Master Thesis

im Rahmen des
Universitätslehrganges „Geographical Information Science & Systems“
(UNIGIS MSc) am Interfakultären Fachbereich für GeoInformatik (Z_GIS)
der Paris Lodron-Universität Salzburg

zum Thema

„Estimating the benefit of landscape metrics in a Maxent model“

Experimental application of landscape metrics surfaces at different scales

vorgelegt von

Mag. Olivia Alexandra Ortner
104585, UNIGIS MSc Jahrgang 2016

Betreuer/in:
Prof. Dr. Gudrun Wallentin

Zur Erlangung des Grades
„Master of Science (Geographical Information Science & Systems) – MSc(GIS)”

Wals, 30.09.2019

Science Pledge

By my signature below, I certify that my thesis is entirely the result of my own work. I have cited all sources I have used in my thesis and have always indicated their origin.

--- Wals, 30.09.2019

Olivia Alexandra Ortner

“Science is not about building a body of known ‘facts’.

It is a method for asking awkward questions and subject them to a reality-check, thus avoiding the human tendency to believe whatever makes us feel good.”

~Terry Pratchett~

Preface

The content of this work contributes to the field of habitat suitability modelling and the use of landscape metrics in the modelling process.

The thesis consists of two parts: the first part contains the manuscript-based master thesis and the second part is the technical report that describes the work in greater detail. The manuscript was authorized by Olivia Alexandra Ortner (first author) and Gudrun Wallentin (second author). The contributions of the second author were inputs at the conceptual stage and a substantial revision of the draft paper.

The manuscript was written to be submitted to the International Journal on Ecological Modelling and Systems Ecology (impact factor 2.634 2019, 5-year impact factor 2.852, SJR: 1.040) which is concerned with the use of system analysis and mathematical models or description of ecological processes and the sustainable management of resources (https://www.journals.elsevier.com/ecological-modelling).

Table of Contents

Manuscript

Estimating the benefit of landscape metrics in a Maxent model – Experimental application of landscape metrics surfaces at different scales

Olivia Alexandra Ortner[a,b] and Gudrun Wallentin[a]

[a] Department of Geoinformatics – ZGIS, University of Salzburg, Salzburg
[b] Olivia Ortner, ortner.olivia@gmx.at, Seeparksiedlung 10/3, 5071 Wals

Estimating the benefit of landscape metrics in a Maxent model – Experimental application of landscape metrics surfaces at different scales

ABSTRACT A species' distribution across the landscape is not random, but it is bounded by distribution, size, abundance and connectivity of landscape patches. This spatial configuration of a landscape shapes ecological processes, for example the location of home ranges, migration routes and migration ability. Landscape metrics describe the configuration of a landscape quantitatively. While traditional approaches in habitat modelling only consider environmental attributes at a specific location, the integration of landscape metrics adds more functional information. In this paper we evaluated a method of directly incorporating a set of landscape metrics as covariates into a Maxent habitat model. Specifically, we used hexagons as statistical units for the calculation of landscape metrics. We tested this approach for the Smooth snake (*Coronella austriaca*) in the Austrian Alps. The experimental designs resulted in a significant improvement of the habitat models. Moreover, the results demonstrated the benefits of landscape metrics for the model outcomes at different scales.

Keywords: Maxent, landscape metrics, *Coronella austriaca*, ZonalMetrics, tessellations, Carinthia, habitat suitability modelling

1 Introduction

It is fundamental to understand the processes that drive the distribution of species for conservation planning (Rosenzweig 1995). Underlying patterns are not always easy to understand because the involved environmental variables are operating at multiple scales, spatial as well as temporal (Foltete et al. 2012). We modelled the habitat suitability for *Coronella austriaca*, the Smooth snake, in the Austrian Alps and wanted to get an insight in important predictors for habitat suitability in the study area at different scales of habitat perception. The scale as well as the used covariates in the model should be adequate to the environmental requirements and the home ranges of this species to picture the occupied ecological niche in the study area. Our focus lay on the landscape traits that characterise the habitats of *Coronella austriaca*.

To fulfill this task we used the Maxent algorithm (Phillips 2004) for modelling the habitat suitability for *Coronella austriaca*. Habitat suitability modelling is used in numerous studies and many areas of biodiversity research, conservation and estimating future habitat ranges of species. One of the most frequently used algorithms is Maxent (Phillips 2004), which shows perpetually good results (Merow et al. 2013; Elith et al. 2006). Maxent (Phillips et al. 2006) is a presence-background modelling method, that associates known occurrences of a species with important environmental data in the region of interest. The resulting model extracts the ecological niche that the target species can inhabit in the study area and maps it onto geographic space.

The most commonly used predictors in habitat suitability modelling are factors such as climate, vegetation, soil or altitude employed at multiple scales (Pulliam 2000). An equally important, but often neglected, factor for the distribution of species across areas is the configuration and structure of the landscape, what can be quantified with landscape metrics. Landscape structure and configuration has an important influence on ecosystem functions and therefore habitat suitability and biodiversity (Walz 2011). The spatial scale and extend of the study area affects the landscape metrics performance (Schindler et al. 2013; Turner et al. 2001). To picture the actual habitat needs and possible driving forces of a special target species, scale and grain should be adequate to the size of the home ranges of this species (Holzkämper et al. 2006; Guisan und Thuiller 2005) and adequate to the data quality to avoid pseudo-accuracy.

Modelling methods must have an organism-centred view of landscape structures (Cushman et al. 2008; Li und Wu 2004). Within landscape analysis, the examined scale is a critical factor (Walz 2011) and is characterised by thematic resolution, grain size and extend (Lam und Quattrochi 1992; Turner et al. 2001). Especially the response to changing extend is not consistent (Saura and Martinez-Millan 2001). The underlying gradients of a patchy landscape can lead to an unpredictable behaviour of metrics because of a minor number of patches in the sample (Schindler et al. 2013). Species with higher space demand and higher mobility are influenced by a bigger extend of landscape than small species with low mobility. So, spatial grain of habitat perception is a function of body size, what accords to the decision hierarchy concept of Holling (Holling 1992).

Some studies already dealt with the possibility of enriching species distribution modelling with the additional information of landscape metrics (e.g. Amici et al. 2015; Hasui et al. 2017; Hopkins 2009; Foltete et al. 2012), to predict species richness through landscape metrics (e.g. Schindler et al. 2013) or to predict the distribution of species with landscape metrics (e.g. Ippoliti et al. 2013; Westphal et al. 2003). Nevertheless, landscape metrics have so far not been incorporated as predictors in the habitat modelling process.

The aim of this study was to find a possibility to incorporate landscape metrics into the Maxent modelling process, as covariates (also called predictors), and to examine the potential benefits this could have on the resulting models at different important scales for the target species. To incorporate landscape metrics into the Maxent modelling process we had to find a possibility to create landscape metrics surfaces at different scales, important for the target species. We calculated landscape metrics in hexagonal statistical zones that covered the entire study area. Although these experiments were conducted with Maxent (Phillips et al. 2006) the method can be valuable for other species distribution modelling methods as well. It not only can enhance the status of the model, depending on the quality of the available data, but can also be helpful in identifying the most important landscape traits for the target species in the study area.

2 Material and methods

2.1 Study species and region

The target species of this study was the Smooth snake (*Coronella austriaca*). Although it is distributed across whole Europe, western Siberia and the middle east (Völkl and Käsewieter 2003) it is included in the European Council Directive 92/43/EEC of 21st of May 1992 Annex IV and has been evaluated as being in an "unfavourable state" in Central and Northern European countries (Čeirāns und Nikolajeva 2017). *Coronella austriaca* is a rather small, non-venomous and secretive snake that is mainly threatened through habitat loss and fragmentation, what leads to extinction of populations and reduces the gene flow between persisting populations. This can lead to degeneration of the remaining populations (Pernetta et al. 2011; Reading 2012). *C. austriaca* is one of the typical elements of the European cultural landscape and is very ductile in its habitat selection. It inhabits a wide spectrum of open and half-open landscapes and can be seen as xerothermophile species that sometimes also inhabits wet to alternating wet areas (Völkl and Käsewieter 2003). What all these habitats have in common is a high edge density and a highly structured landscape with adequate microhabitat structures like immature soil, dry grass, stone and rock and deadwood (Käsewieter 2002).

The study area was Carinthia, the most southern province of Austria. For this province the necessary data (vegetation layer in adequate resolution, enough sample points of *Coronella austriaca*) was available at sufficient detail and accuracy. The final model should cover the whole area of Carinthia, but to limit the time for landscape metrics calculation a test area with the size of about a fourth of the area of Carinthia was delimited (figure 1). Within this test area, Maxent models that only contained the landscape metrics surfaces were calculated to decide which of them, and at what resolution, should take part at the final models.

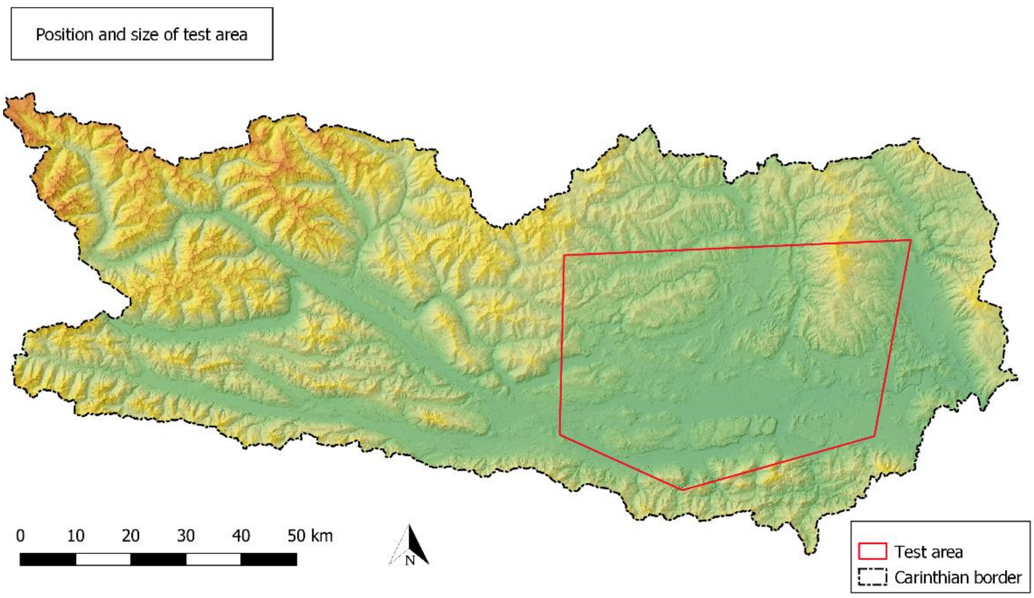


Figure 1. Map showing the province of Carinthia with the position and size of the test area.

2.2 Occurrence data and environmental data

Coronella austriaca occurrence data was obtained from the "herpetofaunistic database of the Museum of Natural History, Vienna"[1] and from the "Consortium nature conservation, Klagenfurt"[2]. From both databases together we got 1208 occurrence records. These records had to be split in groups of high and low spatial accuracy. Only records with an uncertainty of 100m and less were used for modelbuilding. After filtering, 129 occurrence records were left. 46 of the occurrence records where situated in the test area. Before modelbuilding the *Coronella austriaca* sample points were spatially filtered to reduce bias through spatial autocorrelation (Boria et al. 2014; Anderson und Gonzalez 2011). Biased occurrence records can lead to overfit model outputs in Maxent (Peterson et al. 2007), which means that the model is more complex than the real relationships between the included environmental variables and the specie´s niche (Peterson 2011). Only occurrences with a distance of 500m and more should take part in the model. Therefore, 500m-buffers were created around the sample points. Points

[1] Herpetofaunistische Datenbank des Naturhistorischen Museums, Wien
[2] Arge NATURSCHUTZ, Klagenfurt

inside this buffer distance were deleted arbitrarily. After spatial filtering, 38 samples were left in the test area and 94 samples in the whole area of Carinthia.

The current vegetation of Carinthia[3] was used for the landscape metrics calculation with a detection scale of 1:50000. This layer was partly missing information about water bodies, wetlands and some parts of alpine areas and had to be updated. The missing information could be obtained from the generalized land use of Carinthia[3] and from the “Map of the current vegetation of Carinthia” (Hartl et al. 2001). After completion of the vegetation layer, further information was added. To calculate landscape metrics at the scale relevant for *Coronella austriaca* the vegetation layer had to be updated with information concerning the waterbodies. Therefore, the water body network of Carinthia[3] was used. Buffers depending on the size range of the rivers were created for all water bodies except the river “Drau” – it was already contained in the vegetation layer file. Afterwards the vegetation layer file was updated with the buffers. After finishing the refinement, the vegetation layer contained 51 classes.

For some of the further landscape metrics calculations (contrast, connectance), the vegetation layer classes were aggregated to higher level categories that represent alike functions for *Coronella austriaca*. This high-level aggregation resulted in seven classes. A second low-level aggregation was conducted to speed up calculation time a little bit. Here vegetation classes were aggregated very gentle to 24 classes with the intention to keep characteristics of vegetation classes such a wet or dry ground.

Name	*Lower level aggregation*	*Higher level aggregation*
acre-grassland	acer-grassland	intensive grassland
expressway	compact settlement	compact settlement
premises	compact settlement	compact settlement
airport	compact settlement	compact settlement
compact settlements	compact settlement	compact settlement
beech- fir tree- spruce forest, beech- fir forest, fir forest on carbonate ground	beech- fir tree- spruce forest	forest
beech- fir tree- spruce forest, beech- fir forest, fir forest on silikate ground	beech- fir tree- spruce forest	forest
beech forest	beech forest	forest
grey alder forest	alder_willow	planted
black alder forest	alder_willow	planted
willow forest	alder_willow	planted
wet mixed deciduous woodland	wet mixed deciduous woodland	forest
wetlands, bogs	wetlands	grassland
peat bog	wetlands	grassland
fen	wetlands	grassland
spruce-larch forest	spruce and mixed forest	forest
spruce forest, secondary spruce forest on carbonate ground	spruce and mixed forest	forest
spruce forest, secondary spruce forest on silikate ground	spruce and mixed forest	forest
Scotch pine-spruce mixed forest	pine forest	forest
Scotch pine forest	pine forest	forest
European black pine forest	pine forest	forest
glacier areas	glacier areas	compact settlement
larch-spruce forest	larch forest	forest
Swiss stone pine forest and larch-Swiss stone pine forest	larch forest	forest
larch meadows	larch meadows	grassland
dwarf pine knee timber	dwarf pine knee timber	planted

[3] https://data.gv.at/katalog/dataset

coniferous-deciduous mixed forest (Scotch pine-beech forest, spruce-beech forest)	mixed forest	forest
coniferous mixed forest with deciduous parts	mixed forest	forest
montane-subalpine deciduous scrubs	montane-subalpine deciduous scrubs	planted
historic heritage, castles and monasterys	light building density	coverd with buildings
light building density	light building density	coverd with buildings
pioneer vegetation on boulder and rocks	pioneer vegetation on boulder and rocks	coverd with buildings
cane brake and large sedge	cane brake and large sedge	planted
sports areas	sports areas and parks	intensive grassland
municipal grass area and sports areas	sports areas and parks	intensive grassland
subalpine and alpine grassland and pasture on carbonate ground	subalpine and alpine grassland and pasture	grassland
subalpine and alpine grassland and pasture on silikate ground	subalpine and alpine grassland and pasture	grassland
warm mixed deciduous forest (manna ash, European hop-hornbeam, whitebeam, oak)	warm mixed deciduous forest (manna ash, European hop-hornbeam, whitebeam, oak)	forest
waterbodies	waterbodies	waterbodies
waterbodies 3	waterbodies	waterbodies
waterbodies 4	waterbodies	waterbodies
waterbodies 5	waterbodies	waterbodies
waterbodies 6	waterbodies	waterbodies
waterbodies 7	waterbodies	waterbodies
pastures and mountainious hay meadows on carbonate ground	pastures and mountainious hay meadows	grassland
pastures and mountainious hay meadows on silikate ground	pastures and mountainious hay meadows	grassland
expressway tunnel	cultivated grassland (pastures and hay meadows)	grassland
winter sports areas	cultivated grassland (pastures and hay meadows)	intensive grassland
cultivated grassland (pastures and hay meadows)	cultivated grassland (pastures and hay meadows)	intensive grassland
dwarf shrub heathland, mosaic of dwarf shrub and pastures on carboante ground	pastures and mountainious hay meadows	grassland
dwarf shrub heathland, mosaic of dwarf shrub and pastures on silikate ground	pastures and mountainious hay meadows	grassland

Table 1. Vegetation units of the layer used for landscape metrics calculation.

For the final models of the whole province climatic layers (mean annual global radiation, average accumulated precipitation, average accumulated summer precipitation, mean snow cover duration, average start of snow cover, average end of snow cover, average equivalent temperature in July)[4] and the vegetation layer itself were additionally used for model building.

2.3 Experimental design

To investigate the possibility to use landscape metrics in Maxent as covariates we had to build surfaces of them for the study area. We constructed regular tessellation hexagon layers of different sizes (5ha, 10ha, 15ha, 25h, 35ha per hexagon) for the test area that should be used as statistical units for landscape metrics calculation. Advantages of using hexagons

[4] https://data.gv.at/katalog/dataset

(Jurasinski and Beierkuhnlein 2006) instead of triangles or squares are that they share a real border with every neighbouring zone and that any point inside a hexagon is closer to the centre of the hexagon than this would be the case in an equal area triangle or square (Adamczyk and Tiede 2017). To fulfill this task, the ZonalMetrics python tool box (Adamczyk and Tiede 2017) together with ArcGIS 10.5 (Esri 2011) was used. To build organism-centred models for the target species, the size of the hexagons was at one hand adjusted to the habitat size requirements of *Coronella austriaca* populations (Völkl und Käsewieter 2003) and on the other hand we experimented with the sizes of the hexagons to get an insight on how the landscape metrics reacted. We also considered data quality to avoid pseudo-accuracy in the modelling process. So, we limited the smallest hexagon unit size to 5ha and the raster cell size to 100mx100m, because of the resolution of the vegetation layer and the inaccuracies of the *Coronella austriaca* occurrence data. Additionally, we used the catchment areas of Carinthia, cut to the size of the test area, as natural ecological units for landscape metrics calculation.

2.4 Landscape metrics calculation

There are three ways to deal with landscape patches that overlap the border of the respective statistical zone: 1) Clip all patches that overlap the statistical zone to the extent of this zone. 2) Select all overlapping patches and calculate metrics for the whole patch intersecting the zone. The patches can be considered in several zones. 3) Select patches whose centroid is in the statistical zone. No double counting is allowed (Adamczyk and Tiede 2017). We decided to cut the patches that overlap the statistical zone because the zones should picture the home ranges of *C. austriaca* individuals and populations. So, in case of the statistical zones the borders do not represent natural environmental units. The size of the statistical zones defines the scale of analysis what should be considered because every analysed phenomenon can have a particular scale domain where it reveals (Levin 1992; Turner et al. 1989).

For all statistical layers and the catchment areas, five types of landscape metrics plus the edge density via line kernel density (Cai et al. 2013) were calculated for the important habitat elements of *C. austriaca*:

1) Area metrics for open areas important for *C. austriaca* (not for woodland) of the lower level aggregation: percent of the area of the whole statistical zone taken by the patch (pz<class-name>).
2) Largest patch index for all classes: percentage of the total area of the statistical zone taken by the largest patch (lpi).
3) Connectance Metrics for the higher-level aggregated classes: the maximum connectance distance was 500m with an offset of 100m. The examined classes (covered with buildings, planted, grassland, intensive grassland) were merged. The resulting values were the number of distinct (by FID) connected classes (ci_np), the percentage of patch area that lies within the range of connection to the statistical zone (ci_pp) and the percentage of the connection zone between the patches in comparison to the statistical zone (ci_cp).
4) Contrast metrics for the higher-level aggregated classes: the analysed classes (one at a time) were covered with buildings, intensive grassland, planted and grassland. The contrast classes were compact settlement, waterbodies and forest. The resulting value was the contrast index which is calculated as the percentage of the edge length of the focus classes shared with the contrast classes (cce<className>).
5) The Shannon Diversity Index for all classes (shdi).

This landscape metrics are implemented in the ZonalMetrics toolbox because of their ability to deal with the restricted zones, that can be seen as small subsets of the landscape, better than other existing metrics that for example are composed of more complex equations or are calculated through the examination of all patches of the whole landscape (Adamczyk und Tiede 2017). Mainly weighted metrics were used because of irregular sizes of the catchment areas and the fact that also regular tessellation surfaces are cut at the edge of the study area and therefore also contain irregular units.

