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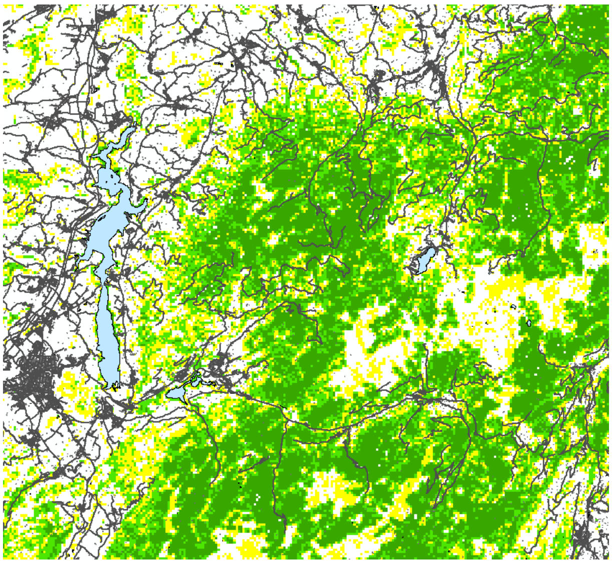
Habitat model of the European wildcat *(Felis silvestris silvestris)* for the Swiss Jura Mountains, Plateau and near Pre-alpine regions



Master Thesis

Swiss Federal Institute for Forest, Snow and Landscape Research WSL
KORA Carnivore Ecology and Wildlife Management

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I enjoyed the work on my master thesis a lot and hope it can be a small piece of puzzle for further research and protection of the Swiss wildcats.

Front cover images:

- A wildcat in the Jura Mountains (left) (© L. Brochard, 2017)
- An small outtake of the habitat model (right) (S. Weber, 2018)

Habitat model of the European wildcat *(Felis silvestris silvestris)* for the Swiss Jura Mountains, Plateau and near Pre-alpine regions

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Abstract

After the near extinction in the 19th century - caused by habitat degradation and extensive hunting - the European wildcat (Felis silvestris silvestris) is slowly returning to its former habitat in the Swiss Jura Mountains. Listed as “least concerned” in the IUCN red list, little is known about this elusive cat. In order to gain a better understanding of the environmental requirements and to draw potential occurrence maps, a habitat modelling was carried out in this study. For this purpose, the wildcat observations were supplemented by background points and then equipped with various environmental variables. After a subsampling of the data sets, the prediction performance of the variables was tested with Boosted Regression Trees to sort out unimportant and correlated predictors. Of 26 initial variables, 15 could be skipped. According to the temporal distribution of the observations, a whole-year and a winter model were created with two different background data sets each. With the eleven final variables, the four models were used to assess the predictor performance. Distance to forest edge, Snow-water equivalent and Elevation are among the best predictors, while Roughness and Aspect are among the weakest. After a model performance test, the two best ones were used to extrapolate to the biogeographical regions of the Jura Mountains, the Swiss Plateau and the Pre-Alps. With two raster resolutions of $1km^2$ and 1ha, the potential wildcat habitat was assessed using the predictive values and compared with unused data points and GPS-locations of three wildcats. According to the three study areas the model performance is high for the Jura Mountains, medium for the Pre-Alps and low for the Plateau.

Key words: Wildcat, habitat model, boosted regression trees, predictor variable, occurrences, background points

Introduction

Myriad of species worldwide have suffered major population losses or even extinction events in recent centuries or decades (Groombridge, 1992). Ceballos and Ehrlich (2002) showed that these events seem to be concentrated in areas with high human population density or human impact. In the class of mammals, predator species are especially vulnerable because - additionally to the usual threats like habitat degradation - they were often seen as competitors for hunters (Fryxell et al., 2014). With exception of the last one, these threats are often not directed at one species, but due to the lack of information and ignorance.

An example for a poorly known and nearly eradicated predator species is the European wildcat (*Felis silvestris silvestris*, Schreber 1777). Once widely distributed throughout Europe and Switzerland, this medium-sized carnivore has suffered significant population loss in the 19th century due to extensive hunting and trapping (Piechocki, 1990) as well as habitat destruction. Seen as serious competitors for hunters, the wildcats were almost exterminated in the Jura Mountains at that time (Liberek, 1999). Legal protection 1962 under the Swiss hunting law, 1979 under the Berne Convention (Appendix II) and 1992 under the European Habitat Directive 92/43/EEC (Appendix IV) have led to a recovery of the wildcat population in a few countries of the western Europe like Germany, France and Switzerland (Say et al., 2012; Streif et al., 2012; Weber et al., 2010) whereas the database for the Southeast European and the Iberian wildcat population is strongly ambivalent and the Scottish wildcat population is directly threatened with extinction (Yamaguchi et al., 2015). Moreover, in some countries where the wildcat was originally widespread, such as Austria, it has not yet been able to gain a foothold (Slotta-Bachmayr et al., 2016). After the most recent development, the wildcat is now listed as “least concern” in the IUCN red list (Yamaguchi et al., 2015).

Due to the inconspicuous behaviour of wildcats and the easy confusion with its domesticated relatives (Klar et al., 2008), the feral cat (*Felis silvestris catus*), it was almost overlooked that this cat species slowly returned to the forests of the Swiss Jura Mountain. 1958 was the first proof of a return with some other sights in the 1960th and 1970th (Lüps, 1981). Since then the wildcat is slowly reclaimed its former distribution area in the Jura Mountains, most likely through immigration from the French Jura population (Lüps, 1981) and possibly also through a few releases (Liberek, 1999). Recently, even a handful of observations have been made in the Pre-Alps (KORA, 2018).

Despite the natural return, changes in the landscape appear to have very complex effects on the development of the wildcat population. Increasing habitat potential could be beneficial for the species (Dietz et al., 2016). More and more forest – as the main habitat for wildcats - are managed in a natural way, leading for example to more deadwood structures offering new hiding places, which is important for the raising of their kittens. Changes in agricultural and forestry practices (e.g. significantly reduced use of rodenticides) additionally increase the food supply for wildcats (voles and other rodents as their main prey) (Biro et al., 2005). On the other hand, settlements and the intensively used and poorly structured agricultural land – as unsuitable habitats for wildcats – have a strong barrier effect due to the fragmentation of the landscape (Pierpaoli et al., 2003; Stahl and Artois, 1994).

In order to better protect and conserve wildcats and to make appropriate conservation and management decisions, various information about its former and current distribution, the past and actual population size and potential threat (e.g. anthropogenic mortality or hybridization with domestic cats) must be collected. The actual and potential distribution are important aspects in wildlife conservation planning for this species (Peterson and Dunham, 2003). Habitat models have the potential to visualize potential wildcat occurrences and serve as planning tools for management decisions such as the planning of future nature reserves or the construction of wildlife bridges (Guisan and Thuiller, 2005).

The aim of this master thesis is to create a statistical, fine-scale habitat model for the European Wildcat for the Swiss Jura Mountains, the adjoining Plateau and the Pre-Alps. The following research questions should help to fulfil this task:

1) What are the driving environmental variables for the observed wildcat occurrences?
2) Where are potential distribution areas for the wildcat in the Swiss Jura Mountains and do they correspond with the most recent observations?
3) Is it possible to extrapolate the model to the Plateau and the Pre-Alps?

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Material and Methods

Study area

Switzerland can be divided into six biogeographical regions, namely the Jura, Plateau, Northern and Southern Alps and Western and Central Alps (Gonseth and Buttler, 2001). These regions differ in climate and topography (Landolt et al., 1992) and can be classified in four broad land use categories; settlements and urban areas (7.5% of the total surface area), unproductive areas (lakes and rivers, glaciers and perpetual snow areas, rocks and unproductive vegetation, 25.3%), forests and woods (31.3%) and agricultural areas (35.9%) (Schubarth and Weibel, 2013).

