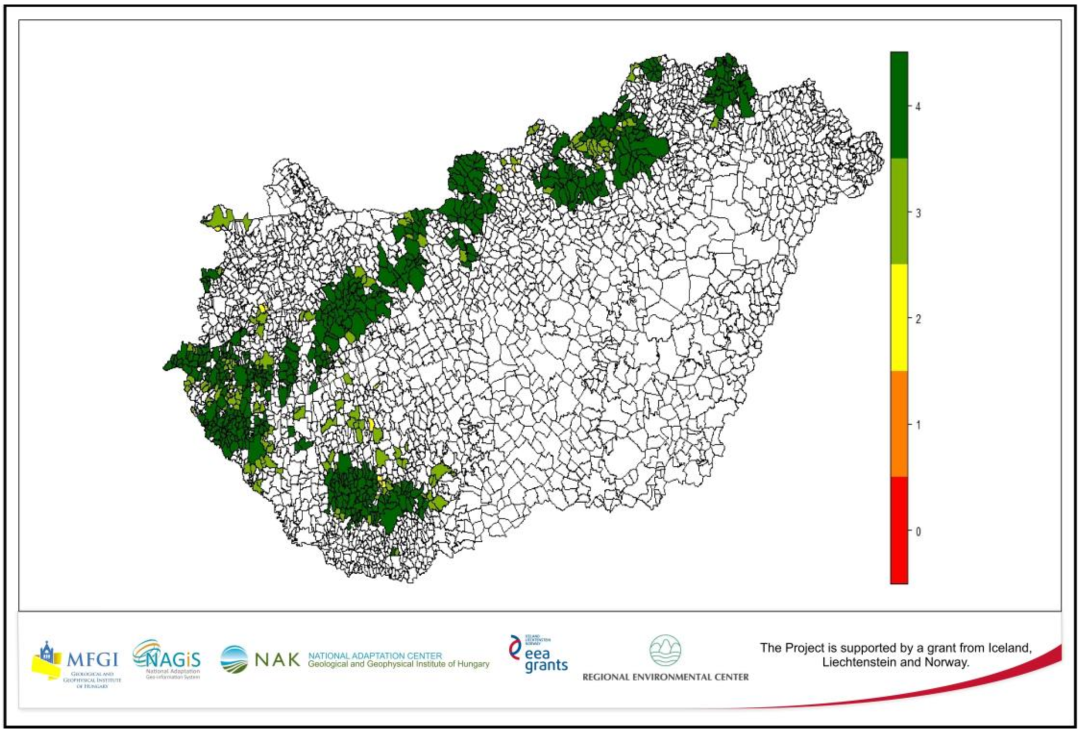

Figure 15. Adaptive Capacity (AC) of beech forests (K5_K7a) – aggregated for settlement boundaries. AC increases from 0 to 4 (red to green)

Table 9. Adaptive capacity (AC) pattern of climate sensitive habitats (CHS) within the country. A summary of spatial patterns visible in the maps resulting from the landscape analysis

Habitat codes	Adaptive capacity
N13	high in the centre of its block, low at the edges
LY2	medium North to Lake Balaton and Mecsek, high elsewhere
F5	medium to high
K5_K7a	high in the centre of its block, low at the edges
B1b	medium to high
L5	low to medium
H5a	high in southeast, low in southwest
L2x_M2	equal proportion of low an high AC locations - high AC at the foot of the Northern Medium Range
L2a_L2b	high
H4	medium to high
J1a	medium
K1a_K2_K7b	high in the centre of its block, low at the edges

3.5 VULNERABILITY

The most central part of a CIVAS assessment is quantifying the vulnerability. Vulnerability is essentially a (set of) high-level aggregated indicators, which establish a balanced information over all of the individual CIVAS components. The main goal of vulnerability is to give a quick but insightful overview of the assessment outcomes for decision makers, policy uses and the general public. As there are many valid possible policy and decision-making contexts, there is no single “default” aggregation formula or vulnerability indicator either. The construction of a vulnerability indicator and the resulting vulnerability map highly depends on the decisions taken during its construction, which should ideally be customized for a specific policy context and designed in a participatory process involving key stakeholders.