To incorporate the edge density in the modelling process, we dissolved the vegetation layer polygons to lines and merged the resulting layer with the transport network of Carinthia. The decision for a bandwidth is a key step in kernel density estimation, depending on the smoothing of the resulting surface (Cai et al. 2013). As a rule of thumb ArcGis (Esri 2011) works with the rule of Silverman (Silverman 1986) , which is based on a quadratic kernel function. The first surface was calculated with the suggested bandwidth of 1741,11m. To compare this surface with other outcomes, three more surfaces with bandwidths of 500m, 1000m and 1500m were created. To picture the edge density of the test area in an appropriate way, the smoothing should not be to ample. Through comparison with the line data set we choose the surface with the 1000m bandwidth and a resolution of 100mx100m for the modelling process. After metrics were calculated the polygon shape files had to be converted to raster data sets with a cell size of 100mx100m, masked and converted to ASCII files. In the end, 26 landscape metrics surfaces at six resolutions were ready to use for the test area models.

		pz<class name> Percent of the area of the whole statistical zone taken by the patch
1	pz_glint	cultivated grassland
2	pz_offbau	light building density
3	pz_feucht	wetlands
4	pz_weide	pastures and mountainious hay meadow
5	pz_acker	acre-grassland
6	pz_latsche	dwarf pine knee timber
7	pz_pionier	pioneer vegetation on boulder and rocks
8	pz_subalp	subalpine and alpine grassland and pastures
		Diversity Metric Shannon Diversity Index
9	shdi	shannon diversity index
		Connectance Metrics Maximum connectance distance: 500m, offset 100m, covered w. buildings, int. grassland, planted, grassland (merged)
10	ci_np	number of distinct (by FID) connected classes
11	ci_pp	percentage of patch area that lies within the range of connection to the statistical zone
12	ci_cp	percentage of the connection zone between the patches in comparison to the statistical zone
		Largest Patch Index
13	lpi	percentage of the total area of the statistical zone taken by the largest patch
		Contrast Metrics Analyzed (one at a time): covered w. buildings, int. grassland, planted, grassland, Contrast classes: compact settlement, waterbodies, forest.
	covered w. buildings	
14	cce_beb_bau	contrast: compact settlement
15	cce_beb_was	contrast: water bodies

16	cce_beb_wa	contrast: forest
	intensive grassland	
17	cce_gli_bau	contrast: compact settlement
18	cce_gli_was	contrast: water bodies
19	cce_gli_wa	contrast: forest
	planted	
20	cce_bes_bau	contrast: compact settlement
21	cce_bes_was	contrast: water bodies
22	cce_bes_wa	contrast: forest
	grassland	
23	cce_gl_bau	contrast: compact settlement
24	cce_gl_was	contrast: water bodies
25	cce_gl_wa	contrast: forest
		Kernel Density – Edge Density
26	kernel	line kernel density to represent edge density

Table 2. Landscape metrics abbreviations used for model building.

2.5 Modelling the test area

To determine which landscape metrics surfaces should take part in the final Maxent model of Carinthia, six Maxent model runs with Maxent GUI 3.4.1 (Phillips et al. 2006, Internet 1) including solely the different landscape metrics surfaces were conducted for the test area. There are different approaches how to select covariates in ecological modelling with Maxent. One recommends reducing correlation between them to a minimum before starting the modelling process through correlation analysis, clustering analyses or another reduction method, because the complex features used by Maxent often produce highly correlated outputs. Reducing the covariates prior to modelbuilding should result in models that are better interpretable. This is corresponding to the approach to treat Maxent as traditional statistical model (Renner und Warton 2013). An alternative point of view considers Maxent as machine learning approach and lets the algorithm decide, which covariates to use for modelbuilding through regularization (Phillips et al. 2006). We concluded to let the algorithm decide and not to filter the covariates before modelbuilding. Through this approach, the most contributively environmental variables in the model can be detected.

To keep things simple at this stage of the experiment, only linear and quadratic features were allowed for model settings (Phillips 2004). The feature classes determine the constraints that are permitted in a model. They are functions of the environmental variables and can be combinations of six classes or just a single one: linear (L), quadratic (Q), product (P), threshold (T), hinge (H) or a category indicator (C) (Phillips et al. 2006). The constraints of this feature classes on the model result in models of diversified complexity (Phillips und Dudík 2008). Using complex feature combinations allows Maxent to build a model that is very sensitive to a species environmental tolerance, what can possibly lead to an overfit model (Shcheglovitova and Anderson 2013). The regularisation multiplier, which controls the intensity of regularization across all features, was set to two. The default regularization multiplier is one. The larger multiplies should result in less discriminatory predictions and decrease the chance that the model is overfitted to bias or noise in the sample points (Radosavljevic and Anderson 2014). To choose which resolution of the statistical surfaces should be used in the final model, AUC (area under the ROC curve) and omission rate (OR), two common metrics of model performance, were consulted (Shcheglovitova and Anderson 2013). Some studies identified AUC value, calculated with presence-background data, as an arguable measure for the performance of models (Lobo et al. 2008; Warren und Seifert 2011), but it can be used to compare models of single species in an identical study area, what is the case in this study (Peterson 2011).

AUC and OR were examined for each result to choose which resolution of the landscape metrics surfaces had the best model performance. Additionally, we were interested in the most contributively environmental variables in model building. Therefore, we examined the percentage of model contribution. Only landscape metrics with a contribution of 4% and more should take part in the final model.

To monitor the behaviour of the landscape metrics surfaces, we calculated Pearson correlation coefficient for the pairwise comparison of raster files via ENMTool (Warren et al. 2010a) and visualized it with the R package "corrplot" (Wei and Simko 2017). For a quantitative measure of the "difference" of the model results in geographic space, Schoeners *D* (Schoener 1968) and *I* statistics (Warren et al. 2008) were computed. The metrics are calculated by determining the differences between the models in suitability score per grid cell after standardizing the suitability to sum up to 1 over the measured geographic space. The metrics reach from 0 (no overlaps) to 1 (identical models). *I* often overestimates model similarity, whereas *D* is a more conservative measure (Rödder und Engler 2011).

2.6 Final models

For the final models, statistical layers at the desired resolution were built for the whole province. Only the most contributively landscape metrics surfaces (percentage of contribution of 4% and more in the test area models) were calculated and used for model building. Edge density via line kernel density was computed for the whole province identically to the test area. Raster resolution was 100mx100m for all covariates. Additional covariates in the final model were the climatic layers and the vegetation layer.

The models should be built at the landscape metrics scale with the best AUC and OR values of the test area, but these values performed equally well for all models. We decided to build 3 models of important scales for *Coronella austriaca* (Völkl und Käsewieter 2003). One should picture the population scale (5ha), one the metapopulation scale (25ha) and the third one consisted of the catchment areas as natural ecological units. To detect differences between models using landscape metrics and models without them, we computed each model two times: 1) with all parameters (landscape metrics, climatic variables, vegetation layer), 2) with landscape metrics only, plus one model without landscape metrics at all. Logistic output was used for visualisation (Phillips und Dudík 2008).

The seven models were calculated two times: the first time we used the test area model settings, the second time we tuned the model settings to enhance the outcomes and to detect improvement. The choice of features in the tuned models was led by tuning experiments of Phillips and Dudik 2008: all feature classes should be used for models of at least 80 occurrence records. The regularisation multiplier was set to one. After finishing the modelling process, AUC values of the different model settings were compared.

We again calculated Schoeners *D* (Schoener 1968) and the *I* statistic (Warren et al. 2008) with EMNTool (Warren et al. 2010b) to get an insight in the difference of the model results in geographic space.

5ha - population level	*25ha - metapopulation level*	*Natural ecological units (GEZG)*
cce_be_was	shdi	cce_gl_was
pz_offenbau	lpi	pz_glint
lpi	pz_glint	kernel
shdi	kernel	pz_offbau
cce_bau_wa	cce_bes_was	cce_gli_wa
kernel	vegetation layer	pz_acker
vegetation layer	GS – mean annual global radiation (kWh/m2)	shdi
GS – mean annual global radiation (kWh/m2)	N – average accumulated precipitation (mm)	vegetation layer
N – average accumulated precipitation (mm)	NJJA – average accumulated summer precipitation (mm)	GS – mean annual global radiation (kWh/m2)
NJJA – average accumulated summer precipitation (mm)	SD – mean snow cover duration (days)	N – average accumulated precipitation (mm)
SD – mean snow cover duration (days)	SDB – average start of snow cover (day of the year)	NJJA – average accumulated summer precipitation (mm)
SDB – average start of snow cover (day of the year)	SDE – average end of snow cover (day of the year)	SD – mean snow cover duration (days)
SDE – average end of snow cover (day of the year)	AET07 – average equivalent temperature in July (°C)	SDB – average start of snow cover (day of the year)
AET07 – average equivalent temperature in July (°C)		SDE – average end of snow cover (day of the year)
		AET07 – average equivalent temperature in July (°C)

Table 3. Covariates used in the final models.

3 Results

3.1 Test area

The correlations for the 26 test area landscape metrics layers can be seen in figure 2. They tend to get stronger in both directions, the large the statistical surface units get. Only a few strong correlations between the layers existed. The strongest evolved in the catchment areas (GEZG) layers.

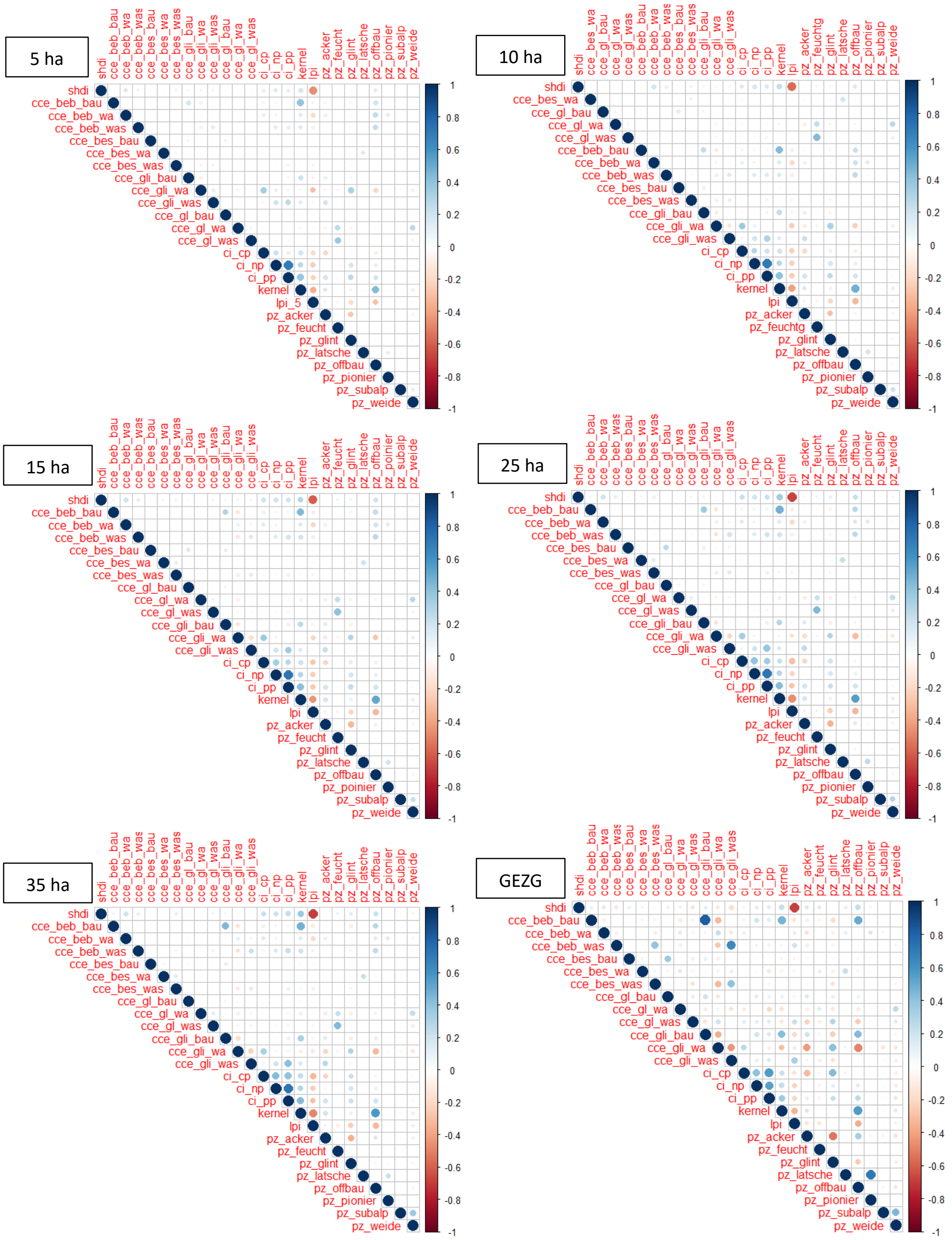


Figure 2. Correlation matrices for the landscape metrics surfaces used in the test area models. For further explanations of the labeling see table 2.

The model outputs for the six different test area resolutions showed an equal performance respective the resulting AUC and OR values. All values were between an AUC of 0,843 and 0,890 and OR was between 0,327 and 0,369 for all models. The model with the best AUC value was the 25ha model. The lowest AUC value was displayed by the 10ha surface resolution. The lowest OR showed the 35ha model and the highest OR was displayed by 5ha model (see table 4). Additionally, the percent contribution and the permutation importance were examined for further modelbuilding. Percent contribution is calculated by assigning the increase in gain of every step of the Maxent algorithm to the covariates that a feature depends on and converting this value to percentage at the end of the training process. These values are only heuristically defined and depend on the path Maxent uses to find the optimal solution. Permutation importance values depend only on the final Maxent model without the used path to obtain the results (Phillips et al. 2006). The percentage of contribution and permutation importance changed with the size of the statistical zones. The 5ha and the 10ha model contain five covariates with a 0% contribution and permutation importance (cce_gl_bau, pz_pionier, cce_bes_bau, pz_subalp, pz_latsche), the 15ha model contains four covariates with 0% contribution (cce_gl_bau, pz_pionier, pz_latsche, pz_subalp) and five covariates with 0% permutation importance (cce_bes_bau, cce_gl_bau, pz_pionier, pz_latsche, pz_subalp). The 25ha model has four covariates with 0% contribution and permutation importance (cce_gl_bau, pz_pionier, pz_latsche, pz_subalp). The 35ha model has only two covaritaes with 0% contribution and permutation importance (pz_subalp, pz_latsche) and the model with the maximum zone size (GEZG, catchment areas) only has one layer that did not contribute (pz_subalp).

Surface	AUC	OR
5 ha	0,8642	0,3686
10 ha	0,8432	0,3685
15 ha	0,8579	0,3608
25 ha	0,8899	0,3461
35 ha	0,8849	0,3271
GEZG	0,8854	0,3511

Table 4. AUC and OR values for the test area models.

Despite the similarities in AUC and OR values between the different model results, we observed differences in geographic space. Schoeners *D* (Schoener 1968) showed greater differences and less similarity than *I* statistic (Warren et al. 2008), as expected. The highest *D* value was 0,817 between the 5ha and the 10ha model. The lowest *D* value, and therefore the highest difference showed the models GEZG and 5ha with 0,676. The average *D* value was 0,749. The highest *I* value was 0,971 between the 10ha and the 15ha model, the lowest *I* value was 0,907 between the 5ha and the GEZG model. The average *I* value was 0,942.

3.2 The final models

The final models showed good AUC values after tuning (see table 5). For all three model resolutions the best values were shown by the models with all covariates together (climatic, vegetation and landscape metrics surfaces). The best value was 0,928 from the 25ha model. The 5ha model showed an AUC value of 0,920 and the GEZG models AUC was 0,919. The AUC value of the model without landscape metrics surfaces was 0,893 and the values for the models with only landscape metrics were between 0,850 and 0,879, increasing with the size of the statistical zones. Here the model with the largest statistical surface units showed the best results. Compared to the settings of the test area, model tuning resulted in better AUC values for all models.

	AUC	
model	tuned	test
5ha all	0,920	0,882
5ha LM	0,850	0,832
25ha all	0,928	0,888
25ha LM	0,859	0,834
GEZG all	0,919	0,876
GEZG LM	0,879	0,847
without LM	0,893	0,857

Table 5. AUC values for the final models. xxha all: model contains all covariates, xxha LM: model contains only landscape metrics, without LM: model without landscape metrics.

Compared to the test areas model runs, Schoeners *D* and *I* statistics both showed increased differences for all models in geographic space. The lowest *D* value with 0,610 appeared between the 5ha model with landscape metrics only and the catchment areas model with all covariates. The highest *D* value was 0,850 between the 25ha model with all covariates and the 5ha model with all covariates. The average *D* value was 0,696. The *I* statistics again showed greater similarities between the models in geographic space. The lowest value was 0,848 between the 25ha landscape metrics model and the model without landscape metrics. The highest value was 0,980 between the 25ha surface with all covariates and the 5ha surface with all covariates. The average *I* value was 0,907.

The correlations between the covariates showed high values between the climatic layers, excluding the *gs* (mean annual global radiation). Also kernel density showed higher correlation (positive as well as negative) with the climatic layers. Again, the larger the statistical surfaces get, the stronger the correlations become.

For the visualization of the model outputs, binary predictions were made with the 10 percentile training presence logistic threshold (see figures 3-9).

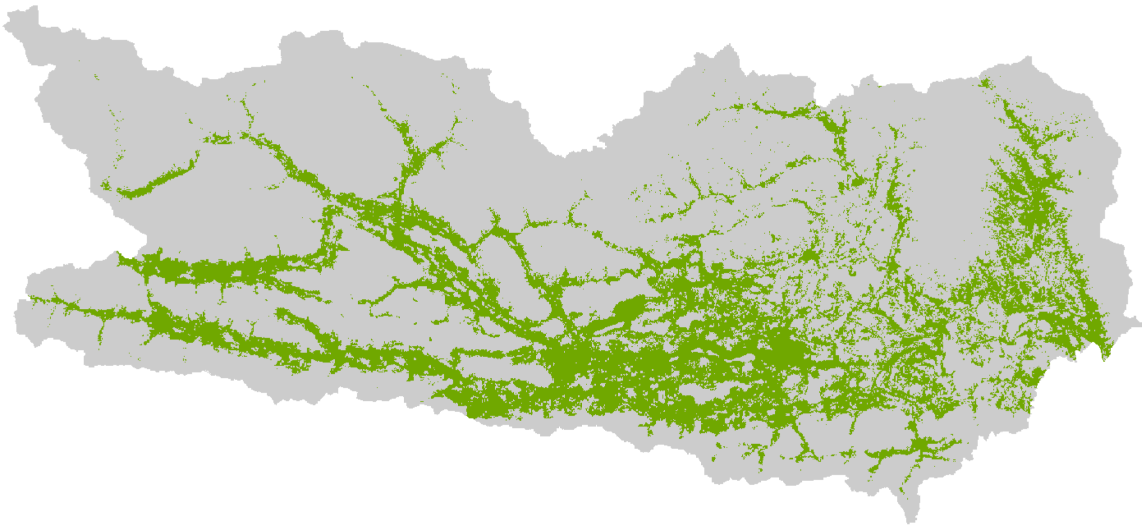


Figure 3. 5ha model with all covariates (landscape metrics, vegetation layer, climatic layers). Green=suitable habitat. (AUC=0,920).

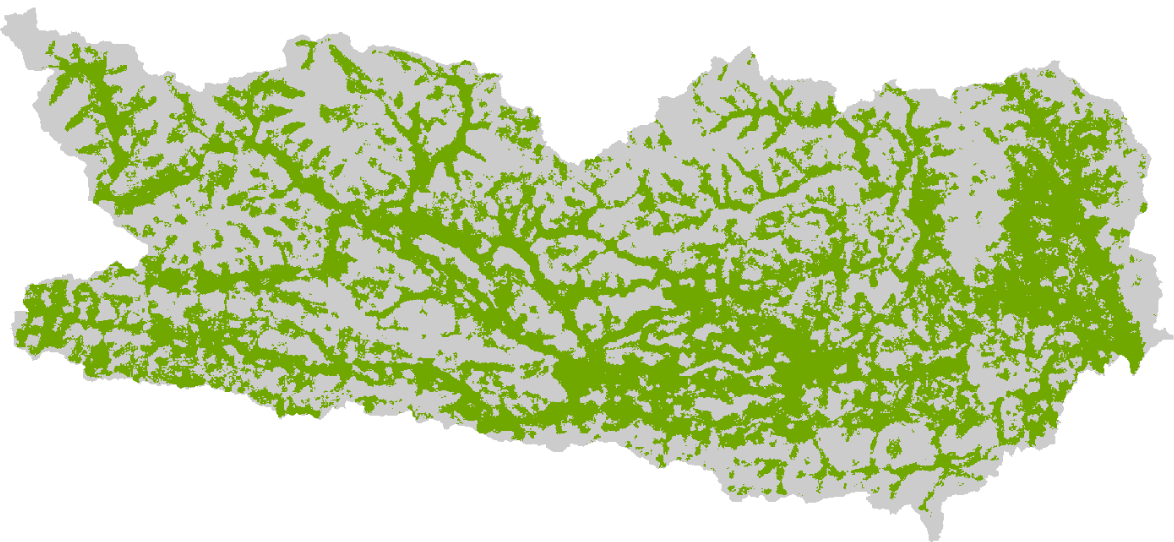


Figure 4. 5ha model with landscape metrics surfaces only. Green=suitable habitat. (AUC=0,850).