The study area (Fig. 1) comprises the biogeographical region of the Jura (without the small part in the canton of Schaffhausen; named as Jura Mountains), the Plateau (named Plateau) and the Northern Alps (named as Pre-Alps). In the Jura Mountains (Jura Mts.) elevation ranges between 269m and 1’679m above sea level with a forest cover of 46.7% of the surface area. The Plateau ranges between 244 and 1’305m a.s.l. with the lowest forest cover of only 28.8%, while the Pre-Alps are embedded between 371 and 4’265m a.s.l. and have a forest cover of 32.2%. In terms of population density, the Pre-Alps contain the lowest permanent habitants with approximately 100/km^2. On the contrary, the Plateau is strongly influenced by human activities with the highest population density as high as 460/km^2 whereas the Jura has a moderate population density of 153/km^2 (Zimmermann, 2004).

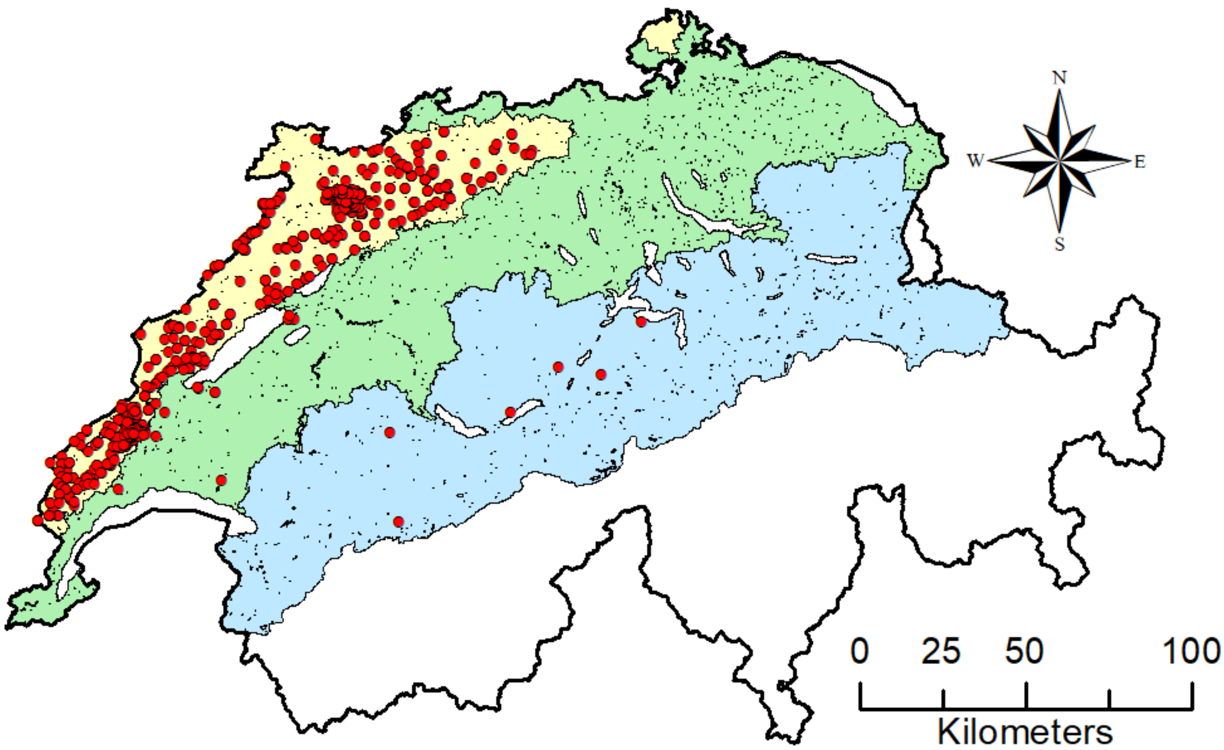


Fig. 1 Map of Switzerland with the three biogeographic regions used. Yellow is the biogeographical region of the Jura Mts., green the Plateau and blue the Pre-Alps. The red dots symbolize the registered wildcat occurrences between 1994 and 2018.

We have chosen the above-mentioned regions because the wildcat is already widespread in the Jura Mts., the Plateau is considered as a former habitat and some recent observation have been made in the Pre-Alps.

Wildcat occurrence data

Only "hard facts" such as dead wildcats, captures, genetic samples from hair or pictures and videos with phenotypical characteristics (SCALP-category 1; (Molinari-Jobin, 2003)) were used for this study. Pictures, videos and hair samples were taken during deterministic wildcat camera trapping (two 10x10-km study areas, one in the northern in winter 2015/16 and 2016/17, the other in the southern Swiss Jura Mts. in winter 2017/18 to estimate wildcat density) or as by-catch during deterministic camera trapping sessions for lynx and wolves. Within the framework of lynx monitoring, eight different reference areas are examined on a two to three year basis during winter (November-April) using camera traps to estimate lynx abundances. The first session took place in the Alps 1998 and in the Jura Mts. 2007. In the summer of 2017, a wolf deterministic camera trapping session was conducted in a reference area in the Jura South with detections of wildcats as by-catch. There were additional recordings of game wardens, hunters and the public by private camera traps, dead bodies or pictures (so-called random observation). From 1994 to the end of February 2018, 1,478 "hard facts" were reported (only data records with coordinates). These records were largely limited to the Swiss Jura Mts. with a few in the Swiss Plateau and the Pre-Alps (Fig. 1).

Unfortunately, we had to exclude several observations. Three observations are missing trustworthy coordinates (declared as road mortality, but with coordinates apart from a street). In addition, all detections before August 2004 and after December 2017 had to be excluded (264 data points) due to a lack of predictive variable data (snow variables and degree day sum). Since the biogeographical region of the Jura Mts. was classified as our model calibration area, we also had to exclude all points outside this area (30 data points). This allowed us to use 1,181 detections at 429 locations (Table 1).

Table 1 Overview of the observation data points used in this study. Most of the evidences was provided during the winter and spring seasons (November to April).

Observations	Nr of detections	Nr of locations	Time periode	Winter	Spring	Sumer	Fall
Wildcat monitoring	535	77	2016 - 2017	141	274	54	66
Lynx monitoring	376	147	2007 - 2017	106	270	-	-
Wolf monitoring	86	21	2017	-	-	34	52
Random observation	184	184	2004 - 2017	38	83	24	39
All detections	1181	429	2004 - 2017	285	627	112	157

Habitat predictor variables

Based on previous wildcat habitat modelling (Graf et al., 2013; Klar, 2009; Klar et al., 2008) and expert knowledge, we have compiled a list of ecological variables, deemed to be important to characterize the habitat requirements of wildcats. In total, we have analysed 26 different variables with different spatial and temporal resolution (Table 2), divided into three different categories. The first category contains topographical variables such as terrain roughness, elevation above sea level or vegetation characteristics. The second category anthropogenic variables such as night-light emission or distance to buildings and the third category meteorological variables with a temporal factor as sums of degree day or accumulated snowfall over the last 72 hours.

Table 2 Overview about the environmental variables used with the reference, spatial and temporal resolution. Category 1 contains topographic variables, category 2 the anthropogenic and category 3 the meteorological variables.