In general, vulnerability is high if PI is large and AC is low. Such considerations can take the form of expert assessment as well. For example the PI is high for beech forests almost everywhere, but AC is also high in the middle of its blocks, thus beech forests in the centre of mountains are less vulnerable to climate change than those at the margins.

The simple vulnerability index presented in this chapter is only one option, created for a general nature conservation planning context. As the rich PI and AC estimations available for each CSH made it possible, we first created a separate vulnerability indicator for each habitat type, which were aggregated into a single value using a maximum statistic. This unweighted statistic can be good for framing general policy discussions, but we encourage all users of our data sets to use custom weightings and aggregating strategies for PI and AC components tailored to their specific needs and the problem in focus.

Our formalised example also demonstrates the uncertainties of climate projections due to differences in climate models. On the other hand, an agreement between the two models shows robust results. Although RegCM shows higher vulnerability in general, long-term (2071-2100) vulnerability of natural habitats is consistent given the two climate models (Fig. 16). Natural vegetation appears most vulnerable in Western Hungary and in the Northern Medium Mountains, as well as in the easternmost corner of Hungary. This is likely in connection with forests being the dominant natural vegetation. Models disagree, however, in the degree of short-term vulnerability. While ALADIN-Climate shows a similar overall pattern to the long-term the estimations, RegCM shows considerable differences. According to the short term estimations using RegCM, vulnerability is lower in central Transdanubia and higher in the South-East part of the Great Hungarian Plain than at the long term. Additionally, to the broader pattern we see an increased vulnerability South to Lake Balaton and in the North-western areas. South to Lake Balaton, there are closed forests at the edge of their environmental tolerance; therefore they are particularly vulnerable to climate change.