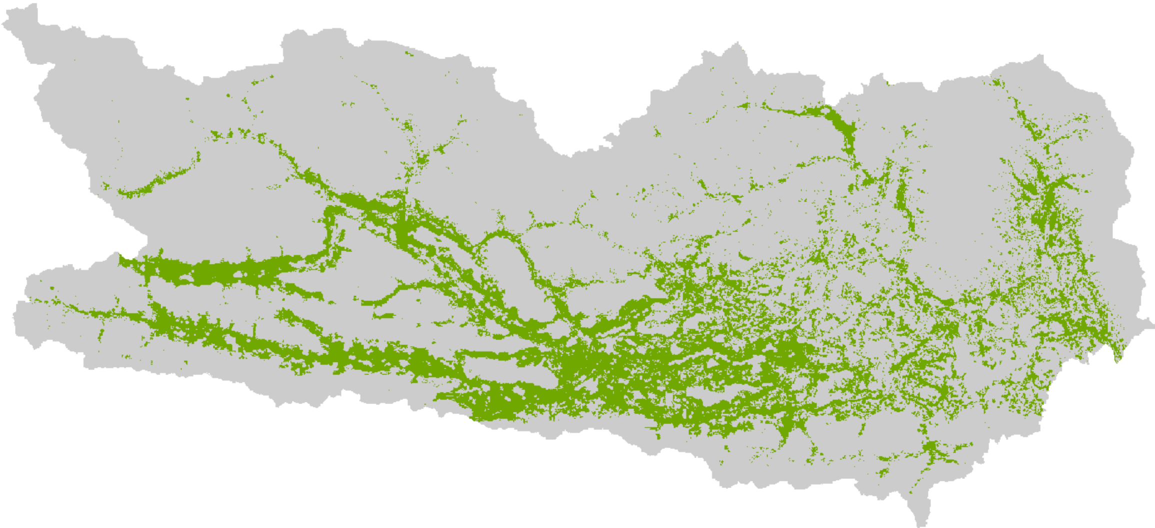


Figure 5. 25ha model with all covariates (landscape metrics, vegetation layer, climatic layers) Green =suitable habitat. (AUC=0,928).

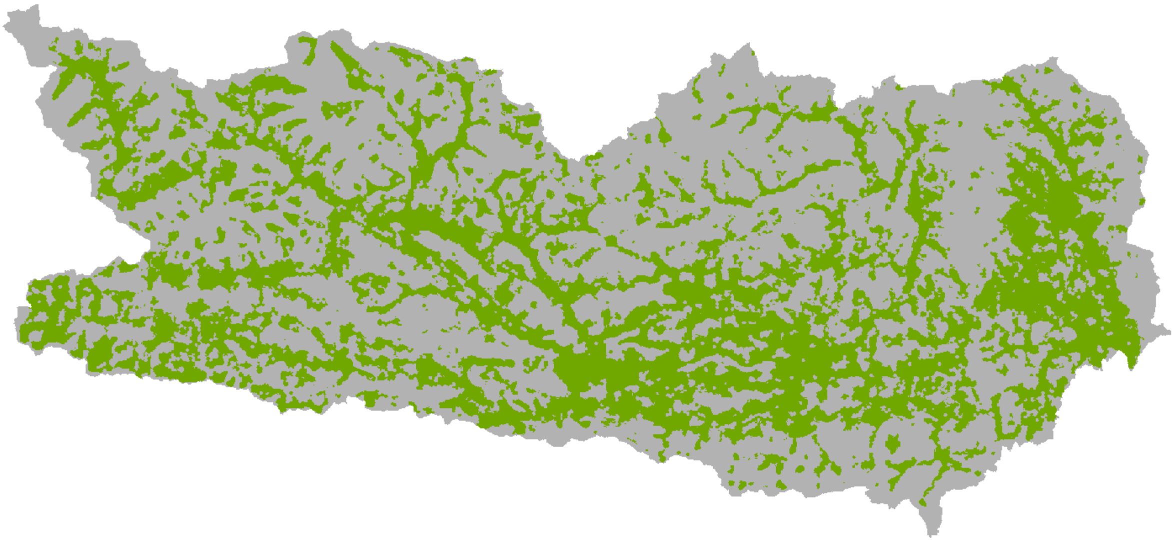


Figure 6. 25ha model with landscape metrics surfaces only. Green=suitable habitat. (AUC=0,859).

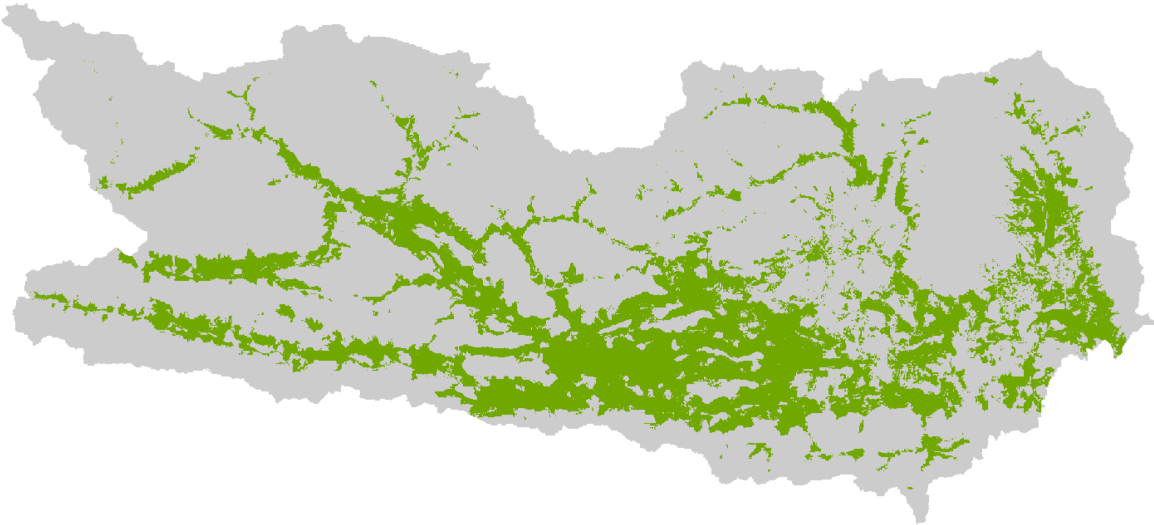


Figure 7. GEZG (catchment areas) model with all covariates (landscape metrics, vegetation layer, climatic layers). Green =suitable habitat. (AUC= 0,919).

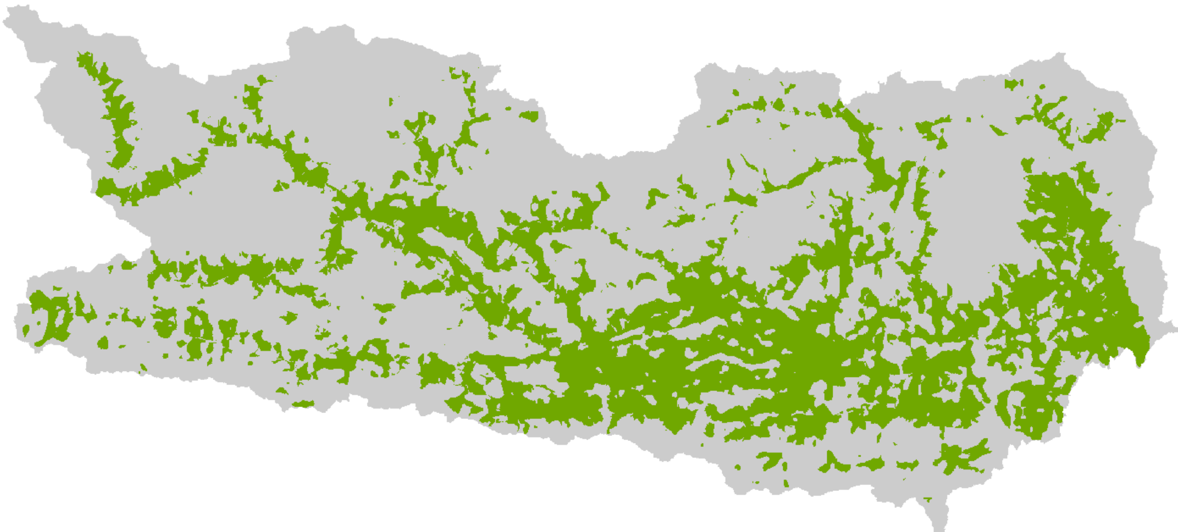


Figure 8. GEZG model with landscape metrics surfaces only. Green=suitable habitat. (AUC=0,879).

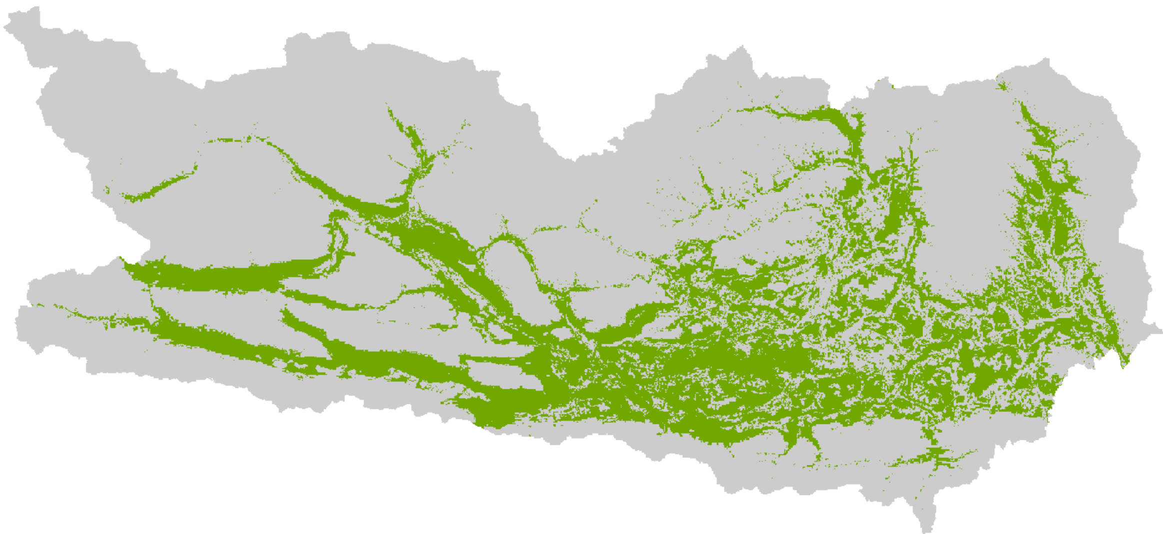


Figure 9. Model without landscape metrics surfaces - only with vegetation and climatic layers. Green=suitable habitat. (AUC= 0,893).

4 Discussion

4.1 Test area models

Although only landscape metrics surfaces were used without model tuning, the six model runs showed good results for the test area in AUC values and performed equally well. Only the grain of the predictions differentiated between the model outputs. It is noticeable that also the model built by the catchment areas did perform equally well, also the predicted suitable area for *Coronella austriaca* showed a different pattern and was less detailed than the statistical surface predictions. Maxent obviously makes the best of the information it gets. There are several critical steps till the surfaces are prepared for modelling. Each of them leads to a higher level of abstraction in comparison to the original landscape metrics. The decision for other sizes of statistical zones and the method of dealing with overlapping patches can lead to other values for the zonal metrics. This is also the case in studies were the home ranges of species are used for landscape metrics calculation (Holzkämper et al. 2006). The method of rasterizing and the resolution of the raster surfaces influence the information content of the resulting surfaces (Turner et al. 2001). So, the descisions to make before modelling are important to overthink and to question. Furthermore this descisions should fit the target species and data at necessary accuracy and thematic resolution must be available.

The position of the test area was a compromise between a sufficient amount of sample data for model building and the consistent representation of all vegetation types throughout Carinthia. In the test area subalpine and alpine regions are underrepresented. *Coronella austriaca* is known to inhabit also subalpine and alpine regions (Völkl and Käsewieter 2003). This regions are also underrepresented in the sample points, because this points come from non-random sampling. Observations were made from people in populated areas were the chance is higher for the snakes to be detected. We tried to decrease this phenomenon by spatial filtering (Boria et al. 2014; Anderson and Gonzalez 2011). When examining the binary predictions of the model outputs it can also be observed that subalpine areas are nevertheless underrepresented.

The most contributively covariates in the modelling process were area metrics, contrast metrics, edge density, largest patch index and the Shannon Diversity Index. From the area metrics the classes light building density, cultivated grassland and acre grassland did contribute the most. This mirrors the fact, that the open habitat types in the test area consist mostly of this kinds with a percentage of 23,6%. This corresponds to the important secondary habitat types *Coronella austriaca* inhabits in cultivated areas (Völkl and Käsewieter 2003). Unfortunately, this habitat types are also characterised by high degradation and fragmentation (Dick and Mebert 2017). In all models, except the 5ha and the 15ha model, edge density had a high contribution in model building. Shannon Diversity Index and largest patch index were important in all models, except for the GEZG model – here only Shannon Diversity Index was contributively. This metrics correspond to the heterogenous habitat requirements of *Coronella austriaca*, are rather simple, have good explanatory ability and are easy to interpret (Holzkämper et al. 2006).

The correlation matrices for the test area covariates show, that correlations get stronger the larger the statistical units get. This accords to the phenomenon that all patterns have a scale at which they reveal (Turner et al. 1989) and shows once more how important it is to coincide the size of the statistical zones with the quality of the available data. If the scale of the data and the thematic resolution is to small for the desired statistical surface size, no useful predictions can be made (Walz 2011; Turner et al. 2001).

For the evaluation of the test area models in geographic space we focus our interpretation on Schoeners *D* because it's a more conservative measure of similarity (Rödder und Engler 2011). The average value of *D* comparing the different test area models was 0,749. That corresponds to an average difference between the models of approximately 25%, what seems to be much when just changing the size of statistical zones but providing the same information. The highest differences are shown between the tessellation surfaces and the natural ecological units. That indicates also, that the information content of the taller statistical surface units is another than the information of the smaller units´ surfaces. So, the decision for a statistical surface can have great influence on model outcome and benefit for the target species.

4.2 Final models

The final models were designed to highlight benefits of the use of landscape metrics surfaces in habitat suitability modelling. Among all seven model outcomes the best AUC values were shown by the models with all available covariates (landscape metrics, climatic, vegetation) together after model tuning. The models with only landscape metrics surfaces showed the lowest AUC values and the model without landscape metrics showed an intermediate value. This allows the conclusion, that landscape metrics surfaces can be beneficial for the modelling process. When examining the visual model outputs with expert knowledge it seems that the landscape metrics surface models of 5ha and 25ha have a better ability to deal with the biased occurrence data of *Coronella austriaca*. In these models the alpine and subalpine areas are not that underrepresented than they are in the other model outputs. Field data collection in August 2019 seems to sustain this hypothesis. Two individuals of *Coronella austriaca* were detected in areas were the high AUC value models didn´t predict them but the landscape surface models.

Again, we focus on Schoeners *D* for the interpretation of the model output differences in geographic space. The average *D* value for comparing the final models was 0,696. This indicates greater differences than in the test models, what depends on the different covariates used for the modelbuilding. The average difference between the models is approximately 30%. This again shows how important it is to choose wisely which covariates are important for the target species.

Another interesting approach could be to mix the resolutions of the statistical surfaces in one model. Therefore knowledge is necessary about the scales depending on the available data and target species, were important patterns reveal.

4.3 Recommendations and prospects

The presented results indicate, that the contribution of landscape metrics surfaces as covarites to habitat suitability modelling holds promise and should be investigated further. Today also the necessary data in required quality can be obtained by satellite images. This procedure is not a quick and easy method to incorporate landscape metrics in the modelling process. Expert knowledge is required in more than one modelling step. Each decision should be questioned and verified on the basis of the available data. The content of this study was just a small blink at this special method and further research also on a multiscale approach would be rewarding.

5 References

Adamczyk, Joanna; Tiede, Dirk (2017): ZonalMetrics - a Python toolbox for zonal landscape structure analysis. In: *Computers & Geosciences* 99, S. 91–99. DOI: 10.1016/j.cageo.2016.11.005.

Amici, Valerio; Eggers, Britta; Geri, Francesco; Battisti, Corrado (2015): Habitat Suitability and Landscape Structure: A Maximum Entropy Approach in a Mediterranean Area. In: *Landscape Research* 40 (2), S. 208–225. DOI: 10.1080/01426397.2013.774329.

Anderson, Robert P.; Gonzalez, Israel (2011): Species-specific tuning increases robustness to sampling bias in models of species distributions: An implementation with Maxent. In: *Ecological Modelling* 222 (15), S. 2796–2811. DOI: 10.1016/j.ecolmodel.2011.04.011.

Boria, Robert A.; Olson, Link E.; Goodman, Steven M.; Anderson, Robert P. (2014): Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. In: *Ecological Modelling* 275, S. 73–77. DOI: 10.1016/j.ecolmodel.2013.12.012.

Cai, Xuejiao; Wu, Zhifeng; Cheng, Jiong (2013): Using kernel density estimation to assess the spatial pattern of road density and its impact on landscape fragmentation. In: *International Journal of Geographical Information Science* 27 (2), S. 222–230. DOI: 10.1080/13658816.2012.663918.

Čeirāns, Andris; Nikolajeva, Larisa (2017): Habitat ecology of the smooth snake Coronella austriaca and its reptilian prey in the degraded bog with implications for artificial refuge surveys. In: *Zoology and Ecology* 27 (1), S. 19–29. DOI: 10.1080/21658005.2016.1252125.

Cushman, Samuel A.; McGarigal, Kevin; Neel, Maile C. (2008): Parsimony in landscape metrics: Strength, universality, and consistency. In: *Ecological Indicators* 8 (5), S. 691–703. DOI: 10.1016/j.ecolind.2007.12.002.

Dick, Daniela C.D.; Mebert, Konrad (2017): Between housing and deep forest: Long-term population biology and dispersal of suburban Smooth snakes (Coronella austriaca). In: *Zoologischer Anzeiger - A Journal of Comparative Zoology* 270, S. 98–106. DOI: 10.1016/j.jcz.2017.09.007.

Elith, Jane; H. Graham, Catherine; P. Anderson, Robert; Dudík, Miroslav; Ferrier, Simon; Guisan, Antoine et al. (2006): Novel methods improve prediction of species' distributions from occurrence data. In: *Ecography* 29 (2), S. 129–151. DOI: 10.1111/j.2006.0906-7590.04596.x.

ESRI (2011): ArcGis Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.

Foltete, Jean-Christophe; Clauzel, Celine; Vuidel, Gilles; Tourant, Pierline (2012): Integrating graph-based connectivity metrics into species distribution models. Lanscape Ecology 27, S 557-569. DOI:10.1007/s10980-012-9709-4.

Guisan, Antoine; Thuiller, Wilfried (2005): Predicting species distribution: offering more than simple habitat models. In: *Ecol Letters* 8 (9), S. 993–1009. DOI: 10.1111/j.1461-0248.2005.00792.x.

Hartl, Helmut; Stern, Roland; Seger, Martin (2001): Karte der aktuellen Vegetation von Kärnten (M 1 : 150.000) ;. = map of the actual vegetation of Carinthia, Austria: das Vegetationsgefüge einer inneralpinen Region im Süden Österreichs. Klagenfurt: Naturwissenschaftlicher Verein für Kärnten.

Hasui, Érica; Silva, Vinícius X.; Cunha, Rogério G. T.; Ramos, Flavio N.; Ribeiro, Milton C.; Sacramento, Mario et al. (2017): Additions of landscape metrics improve predictions of occurrence of species distribution models. In: *J. For. Res.* 28 (5), S. 963–974. DOI: 10.1007/s11676-017-0388-5.

Holling, C. S. (1992): Cross-Scale Morphology, Geometry, and Dynamics of Ecosystems. In: *Ecological Monographs* 62 (4), S. 447–502. DOI: 10.2307/2937313.

Holzkämper, Annelie; Lausch, Angela; Seppelt, Ralf (2006): Optimizing landscape configuration to enhance habitat suitability for species with contrasting habitat requirements. In: *Ecological Modelling* 198 (3-4), S. 277–292. DOI: 10.1016/j.ecolmodel.2006.05.001.

Hopkins, Robert L. (2009): Use of landscape pattern metrics and multiscale data in aquatic species distribution models: a case study of a freshwater mussel. In: *Landscape Ecol* 24 (7), S. 943–955. DOI: 10.1007/s10980-009-9373-5.

Internet 1: Steven J. Phillips, Miroslav Dudík, Robert E. Schapire. Maxent software for modeling species niches and distributions (Version 3.4.1). Available from url: http://biodiversityinformatics.amnh.org/open_source/maxent/. Accessed on 2019-8-1.

Ippoliti, Carla; Gilbert, Marius; Vanhuysse, Sabine; Goffredo, Maria; Satta, Giuseppe; Wolff, Eléonore; Conte, Annamaria (2013): Can landscape metrics help determine the Culicoides imicola distribution in Italy? In: *Geospatial health* 8 (1), S. 267–277. DOI: 10.4081/gh.2013.72.

Jurasinski, Gerald; Beierkuhnlein, Carl (2006): Spatial patterns of biodiversity-assessing vegetation using hexagonal grids. In: *Biology and Environment: Proceedings of the Royal Irish Academy* (106B), S. 401–411. Online www.jstor.org/stable/20728610.

Käsewieter (2002): Ökologische Untersuchungen an der Schlingnatter (Coronella austriaca, Laurenti 1768). In: *Dissertation an der Universität Bayreuth*.