Variable	Reference	Spatial resolution	Temporal resolution	Category	Description
Aspect	DHM25	25 x 25m	1994	1	Compass direction of the location
Elevation	DHM25	25 x 25m	1994	1	Altitude above sea level
Roughness	DHM25	25 x 25m	1994	1	Difference between surrounding areas in terms of steepness
Tri	DHM25	25 x 25m	1994	1	Terrain Roughness Index
Slope	DHM25	25 x 25m	1994	1	Amount of steepness
VHM_mean	DHM25	1a	1994	1	Characterising the height of forests and woody vegetation (mean values)
Forest_type	Landsat-5	25 x 25m	1990-1992	1	Amount of broad leaf trees in the forest
Near_Forest	$SwissTLM^{3D}$	m	2015	1	Linear distance from point to nearest forest edge. Positive values for points inside of forest, negative for outsiders
Near_Water	$SwissTLM^{3D}$	m	2015	1	Linear distance from point to the nearest water course
Near_Buildings	$SwissTLM^{3D}$	m	2015	2	Linear distance from point to the nearest building
Near_Street	$SwissTLM^{3D}$	m	2015	2	Linear distance from point to the nearest paved street
Street_class	$SwissTLM^{3D}$	-	2015	2	Type of nearest paved street
Human_impact	$SwissTLM^{3D}$	$1km^2$	1992 - 2013	2	Amount of human influence
Population_density	$SwissTLM^{3D}$	1ha	2015	2	Amount of inhabitants per area
Light_2010_2012	DMSP	$1km^2$	2010-2012	2	Mean night-light emission over three years (2010-2012) measured by satellites
Naturalness	$SwissTLM^{3D}$	$1km^2$	1992 - 2013	2	Degree of deviation in composition of habitats and species from what would be expected to occur naturally
Remoteness	$SwissTLM^{3D}$	$1km^2$	1992 - 2013	2	Distance to human impacts
Wilderness	$SwissTLM^{3D}$	$1km^2$	1992 - 2013	2	Class of remoteness, naturalness and human impact of a landscape
Land-use_categories	$SwissTLM^{3D}$	1a	2016	2	Different land types
Fragmentation_area	$SwissTLM^{3D}$	m^2	2014	2	Coherent landscape area without major streets and other barriers
Fragmentation_value	$SwissTLM^{3D}$	m^2	2014	2	Fragmentation area divided by the shape outline lenght
Fragmentation_index	$SwissTLM^{3D}$	m^2	2014	2	Fragmentation area grouped by 5 size classes
Snow_SWE	MeteoSchweiz	$1km^2$	2004 - 2017	3	Snow-water equivalent = kg Snow per m^2
Snow_CF	MeteoSchweiz	$1km^2$	2004 - 2017	3	Snow-cover fraction = % of landscape covered by snow
Snow_72h	MeteoSchweiz	$1km^2$	2004 - 2017	3	Amount of snowfall over the last 72h
Degree_day	MeteoSchweiz	$1km^2$	2004 - 2017	3	Sum of days over 5.56°C (= Vegetation periode)

Analysis concept

According to Guisan (2017), the conceptual framework - or named here analysis concept - figured as an important step in the process of suitable habitat modelling. Therefore, we created a graphical illustration of the individual steps with three main sections (Fig. 2). In the first section, we collected all available wildcat records and created background data. The resulting data set was equipped with all possible environmental variables prior to the subsampling process. The main model performing process took place with a model building process (specify of the different model parameter), a variable reduction and a model evaluation process in the second section. In the end, we extrapolated the best performing models to create potential wildcat distribution maps in the third and final section. These were then cross-validated with unused observation points.

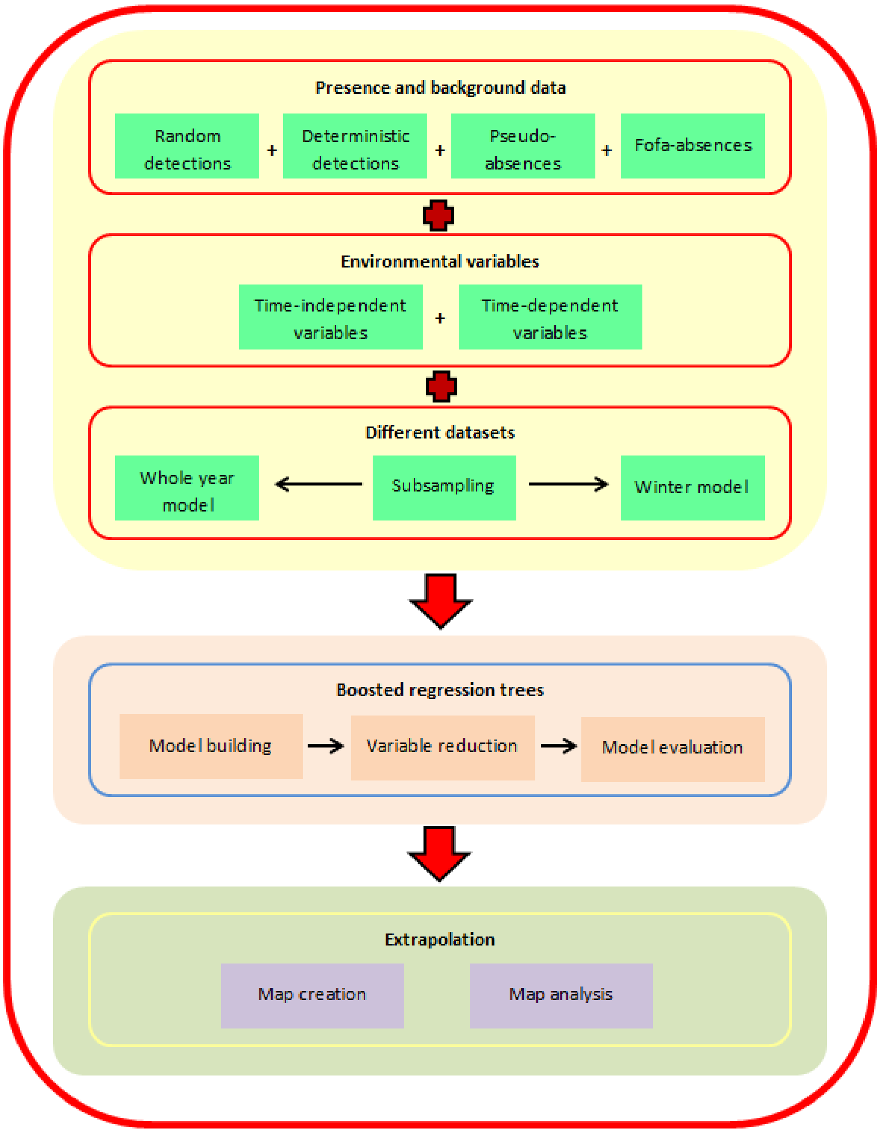


Fig. 2 Graphical illustration of the analysis concept for this thesis.

Modelling Wildcat distribution

Observations of wildcats in the Jura Mts. are not evenly distributed in space and time (see Fig.1; Table 1). This is caused by the spatial and temporal conditions of the deterministic camera trap studies, e.g. the wildcat camera trap study from 2016/17 had 64 different camera trap positions on a 100km^2 grid. This results in a spatial concentration of the detections. In addition, some camera traps produced over 35 images of wildcats over a period of two month, while others took no images at all. These two accumulations increased the spatial and temporal autocorrelation of the data set. For the later modelling we had to reduce the autocorrelation to a moderate level with a subsampling of the original data set. To achieve this, we used several subsampling methods at spatial, temporal and mixed scale (Table 3). The spatial subsampling was performed between neighbourhood points, while the temporal subsampling was performed for multiple detections at the same location. Each spatial subsample was mixed with each temporal subsample. The resulting data sets were tested for autocorrelation with the Moran's Index (Dormann et al., 2007) in ArcGIS to order to come as close as possible to a random distribution (z-scores of <1.65).

Table 3 Overview of all spatial and temporal subsampling. Each spatial subsampling was also combined with each temporal subsampling.

Spatial subsampling's	0m		800m		1'600m		2'400m		3'200m		
Temporal subsampling's	0 day	1 day	2 days	5 days	7 days	14 days	1 month	2 month	6 month	1 year	14 years

The sampling design of the deterministic camera trap studies and the random observations were not made for wildcat distribution modelling, so that we had no observed absence data. Therefore, we randomly generated a similar number of pseudo-absence points as presence points (later called pseudo-absences) in the whole area of the Jura Mts. These background points were located in wildcat useable areas, defined as all areas outside paved roads and streets, water courses and sealed surfaces (Piechocki, 1990). Since false absence data can reduce the reliability of prediction models (Loiselle et al., 2003) and out of personal interest, we have created a second set of background points by extracting positions of camera traps from the deterministic KORA-monitoring's without wildcat detections (later called fofa-absences). These fofa-absences do not show real absences and must be considered as imperfect absence data (Burton et al., 2015).