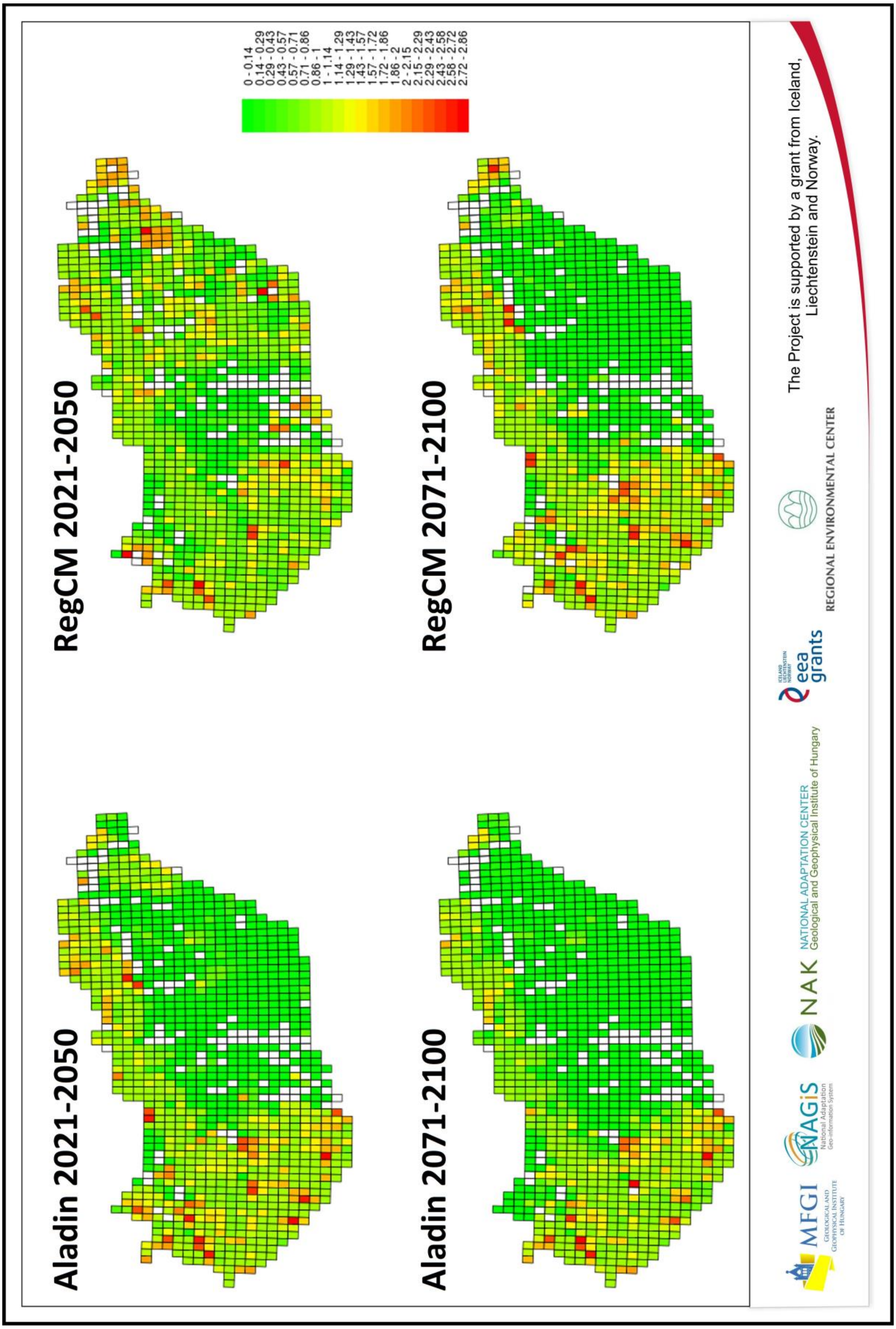

Figure 16. Overall climatic vulnerability of natural vegetation in Hungary. Subfigure titles refer to the climate model and the future period in relation to which vulnerability was examined. Vulnerability increases from green to red

4 CONCLUSIONS

The analysis presented shows that the elements of the CIVAS framework can be effectively interpreted in and adapted to specific sectorial contexts. The specific solutions (components of AC, aggregation schemes, etc.) can be used as an orientation in further similar studies. Furthermore, the entire analysis can be re-used as an embedded part of a large multi-sectoral CIVAS assessment.

The databases produced allow a wide range of applications. As most of the zonal habitats of Hungary can be found among the 12 selected climate sensitive habitats (CSH), our results give a reliable overview about the expected ecological impacts of climate change. As a general rule the modelled PI was predominantly negative for forested habitat types, but for grassland types we experienced at least partially positive predicted responses in most of the cases. This result is congruent with the expectation that Hungary, lying roughly at the biogeographic boundary between forest and steppe zones, should experience a shift towards more open habitat types. Furthermore, the natural vegetation of mountainous areas, predominantly forests, appears to be more vulnerable than that of the lowlands. This foreshadows that maintaining forests in Hungary might become more difficult and that more open habitat types may become more sustainable. It is also important to note that the lower level of modelled impacts in the lowland landscapes applies only to the natural landscape elements there (i.e. space covered by natural or seminatural vegetation). The vulnerabilty of agricultural fields or settlements can greatly differ from this pattern.

We can be most confident in estimations if the results regarding all climate periods and climate models consistently suggest reliable results. This kind of consistence was experienced for all zonal forests and two of the grasslands, for example. Estimations should be handled with care however, when climate models disagree in outcome or when trends change between the two future periods. We did experience such patterns, as well. In such cases, future research should cover more climate models and wider time periods to reduce uncertainty. On the other hand, it is important to view uncertainty as a necessary component of any climate projections, as well as the impact assessments relying on them. Uncertainty should not be considered as a shortcoming of the analysis, rather as an informative warning that the behaviour of some objects or subsystems is less predictable. This can be caused by several factors, including uncertainties in the input data, a limited understanding of system functioning, but also can be an inherent characteristic of the object in question (in our case habitats), which cannot and should not be eliminated. Informed decisions need to be aware of the sources and magnitude of uncertainties.

In accordance with the considerations above, we supplied estimations on PI and AC in a very detailed way for the NAGIS database. Most predictive distribution models used in climate impact studies are only evaluated at locations where the species / habitats studied are (or used to be) present. We also followed this convention, and used the model predictions to build PI values at places with existing stands of the habitat only. Similarly, AC was calculated for spatial units with existing stands. Therefore the data supplied are restricted to such spatial units and they support the answers to questions about existing stands. Regarding PI, results can be compared and custom-weighted per habitat type, climate model, and time period, thus allowing a free choice for future users (e.g. to select the time span depending on the habitat/habitats in focus). AC estimations are also available separately for each habitat. These can be used in a wide range of assessment of scientific questions and applications.