Lam, Nina Siu-Ngan; Quattrochi, Dale A. (1992): On the Issues of Scale, Resolution, and Fractal Analysis in the Mapping Sciences*. In: *The Professional Geographer* 44 (1), S. 88–98. DOI: 10.1111/j.0033-0124.1992.00088.x.

Levin, Simon A. (1992): The Problem of Pattern and Scale in Ecology: The Robert H. MacArthur Award Lecture. In: *Ecology* 73 (6), S. 1943–1967. DOI: 10.2307/1941447.

Li, Harbin; Wu, Jianguo (2004): Use and misuse of landscape indices. In: *Landscape Ecol* 19 (4), S. 389–399. DOI: 10.1023/B:LAND.0000030441.15628.d6.

Lobo, Jorge M.; Jiménez-Valverde, Alberto; Real, Raimundo (2008): AUC: a misleading measure of the performance of predictive distribution models. In: *Global Ecol Biogeography* 17 (2), S. 145–151. DOI: 10.1111/j.1466-8238.2007.00358.x.

Merow, Cory; Smith, Matthew J.; Silander, John A. (2013): A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. In: *Ecography* 36 (10), S. 1058–1069. DOI: 10.1111/j.1600-0587.2013.07872.x.

Pernetta, A. P.; Allen, J. A.; Beebee, T. J. C.; Reading, C. J. (2011): Fine-scale population genetic structure and sex-biased dispersal in the smooth snake (Coronella austriaca) in southern England. In: *Heredity* 107 (3), S. 231–238. DOI: 10.1038/hdy.2011.7.

Peterson, A. Townsend (2011): Ecological niches and geographic distributions. Princeton N.J.: Princeton University Press (Monographs in population biology, 49).

Peterson, A. Townsend; Papeş, Monica; Eaton, Muir (2007): Transferability and model evaluation in ecological niche modeling: a comparison of GARP and Maxent. In: *Ecography* 30 (4), S. 550–560. DOI: 10.1111/j.0906-7590.2007.05102.x.

Phillips, Steven J. (2004): A Maximum Entropy Approach to Species Distribution Modelling. In: *Proceedings of the Twenty-First International Conference on Machine Learning* 2004, S. 655–662.

Phillips, Steven J.; Anderson, Robert P.; Schapire, Robert E. (2006): Maximum entropy modeling of species geographic distributions. In: *Ecological Modelling* 190 (3-4), S. 231–259. DOI: 10.1016/j.ecolmodel.2005.03.026.

Phillips, Steven J.; Dudík, Miroslav (2008): Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. In: *Ecography* 0 (0), 080328142746259-??? DOI: 10.1111/j.0906-7590.2007.5203.x.

Pulliam, H. Ronald (2000): On the relationship between niche and distribution. Ecology Letters 3: 349-361. DOI: https://doi.org/10.1046/j.1461-0248.2000.00143.x

Radosavljevic, Aleksandar; Anderson, Robert P. (2014): Making better M axent models of species distributions: complexity, overfitting and evaluation. In: *J. Biogeogr.* 41 (4), S. 629–643. DOI: 10.1111/jbi.12227.

R Core Team (2019): R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.URL http://www.R-project.org/.

Reading, C. J. (2012): Ranging behaviour and home range size of smooth snake inhabiting lowland heath in southern England. In: *Herpetological Journal* (22), S. 241–247.

Renner, Ian W.; Warton, David I. (2013): Equivalence of MAXENT and Poisson point process models for species distribution modeling in ecology. In: *Biometrics* 69 (1), S. 274–281. DOI: 10.1111/j.1541-0420.2012.01824.x.

Rosenzweig, Michael L. (1995): Species Diversity in Space and Time. Cambridge University Press. DOI: https://doi.org/10.1017/CBO9780511623387.

Rödder, D.; Engler, J. O. (2011): Quantitative metrics of overlaps in Grinnellian niches: advances and possible drawbacks. In: *Global Ecol Biogeography* 20 (6), S. 915–927. DOI: 10.1111/j.1466-8238.2011.00659.x.

Saura, S.; Martinez-Millan, J. (2001): Sensitivity of Landscape Pattern Metrics to Map Spatial Extent. In: *Photogrammetric Engineering and Remote Sensing* (67), S. 1027–1036.

Schindler, Stefan; Wehrden, Henrik von; Poirazidis, Kostas; Wrbka, Thomas; Kati, Vassiliki (2013): Multiscale performance of landscape metrics as indicators of species richness of plants, insects and vertebrates. In: *Ecological Indicators* 31, S. 41–48. DOI: 10.1016/j.ecolind.2012.04.012.

Schoener, Thomas W. (1968): The Anolis Lizards of Bimini. Resource Partitioning in a Complex Fauna. In: *Ecology* 49 (4), S. 704–726. DOI: 10.2307/1935534.

Shcheglovitova, Mariya; Anderson, Robert P. (2013): Estimating optimal complexity for ecological niche models: A jackknife approach for species with small sample sizes. In: *Ecological Modelling* 269, S. 9–17. DOI: 10.1016/j.ecolmodel.2013.08.011.

Silverman, B. W. (1986): Density Estimation for Statistics and Data Analysis. Boston, MA, s.l.: Springer US (Monographs on Statistics and Applied Probability). Online http://dx.doi.org/10.1007/978-1-4899-3324-9.

Turner, Monica Goigel; Dale, Virginia H.; Gardner, Robert H. (1989): Predicting across scale: Theory development and testing. In: Landscape Ecol 3, S. 245–252. Online http://dx.doi.org/10.1007/bf00131542.

Turner, Monica Goigel; Gardner, R. H.; O'Neill, Robert V. (2001): Landscape ecology in theory and practice. Pattern and process. New York: Springer. Online http://lib.myilibrary.com?id=18739.

Völkl, Wolfgang; Käsewieter, Daniel (2003): Die Schlingnatter. Ein heimlicher Jäger. Bielefeld: Laurenti-Verl. (Zeitschrift für Feldherpetologie Beiheft, 6).

Walz, U. (2011): Landscape Structure, Landscape Metrics and Biodiversity. In: Living Reviews in Landscape Research 2011 (5). Online http://www.livingreviews.org/lrlr-2011-3 in.

Warren, Dan L.; Glor, Richard E.; Turelli, Michael (2008): Environmental niche equivalency versus conservatism: quantitative approaches to niche evolution. In: Evolution; international journal of organic evolution 62 (11), S. 2868–2883. DOI: 10.1111/j.1558-5646.2008.00482.x.

Warren, Dan L.; Glor, Richard E.; Turelli, Michael (2010a): ENMTools: a toolbox for comparative studies of environmental niche models. In: Ecography 35, S. 1160. DOI: 10.1111/j.1600-0587.2009.06142.x.

Warren, Dan L.; Glor, Richard E.; Turelli, Michael (2010b): ENMTools: a toolbox for comparative studies of environmental niche models. In: Ecography 35, S. 1160. DOI: 10.1111/j.1600-0587.2009.06142.x.

Warren, Dan L.; Seifert, Stephanie N. (2011): Ecological niche modeling in Maxent: the importance of model complexity and the performance of model selection criteria. In: *Ecological Applications* 21 (2), S. 335–342.

Wei, Taiyun; Simko, Viliam (2017): R package "corrplot": Visualization of a Correlation Matrix (Version 0.84). Available from https://github.com/taiyun/corrplot

Westphal, Michael I.; Field, S. A.; Tyre, A. J.; Paton, D.; Possingham, H. P. (2003): Effects of landscape pattern on bird species distribution in the Mt. Lofty Ranges, South Australia. In: *Landscape Ecol* 18 (4), S. 413–426. DOI: 10.1023/A:1026115807529.

Report

Incorporating landscape metrics as surfaces into a habitat suitability modelling process

1 Introduction

A detailed description of the modelling process is presented in this part of the master thesis.

Landscape metrics are calculated with special algorithms and quantify the spatial characteristics of patches, classes or the entire landscape. So, they in a way mirror the ecological processes that are present in the corresponding landscape, which is a key factor for the suitability of the environment and the distribution of animals and plants.

The aim of this study is to try to find a possibility to use landscape metrics for habitat suitability modelling and examine if thereby useful models of sound quality can be built. Therefore, it is necessary to construct surfaces of this landscape metrics, because HSM algorithms need this kind of ecological information to form the niche of a species and project it into geographic space.

The algorithm of choice to work with is Maxent (Phillips et al. 2006). Maxent is a presence only habitat suitability modelling method, which perpetually shows good results and is gladly used in many publications.

Target area is Carinthia, Austria; target species is *Coronella austriaca*, the Smooth Snake.

2 Materials

Spatial data used to build the models and to create the surfaces:

Description	Type	Source	Reference System	Resolution/ Accuracy
Distribution data of *Coronella austriaca*, Carinthia	Point data, Shapefile	Herpetofaunistische Datenbank – Naturhistorsiches Museum Wien	WGS84	50m-4000m
Distribution data of *Coronella austriaca*, Carinthia	Point data, Excel File	Arge NATURSCHUTZ, Klagenfurt	BMN M31, WGS84	10m-1245m
Realraumanalyse Kärnten - generalized landuse Carinthia	Shapefile	https://www.data.+D6:D10gv.at/katalog/dataset/a944a696-767e-408f-a716-49ccf5da866d, Land Kärnten, Abteilung 3	EPSG:31258	Digitizing of satellite images and orthophotos, survey, areal images, maps, ÖK50

Aktuelle Vegetation Kärntens - current vegetation of Carinthia	Shapefile, incomplete	https://www.data.gv.at/katalog/dataset/7650f523-35c9-46ba-a40e-50ee5e8b1467, Land Kärnten, Abteilung 3	EPSG:31258	Detection scale 1:50000
EU Berichtsgewässernetz Land Kärnten - water body networks Carinthia	Shapefile	https://www.data.gv.at/katalog/dataset/521be3fe-e805-4011-9dc6-161e22261043, Land Kärnten, Abteilung 8	EPSG:31258	Digitizing based on 1m-DTM and orthophotos
Verkehrsnetz Kärnten - Transport Network	Shapefile	https://www.data.gv.at/katalog/dataset/4cdb8791-fbe7-480d-90b8-2e50008ab0bd, Land Kärnten, Abteilung 7	EPSG:31258	Digitising (1:1000), survey
Gewässereinzugsgebiete Kärntens - Catchment areas of the water bodies of Carinthia	Shapefile	Zur Verfügung gestellt von / provided by: http://www.kagis.ktn.gv.at, Hr. Ing. Christian Mairamhof MSc (GIS)	EPSG:31258	Based on the catchment area of the river Drau
Klimaatlas Kärnten Klimaelement komplexe Klimagrößen -Climate Atlas of Carinthia - climatic element complex climate values	ASCII	https://www.data.gv.at/katalog/dataset/073a0324-e258-41ff-bfe2-b291e7be755f, Land Kärnten, Abteilung 8	EPSG:31258	250x250m
Klimaatlas Kärnten Klimaelement Niederschlag - Climate Atlas of Carinthia - climatic element precipitation	ASCII	https://www.data.gv.at/katalog/dataset/52d21708-fe51-4744-9dec-8f166d412260, Land Kärnten, Abteilung 8	EPSG:31258	250x250m
Klimaatlas Kärnten Klimaelement Schneefall und Schneedecke - Climate Atlas of Carinthia - climatic element snow fall and snow cover	ASCII	https://www.data.gv.at/katalog/dataset/1a71a739-7c92-4bd0-ad44-05044ccddae8, Land Kärnten, Abteilung 8	EPSG:31258	250x250m
Klimaatlas Kärnten Klimaelement Strahlung - Climate Atlas of Carinthia - climatic element radiation	ASCII	https://www.data.gv.at/katalog/dataset/19979e7a-bfe1-4019-a3f1-1c9f32e46314, Land Kärnten, Abteilung 8	EPSG:31258	250x250m
Klimaatlas Kärnten Klimaelement Temperatur - Climate Atlas of Carinthia - climatic element temperature	ASCII	https://www.data.gv.at/katalog/dataset/9ebdeecf-37ff-4c0b-ab1e-8aff8f95cfea, Land Kärnten, Abteilung 8	EPSG:31258	250x250m

Table 1: Data used for model building.

Software and extensions / packages used to conduct the experiments:

ArcGis 10.5.1 (ESRI 2011)
R (R Core Team 2019)
Corrplot (Wei and Simko 2017)
ZonalMetrics Toolbox (Adamczyk und Tiede 2017)
ENMTool (Warren et al. 2010)
Maxent 3.4.1 (Phillips et al. 2006)
QGis (QGIS Development Team 2019)

3 Methods

3.1 Filtering distribution data

After transformation of the distribution points to EPSG:31258 the obtained distribution data of *Coronella austriaca* was split in useful and useless groups. For this survey, only points with an uncertainty of 100 m or less should be used. From the "Herpetofaunistische Datenbank – Naturhistorisches Museum Wien" 1083 points were obtained from which 103 distribution points will be used for modelling. From the "Arge NATURSCHUTZ" 125 points were transferred from which 26 will be used.

Accuracy of points:

source	100m	50m	30m	20m	10m	Total
Herpetofaunistische Datenbank	36	63	-	4	-	103
Arge NATURSCHUTZ	5	1	1	12	7	26
Sum	41	64	1	16	7	129

Table 2: Sample points of *Coronella austriaca* and their accuracy.

As a total **129 sample points** can be used for model building.

3.2 Updating the vegetation layer

The unfortunately incomplete vegetation data file from Carinthia must be updated and refined for the purpose of the survey. The missing data (mostly water bodies, transport facilities, urban areas, some wetlands and some parts of alpine areas) was taken from the layer "Realraumanalyse Kärnten". After some modifications of the attribute table (the columns must have the same names and data types in both data files) the missing information could be added via "update feature class" in ArcGis (ESRI 2011). Still some empty areas could be found in the file. This information was added via digitizing and the assistance of information from the "Realraumanalyse" and the "Karte der aktuellen Vegetation Kärntens" (Hartl et al. 2001).

Subsequently to the completing of the vegetation layer, the correct topology was reviewed and, if necessary, improved.

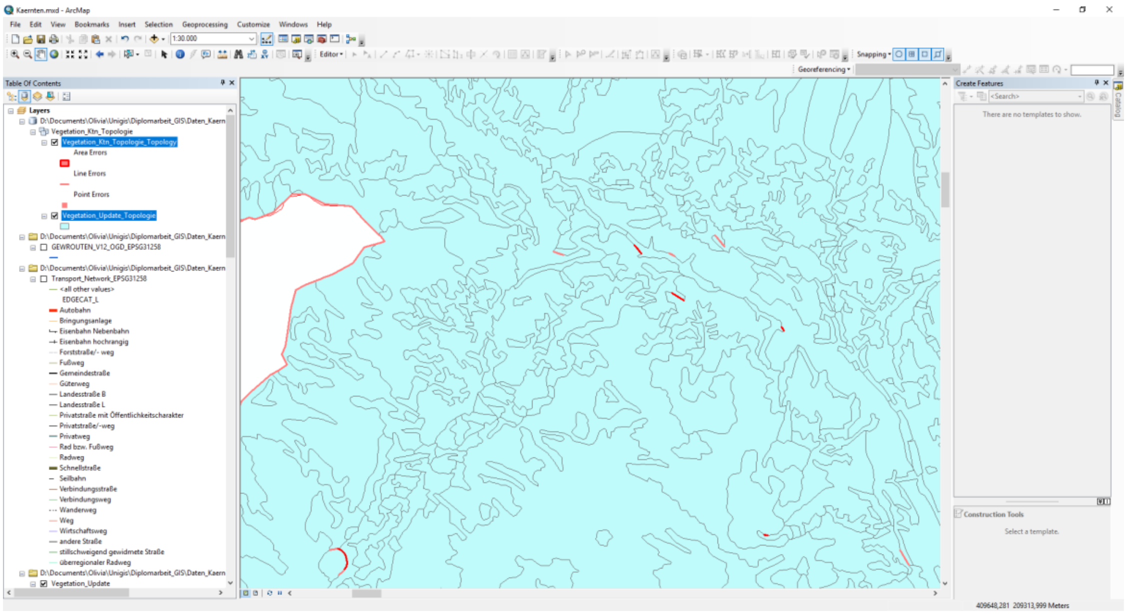


Figure 1: Cutout of the ArcGis (ESRI 2011) desktop during topology check.

After the completion of the vegetation layer further information had to be added for the purpose of the survey. To calculate realistic landscape metrics in a scale relevant for *Coronella austriaca* the vegetation layer was updated with information concerning water bodies (brooks and rivers). Therefore, buffers were created, depending on the size of the brook. To distinguish between the different sizes of rivers/brooks the “Einzugsgebietsgrößenklassen” GRKATWRRL (Eisenkölb and Vinzce 2009) were considered. All watercourses of a category were exported from the feature class – except for category one: it only contained the river “Drau”, which was already included in the vegetation layer. The buffer size was a reasonable compromise, because the size of a stream of course increases downstream and is not constant all the time. The buffers are afterwards merged for each river category, exported as feature class and added to the vegetation layer (update feature class).

Categories of brooks and the buffer size used:

Category	Buffer size	Feature class
1	-	Already existing in the vegetation layer (“Gewässer”)
3	12,5 m	KAT_3_Buffer
4	10 m	KAT_4_Buffer
5	7,5 m	KAT_5_Buffer
6	5 m	KAT_6_Buffer
7	3 m	KAT_7_Buffer

Table 3: Buffer sizes for the different river categories.

After the update, the topology was reviewed again and corrected.

Subsequently to the finishing of the corrections, the vegetation layer of Carinthia consisted of 51 classes, where the different categories of rivers/brooks (Kat_3-Kat_7) could be aggregated to one class:

Name_Agg	Name
Bau_geschl	Autobahn
Bau_geschl	Betriebsgelaende
Bau_geschl	Flughafen
Bau_geschl	Geschlossene bzw dichte Bebauung
Bau_geschl	Gletscherflaechen
Bebaut	Historisches Erbe, Schloss- und Klosteranlagen
Bebaut	Offene Bebauung, unterschiedlicher Art
Bebaut	Pioniervegetation auf Schutt und Fels
Bestockt	Grauerlenbestaende
Bestockt	Latschenkrummholz
Bestockt	Montan - subalpines Laubbuschwerk
Bestockt	Roehrichte- und Großseggenfluren
Bestockt	Schwarzerlenbestaende
Bestockt	Weidenbestaende
Gewaesser	Gewaesser
Gewaesser	Kat_3
Gewaesser	Kat_4
Gewaesser	Kat_5
Gewaesser	Kat_6
Gewaesser	Kat_7
GL_Intensiv	Acker-Gruenlandkomplexe
GL_Intensiv	Sportflaechen (Golfplaetze, etc.)
GL_Intensiv	Staedtisches Gruen und diverse Sportflaechen
GL_Intensiv	Wintersportgelaende
GL_Intensiv	Wirtschaftsgruenland (Maehwiesen und Weiden)
Gruenland	Autobahn-Tunnel
Gruenland	Feuchtgebiete, Moore
Gruenland	Hochmoor
Gruenland	Laerchenwiesen
Gruenland	Niedermoor
Gruenland	Subalpine u. alpine Rasen, Extensiv-Weiden ueber Karbonatgestein
Gruenland	Subalpine u. alpine Rasen, Extensiv-Weiden ueber Silikatgestein
Gruenland	Weiderasen u. Bergmaehder ueber Karbonatgestein
Gruenland	Weiderasen u. Bergmaehder ueber Silikatgestein
Gruenland	Zwergstrauchheiden, Mosaik Zwergstrauchheiden/Weiderasen ueber Karbonatgestein
Gruenland	Zwergstrauchheiden, Mosaik Zwergstrauchheiden/Weiderasen ueber Silikatgestein
Wald	(Buchen)-Tannen-Fichtenwald. Buchen-Tannenwald, Tannenwald ueber Karbonatgestein
Wald	(Buchen)-Tannen-Fichtenwald. Buchen-Tannenwald, Tannenwald ueber Silikatgestein
Wald	Buchenwald
Wald	Feuchter Laubmischwald (Erlen-,Eschen-,Weiden-,Bergahorn)
Wald	Fichten-Laerchenwald
Wald	Fichtenwald, sekundaere Fichtenforste ueber Karbonatgesetein
Wald	Fichtenwald, sekundaere Fichtenforste über Silikatgesetein
Wald	Laerchen-Fichtenwald
Wald	Nadel-Laubmischwald (Rotfoehren-Buchenwald, Fichten-Buchenwald)
Wald	Nadel-Mischwald mit Laubholzeinsprengungen
Wald	Rotfoehren-Fichtenmischwald
Wald	Rotfoehrenwald
Wald	Schwarzfoehrenwald
Wald	Warmer Laubmischwald (Manna-Esche, Hopfenbuche, Mehlbeere, Eichen)
Wald	Zirbenwald und Laerchenzirbenwald

Table 4: Aggregation of the vegetation classes.

For some of the further landscape metrics calculations (Contrast, Connectance), the classes were aggregated to fewer atop-classes that represent special and alike ecological functions for *Coronella austriaca* (Name_agg – see Table 4). That's why for example "Pinoniervegetation auf Schutt und Fels" (pioneer vegetation on boulder and rocks) was dedicated to the atop class "Bebaut" (covered with buildings) together with 2 other forms of "real" house building.

A second, lower level aggregation was conducted for the area metrics calculation for the whole of Carinthia to speed up calculation time a little bit. I aggregated the vegetation classes very gentle to lose as less information as possible for the calculation of landscape metrics – and keep characteristics of vegetation classes such as dry or wet ground.