To analyse wildcat's habitat selection and potential wildcat occurrences, we used Boosted Regression Trees (BRT). BRT aim to improve the performance of a single model by fitting several models and combining them for predictions (Elith et al., 2008). This can be achieved by using the two algorithms regression trees and boosting. Boosting stands for the combination of regression algorithms and machine learning techniques and builds a collection of small regression trees by adding a new tree at each iteration that best minimizes the loss function (Elith et al., 2008). After Elith et al. (2008), BRT are known for their high predictive performance. BRT often outperform other alternative model algorithms in identifying relevant predictor variables and interactions when model settings are chosen accordingly (Elith et al., 2008; Friedman et al., 2001). In addition, BRT can be used to optimize the predictive performance of a single best model by adjusting multiple models and using them for further prediction (Elith and Leathwick, 2017).

We fitted the BRT models in R using the "gbm" and "dismo" packages and the "gbm.step" function. A Bernoulli distribution was used to consider for the binary result such as presence and background data. We manipulated three parameters in the models; learning rate (*lr*), tree complexity (*tc*) and bag fraction to achieve the best results. The learning rate is defined as the influence of a single tree to the whole model, with smaller values resulting in larger number of required trees for modelling (Elith et al., 2008). Normally, *lr* values between 0.1 and 0.001 are used, with smaller values leading to lower prediction errors, but with higher required computations (De'ath, 2007). Tree complexity specifies the number of nodes in a single tree.

According to Elith and Leathwick (2009), increased *tc* values usually lead to increased predictive performance. Stochasticity is introduced by the bag fraction parameter, which defines how much of the training data set is selected for the model building process at each iteration (Elith et al., 2008). Usually the parameter is set in the range between 0.4 - 0.6 (De'ath, 2007) respectively between 0.5 – 0.75 for best results (Elith et al., 2008). The three parameters mentioned above were defined with a cross-evaluation of the data sets used. The biogeographical area of the Jura Mts. (excluding the north-eastern part in the Canton of Schaffhausen) was used as our model calibration area.

To avoid model overfitting (Harrell et al., 1996) and multicollinearity of variables (Dormann et al., 2013), we reduced the initial set of 26 predictor variables. We removed variables with the least influence in the BRT models and excluded variables that were strongly correlated with others. To remove the least influence variable, we used the relative importance of the variable as a criterion and decided to remove all variable with a mean value of less than 5% and no or only minimal influence on the other predictors. For the correlation, we illustrated the multicollinearity and calculated the Pearson correlation factor (CF) and the Variable-Inflation Factor (VIF) in R Studio. A CF above ±0.70 means a high correlation and should be avoided (Hinkle et al., 1988) whereas a VIF greater than 10 means a high correlation (Wollschläger, 2015). As a correlation threshold, we used the two above mentioned values of ±0.70 for the CF and 10 for the VIF. All remained variables were further discussed with wildcat experts from KORA about their biological significance.

For the final models, we have used BRT to determine the relative influence of each predictor variables and created Partial Dependence Plots (PDP) for each one. They are used to visualize fitted functions by showing the effect of the predictor variables on the response after taking into account the average effects of all other predictors in the models (Friedman and Meulman, 2003).

To assess the model accuracy, each of the final models was split into a training data set and a test data set. 80% of each data set was used for the model building (training data) and the remaining 20% for model evaluation (test data). For measuring and comparing the predictive performance of the different models, the area under the receiver operating characteristic curve (AUC) was used - an effective indicator of model accuracy (Duan et al., 2014). According to Swets (1988) AUC score between 0.5 – 0.7 indicate low predictive performance accuracy, values between 0.7 – 0.9 indicate useful accuracy and values above 0.9 indicate high accuracy.

In a final step, we used the model parameter with the best model performance (according to the AUC score) to extrapolate potential wildcat occurrences in areas with no presence data. We extrapolated the model to the remaining Jura Mts., the Plateau and the Pre-Alpine regions of Switzerland with a raster resolution of 1km^2 as the coarsest resolution of all predictor variables. Since this resolution could be too coarse for several variables (e.g. the distance to variables), we converted the used variable with a 1km^2 resolution to a 1ha resolution (interpolation between the cells). This was used to extrapolate the model with resolution of 1ha. For the habitat distribution maps, we had to classify the raster-cell values. Therefore, we created five classes

for potential habitat suitability (none, little, moderate, good and excellent) with the mean values for presence and background points and the median between them.
To test the extrapolation performance, we used 185 locations of wildcat occurrences (not used for modelling; named evaluation data set) and compared the predicted values of the points with the predicted values of the used model data points. In addition, the GPS-coordinates of three collared wildcats were used to test the modelling performance.

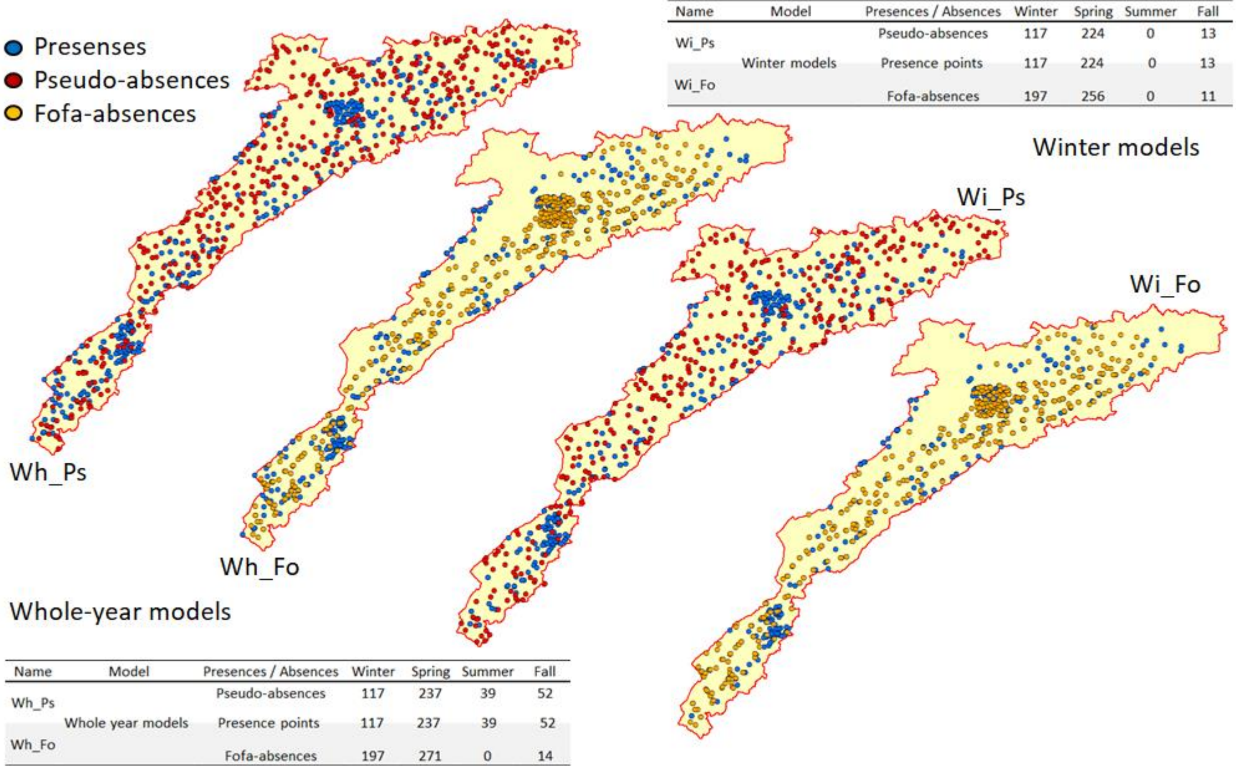
Results

Subsampling

The autocorrelation of the initial model (including all 1,181 detections) was really high, reaching Moran's Index z-score values between 28 and 38. Subsampling allowed us to reduce the autocorrelation to a moderate level (z-scores between 2 and 5) near a random distribution (see supplement material S1 for more information). In general, temporal subsampling performed better than spatial subsampling in terms of z-value reduction. With a minimum time difference of two month between detections at the same location, we could lower the z-value below the value of 5, while using the highest spatial subsampling of 3,200m between adjacent detections to achieve this. Therefore, it was obvious that temporal subsampling has a higher influence on the autocorrelation that a spatial subsampling.