Following the policy oriented logic of the CIVAS assessment scheme we provided an aggregated headline indicator to characterize the overall vulnerability of a location with respect to climate change. This indicator is based on maximum values: the aggregated value reflects the vulnerability of the most vulnerable habitat type. This setup is appropriate for broad overviews with an underlying "is there a risk here?" type question, whereas the more detailed map layers (PI, AC) are necessary to explore the specific "risks". For those who would like to use our results in more specific scientific or policy contexts, we recommend to craft their own aggregation (vulnerability indicator) giving appropriate weights to the detailed data layers, rather than using a general, maximum-type vulnerability layer. There is no single "default" vulnerability layer, which could give a reliable answer to all possible research or policy questions. For specific questions applying to a smaller extent, expert decision relying on visual inspection of the PI and AC layers can be very effective, while for country-wide assessments we suggest to develop a structured aggregation model (e.g. multi-criteria decision analysis, MCDA) with the involvement of all relevant stakeholders.

There are several policy sectors where the results of a climatic vulnerability assessment on natural ecosystems can provide easily interpretable and relevant inputs. Major applications are expected in the field of nature conservation and restoration prioritisation, as well as in landscape evaluations. Maps from a habitat-oriented vulnerability assessment can effectively support the prioritisation of the different stands of a threatened habitat type for nature conservation. Locations which are least vulnerable to climate change are likely the ones which can be most cost-effectively conserved in their current state. On the other hand, high vulnerability does not mean that a stand should be given up by nature conservation, it rather shows that in those location a nature conservation action should take the form of promoting natural processes, i.e. the natural transformation of a stand to a less sensitive habitat or even to a habitat that endures the new climate better. Emphasis is on natural processes here, which can also be a target of conservation and may thus serve biodiversity protection, as well as ecosystem service maximisation.

For restoration and forestry planning it is also crucial to consider the future state of the location. Modern restoration theory and practice is moving away from restoring past vegetation and aims at creating self-sustainable stands (SOMODI et al. 2012, TÖRÖK et al. submitted), which maintain themselves under the actual, as well as the future climatic conditions. To this end it is important at each studied location to identify the list of habitats that find their requirements both now and in the future, and least vulnerable habitats should be selected as restoration targets. For example, according to our results beech forests (K5_K7a) seem to be relatively inappropriate to become such restoration targets, and forestry decisions may have to weight in their vulnerability at places. However, ecosystems with natural species composition and dynamics generally need less maintenance efforts and provide a more balanced portfolio of ecosystem services than artificial green spaces, thus natural habitat types should be preferred as restoration targets wherever possible.

As our analysis was designed and restricted to existing stands, our results are not fully informative for local restoration priorization purposes. However, the messages that emerged from this vulnerability analysis are useful for restoration considerations as well. Grasslands (loess steppes and saline ones) that appeared to benefit from climate change in our analysis are among the potentially most promising (sustainable and cost-effective) restoration targets. From forests, turkey oak woodlands (L2a_L2b) appear to be the best candidates, because their exceptionally high AC can hopefully balance the negative direct impacts that even this forest type seems to face.

Finally, landscape evaluation and landscape planning can benefit from the use of these layers. Any adjustment in the elements of ecological networks or green infrastructure has to consider whether the proposed change in the network will make it more or less vulnerable under climate change. Furthermore, restoration efforts may be efficiently directed to network elements with high vulnerability.

Broad-scale landscape architecture, i.e. spatial planning and regional planning, and landscape rehabilitation may gain such information from our result that enable them to be more scientifically sound and to be more prepared for potential land use conflicts. Those landscape architecture and rehabilitation projects that are informed by our results are able to reflect more on ecological processes and let the decision makers cost-effectively avoid conflicts and disasters that are somehow connected to natural patterns and processes, including infrastructure investments on vulnarable areas, policy-driven land use change (e.g. afforestation), top-down designation of nature reserve areas, etc. Recognizing the future perspectives on PI, AC, and V of (semi)natural habitats should significantly and essentially alter some widely used and non-informed landscape planning strategies.

As a general summary, we have provided detailed results for the NAGIS databases and have given an outlook on their potential use, while many other applications are possible. With our vulnerability analysis we drew the attention towards the vulnerability of Hungary's mountain regions and demonstrated a possible approach to exploring the opportunities the supplied databases provide. Future research needs to be directed towards assessing a wider range of climate scenarios, time periods and habitats as well as providing detailed analysis of the PI and AC results for questions in the field of ecology.