Name	**Agg_2_light**
Acker-Gruenlandkomplexe	Acker-Gruenlandkomplexe
Autobahn	Bau_Geschlossen
Betriebsgelaende	Bau_Geschlossen
Flughafen	Bau_Geschlossen
Geschlossene bzw dichte Bebauung	Bau_Geschlossen
(Buchen)-Tannen-Fichtenwald. Buchen-Tannenwald, Tannenwald über Karbonatgestein	Buchen_Tannen_Fichten_Wald
(Buchen)-Tannen-Fichtenwald. Buchen-Tannenwald, Tannenwald über Silikatgestein	Buchen_Tannen_Fichten_Wald
Buchenwald	Buchenwald
Grauerlenbestaende	Erle_Weide
Schwarzerlenbestaende	Erle_Weide
Weidenbestaende	Erle_Weide
Feuchter Laubmischwald (Erlen-,Eschen-,Weiden-,Bergahorn-)	Feuchter Laubmischwald (Erlen-Eschen-Weiden-Bergahorn)
Feuchtgebiete, Moore	Feuchtgebiete
Hochmoor	Feuchtgebiete
Niedermoor	Feuchtgebiete
Fichten-Laerchenwald	Fichten_und_Mischwald
Fichtenwald, sekundaere Fichtenforste über Karbonatgesetein	Fichten_und_Mischwald
Fichtenwald, sekundaere Fichtenforste über Silikatgesetein	Fichten_und_Mischwald
Laerchenwiesen	Laerchenwiesen
Rotfoehren-Fichtenmischwald	Foehrenwald
Rotfoehrenwald	Foehrenwald
Schwarzfoehrenwald	Foehrenwald
Gletscherflaechen	Gletscherflaechen
Laerchen-Fichtenwald	Laerchenwald
Zirbenwald und Laerchenzirbenwald	Laerchenwald
Latschenkrummholz	Latschenkrummholz
Nadel-Laubmischwald (Rotfoehren-Buchenwald, Fichten-Buchenwald)	Mischwald
Nadel-Mischwald mit Laubholzeinsprengungen	Mischwald
Montan - subalpines Laubbuschwerk	Montan - subalpines Laubbuschwerk
Historisches Erbe, Schloß- und Klosteranlagen	Offene_Bebauung
Offene Bebauung, unterschiedlicher Art	Offene_Bebauung
Pioniervegetation auf Schutt und Fels	Pioniervegetation auf Schutt und Fels
Roehrichte- und Großseggenfluren	Roehrichte- und Grossseggenfluren
Sportflaechen (Golfplaetze, etc.)	Sport_Park
Staedtisches Gruen und diverse Sportflaechen	Sport_Park

Subalpine u. alpine Rasen, Extensiv-Weiden ueber Karbonatgestein	Subalpine_alpine_Rasen_Extensivweiden
Subalpine u. alpine Rasen, Extensiv-Weiden ueber Silikatgestein	Subalpine_alpine_Rasen_Extensivweiden
Warmer Laubmischwald (Manna-Esche, Hopfenbuche, Mehlbeere, Eichen)	Warmer Laubmischwald (Manna-Esche Hopfenbuche Mehlbeere Eichen)
Gewaesser	Wasser
Kat_3	Wasser
Kat_4	Wasser
Kat_5	Wasser
Kat_6	Wasser
Kat_7	Wasser
Weiderasen u. Bergmaehder über Karbonatgestein	Weiderasen_Bergmaehder
Weiderasen u. Bergmaehder über Silikatgestein	Weiderasen_Bergmaehder
Autobahn-Tunnel	Wirtschaftsgruenland_Maehwiesen (GL_int)
Wintersportgelaende	Wirtschaftsgruenland_Maehwiesen (GL_int)
Wirtschaftsgruenland (Maehwiesen und Weiden)	Wirtschaftsgruenland_Maehwiesen (GL_int)
Zwergstrauchheiden, Mosaik Zwergstrauchheiden/Weiderasen über Karbonatgestein	Weiderasen_Bergmaehder
Zwergstrauchheiden, Mosaik Zwergstrauchheiden/Weiderasen über Silikatgestein	Weiderasen_Bergmaehder

Table 5: Lower level aggregation of the vegetation classes.

3.3 Test area and landscape metrics

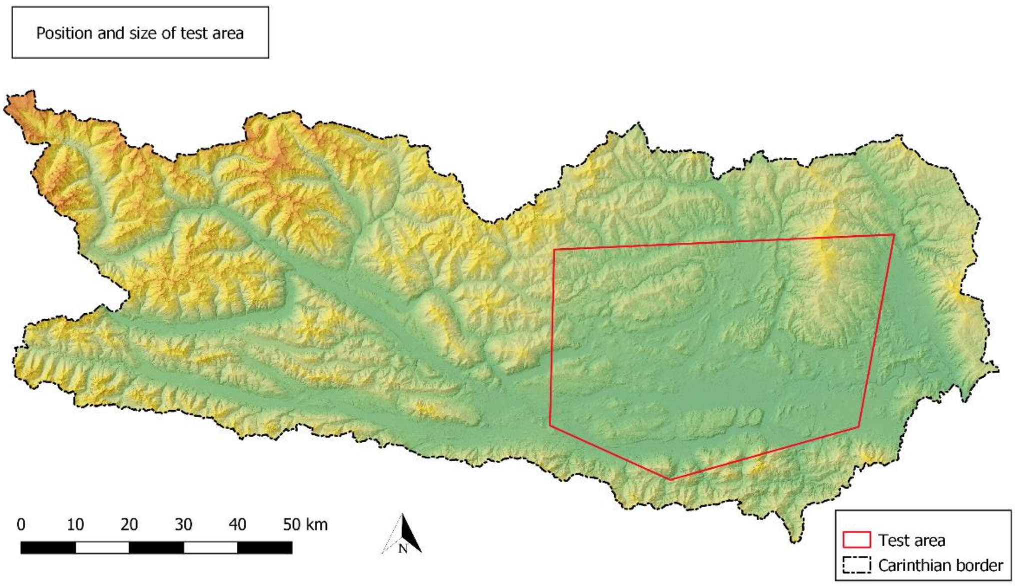


Figure 2: Size and position of the delimited test area for landscape metrics calculation.

To examine which landscape metrics surfaces could be appropriate for the task, a test area was delimited. Its size is about a fourth of the area of Carinthia. It contains 46 locations where *Coronella austriaca* was detected. This was necessary because of the huge amount of data to limit the calculation time that it takes to fulfill the landscape metrics calculations. The final model will include the whole area of Carinthia.

The vegetation layer was clipped to the size of the test area. Also the layer of the catchment areas of the rivers in Carinthia, which will be used as statistical layer for the zonal metrics (Adamczyk und Tiede 2017) calculation, was clipped.

As next step regular tessellation surfaces (hexagons) in different cell sizes where generated for the test area with the ZonalMetrics toolbox (Adamczyk und Tiede 2017). The cell size was approximately 5ha, 10ha, 15ha, 25ha and 35ha. The approximation depends on the fact that the ZonalMetrics tool works with the shorter diagonal of the hexagon to determine the size of the statistic zone (the size of each hexagon). So, for the 5ha tessellation surface the size of the shorter diagonal was 242m, for 10ha 340 m, 15ha 416m, 25ha 538m and 35ha 636m.

For the vegetation layers attribute table to be used in the landscape metrics calculation with the ZonalMetrics toolbox, all mutated vowels (ä, ö, ü) and special signs (ß) had to be eliminated. Also, the attribute table of the catchment areas had to be modified because of mutated vowels and special signs (some columns where deleted).

Landscape metrics that can be used within the ZonalMetrics toolbox are selected because of their ability to deal with the restriction that the statistical zones insert and their importance for the target species. Statistical zones are small subsets of the whole landscape. There are 3 possibilities to deal with the patches that overlap the statistical zone: you can cut them, select all overlapping patches and calculate the metrics for each whole patch - repeatedly counting is allowed, or select the patches whose centroid is located inside the zone - no repeatedly counting of patches is allowed (Adamczyk und Tiede 2017). I decided to select the "cut" option, because the statistical zones in that case should picture the home ranges of *Coronella austriaca* individuals or populations.

<u>So, for all statistical area datasets (5ha, 10 ha, 15ha, 25ha, 35ha, Gewässereinzugsgebiete (GEZG - catchment areas) the following landscape metrics were calculated:</u>

Not all calculated landscape metrics could be used for model building. The italicized metrics where not used in this study.

-**Area Metrics (for Agg_2_light):**

Not for woodlands – only for open habitat types:

ca<className> Class area (patch) for each class in the respective statistical zone

npc<className> Number of patches for each class per zone

pz<className> Percent of the area of the whole statistical zone taken by the patch (especially important for the catchment areas because of their unequal sizes and tessellation surface edge zones)

-**Largest Patch Index (for all classes):**

lpi Percentage of the total area of the statistical zone taken by the largest patch

lpi_class Name of the largest patch class

-**Connectance Metrics (for the high-level aggregated classes – Name_Agg)**

Maximum connectance distance: 500m, Offset: 100m, classes: Bebaut, Bestockt, GL_intensiv, Gruenland (merged) ci_np Number of distinct (by FID) connected classes

ci_pa Patch area within the range of connection

ci_pp Percentage of patch area that lies within the range of connection to the statistical zone

ci_ca The Area of the connection zone between the patches

ci_cp Percentage of the connection zone between the patches in comparison to the statistical zone

-**Contrast Metrics (for the high-level aggregated classes – Name_Agg)**

Analyzed (one at a time): Bebaut, GL_intensiv, Bestockt, Gruenland, Contrast classes: Bau_geschl, Gewaesser, Wald.

el_a_class Edge length of the focus class

el<className> Edge length of the boundary of the focus class which is shared with the contrast classes

cce<className> Contrast index which is calculated as the percentage of the edge length of the focus class shared with the contrast class(es)

-**Diversity Index (for all classes)**

shdi Shannon Diversity-value for selected classes per zone

- **Line kernel density surface of the edge density**

Overall, four kernel density surfaces were created to test their representation abilities for the edge density in the test area.

The vegetation layer of the test area was converted from polygon to polyline. After that, the transport system shape file was cut to the extent of the test area and then merged with the line shapefile of the former vegetation layer. So, all possible edges in the test area should be represented.

Now the line kernel density of this data set was calculated with ArcGis (ESRI 2011). The decision for a bandwidth is a key step in kernel density estimation, depending on the smoothing of the resulting surface. As a rule of thumb ArcGis (Esri 2011) works with the rule of Silverman (Silverman 1986) which is based on quadratic kernel function. So, to get a coarse overview the first surface was calculated with the suggested bandwidth of 1741,1125 m. To compare this surface with other outcomes, three more surfaces with bandwidths of 500m, 1000m and 1500m where created. To picture the edge densities in an appropriate way, the smoothing of the surface should not be to ample. So, in my professional opinion and the comparison with the line-dataset, the surface with the bandwidth of 1000m shows an appropriate compromise between over- and undersmoothing for this special purpose.

pz<class name> Percent of the area of the whole statistical zone taken by the patch		
1	pz_glint	cultivated grassland
2	pz_offbau	light building desity
3	pz_feucht	wetlands

4	pz_weide	pastures and mountainious hay meadow
5	pz_acker	acre-grassland
6	pz_latsche	dwarf pine knee timber
7	pz_pionier	pioneer vegetation on boulder and rocks
8	pz_subalp	subalpine and alpine grassland and pastures
		Diversity Metric Shannon Diversity Index
9	shdi	shannon diversity index
		Connectance Metrics Maximum connectance Distance: 500m, Offset 100m, covered w. buildings, int. grassland, planted, grassland (merged)
10	ci_np	number of distinct (by FID) connected classes
11	ci_pp	percentage of patch area that lies within the range of connection to the statistical zone
12	ci_cp	Percentage of the connection zone between the patches in comparison to the statistical zone
		Largest Patch Index
13	lpi	percentage of the total area of the statistical zone taken by the largest patch
		Contrast Metrics Analyzed (one at a time): covered w. buildings, int. grassland, planted, grassland, Contrast classes: compact settlement, waterbodies, forest.
	covered w. buildings	
14	cce_beb_bau	contrast: compact settlement
15	cce_beb_was	contrast: water bodies
16	cce_beb_wa	contrast: forest
	intensive grassland	
17	cce_gli_bau	contrast: compact settlement
18	cce_gli_was	contrast: water bodies
19	cce_gli_wa	contrast: forest
	planted	
20	cce_bes_bau	contrast: compact settlement
21	cce_bes_was	contrast: water bodies
22	cce_bes_wa	contrast: forest
	grassland	
23	cce_gl_bau	contrast: compact settlement
24	cce_gl_was	contrast: water bodies
25	cce_gl_wa	contrast: forest
		Kernel Density - lines
26	kernel	line kernel density to represent edge density

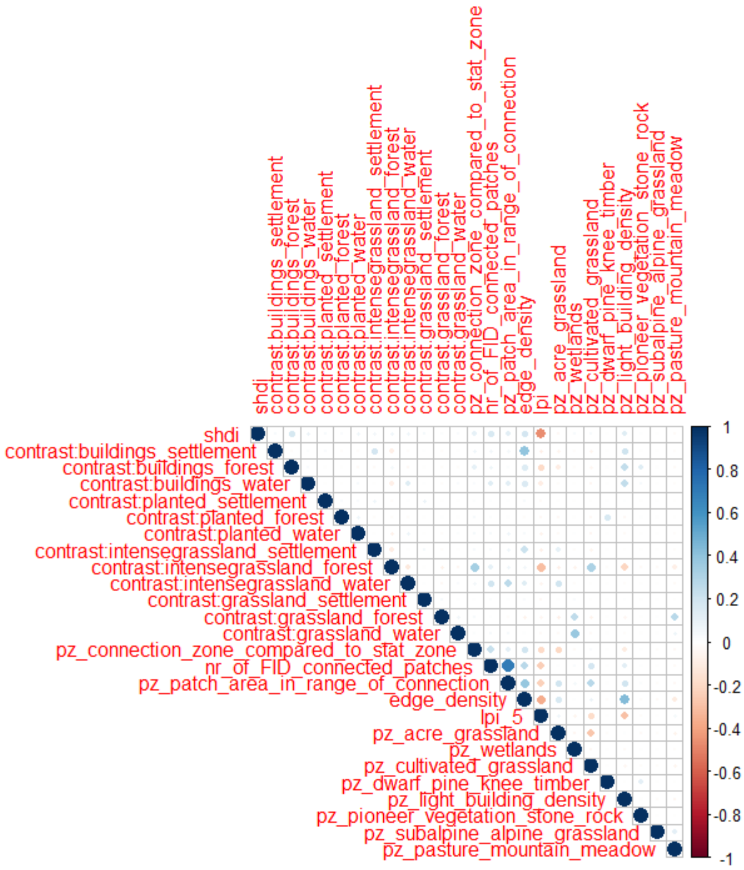
Table 6: Composition of the different landscape metrics layers used for model building.

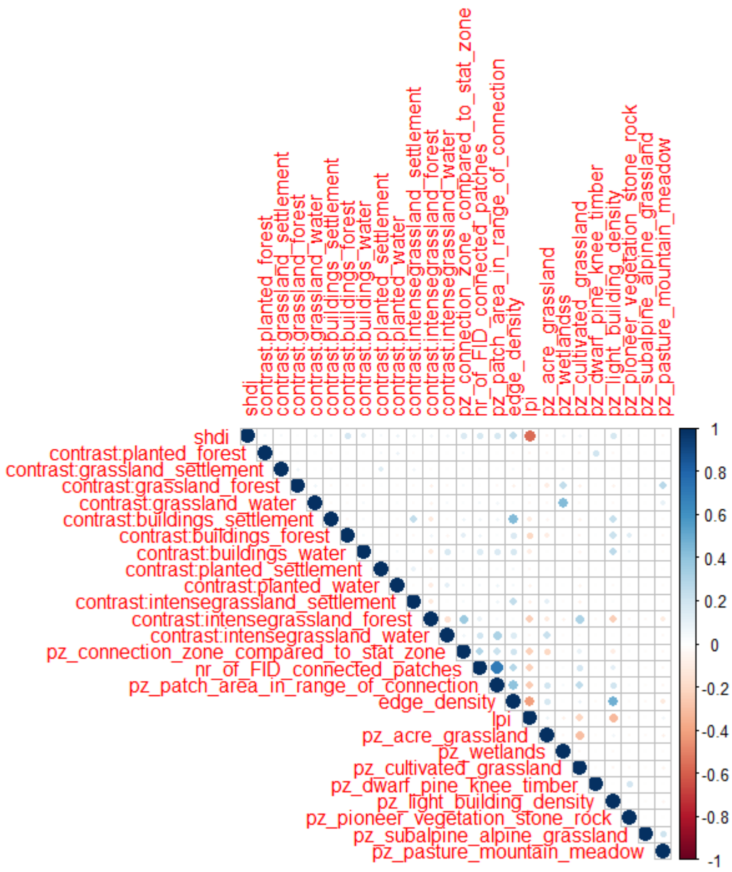
To be able to use this data for ecological modelling, all vector data sets had to be converted in raster data. The resolution was 100m – because of the partly large inaccuracies of *Coronella austriaca* data. Resampling method was “bilinear” and for the conversion process “maximum combined area” was chosen.

After converting vector data to raster data, all layers were extracted by mask to make sure that extend and raster snapping is the same for all of them. As last step, all layers were converted to ASCII files, the format, Maxent works with.

In the end, 26 surfaces where ready to use for Maxent (Phillips 2004) modelling.

To get an insight in how the size of the statistical areas influences the correlation between the layers (scale dependency), correlation matrices for the 6 different “resolutions” of landscape metrics and all 26 layers were calculated with EMNTool (Warren et al. 2010) and visualized with the R package “corrplot” (Wei and Simko 2017).





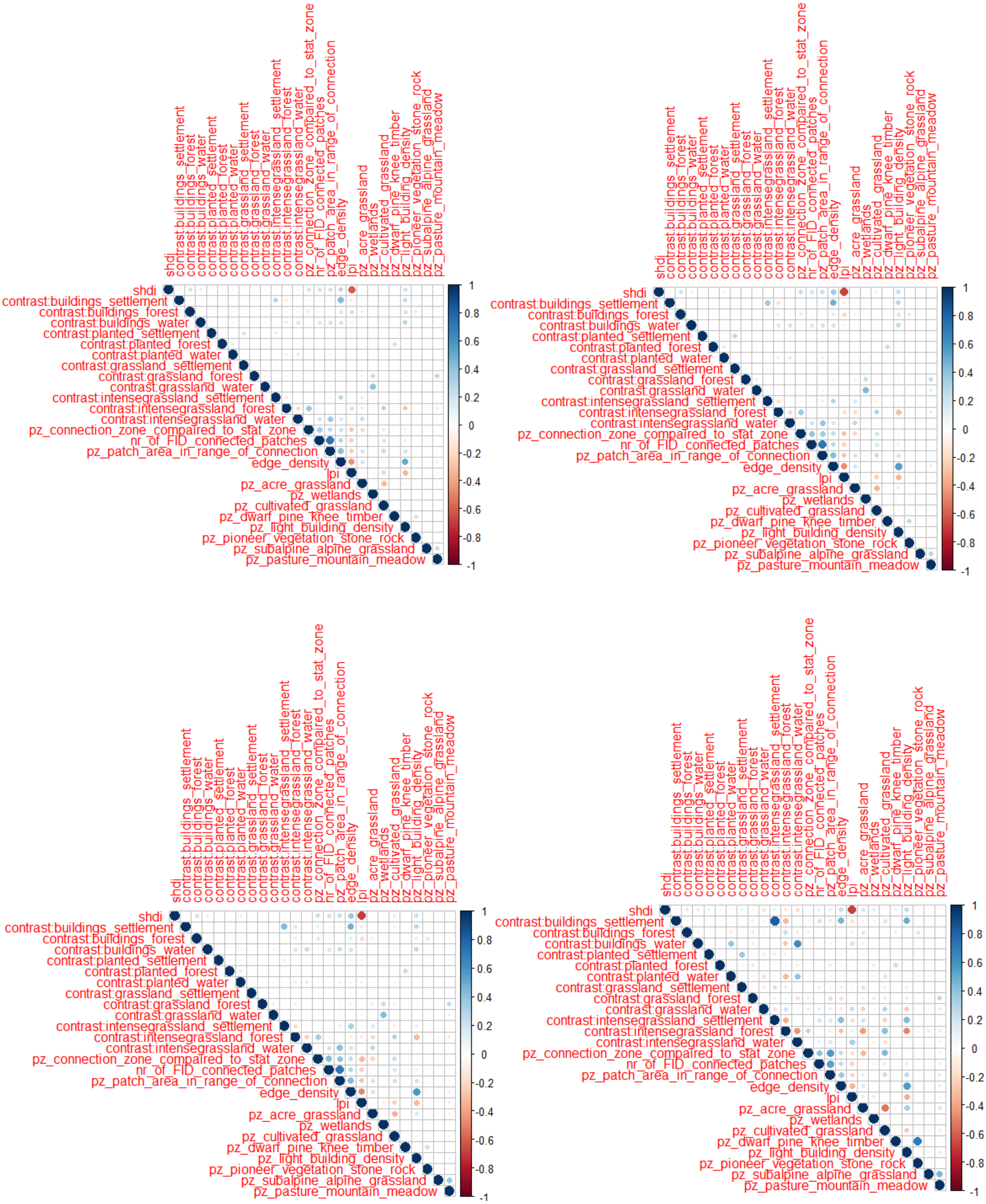


Figure 3: The 6 correlation matrices show the relationships between the 26 input layers (top left: 5ha, top right: 10ha, middle left: 15ha, middle right: 25ha, bottom left: 35ha, bottom right: catchment areas (GEZG).