According to the z-scores of the subsamples and the need to take as many data points as possible, we have chosen a setting with one data point per site per year, but no spatial restrictions. Together with the different distribution of occurrences over the year (more occurrences in winter than in summer) we created two data sets (to avoid over-representation of winter aspects). One data set contained occurrences over the whole year and one data set contained only occurrences in the winter half between the 1st of November and 30th of April. With the two background point data sets we ended with four different models (Fig. 3).

Name	Model	Presences / Absences	Winter	Spring	Summer	Fall
Wi_Ps		Pseudo-absences	117	224	0	13
	Winter models	Presence points	117	224	0	13
Wi_Fo		Fofa-absences	197	256	0	11



Name	Model	Presences / Absences	Winter	Spring	Summer	Fall
Wh_Ps		Pseudo-absences	117	237	39	52
	Whole year models	Presence points	117	237	39	52
Wh_Fo		Fofa-absences	197	271	0	14

Fig. 3 Overview of the four final models used in this study with their data point distribution. Considering that the seasons contain three month each (winter = December, January and February; spring = March, April, May; summer = June, July, August; fall = September, October and November). The winter models contain data points from 1st of November to 30th of April.

Variable reduction

Street_class and *Fragmentation_index* were removed as there were no considerable outputs. According to the relative predictor influence for each variable - from the BRT for all four models - we were able to skip *Land-use_categories*, *Remoteness* and *Naturalness,* whose relative influence in all models was among the weakest and never exceeded the value of 0.60% relative to the others. In addition, *Forest_type*, *Human_impact*, *Population_density* and *Wilderness* also had a weak predictor influence of a maximum of 3.10% without significant influence on the other variables. They were skipped as well.

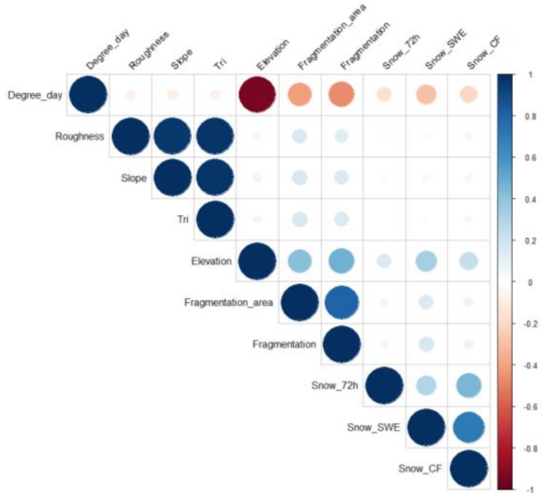


Fig. 4 Correlation plot for the Wh_Ps model. The darker and larger the dots, the higher the correlation between the variables. Blue means a positive correlation and red a negative.

In the correlation plots in R (Fig. 4), we visualized the degree of correlation between different variables and saw that *Degree_day* has a correlation with *Elevation*, *Roughness* and *Slope* with *Tri*, *Fragmentation_area* with *Fragmentation_value* and *Snow_SWE* with *Snow_CF* and *Snow_72h*. A CF above ±0.70 could be observed for *Elevation* and *Degree_day* (negative) and for *Roughness*, *Slope* and *Tri* as well as for *Fragmentation_area* and *Fragmentation_value* and for *Snow_SWE* and *Snow_CF* (Table 4). A VIF over 10 is only valid for *Slope*, *Roughness* and *Tri*. *Elevation* and *Degree_day* are close to a high correlation whereas the snow variables showed a low correlation.

Table 4 CF and VIF for each package of variables. Bold and red are values over the specified threshold.

Package	CF	VIF
Elevation vs. Degree_day	**-0.94**	9.29
Roughness vs. Slope	**0.96**	**14.22**
Roughness vs. Tri	**0.97**	**19.79**
Slope vs. Tri	**0.98**	**22.59**
Fragmentation_area vs. Fragmentation_value	**0.81**	2.89
Snow_SWE vs. Snow_CF	**0.71**	2.01
Snow_SWE vs. Snow_72h	0.29	1.09
Snow_CF vs. Snow_72h	0.45	1.26

None of the correlated variables showed a significantly higher or lower influence on the other variables than the correlated partner variable (e.g. Fig. 5). According to CF and VIF, we skipped the variables with the lower relative influence (*Degree_day, Slope, Tri, Fragmentation_area* and *Snow_CF*). Additionally, wildcats tend to freeze their movements in times with high snowfall, i.e. with new fallen snow the cats remain in their shelter until the snow has melted or it is more compact to walk on it (Piechocki, 1990). According to this theory, we have removed the variable *Snow_72h* because of a possible distorting effect - as it can negatively affect the detection probability for wildcats after snowfall (a general conclusion) - would implement in the model that wildcats would avoid areas with high values of 72h cumulative snowfall. But staying in shelter until the snow melts or is more compact - and thus no detections take place in this time – does not mean that the cat is not present. In the end, we could reduce the environmental variables from initial 26 to final 11 variables (Table 5).

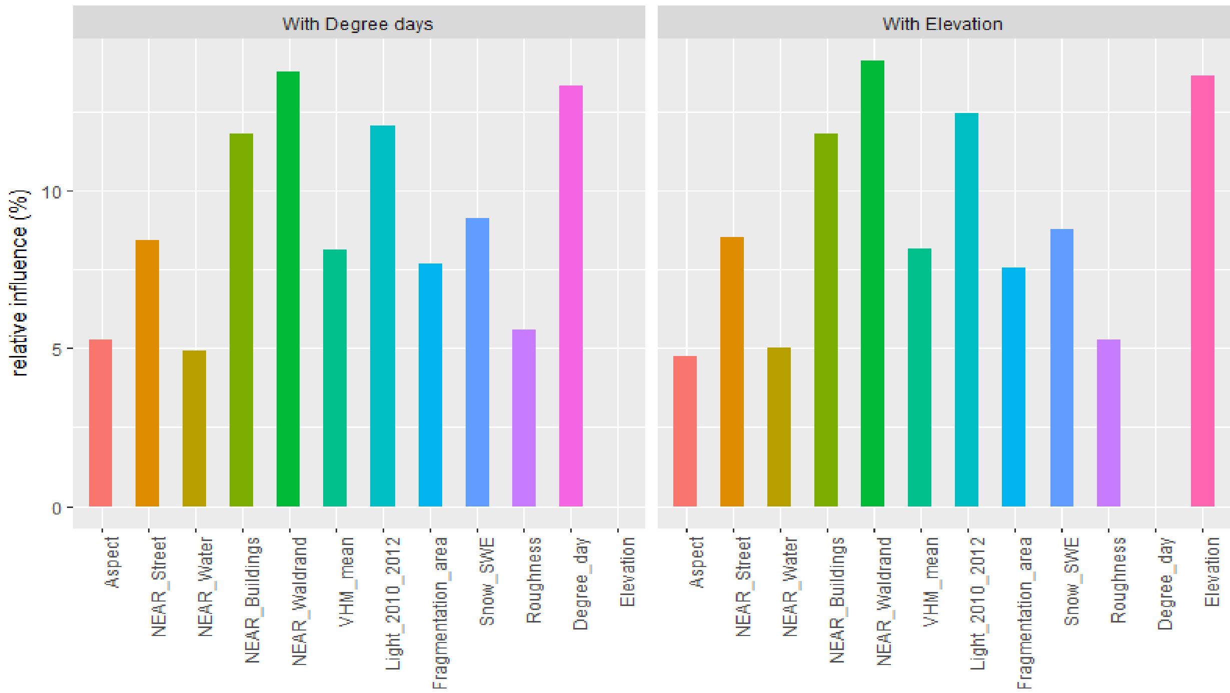


Fig. 5 An example for the relative influence of *Degree_day* or *Elevation*. On the left there is *Degree_day* present and *Elevation* is missing and vice versa on the right. It can be seen that the relative influence of these two variables on the other variables remains the same regardless of the variable selected.