5 APPENDICES

Appendix 1. PI estimations for settlements in Hungary.

Appendix 2. AC estimations for settlements in Hungary. For a few settlements near the Hungarian border AC estimations were not possible, these are indicated by NA (not available).

Both appendices are supplied on a Compact Disc (CD) and are provided electronically.

6 REFERENCES

BELSLEY, D. A. 1991: Conditioning diagnostics: collinearity and weak data regression. — New York, NY, USA: Wiley.

BÖLÖNI, J., MOLNÁR, ZS. & KUN, A. (eds) 2011: Magyarország élőhelyei. A hazai vegetációtípusok leírása és határozója. — ÁNÉR 2011. MTA ÖBKI, pp. 441. (Habitats in Hungary. Description and identification guide of the Hungarian vegetation.) In Hungarian with English summary.

BREIMAN, L. 2001: Random forests. — Machine Learning 45, 5–32.

BÜHLMANN, P., HOTHORN, T., 2007: Boosting algorithms: regularization, prediction and model fitting. — Statistical Science 22, 477–505.

CARTER, T. R., JONES, R. N., LU, X., BHADWAL, S., CONDE, C., MEARNS, L. O., O'NEILL, B. C., ROUNSEVELL, M. D. A. & ZUREK, M. B. 2007: New assessment methods and the characterisation of future conditions. — In: PARRY, M. L., CANZIANI, O. F., PALUTIKOF, J. P., VAN DER LINDEN, P. J. & HANSON, C. E. (ed): Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK. 133–171.

CHENNAMANENI, P. R., ECHAMBADI, R., HESS, J. D., & SYAM, N. 2016. Diagnosing harmful collinearity in moderated regressions: A roadmap.International. — Journal of Research in Marketing. 33, 172–182

CLAVIER project: Climate Change and Variability: Impact in Central and Eastern Europe EU Framework Programme 6. — GOCE Contract Number: 037013.

COLLINS, F. C. 1995: A comparison of spatial interpolation techniques in temperature estimation. — PhD Thesis. Virginia Polytechnic Institute and State University, USA.

COOK, E. A. 2002: Landscape structure indices for assessing urban ecological networks. — Landscape and urban planning 58, 269–280.

CZÚCZ, B., TORDA, G., MOLNÁR, ZS., HORVÁTH, F., BOTTA-DUKÁT, Z. & KRÖEL-DULAY GY. 2009: A spatially explicit, indicator-based methodology for quantifying the vulnerability and adaptability of natural ecosystems. — In: FILHO, W. L. & MANNKE, F. (eds): Interdisciplinary Aspects of Climate Change. — Peter Lang Scientific Publishers, Frankfurt, 209–227.

CZÚCZ, B., CSECSERITS, A., BOTTA-DUKÁT, Z., KRÖEL-DULAY, GY., SZABÓ, R., HORVÁTH, F. & MOLNÁR, ZS. 2011: An indicator framework for the climatic adaptive capacity of natural ecosystems. — Journal of Vegetation Science 22, 711–725.

CZÚCZ, B., MOLNÁR, Z., HORVÁTH, F., NAGY, G. G., BOTTA-DUKÁT, Z., TÖRÖK, K., 2012: Using the natural capital index framework as a scalable aggregation methodology for regional biodiversity indicators. — Journal for Nature Conservation, 20, 144–152.

DORMANN, C. F. , ELITH, J., BACHER, S., BUCHMANN, C., CARL, G., CARRÉ, G., GARCÍA MARQUÉZ, J. R. , GRUBER, B., LAFOURCADE, B., LEITÃO, P. J., MÜNKEMÜLLER, T., MCCLEAN, C., OSBORNE, P. E., REINEKING, B., SCHRÖDER, B., SKIDMORE, A. K., ZURELL, D., LAUTENBACH, S. 2013: Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. — Ecography 36, 27–46.

DRYAS, I., USTRNUL, Z., 2007: The Spatial Analysis of the Selected Meteorological Fields in the Example of Poland. — In: DOBESCH, H. et al. (ed.): Spatial interpolation for climate data: the use of GIS in climatology and meteorology. 87–96. London: ISTE Ltd.