R script for the correlation plots (example for the 10ha surface):

```
library(corrplot)

setwd('D:/ENMTool_Output_alle/')

corr10_mat <- read.csv2('Correlation_10/Correlation_10_2.csv', header = TRUE, sep = ',', dec = '.')

#making a decent matrix#

rownames(corr10_mat) <- corr10_mat$SPECIES

corr10_mat$SPECIES <- NULL

corr10_mat <- as.matrix(corr10_mat)

corrplot(corr10_mat, method="circle", type="upper")
```

As you can see from the plots, the correlations vary for the same landscape metrics layers for all 6 resolutions. Also, the correlations tend to get stronger, positive as well as negative, the larger the statistical surfaces get. That strangely is the opposite outcome than “Toblers law” (Tobler 1970) may let expect, where near things should be more related than distant things. This could be an effect of the changing extend by varying the hexagon size of the statistical units (Schindler et al. 2013).

3.4 Model runs for the test area

After preparation of the input data sets, model building with Maxent GUI (Phillips et al. 2006) was started. 26 surfaces of landscape metrics where ready to use and to evaluate which of them, and which “resolution” of them, should be part of the final model for the whole of Carinthia. I also just used the landscape metrics surfaces for the model runs, to focus on the influence of this special predictors alone. Through this approach also the most contributive environmental variables can be detected. In the final model also other predictors like insolation and precipitation for example shall take part.

The sample points of *Coronella austriaca* were spatially filtered to clean the data and reduce bias (Boria et al. 2014). Only points with a distance of at least 500m should be used for model building. Therefore, a 500m buffer was built around the sample points. Points inside the 500m buffer were deleted from the dataset arbitrarily. After cleaning, 38 of 46 points could be used for model building.

To keep things simple and conservative (no overfitting and at this state no tuning) only linear and quadratic features were allowed for the model settings (Phillips 2004). The regularization multiplier, which controls the intensity of regularization across all features, was set to two. The default regularization multiplier is one. The larger multiplier should result in a less discriminating prediction (Radosavljevic und Anderson 2014). These settings were the same for the 6 model runs. Number of iterations was 20 and jackknife was used for model evaluation, random test percentage was 25%, number of background points was 10000. Logistic output was chosen for the model output.

To choose which resolution of the statistical surfaces should be used in the final model, AUC (area under the ROC curve) and the omission rate (OR), two common metrics of model performance, were consulted (Shcheglovitova und Anderson 2013).

4 Results for the test area

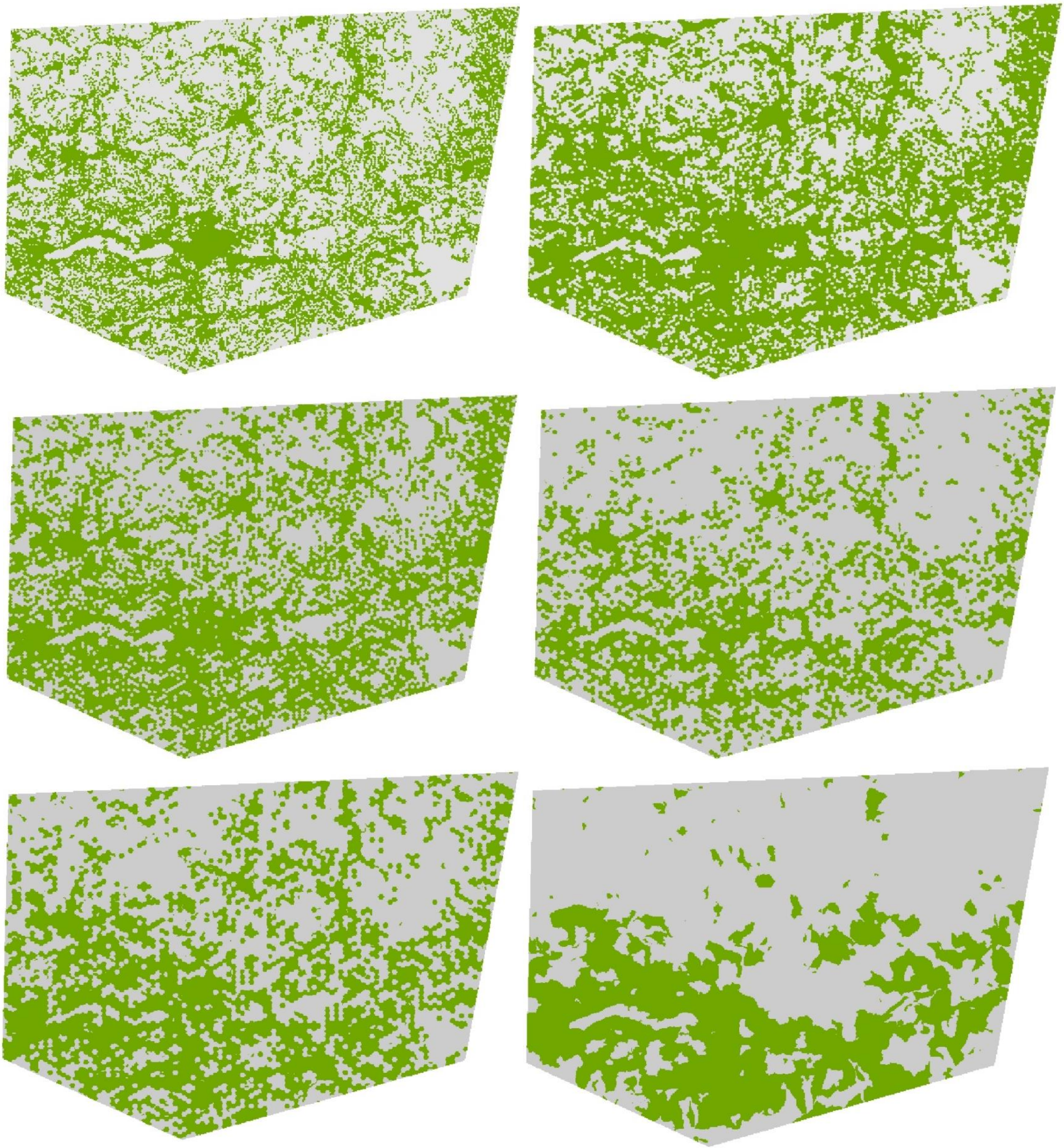


Figure 4: The 6 model outputs with 10 percentile training presence logistic threshold to distinguish between suitable (green) and unsuitable (gray) habitat. Top left: 5ha, top right: 10ha, middle left: 15ha, middle right 25ha, bottom left: 35ha, bottom right: GEZG (catchment areas).

5ha			10ha			15ha		
Variable	% contribution	Perm. importance	Variable	% contribution	Perm. importance	Variable	% contribution	Perm. importance
cce_be_was	20.8	5.2	ce_bes_was10a	20.7	12	lpi_15a	21.6	6.5
pz_offenbau	15.9	4.7	lpi_10	18	3.4	shdi_15a	19.1	20.3
lpi_5	13.5	1.9	pz_offbau10a	13.6	3.9	ce_gli_bau15a	11	5.9
shdi_5	10.1	26.2	shdi_10a	12.8	29	ce_bes_was15a	10.8	4.9
cce_bau_wa	6.1	1.8	cce_gl_was10a	7	3.2	pz_glint15a	6.6	19.3
kernel_edge	3.8	12.2	ce_gli_wa10a	5.5	3	ce_beb_wa15a	4.7	2.6
cce_gr_wa	3	3.7	kernel_10a	5	10.4	pz_offbau15a	4.2	3
cce_gr_was	2.9	1.2	pz_glint10a	2.4	7.4	pz_acker15a	3.3	5.3
cce_bau_was	2.9	9.2	ce_beb_was10a	2.3	3.5	kernel_15a	3.1	4.5
pz_acker	2.7	8.4	ci_pp_10a	2	1.7	ce_gli_was15a	2.1	4.6
cce_bau_ges	2.5	0.6	ce_gli_bau10a	1.7	3	ce_beb_bau15a	2	4
pz_glintensiv	2.4	4.4	ce_beb_bau10a	1.4	1	ce_gl_wa15a	2	1.8
ci_pp_5	2.3	5	ci_cp_10a	1.2	5.2	ce_gli_wa15a	1.8	2
cce_gl_ges	2.2	1.7	ce_gli_was10a	1.1	1.7	ce_beb_was15a	1.5	7.4
cce_gl_was	2.1	1.3	ce_beb_wa10a	1	1.8	ci_np_15a	1.3	0.6
ci_cp_5	1.7	1.2	cce_gl_wa10a	0.9	2.3	ce_gl_was15a	1.2	1.8
pz_feuchtgeb	1.3	0.8	pz_weide10a	0.8	0.1	ci_pp_15a	0.9	1.5
cce_gl_wa	1.2	2.6	ci_np_10a	0.8	2.4	ci_cp_15a	0.8	0.4
pz_weiden	1.2	7.1	cce_bes_wa10a	0.7	0.3	ce_bes_wa15a	0.8	0.3
cce_be_wa	0.8	0.2	pz_acker10a	0.6	4.5	pz_weide15a	0.8	0.4
ci_np_5	0.5	0.8	pz_feuchtg10a	0.4	0.2	pz_feucht15a	0.2	2.9
cce_gr_ges	0	0	cce_gl_bau10a	0	0	ce_bes_bau15a	0.2	0
pz_pionierveg	0	0	ce_bes_bau10a	0	0	ce_gl_bau15a	0	0
cce_be_ges	0	0	pz_subalp10a	0	0	pz_poinier15a	0	0
pz_subalpin	0	0	pz_pionier10a	0	0	pz_latsche15a	0	0
pz_latschenkr	0	0	pz_latsche10a	0	0	pz_subalp15a	0	0

25ha			35ha			GEZG		
Variable	% contribution	Perm. importance	Variable	% contribution	Perm. importance	Variable	% contribution	Perm. importance
shdi_25a	35.7	17.7	lpi_35a	28.9	7.5	ce_gl_wasga	19.4	10.3
lpi_25a	18.4	8.7	pz_glint35a	13.3	29.4	pz_glint_gea	14.1	19
pz_glint25a	12.4	24.5	shdi_35a	8.9	8.2	kernel_gezga	12.6	9.1
kernel_25a	7.3	7.7	kernel_35a	8.7	14.3	ci_cp_gezga	9.1	4
ce_bes_was25a	6.2	2.7	ce_bes_was35a	8.1	6.4	pz_ofbau_gea	7.4	0.2
pz_acker25a	3.1	6.7	ce_gl_wa35a	4.2	4.5	ce_gli_waga	6.5	5.2
ce_gl_was25a	2.3	3.3	ce_beb_bau_35a	4	1.7	pz_acker_gea	4.8	15.8
ce_gli_bau25a	1.8	0.5	ce_gli_wa35a	3.8	3.9	shdi_gezga	4.2	6.2
ce_beb_bau25a	1.6	1.9	ce_bes_bau35a	2.3	1.1	ce_gli_wasga	2.9	3.2
ci_cp_25a	1.5	5.8	ce_beb_wa35a	2.3	1	lpi_gezga	2.6	0.3
pz_feucht25a	1.5	8.6	pz_feucht35a	2.2	0.9	ce_gl_bauga	2.6	3.4
ce_beb_was25a	1.4	0.8	pz_offbau35a	2.1	0.7	ce_beb_wasga	2.4	6.2
ce_beb_wa25a	1.2	3.1	ce_gli_bau35a	2.1	5.4	ce_beb_bauga	2.1	3
ce_gl_wa25a	1.1	3.1	ci_cp_35a	1.6	1.6	ce_bes_waga	2	4.2
ce_bes_wa25a	0.9	1.2	pz_acker35a	1.5	5.5	pz_feucht_gea	1.7	3.5
ce_bes_bau25a	0.8	0.2	ce_gl_was35a	1.5	0.7	ce_bes_wasga	1.1	0.6
ce_gli_was25a	0.8	1.6	ce_beb_was35a	1.4	3.2	ce_gl_waga	1.1	2.6
ce_gli_wa25a	0.7	0.3	ce_bes_wa35a	1.1	0.1	ce_beb_waga	0.7	0.9
pz_offbau25a	0.5	1.2	pz_weide35a	0.8	0.3	ci_pp_gezga	0.6	1.2
ci_pp_25a	0.4	0.3	ci_np_35a	0.5	0.7	ci_np_gezga	0.5	0.1
pz_weide25a	0.2	0	ce_gli_was35a	0.4	2	pz_weide_gea	0.5	0.2
ci_np_25a	0.1	0.1	ci_pp_35a	0.2	0.7	ce_bes_bauga	0.5	0.1
ce_gl_bau25a	0	0	ce_gl_bau35a	0.1	0	ce_gli_bauga	0.4	0.1
pz_latsche25a	0	0	pz_pionier35a	0	0.1	pz_pion_gea	0.1	0.5
pz_pionier25a	0	0	pz_subalp35a	0	0	pz_latsch_gea	0.1	0.3
pz_subalp25a	0	0	pz_latsche35a	0	0	pz_subal_gea	0	0

Table 7: Percentage of contribution of each layer and its permutation importance for the 6 resolutions.

Surface	AUC	OR
5 ha	0,8642	0,3686
10 ha	0,8432	0,3685
15 ha	0,8579	0,3608
25 ha	0,8899	0,3461
35 ha	0,8849	0,3271
GEZG	0,8854	0,3511

Table 8: AUC (Area under the ROC curve) and OR (Omission Rate) values for the 6 model runs.

To get a quantitative measure for the "difference" of the model run outcomes in geographic space, three measures of niche overlap were calculated with ENMTool (Warren et al. 2010). Schoeners *D* (Schoener 1968), *I* statistic (Warren et al. 2008) and relative rank *RR* (Warren und Seifert, S. N. 2011) *D* is a rather conservative measure whereas *I* often overestimates the similarity of the models. The three metrics reach from 0 (no overlaps) to 1 (identical models). For *D* and *I* the metrics are calculated by determining the difference between the models in suitability score per grid cell after standardizing the suitabilities to sum up to 1 over the measured geographic space. The *RR* statistic is calculated differently: it does not consider the quantitative difference of suitability estimates. Instead it estimates the probability that the relative ranking of two random patches of habitat is the same for the compared models. Because *RR* is based on ranks its results can differ from *D* and *I* results.

D	5ha	10ha	15ha	25ha	35ha	GEZG
5ha	1	0,8169	0,79864	0,73448	0,75243	0,67603
10ha	x	1	0,81459	0,74708	0,77144	0,70088
15ha	x	x	1	0,76149	0,77971	0,69300
25ha	x	x	x	1	0,77744	0,69073
35ha	x	x	x	x	1	0,71369
GEZG	x	x	x	x	x	1

Table 9: Schoeners D (Schoener 1968) matrix for the 6 model outcomes.

I	5ha	10ha	15ha	25ha	35ha	GEZG
5ha	1	0,96892	0,96429	0,93859	0,94569	0,90716
10ha	x	1	0,97079	0,94436	0,95521	0,92221
15ha	x	x	1	0,94973	0,95688	0,91844
25ha	x	x	x	1	0,95343	0,91431
35ha	x	x	x	x	1	0,92535
GEZG	x	x	x	x	x	1

Table 10: I statistic (Warren et al. 2008) matrix for the 6 model outcomes.

RR	5ha	10ha	15ha	25ha	35ha	GEZG
5ha	1	0,74081	0,74695	0,70321	0,69733	0,59876
10ha	x	1	0,74674	0,70455	0,71101	0,62127
15ha	x	x	1	0,73850	0,73786	0,62415
25ha	x	x	x	1	0,75728	0,65928
35ha	x	x	x	x	1	0,66882
GEZG	x	x	x	x	x	1

Table 11: Relative Rank RR (Warren und Seifert, S. N. 2011) matrix for the 6 model outcomes.

5 The final models of Carinthia

The aim was to model habitat suitability for *Coronella austriaca* for Carinthia, the most southern province of Austria, and to use the most helpful landscape metrics surfaces for this species and this purpose, together with additional important habitat parameters.

To find out which landscape metrics at what scale are important for *Coronella austriaca*, the data of the test area model runs was used. Only landscape metrics surfaces with a contribution of four or more percent in the test area should take part in the final models. The only exception was the kernel density layer for the 5ha surface. The percentage of contribution was only 3,8 percent but the permutation importance was high with 12,2 percent. So, I decided to include this predictor as well. To decide, at which scale the model works best, AUC and OR were considered. Some studies identified the AUC value, calculated with presence – background data, as an arguable measure for the performance of models (Lobo et al. 2008; Warren and Seifert 2011) but it can be used to compare models of single species in a single study region, what is the case in this study (Shcheglovitova und Anderson 2013). AUC and OR showed very similar performance in the six model runs of the test area. So, I decided to examine the models at three important scales:

- population scale (5ha)

- metapopulation scale (25ha)

- natural ecological units – catchment areas (GEZG)

Covariates used in the final models:

5ha - population level	*25ha - metapopulation level*	*Natural ecological units (GEZG)*
cce_be_was	shdi	cce_gl_was
pz_offenbau	lpi	pz_glint
lpi	pz_glint	kernel
shdi	kernel	pz_offbau
cce_bau_wa	cce_bes_was	cce_gli_wa
kernel	vegetation layer	pz_acker
vegetation layer	GS – mean annual global radiation (kWh/m2)	shdi
GS – mean annual global radiation (kWh/m2)	N – average accumulated precipitation (mm)	vegetation layer
N – average accumulated precipitation (mm)	NJJA – average accumulated summer precipitation (mm)	GS – mean annual global radiation (kWh/m2)
NJJA – average accumulated summer precipitation (mm)	SD – mean snow cover duration (days)	N – average accumulated precipitation (mm)
SD – mean snow cover duration (days)	SDB – average start of snow cover (day of the year)	NJJA – average accumulated summer precipitation (mm)
SDB – average start of snow cover (day of the year)	SDE – average end of snow cover (day of the year)	SD – mean snow cover duration (days)
SDE – average end of snow cover (day of the year)	AET07 – average equivalent temperature in July (°C)	SDB – average start of snow cover (day of the year)
		SDE – average end of snow cover (day of the year)
AET07 – average equivalent temperature in July (°C)		AET07 – average equivalent temperature in July (°C)

Table 12: Covariates used in the final models.

Unfortunately, the landscape metrics layer ci_cp for the catchment areas (GEZG) could not be considered for the final model, despite its high contribution (but low permutation importance) in the test models, because of ongoing calculation errors.

The calculation of landscape metrics, conversion to raster (bilinear, maximum combined area), resolution (100x100m), masking and conversion into ASCII files was executed the same way as for the test area data. With one exception: the layers used for the catchment area (GEZG) model had to be clipped to the size of the catchment areas, because they did not cover exactly the whole area of Carinthia. But no sample point of *Coronella austriaca* occurrence data fell in the missing area. So, all models were calculated with the same amount of sample points. Climatic layers had to be resampled from a resolution of 250x250m to 100x100m.

Coronella austriaca occurrence data consisted of 129 sample points. After spatial filtering (buffer of 500m) to reduce bias through spatial autocorrelation, 94 sample points remained for modelbuilding (see test area data preparation).

At this modelling step, also tuning of the final models was allowed. The models at first were calculated with the same settings as the test area models, to have a result to compare the tuned models to. The choice of features in the tuned models was led by the outcome of tuning experiments, made by Phillips and Dudik (Phillips und Dudík 2008): all feature classes for sample sizes of at least 80 occurrences. The regularization multiplier was set to one. Random test percentage was 25%, replicate runs 20, type: bootstrap, maximum iterations 5000, maximum number of background points: 10000, logistic output.

To show differences in the model results, each model for the three different scales/resolutions was calculated two times plus one model without landscape metric layers:

-with all parameters (xha all)

-with landscape metrics only (xha LM)

-with climatic and vegetation parameters only (without LM)

The results of the tuned models showed better AUC values than the model runs with the conservative settings of the test area models.

	AUC	
surface	tuned	test
5ha all	0,920	0,882
5ha LM	0,850	0,832
25ha all	0,928	0,888
25ha LM	0,859	0,834
GEZG all	0,919	0,876
GEZG LM	0,879	0,847
without LM	0,893	0,857

Table 13: AUC (Area under the ROC curve) values for the different model settings.

5.1 Visualization of the model outcomes

10 percentile training presence logistic threshold was chosen to distinguish between suitable (green) and unsuitable (gray) areas.