Table 5 Overview of the minimum and maximum values of the 11 final environmental variables.

	Whole year models						Winter models					
	Presence		Pseudo-absence		Fofa-absence		Presences		Pseudo-absences		Fofa-absences	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Aspect	0.0	358.0	0.0	360.0	0.0	359.0	0.0	358.0	0.0	360.0	0.0	359.0
Elevation	333.0	1484.0	337.0	1550.0	431.0	1448.0	389.0	1421.0	347.0	1573.0	431.0	1437.0
Roughness	0.0	50.0	0.0	31.0	1.0	50.0	0.0	50.0	0.0	41.0	1.0	50.0
VHM_mean	0.0	36.8	0.0	35.7	0.0	34.4	0.0	36.8	0.0	37.4	0.0	34.4
Near_Forest	-290.0	639.6	-854.2	455.2	-115.0	512.2	-290.0	490.3	-758.6	325.0	-115.0	412.2
Near_Water	0.8	4203.2	6.0	3457.9	2.8	3246.8	1.3	2881.4	6.0	3611.5	2.8	3246.8
Near_Buildings	0.0	950.5	0.0	882.2	28.4	894.5	0.0	950.5	0.0	704.7	28.4	894.5
Near_Street	0.0	1847.4	2.8	1785.9	0.1	1342.8	0.0	1566.5	3.3	1330.0	0.1	1342.8
Light_2010_2012	3.2	360.1	7.3	454.7	1.6	341.4	7.3	360.1	5.8	389.0	1.6	341.4
Fragmentation_area	0.1	95.1	0.0	95.1	0.4	95.1	0.1	95.1	0.0	95.1	0.4	95.1
Snow_SWE	0.0	476.6	0.0	627.1	0.0	344.9	0.0	476.6	0.0	627.1	0.0	344.9

Relative importance of predictor variables

The variable *Near_Forest* is the strongest predictor in three of the four models, with values around 14.30% (Table 6). Only for the Wi_Ps model the variable *Elevation* is the stronger predictor with 14.73% (11.36% for *Near_Forest*). *Elevation, Snow_SWE* and *Fragmentation_area* are also among the most important predictor variables with values between 7.24% (*Fragmentation_area* for Wh_Ps) and 14.73 (*Elevation* for Wi_Ps). *Light_2010_2012*, *VHM_mean, Roughness* and *Near_Street* are medium-strong predictors with values between 5.46% (*Roughness* for Wh_Ps) and 10.46% (*Light_2010_2012* for Wh_Ps).

Near_Buildings and *Near_Water* are less important predictor variables and *Aspect* is the weakest overall predictor with values between 6.10% and 7.40%.

There are some differences between the two whole-year models (Table 6). The most striking difference is shown by the predictor variable *Fragmentation_area* (third weakest value in the Wh_Ps model with 7.24% but second strongest value in the Wh_Fo model with 11.91%). *Roughness* show also similar differences, while *Near_Buildings* have opposite influences. In the winter models, the differences are much smaller. *Near Buildings* and *Elevation* have the largest differences between the pseudo-absence model and the fofa-absence model with higher values for both in the pseudo-absence model. In contrast, the difference between the two pseudo-absence models and fofa-absence models is much smaller than between the winter and the whole-year models. The predictor variable *Elevation* shows the largest value difference with a value of 10.97% for the Wh_Ps model and 14.73% for the Wi_Ps model. *Fragmentation_area* has also a moderate difference between the two whole-year model (7.24% for the Wh_Ps model and 9.81% for the Wi_Ps model). For the two fofa-absence models, the differences are even smaller with a maximum difference of 1.54% between the values of the predictor variable *Roughness*. The individual predictor influence of each variable with PDP can be seen in the supplementary material S2.

Table 6 Overview about the relative importance values [%] of the predictor variables for all four models and the model performance. Bold green are the top three values of each model and bold red are the weakest three values. The AUC scores represent the model performance.

Dataset	AUC training data	AUC CV	Near Forest	Elevation	Snow SWE	Fragmentation area	Light 2010_2012	VHM mean	Roughness	Near Street	Near Buildings	Near Water	Aspect
Wh_Ps	0.994	0.846 (0.012)	**14.17**	**10.97**	9.52	**7.24**	**10.46**	8.98	**5.46**	8.96	10.19	7.42	**6.63**
Wh_Fo	0.934	0.740 (0.011)	**14.44**	10.84	**11.32**	**11.91**	8.12	8.16	10.60	7.09	**4.78**	**6.18**	**6.56**
Wi_Ps	0.997	0.863 (0.014)	**11.36**	**14.73**	**10.66**	9.81	8.59	8.10	**6.19**	**7.43**	9.20	7.83	**6.10**
Wi_Fo	0.935	0.715 (0.021)	**14.53**	11.14	**12.40**	**11.86**	**6.70**	8.62	9.06	7.52	**5.21**	**5.60**	7.40

According to AUC, all four models have useful accuracy, as they are all between 0.7 and 0.9 (Table 6). The two models with pseudo-absences achieve higher values between 0.846 (Wh_Ps) and 0.863 (Wi_Ps) than the fofa-absence models with values between 0.715 (Wi_Fo) and 0.740 (Wh_Fo).

Model evaluation

Based on the model evaluation, all four models show extremely high accuracy with AUC-values between 0.939 for the Wh_Fo model and 0.997 for the Wi_Ps model. Overall, the two models with pseudo-absences have a slightly higher AUC-value and were around 0.996 whereas the fofa-absence models tended to be around 0.950. We have defined that we use the model with the best predictive performance for the extrapolation, which is the Wi_Ps model with an AUC-value of 0.997. Since the Wh_Ps model showed only a minimal lower AUC-value of 0.996, we also extrapolated this model.

Prediction maps

Table 7 Classification of the prediction values for the two models with the colouration.

1km2			1ha	
Prediction values Wh_Ps	Prediction values Wi_Ps	Habitat suitability	Prediction values Wh_Ps	Prediction values Wi_Ps
0.00000 - 0.24738	0.00000 - 0.19723	none	0.00000 - 0.21756	0.00000 - 0.17662
0.24738 - 0.31796	0.19723 - 0.27893	little	0.21756 - 0.35529	0.17662 - 0.31911
0.31796 - 0.38854	0.27893 - 0.36062	moderate	0.35529 - 0.49303	0.31911 - 0.46159
0.38854 - 0.64564	0.36062 - 0.61549	good	0.49303 - 0.65356	0.46159 - 0.62861
0.64564 - 1.00000	0.61549 - 1.00000	excellent	0.65356 - 1.00000	0.62861 - 1.00000

Extrapolation was made to a resolution of 1km^2 and 1ha. Using the predicted values for each raster cell in the calibration area, we extracted the values for the presence and absence points of both models (Wh_Ps and Wi_Ps) and both resolutions. From these values, we have defined five value-ranges for the potential habitat suitability (none to excellent) for each model and resolution (Table 7). As classification values we used the mean value for the presence and absence points in combination with the median between these two values and the highest total value. Each of the five categories received a predictive colour for the prediction maps.

The resulting prediction values for both raster grids (1km^2 and 1ha resolution) show more or less similar results, e.g. the category “excellent” suitable habitat for the Jura Mts. cover an area of 4.57% in the 1km^2 resolution and 4.72% in the 1ha resolution (Table 8). The biggest difference lies in the category “good” suitable habitat in the Pre-Alps with a percentage of 27.57% in the 1km^2 resolution and only 14.94% in the 1ha resolution. If one compares the whole-year with the winter model, it can be seen that there are only small differences in the percentage of the habitat suitability categories (Table 8). The biggest difference can be found in the 1km^2 resolution for the category “excellent” suitable habitat in the Pre-Alps with 15.42% (whole-year model) and 2.29% (winter model). In general, the different values are due to a redistribution to the nearest higher or lower class.

Table 8 Percentage of the single habitat suitability category for each model and biogeographical region.