ELITH, J., GRAHAM, C. H., ANDERSON, R. P., DUDÍK, M., FERRIER, S., GUISAN, A., HIJMANS, R. J., HUETTMANN, F., LEATHWICK, J. R., LEHMANN, A., LI, J., LOHMANN, L. G., LOISELLE, B. A., MANION, G., MORITZ, C., NAKAMURA, M., NAKAZAWA, Y., OVERTON, J. M., PETERSON, A. T., PHILLIPS, S. J., RICHARDSON, K. S., SCACHETTI-PEREIRA, R., SCHAPIRE, R. E., SOBERÓN, J., WILLIAMS, S., WISZ, M. S. & ZIMMERMANN, N. E. 2006: Novel methods improve prediction of species' distributions from occurrence data. — Ecography 29, 129–151.

ELITH, J., LEATHWICK, J. R., HASTIE, T. 2008: A working guide to boosted regression trees. — Journal of Animal Ecology 77, 802–813.

FRANKLIN, J. 1995: Predictive vegetation mapping: geographic modeling of biospatial patterns in relation to environmental gradients. — Progress in Physical Geography 19, 474–499.

FRIEDMAN, J. H. 2002: Stochastic gradient boosting. — Computational Statistics & Data Analysis 38, 367–378.

GOOVAERTS, P. 1999: Using elevation to aid the geostatistical mapping of rainfall erosivity. — Catena 34, 227–242.

GOOVAERTS, P. 2000: Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. — Journal of Hydrology 228, 113–129.

HAIR, J. F. JR., ANDERSON, R. E., TATHAM, R. L., BLACK, W. C. 1995: Multivariate data analysis. — Upper Saddle River, NJ, USA: Prentice-Hall.

HARTKAMP, A. D., DE BEURS, K., STEIN, A. & WHITE J. W. 1999: Interpolation Techniques for Climate Variables. Geographic Information Systems Series 99-01. —International Maize and Wheat Improvement Center (CIMMYT).

HENGL, T., HEUVELINK, G. B. M., ROSSITER, D. G., 2007: About regression-kriging: From equations to case studies. — Computers & Geosciences 33, 1301–1315.

HEVESI, J. A., ISTOK, J. D. & FLINT, A. L. 1992: Precipitation Estimation in Mountainous Terrain Using Multivariate Geostatistics. Part I: Structural Analysis. — Journal of Applied Meteorology 31/7, 661–676.

HIJMANS, R. J., CAMERON, S. E., PARRA, J. L., JONES, P. G. & JARVIS, A. 2005: Very high resolution interpolated climate surfaces for global land areas. — International Journal of Climatology 25, 1965–1978.

HOLDAWAY, M. R. 1996: Spatial modeling and interpolation of monthly temperature using kriging. — Climate Research 6, 215–225.

HORVÁTH, F., MOLNÁR, ZS., BÖLÖNI, J., PATAKI, ZS., RÉVÉSZ, A., OLÁH, K., KRASSER, D. & ILLYÉS, E. 2008: Fact sheet of the MÉTA database. — Acta Botanica Hungarica 50, 11–34.

IPCC 2007: Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (ed: PARRY, M. L., CANZIANI, O. F., PALUTIKOF, J. P., VAN DER LINDEN, P. J. &HANSON, C. E.). Cambridge University Press, Cambridge, UK 976 p.

KINDLMANN, P., BUREL, F. 2008: Connectivity measures: a review. — Landscape ecology 23, 879–890.

KNOTTERS, M., BRUS, D. J. & OUDE VOSHAAR, J. H., 1995: A comparison of kriging, co-kriging and kriging combined with regression for spatial interpolation of horizon depth with censored observations. — Geoderma 67, 227–246.

KRIGE, D. G. 1966: Two-dimensional weighted average trend surfaces for ore-evaluation. — Journal of the South African Institute of Mining and Metallurgy 66, 13–38.

LAM, N. S. 1983: Spatial interpolation methods: a review. — The American Cartographer 10, 129–135.

LI, J. & HEAP, A. J. 2014: Spatial interpolation methods applied in the environmental sciences: A review. — Environmental Modelling & Software 53, 173–189.