5 ha surfaces:

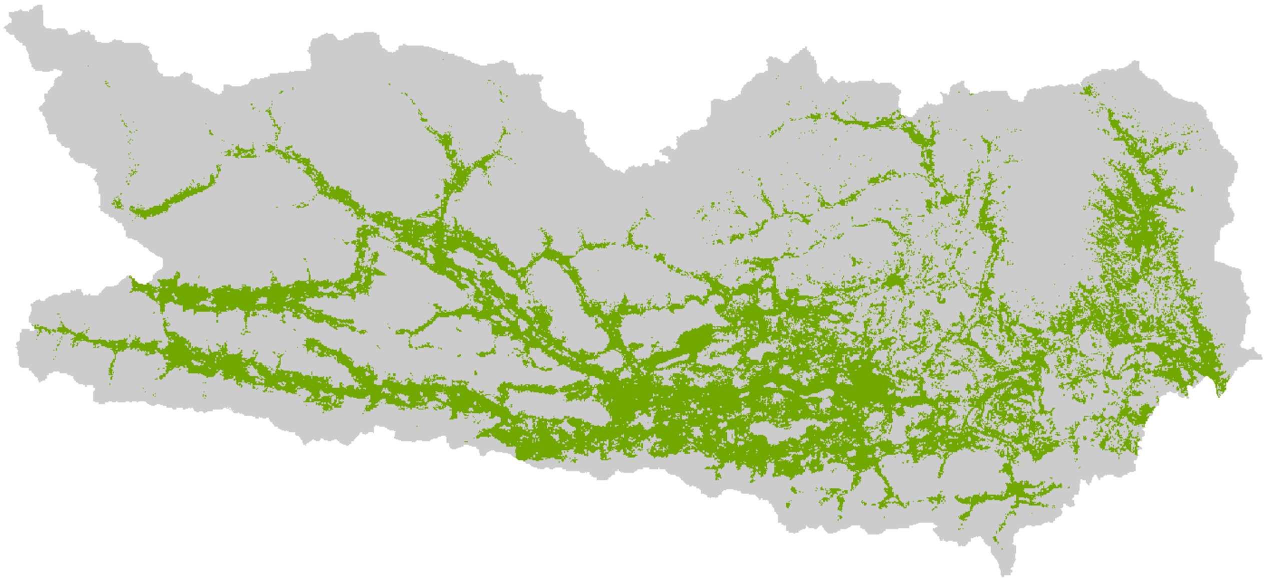


Figure 5: 5ha model with all covariates (landscape metrics, vegetation layer, climatic layers) (AUC= 0,920).

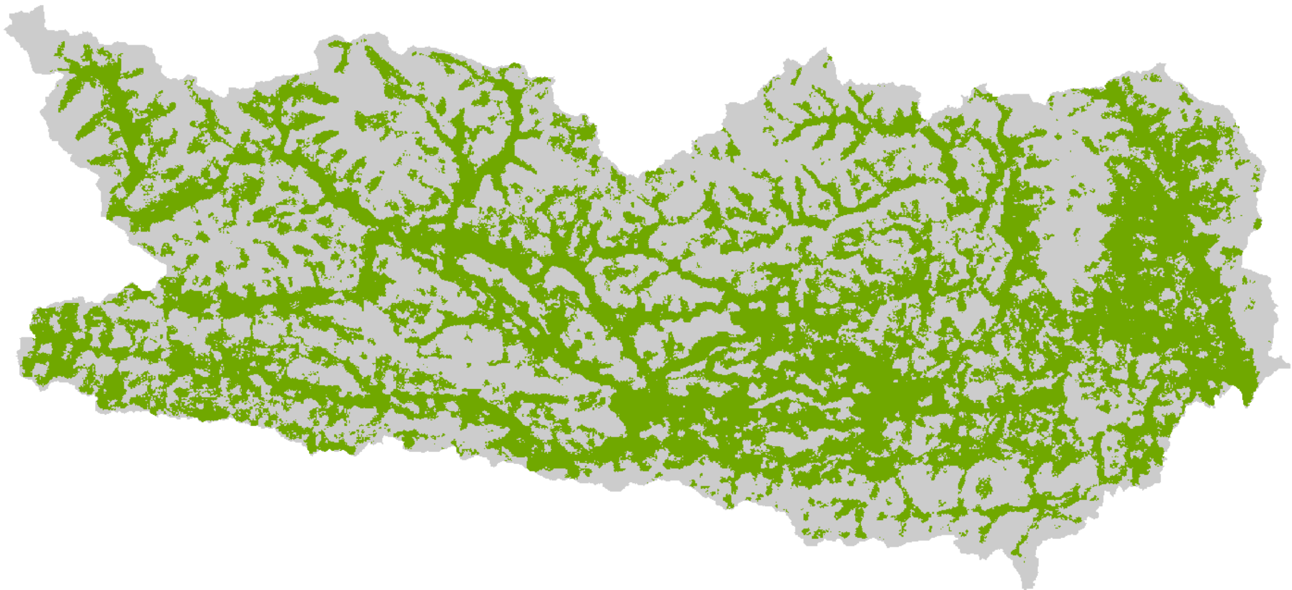


Figure 6: 5ha model with landscape metrics surfaces only (AUC=0,850).

25 ha surfaces:

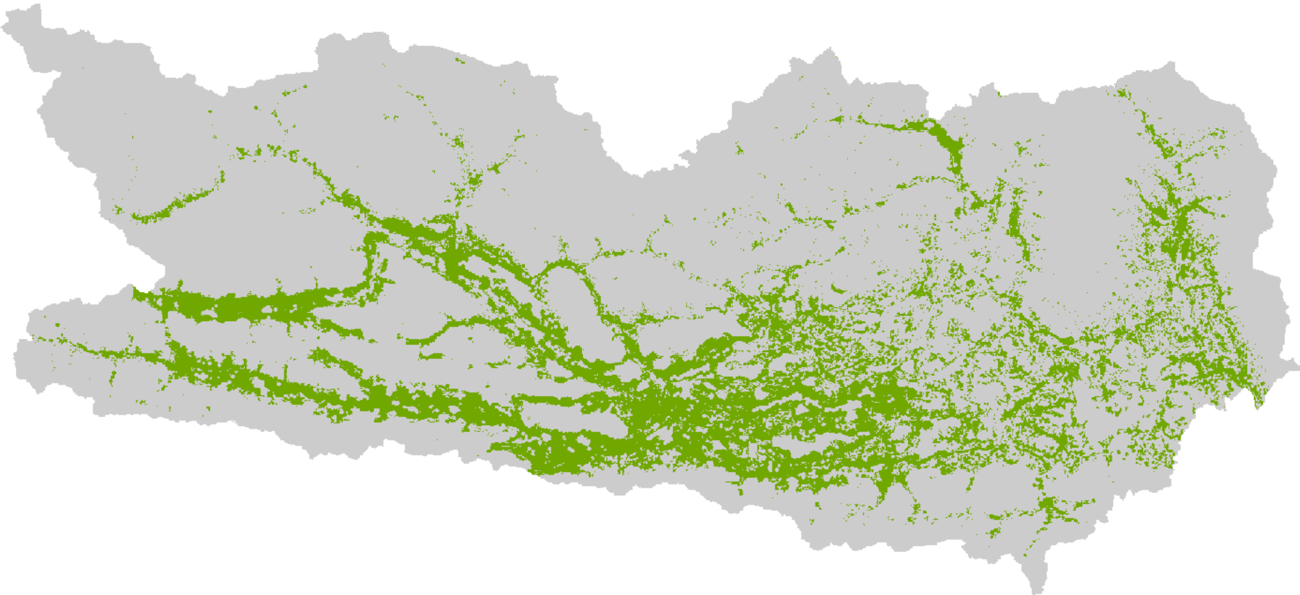


Figure 7: 25ha model with all covariates (landscape metrics, vegetation layer, climatic layers) (AUC= 0,928).

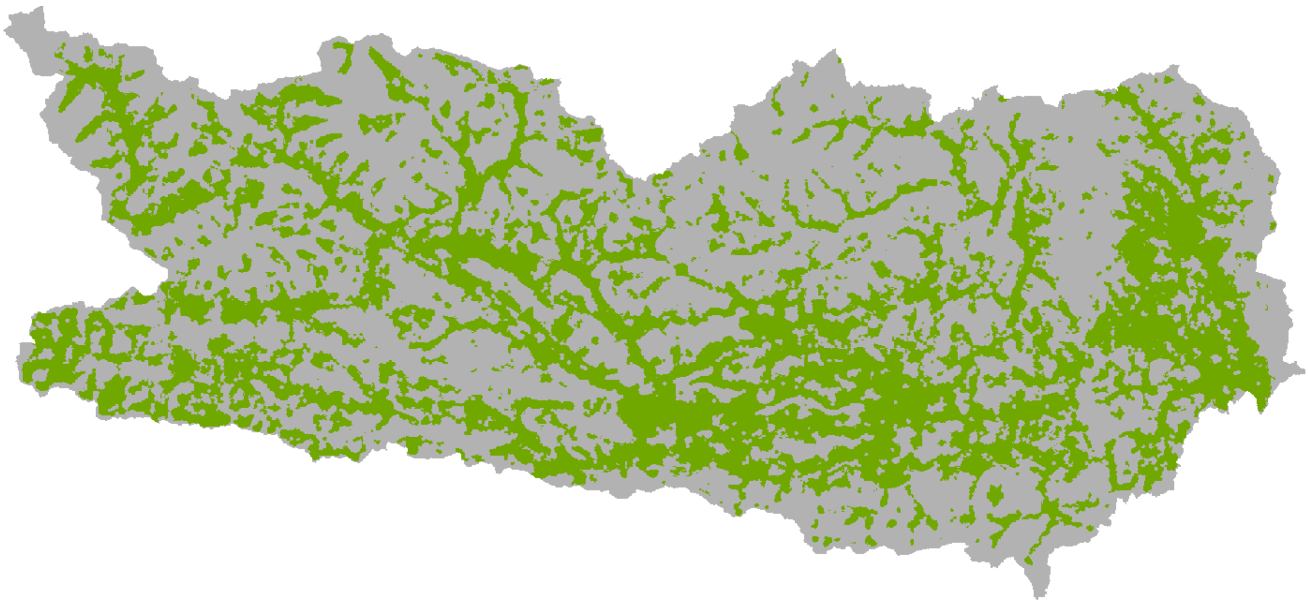


Figure 8: 25ha model with landscape metrics surfaces only (AUC=0,859).

Catchment areas (GEZG):

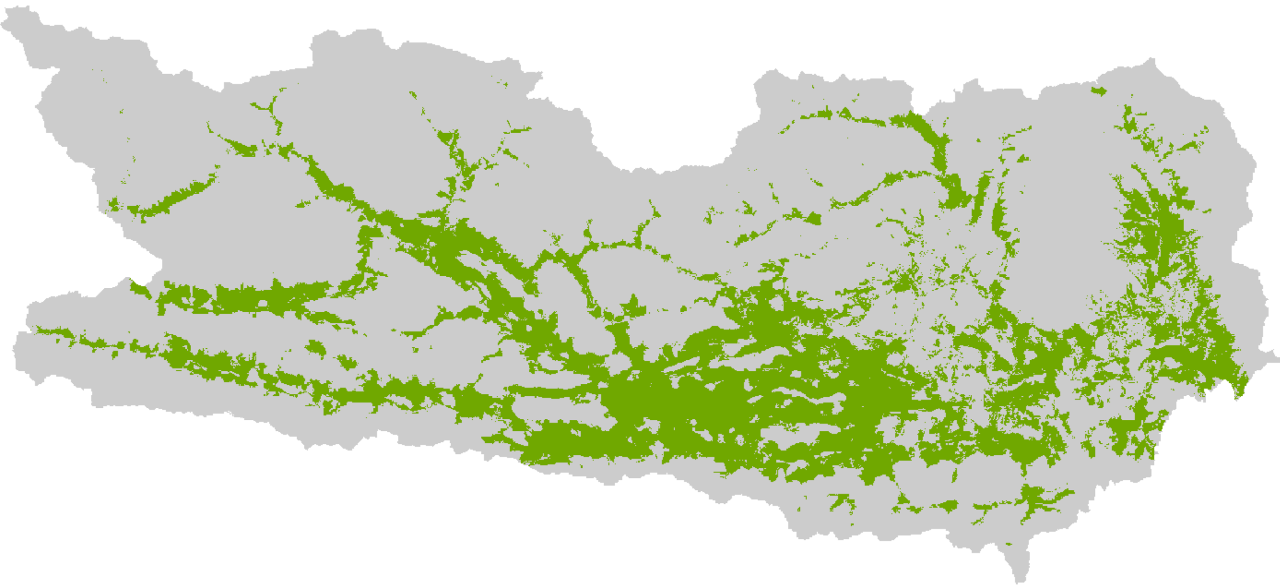


Figure 9: GEZG model with all covariates (landscape metrics, vegetation layer, climatic layers) (AUC= 0,919).

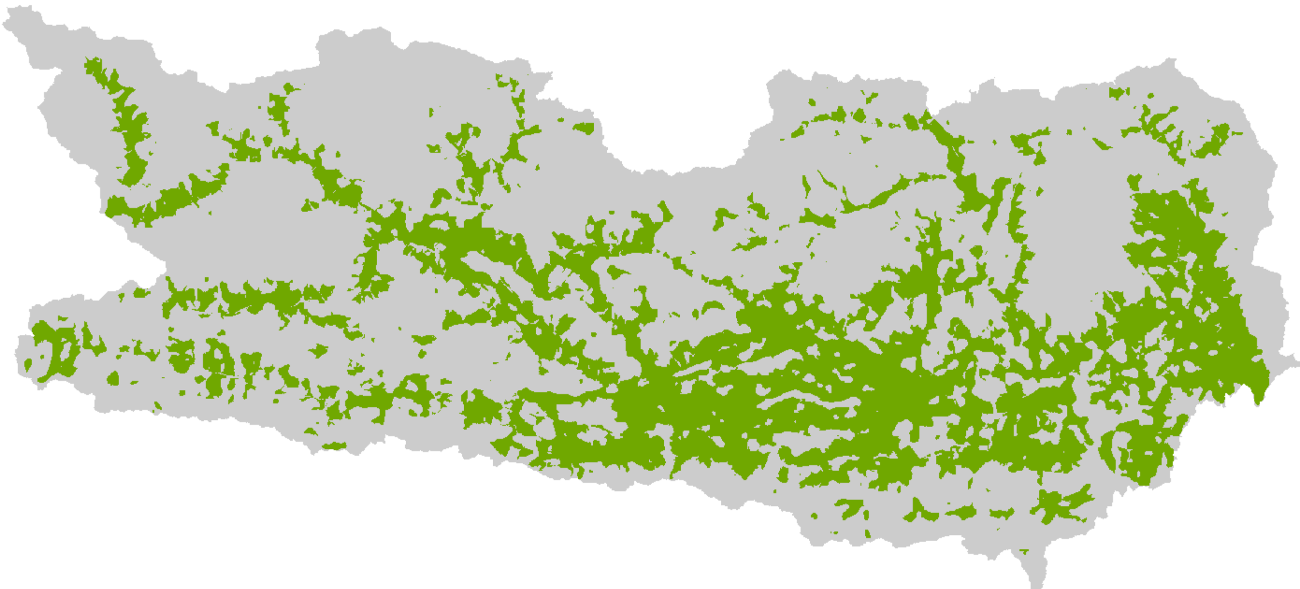


Figure 10: GEZG model with landscape metrics surfaces only (AUC=0,879).

Model without landscape metric surfaces:

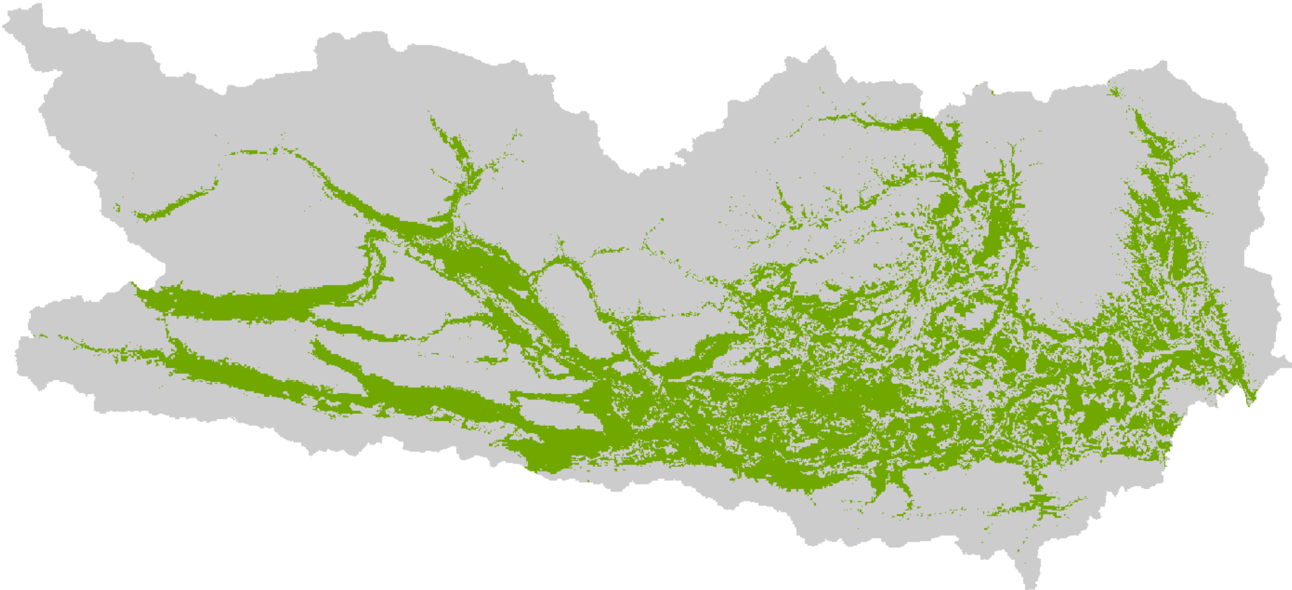


Figure 11: Model without landscape metrics surfaces – only with vegetation and climatic layers. (AUC= 0,893).

5.2 Niche overlap

The three measures of niche overlap were calculated with ENMTool (Warren et al. 2010) for the 7 model result ASCII files. (w/o_LM = without landscape metrics, xxx_all = all surfaces were used for model building, xxx_LM = only landscape metrics were used for model building).

D	w/o_LM	5ha_all	5ha_LM	25ha_all	25ha_LM	GEZG_all	GEZG_LM
w/o_LM	1	0,79558	0,63131	0,79851	0,61195	0,67550	0,64386
5ha_all	x	1	0,72694	0,85001	0,68784	0,66404	0,64501
5ha_LM	x	x	1	0,68085	0,83806	0,60998	0,66627
25ha_all	x	x	x	1	0,69495	0,65881	0,63635
25ha_LM	x	x	x	x	1	0,61438	0,67487
GEZG_all	x	x	x	x	x	1	0,80425
GEZG_LM	x	x	x	x	x	x	1

Table 14: Schoener´s D (Schoener 1968) matrix for the 7 model results.

I	w/o_LM	5ha_all	5ha_LM	25ha_all	25ha_LM	GEZG_all	GEZG_LM
w/o_LM	1	0,95581	0,86487	0,95313	0,84777	0,90464	0,88020
5ha_all	x	1	0,93112	0,97954	0,90920	0,89674	0,88368
5ha_LM	x	x	1	0,91225	0,97797	0,85676	0,89668
25ha_all	x	x	x	1	0,91715	0,89257	0,87821
25ha_LM	x	x	x	x	1	0,85171	0,89360
GEZG_all	x	x	x	x	x	1	0,96216
GEZG_LM	x	x	x	x	x	x	1

Table 15: I statistic (Warren et. al 2008) matrix for the 7 model results.

RR	w/o_LM	5ha_all	5ha_LM	25ha_all	25ha_LM	GEZG_all	GEZG_LM
w/o_LM	1	0,84608	0,67107	0,84205	0,65518	0,76994	0,70657
5ha_all	x	1	0,81495	0,91297	0,78105	0,77600	0,74569
5ha_LM	x	x	1	0,78913	0,87886	0,69275	0,71255
25ha_all	x	x	x	1	0,79425	0,77141	0,73778
25ha_LM	x	x	x	x	1	0,68541	0,70993
GEZG_all	x	x	x	x	x	1	0,85817
GEZG_LM	x	x	x	x	x	x	1

Table 16: Relative Rank RR (Warren and Seifert 2011) matrix for the 7 model results.