1km^2 raster						Habitat suitability	1ha raster					
Whole-year models			Winter models				Whole-year models			Winter models		
Jura Mts.	Plateau	Pre-Alps	Jura Mts.	Plateau	Pre-Alps		Jura Mts.	Plateau	Pre-Alps	Jura Mts.	Plateau	Pre-Alps
57.68%	79.30%	40.81%	58.46%	73.10%	46.33%	none	54.91%	80.76%	34.99%	55.55%	74.29%	41.64%
9.44%	6.32%	9.48%	11.46%	8.97%	17.07%	little	17.95%	11.75%	20.82%	22.42%	15.28%	31.95%
7.27%	3.88%	6.72%	9.15%	5.45%	11.66%	moderate	13.26%	5.47%	13.51%	12.91%	7.49%	17.41%
21.01%	10.16%	27.57%	18.12%	11.88%	22.65%	good	9.16%	1.76%	14.94%	6.77%	2.53%	7.49%
4.57%	0.33%	15.42%	2.78%	0.60%	2.29%	excellent	4.72%	0.26%	15.75%	2.35%	0.41%	1.52%

The difference between the three biogeographical regions, which can be seen on the prediction maps (Fig. 6 and Fig. 7) and based on the percentages (Table 8), is striking. Thus, the Jura Mts. contain 32.86% (Wh_Ps) respectively 30.05% (Wi_Ps) potentially usable wildcat habitat (here defined as areas with the habitat suitability categories “moderate”, “good” and “excellent”) with a resolution of 1km^2, while the proportion for the Plateau lies between 14.38% (Wh_Ps) and 17.94% (Wi_Ps). The highest potentially usable wildcat habitat is in the Pre-Alps with up to 49.71% for the Wh_Ps model at a resolution of 1km^2.

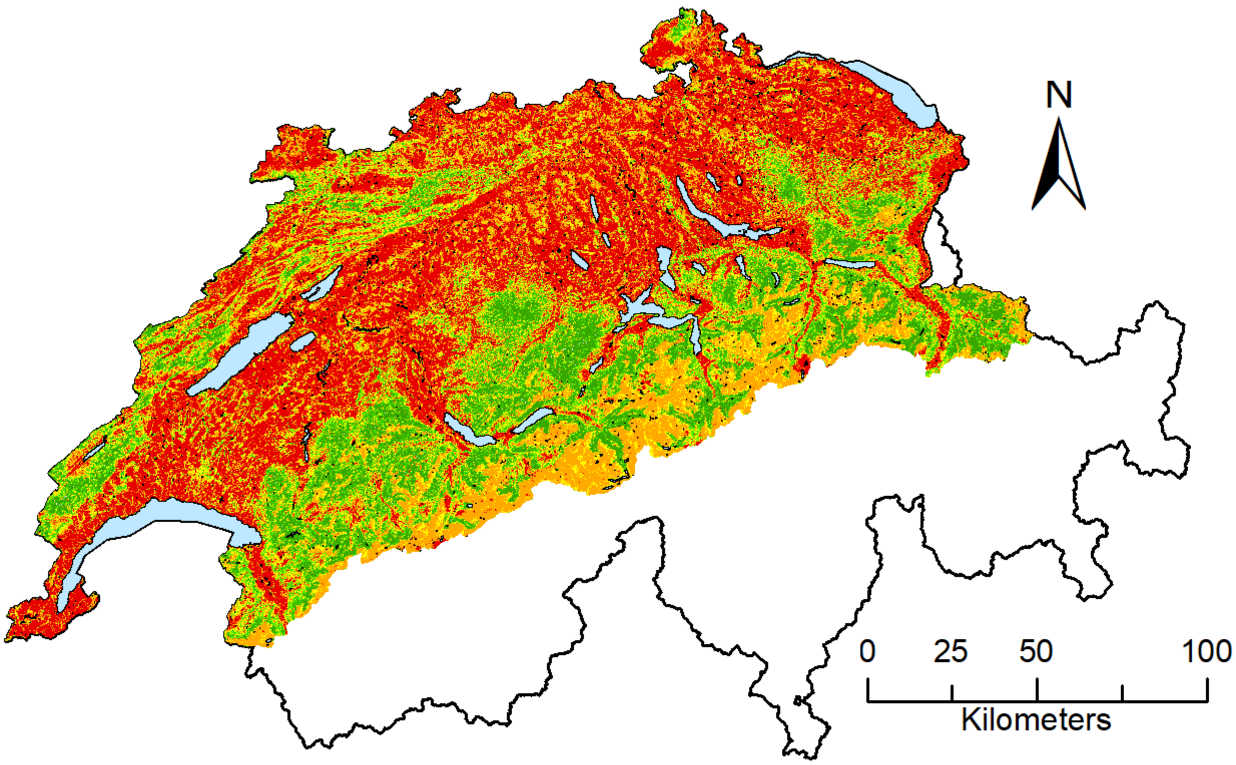


Fig. 6 Whole year model with pseudo absences (Wh_Ps) for the whole study area.

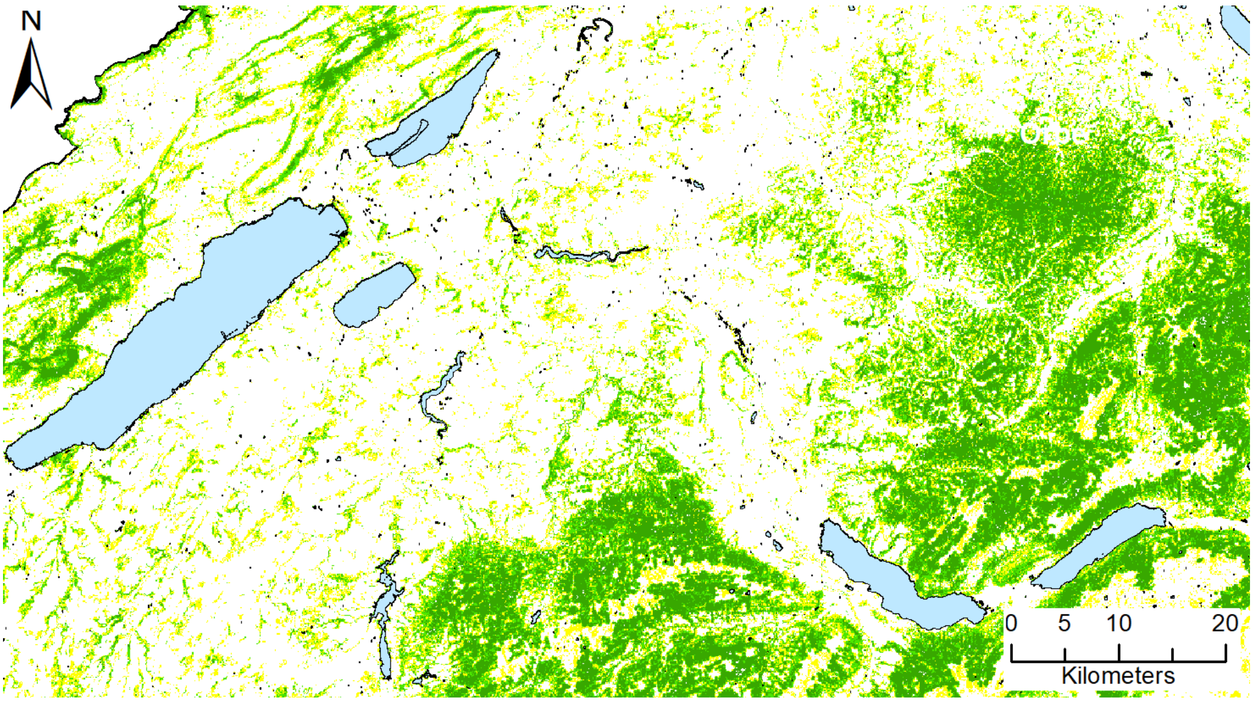


Fig. 7 Potential wildcat habitat map (Wh_Ps model) across the three biogeographical regions. Only “moderate”, “good” and “excellent” potential habitat suitability is demonstrated. Consider the difference between the coloured amount on the left (Jura Mts.), the middle (Plateau) and the right side (Pre-Alps).