LUKACS, P.M., BURNHAM, K.P., ANDERSON, D.R., 2010: Model selection bias and Freedman's paradox. — Annals of the Institute of Statistical Mathematics 62, 117–125.

LUO, W., TAYLOR, M. C. & PARKER, S. R., 2008: A comparison of spatial interpolation methods to estimate continuous wind speed surfaces using irregularly distributed data from England and Wales. — International Journal of Climatology 28, 947–959.

MCCULLAGH, P. & NELDER, J. A. 1989: Generalized Linear Models. — Chapman and Hall, London.

MILLER, J. & FRANKLIN, J. 2002: Modelling the distribution of four vegetation alliances using generalized linear models and classification trees with spatial dependence. — Ecological Modelling 157, 227–247.

MOLNÁR, ZS., BARTHA, S., SEREGÉLYES, T., ILLYÉS, E., BOTTA-DUKÁT, Z., TÍMÁR, G., HORVÁTH, F., RÉVÉSZ, A., KUN, A. & BÖLÖNI, J., 2007: A grid-based, satellite-image supported, multi-attributed vegetation mapping method (MÉTA). — Folia Geobotanica et Phytotaxonomica 42, 225–247.

MOLNÁR, ZS., BIRÓ, M. & BÖLÖNI, J. (eds) 2008: APPENDIX (English names of the Á-NÉR habitat types; Natura 2000 habitats and their Á-NÉR habitats equivalents). — Acta Botanica Hungarica 50 (Suppl.), 249–255.

O'BRIEN, R. M. 2007. A caution regarding rules of thumb for variance inflation factors. — Quality & Quantity 41, 673–690.

PARRY, M. L., CARTER, T. R. 1998: Climate Impact and Adaptation Assessment: A Guide to the IPCC Approach. — Earthscan London, UK. 166 p.

PÁSZTOR, L., LABORCZI, A., TAKÁCS, K., SZATMÁRI, G., DOBOS, E., ILLÉS, G., BAKACSI, ZS. & SZABÓ, J. 2015: Compilation of novel and renewed, goal oriented digital soil maps using geostatistical and data mining tools. — Hungarian Geographical Bulletin 64/1, 49–64.

RIDGEWAY, G. with contributions from others., 2015: gbm: Generalized Boosted Regression Models. R package version 2.1.1. URL: CRAN.R-project.org/package=gbm.

SLUITER, R. 2008: Interpolation methods for climate data. Literature review. KNMI, R&D Information and Observation Technology. — De Bilt.

SOMODI, I., VIRÁGH, K., SZÉKELY, B. & ZIMMERMANN, N. E. 2010: Changes in predictor influence with time and with vegetation type identity in a post-abandonment situation. — Basic and Applied Ecology, available online.

STROBL, C., BOULESTEIX, A.-L., ZEILEIS, A. & HOTHORN, T. 2007: Bias in random forest variable importance measures: Illustrations, sources and a solution. — BMC Bioinformatics 8, Article no.: 25.

SWETS, J. A. 1988: Measuring the accuracy of diagnostic systems. — Science 240(4857), 1285–1293.

SZALAI, S., AUER, I., HIEBL, J., MILKOVICH, J., RADIM, T. STEPANEK, P., ZAHRADNICEK, P., BIHARI, Z., LAKATOS, M., SZENTIMREY, T., LIMANOWKA, D., KILAR, P., CHEVAL, S., DEAK, GY., MIHIC, D., ANTOLOVIC, I., MIHAJLOVIC, V., NEJEDLIK, P., STASTNY, P., MIKULOVA, K., NABYVANETS, I., SKYRYK, O., KRAKOVSKAYA, S.,VOGT, J., ANTOFIE, T. & SPINONI, J. 2013: Climate of the Greater Carpathian Region. Final Technical Report. — www.carpatclim-eu.org.

TABIOS, GQ Ill. & SALAS, J. D. 1985: A comparative analysis of techniques for spatial interpolation of precipitation. — Water Resource Bull. 21, 365–380.

TVEITO, O. E., WEGEHENKEL, M., VAN DER WEL, F. & DOBESCH, H. 2006: The Use of Geographic Information Systems in Climatology and Meteorology. — Final Report COST Action 719.

WU, T. & LI, Y. 2013: Spatial interpolation of temperature in the United States using residual kriging. —Applied Geography 44, 112–120.

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