5.3 Correlations between the input layers

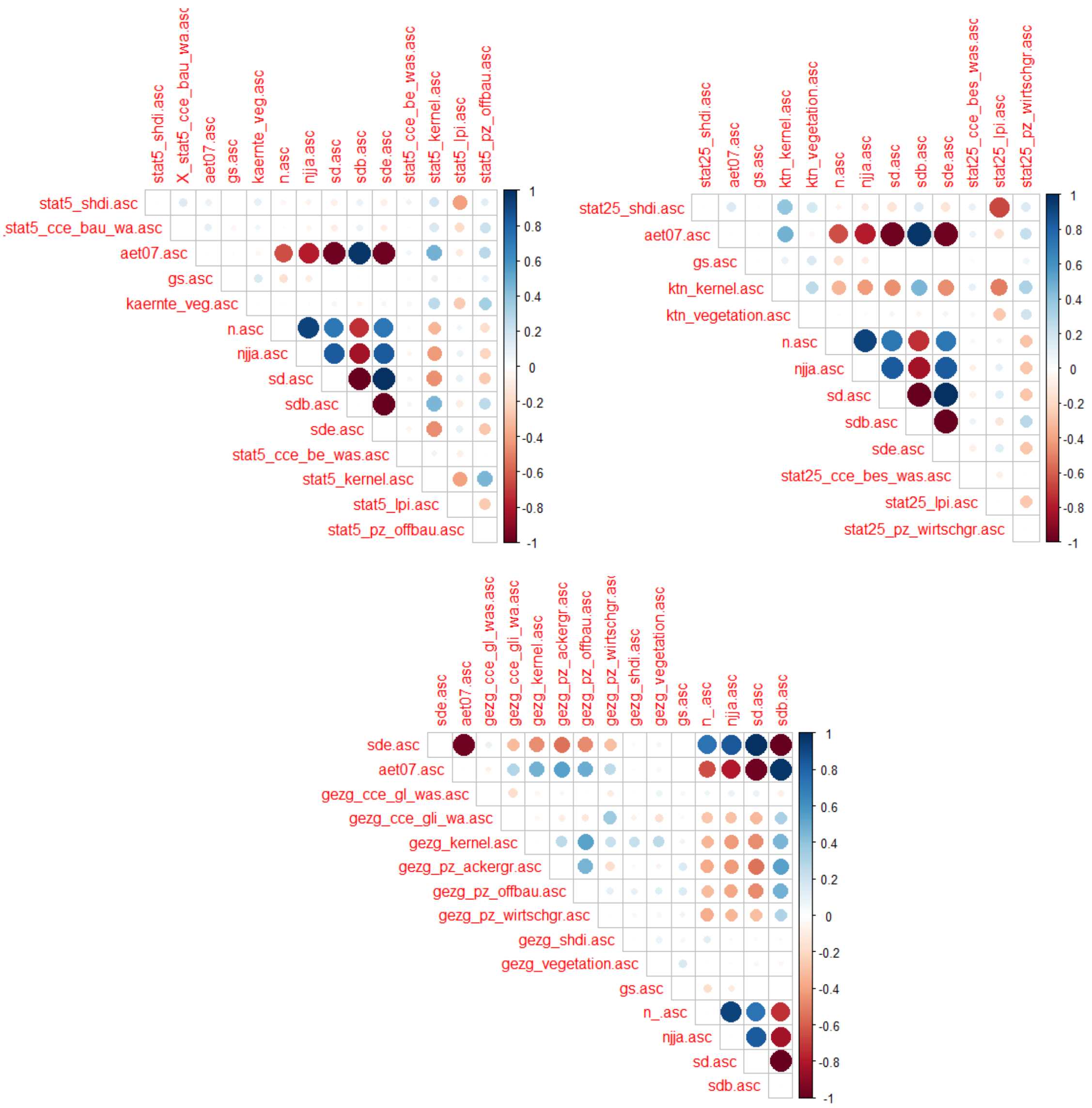


Figure 12: Correlation matrices of the surfaces used to build the final models in 3 different resolutions (top left: 5ha, top right: 25ha, bottom: catchment areas (GEZG).

5.4 Coronella austriaca sample points 2019

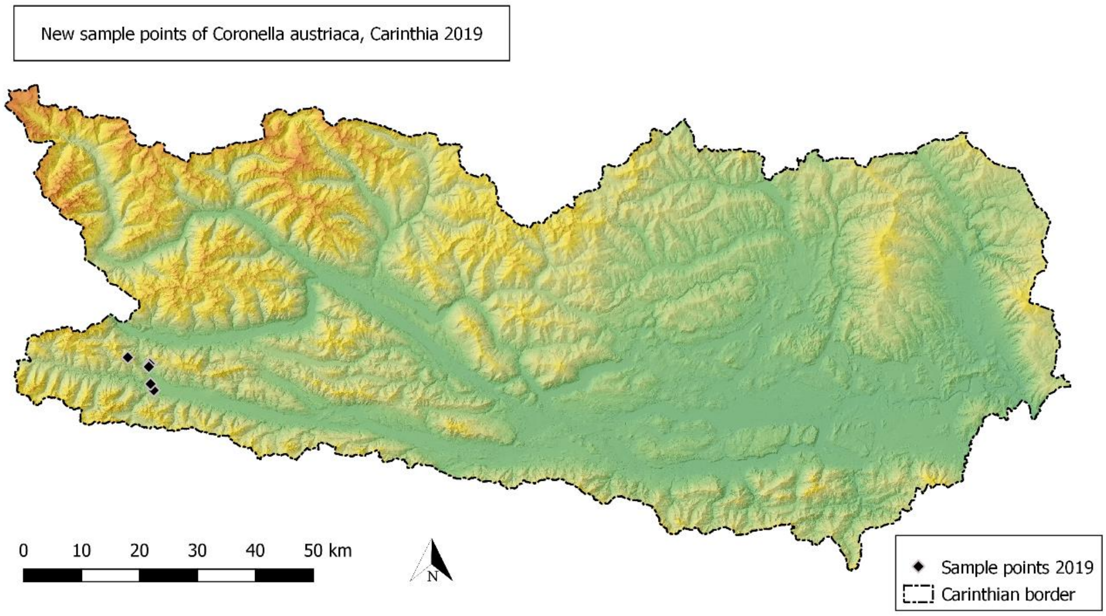


Figure 13: 5 newly collected sample points of *Coronella austriaca* from a field survey 2019.

In the first week of August 2019 I made a field trip to Carinthia to collect new *Coronella austriaca* data. I concentrated on the southwestern part of Carinthia (mainly Upper Gailtal and Dolomites). *Coronella austriaca* was found at five locations.

6 Vegetation of Carinthia in numbers

To get an overview of size and patch number of the different vegetation objects and to avoid misinterpretations of outcomes of this study, 3 tables, each for the different aggregation levels, were made.

The values for the high-level aggregation (Name_Agg) into seven atop classes can be found in table 17. The values for all unaggregated landscape patches can be found in table 18 and the values for the lower level aggregation (Agg_light) into 24 atop classes can be found in table 19.

For the seven classes aggregation, "Wald" (forest) is the largest group with a proportion of 56,3 %, but the class "Bebaut" (covered with buildings) holds the highest number of patches.

Regarding all vegetation elements without any aggregation, "Fichtenwald, sekundaere Fichtenforste ueber Silikatgestein"(forest of common spruce and secondary forests of common spruce on silicate) is the biggest vegetation class with a proportion of 19,32%. "Wirtschaftsgruenland" (meadows and pastures) is the second largest vegetation form with a proportion of 10,17%.

The 24 classes of the low level aggregated vegetation layer show the same outcomes than the not aggregated vegetation layer: the largest vegetation element is "Fichten- und Mischwald" (spruce and mixed forest) with 27,79%, followed by "Wirtschaftsgruenland und Maehwiesen" (meadows and pastures) with 10,46%.

Name_Agg	Anzahl	m2	ha	Prozent
Bau_geschl	1100	130229903,8	13022,99	1,36
Bebaut	8967	809896131,4	80989,61	8,49
Bestockt	1796	199778499,3	19977,85	2,09
Gewaesser	223	152675314,2	15267,53	1,60
GL_intensiv	6263	1862071492	186207,15	19,51
Gruenland	4005	1016936303	101693,63	10,65
Wald	8638	5373410802	537341,08	56,30

Table 17: Number of patches (Anzahl), size in square meters (m2) and hectares (ha) and percentage of the higher-level aggregated vegetation forms.

NAME	Anzahl	m2	ha	Prozent
(Buchen)-Tannen-Fichtenwald. Buchen-Tannenwald, Tannenwald ueber Karbonatgestein	199	203278699,1	20327,87	2,13
(Buchen)-Tannen-Fichtenwald. Buchen-Tannenwald, Tannenwald ueber Silikatgestein	166	152680661,7	15268,07	1,60
Acker-Gruenlandkomplexe	971	849500071,7	84950,01	8,90
Autobahn	20	14562745,89	1456,27	0,15
Autobahn-Tunnel	20	1481153,347	148,12	0,02
Betriebsgelaende	687	38258904,44	3825,89	0,40
Buchenwald	174	43348471,34	4334,85	0,45
Feuchter Laubmischwald (Erlen-,Eschen-,Weiden-,Bergahorn)	1507	181026639,6	18102,66	1,90
Feuchtgebiete, Moore	320	33234298,46	3323,43	0,35
Fichten-Laerchenwald	1004	278233960,3	27823,40	2,91
Fichtenwald, sekundaere Fichtenforste ueber Karbonatgestein	332	529987891	52998,79	5,55
Fichtenwald, sekundaere Fichtenforste ueber Silikatgesetein	636	1844094769	184409,48	19,32
Flughafen	1	2113843,808	211,38	0,02
Geschlossene bzw dichte Bebauung	249	23197258,27	2319,73	0,24
Gewaesser	218	107922757,7	10792,28	1,13
Gletscherflaechen	143	52097151,44	5209,72	0,55
Grauerlenbestaende	512	74942882,28	7494,29	0,79
Historisches Erbe, Schloss- und Klosteranlagen	147	4691798,621	469,18	0,05
Hochmoor	8	577102,0878	57,71	0,01
Kat_3	1	7231746,687	723,17	0,08
Kat_4	1	2576358,596	257,64	0,03
Kat_5	1	6542096,166	654,21	0,07
Kat_6	1	22300135,73	2230,01	0,23
Kat_7	1	6102219,379	610,22	0,06
Laerchen-Fichtenwald	471	520837364,7	52083,74	5,46
Laerchwiesen	86	8318164,701	831,82	0,09
Latschenkrummholz	487	59553477,93	5955,35	0,62
Montan - subalpines Laubbuschwerk	554	49794317,85	4979,43	0,52
Nadel-Laubmischwald (Rotfoehren-Buchenwald, Fichten-Buchenwald)	725	318764083,9	31876,41	3,34
Nadel-Mischwald mit Laubholzeinsprengungen	1233	304244016,1	30424,40	3,19
Niedermoor	24	1677064,817	167,71	0,02
Offene Bebauung, unterschiedlicher Art	8223	401253141,3	40125,31	4,20
Pioniervegetation auf Schutt und Fels	597	403951191,5	40395,12	4,23
Roehrichte- und Grossseggenfluren	31	2192159,417	219,22	0,02
Rotfoehren-Fichtenmischwald	1464	888074670,8	88807,47	9,30
Rotfoehrenwald	149	29766668,3	2976,67	0,31

Schwarzerlenbestaende	145	9241921,456	924,19	0,10
Schwarzfoehrenwald	15	4631283,56	463,13	0,05
Sportflaechen (Golfplaetze, etc.)	121	9795323,704	979,53	0,10
Staedtisches Gruen und diverse Sportflaechen	248	5979917,248	597,99	0,06
Subalpine u. alpine Rasen, Extensiv-Weiden ueber Karbonatgestein	105	47632668,77	4763,27	0,50
Subalpine u. alpine Rasen, Extensiv-Weiden ueber Silikatgestein	307	223719919,1	22371,99	2,34
Warmer Laubmischwald (Manna-Esche, Hopfenbuche, Mehlbeere, Eichen)	168	16552128,64	1655,21	0,17
Weidenbestaende	67	4053740,395	405,37	0,04
Weiderasen u. Bergmaehder ueber Karbonatgestein	365	76110394,47	7611,04	0,80
Weiderasen u. Bergmaehder ueber Silikatgestein	2014	318635826,3	31863,58	3,34
Wintersportgelaende	69	26477090,38	2647,71	0,28
Wirtschaftsgruenland (Maehwiesen und Weiden)	4854	970319089,1	97031,91	10,17
Zirbenwald und Laerchenzirbenwald	395	57889494,34	5788,95	0,61
Zwergstrauchheiden, Mosaik Zwergstrauchheiden/Weiderasen ueber Karbonatgestein	144	19505584	1950,56	0,20
Zwergstrauchheiden, Mosaik Zwergstrauchheiden/Weiderasen ueber Silikatgestein	612	286044127,2	28604,41	3,00

Table 18: Number of patches (Anzahl), size in square meters (m2) and hectares (ha) and percentage of all vegetation forms.

Agg_light	Anzahl	m2	ha	Prozent
Acker_Gruenlandkomplexe	971	849500071,7	84950,01	8,90
Bau_Geschlossen	957	78132752,41	7813,28	0,82
Buchen_Tannen_Fichtenwald	365	355959360,8	35595,94	3,73
Buchenwald	174	43348471,34	4334,85	0,45
Erle_Weide	724	88238544,13	8823,85	0,92
Feuchter_Laubmischwald (Erle, Esche, Weide, Ahorn)	1507	181026639,6	18102,66	1,90
Feuchtgebiete	352	35488465,36	3548,85	0,37
Fichten_und_Mischwald	1972	2652316620	265231,66	27,79
Foehrenwald	1628	922472622,7	92247,26	9,66
Gletscherflaechen	143	52097151,44	5209,72	0,55
Laerchenmischwald	866	578726859	57872,69	6,06
Laerchenwiesen	86	8318164,701	831,82	0,09
Latschenkrummholz	487	59553477,93	5955,35	0,62
Mischwald	1958	623008100	62300,81	6,53
Montan_subalpines_Laubbuschwerk	554	49794317,85	4979,43	0,52
Offene_Bebauung	8370	405944939,9	40594,49	4,25
Pionoervegetation_Schutt_Fels	597	403951191,5	40395,12	4,23
Roehrichte_Grosseggenfluren	31	2192159,417	219,22	0,02
Sport_Park	369	15775240,95	1577,52	0,17
Subalpine_Alpine_Rasen_Extensivweiden	412	271352587,9	27135,26	2,84
Warmer_Laubmischwald(Mannae, Hopfenb, Mehlb, Eich)	168	16552128,64	1655,21	0,17
Wasser	223	152675314,2	15267,53	1,60
Weiderasen_Bergmaehder	3135	700295932	70029,59	7,34
Wirtschaftsgruenland_Maehwiesen	4943	998277332,9	99827,73	10,46

Table 19: Number of patches (Anzahl), size in square meters (m2) and hectares (ha) and percentage of the lower level aggregated vegetation forms.

7 Conclusion

At this point I would like to emphasize the most important findings of this technical report as recommendation for further research. For more information please consult the manuscript.

- This method incorporates many steps of abstraction in the modelling process. This should always be something to keep an eye on. First, landscape metrics are broken down to smaller subsets of the landscape, the statistical units, to calculate the metrics (patch truncation effect!). The method how the single patches are treated when overlapping the statistical zone can make a big difference for the resulting values. Afterwards, this vector data sets are converted to raster files, where the conversion method can make a difference for the resulting surface. The surfaces have a different information content depending on the spatial resolution (raster cell size) (e.g. Turner et al. 2001). All this modelling steps can, and should, be examined much closer to find ideal settings and procedures for a task.
- Scale and grain are of essential importance when wanting to build a model for a single species (what becomes much more complicated when dealing with more than one species with different habitat requirements) (e.g. Guisan und Thuiller 2005). The scale should be adequate for the home ranges of the species. The grain is not always something one can control. It depends on the data available. All decisions should take the available grain in consideration. Pseudo-accuracy should be prevented.
- Accuracy of the sample points is also a sometimes unknown and unaffectable part in the modelling process, except the data comes from own field survey. Also, the age of the sample data plays an important role for the modelling process. At best the time span when the data was collected conforms to the age of the environmental data used for model building. Otherwise once important drivers may not be there anymore, or other drivers are pictured by the environmental layers now that have nothing to do with the former distribution of the target species.
- The position of the test area could have been more representative concerning the distribution of different altitude levels and therefore vegetation forms. Therefore, some of the test area landscape metrics also were not perfectly representative for the whole province.
- A mix of different resolutions of landscape metrics surfaces (the most contributive ones of all experiments) in one model maybe would lead to enthralling outcomes.
- The smallest size of the statistical units in that study depended on the accuracy of sample points and on the grain of the vegetation layer. Population scale for *Coronella austriaca* can be smaller (1-2 ha) and the model outcome for that scale could be different.
- I am perfectly aware that this is not a quick and easy method for incorporating landscape metrics in habitat suitability modelling and therefore in decision making. Expert knowledge is required in more than just one modelling step. Each decision made should be questioned on basis of available data and target species. But in my opinion, it could be very rewarding and interesting to dig deeper in that matter.

8 References

Adamczyk, Joanna; Tiede, Dirk (2017): ZonalMetrics - a Python toolbox for zonal landscape structure analysis. In: *Computers & Geosciences* 99, S. 91–99. DOI: 10.1016/j.cageo.2016.11.005.

Boria, Robert A.; Olson, Link E.; Goodman, Steven M.; Anderson, Robert P. (2014): Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. In: *Ecological Modelling* 275, S. 73–77. DOI: 10.1016/j.ecolmodel.2013.12.012.

Eisenkölb, G., Vincze, G. (2009): Gewässernetz des Bundes als Grundlage zur Erfüllung der Berichtspflichten gem. WRG. Objektmodell – Datenkatalog der Fachdatenbank Gewässernetz, V6. – Umweltbundesamt im Auftrag des BMLFUW, Wien. - 57 S.

ESRI (2011): ArcGis Desktop: Release 10. Redlands, CA: Environmental Systens Research Institute.

Guisan, Antoine; Thuiller, Wilfried (2005): Predicting species distribution: offering more than simple habitat models. In: Ecol Letters 8 (9), S. 993–1009. DOI: 10.1111/j.1461-0248.2005.00792.x.

Hartl, Helmut; Stern, Roland; Seger, Martin (2001): Karte der aktuellen Vegetation von Kärnten (M 1 : 150.000) ;. = map of the actual vegetation of Carinthia, Austria : das Vegetationsgefüge einer inneralpinen Region im Süden Österreichs. Klagenfurt: Naturwissenschaftlicher Verein für Kärnten.

Lobo, Jorge M.; Jiménez-Valverde, Alberto; Real, Raimundo (2008): AUC: a misleading measure of the performance of predictive distribution models. In: *Global Ecol Biogeography* 17 (2), S. 145–151. DOI: 10.1111/j.1466-8238.2007.00358.x.

Phillips, Steven J. (2004): A Maximum Entropy Approach to Species Distribution Modelling. In: *Proceedings of the Twenty-First International Conference on Machine Learning* 2004, S. 655–662.

Phillips, Steven J.; Anderson, Robert P.; Schapire, Robert E. (2006): Maximum entropy modeling of species geographic distributions. In: *Ecological Modelling* 190 (3-4), S. 231–259. DOI: 10.1016/j.ecolmodel.2005.03.026.

Phillips, Steven J.; Dudík, Miroslav (2008): Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. In: *Ecography* 0 (0), 080328142746259-??? DOI: 10.1111/j.0906-7590.2007.5203.x.

QGIS Development Team (2019): QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org

R Core Team (2019): R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.URL http://www.R-project.org/.

Radosavljevic, Aleksandar; Anderson, Robert P. (2014): Making better Maxent models of species distributions: complexity, overfitting and evaluation. In: *J. Biogeogr.* 41 (4), S. 629–643. DOI: 10.1111/jbi.12227.

Schindler, Stefan; Wehrden, Henrik von; Poirazidis, Kostas; Wrbka, Thomas; Kati, Vassiliki (2013): Multiscale performance of landscape metrics as indicators of species richness of plants, insects and vertebrates. In: *Ecological Indicators* 31, S. 41–48. DOI: 10.1016/j.ecolind.2012.04.012.

Schoener, Thomas W. (1968): The Anolis Lizards of Bimini. Resource Partitioning in a Complex Fauna. In: *Ecology* 49 (4), S. 704–726. DOI: 10.2307/1935534.

Shcheglovitova, Mariya; Anderson, Robert P. (2013): Estimating optimal complexity for ecological niche models: A jackknife approach for species with small sample sizes. In: *Ecological Modelling* 269, S. 9–17. DOI: 10.1016/j.ecolmodel.2013.08.011.

Silverman, B. W. (1986): Density Estimation for Statistics and Data Analysis. Boston, MA, s.l.: Springer US (Monographs on Statistics and Applied Probability). Online verfügbar unter http://dx.doi.org/10.1007/978-1-4899-3324-9.

Tobler, W. R. (1970): A Computer Movie Simulating Urban Growth in the Detroit Region. Supplement: Proceedings. International Geographical Union. Commission on Quantitative Methods. In: *Economic Geography* 1970 (46), S. 234–240.

Turner, Monica Goigel; Gardner, R. H.; O'Neill, Robert V. (2001): Landscape ecology in theory and practice. Pattern and process. New York: Springer. Online http://lib.myilibrary.com?id=18739.

Warren, Dan L.; Glor, Richard E.; Turelli, Michael (2008): Environmental niche equivalency versus conservatism: quantitative approaches to niche evolution. In: *Evolution; international journal of organic evolution* 62 (11), S. 2868–2883. DOI: 10.1111/j.1558-5646.2008.00482.x.

Warren, Dan L.; Glor, Richard E.; Turelli, Michael (2010): ENMTools: a toolbox for comparative studies of environmental niche models. In: *Ecography* 35, S. 1160. DOI: 10.1111/j.1600-0587.2009.06142.x.

Warren, Dan L.; Seifert, Stephanie, N. (2011): Ecological niche modeling in Maxent: the importance of model complexity and the performance of model selection criteria. In: *Ecological Applications* 21 (2), S. 335–342.

Wei, Taiyun; Simko, Viliam (2017): R package "corrplot": Visualization of a Correlation Matrix (Version 0.84). Available from https://github.com/taiyun/corrplot