According to the result of the model evaluation, we observe a slight decrease in the mean prediction values of the evaluation data compared to the model data sets. This is not surprising, as 23 points of the evaluation data set lie in the Plateau (17 points) and in the Pre-Alps (6 points). But apart from the slight lower values, the means are still close to the means of the model data sets (Table 9) and far away from the background means. Further potential habitat maps can be found in the supplement material S3.

Table 9 Mean predictor values of presence points for the model data and the evaluation data.

Model	Data	mean prediction values	
		1km^2	1ha
Wh_Ps	Model data	0.38854	0.49303
	Evaluation data	0.34137	0.44274
Wi_Ps	Model data	0.36062	0.46159
	Evaluation data	0.29787	0.41487

If we verify the predicted suitable wildcat habitat with the GPS-locations of the three wildcats AMIRA, BJÖRN and DUNJA at the eastern end of Lake of Neuchâtel in the Fanel (Fig. 8) with the 1ha resolution map, we see that for AMIRA the predicted habitats correspond to reality (apart from points in the water that are actually in the reed belt). Most of her locations lie in “moderate” to “excellent” wildcat habitat. In contrast, about half of the points of DUNJA lie in unfavourable habitats, while BJÖRNs locations lie even mostly in none suitable habitat. The two models (Wh_Ps and Wi_Ps) show similar results, while the resolution of 1km^2 is too coarse for the small scale map.

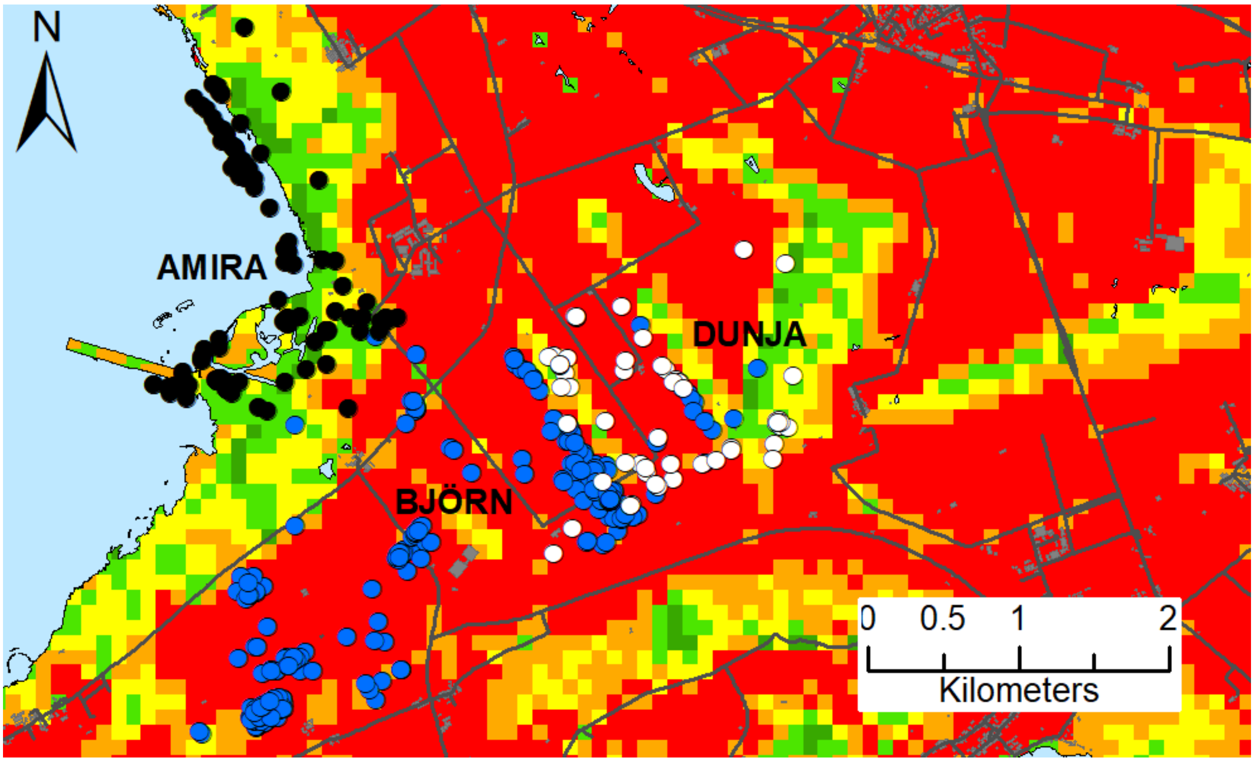


Fig. 8 Potential habitat distribution map from the 1ha extrapolation with the whole-year model (Wh_Ps) for the Fanel at the eastern end of Lake of Neuchâtel. Included are the GPS-locations of three collared wildcats (AMIRA with black dots, BJÖRN with blue dots and DUNJA with white dots).

Discussion

The results of the z-values show that appropriate subsampling can reduse the extent of autocorrelation. With the selected subsampling of one detection per location per year we were able to minimize the autocorrelation to a moderate level with the maximum of data points. According to Crase et al. (2012) BRT can cope with a moderate autocorrelation. With regard to the territorial behaviour of wildcats (Piechocki, 2001) and their average home range sizes of about 2 – 8km^2 (Biro et al., 2004; Breitenmoser et al., 2010; Klar et al., 2008), it would have been better if we had used only one detection per location (over the whole time period) and a spatial distance of 1,600m or 2,400m. But with such a subsampling, we would have ended up with too few data points for a proper modelling.

We have chosen Boosted Regression Trees for our modeling study. According to Elith et al. (2008) BRT have a high predictive power and can identify reliable variable and interactions. Pearce and Boyce (2006) mentioned in their study that regression based modeling perform better for presence-only data than other approaches. It is essential to select appropriate pseudo-absence or background points (Chefaoui and Lobo, 2008). We have decided to use random absence points (pseudo-absences) created in useable wildcat areas throughout the whole Jura Mts. This is a widely used method in habitat modelling (Chefaoui and Lobo, 2008) and, with the right habitat considerations also an appropriate choice (VanDerWal et al., 2009). Out of personal interest we have compiled a second background data set with the deterministic camera trap locations without wildcat detections (fofa-absences). Due to the short sampling period (60 days) and the selected locations for camera-traps (best chance of wildcat detection), these are not observed absences rather a second pseudo-absence data set. The spatial distribution of fofa-absences in the model calibration area is also strongly limited and bundled. This can be seen in the predictive performance of the fofa-absence models which are lower than the pseudo-absence models. Therefore, the modelling of the two data sets with fofa-absences (Wh_Fo and Wi_Fo) was made only out of personal interest and does not provide any relevant results for the habitat predictor values nor for an extrapolation.

Best habitat modelling can be achieved by sampling the data points with a suitable sampling design (Guisan and Zimmermann, 2000). In our case, neither the sampling of random data nor the one of deterministic data (incomplete detections) was based on the idea of performing a habitat model. Despite the fact that we had a lack of observed absences, there is a chance of a distortion effect due to the spatial arrangement of occurrences in the deterministic data set. Especially in the wildcat camera trap studies (Jura North 2015/16 & 2016/17 and Jura South 2017/18), the locations of the installed camera traps were strategically placed so that as many wildcats as possible could be detected. For example, most camera traps were placed near the edge of the forest, which could explain the high performance value for the variable *Near_Forest*. Therefore, the values for the relative importance of predictors should be consicered with caution.

For our study we decided to take a whole year and a winter model. This decision was based on the fact that we had only 91 data points in summer, as opposed to 354 winter points. So we were careful that the over-representation of winter detections did not affect the general predictions (especially for the variable *Snow_SWE* and *Elevation*). The winter model performed better in terms of the AUC-score than the whole-year model, but surprisingly the differences between the two are smaller than expected. This may be because only one predictor variable shows seasonal variability (*Snow_SWE*).

Wildcats are known to avoid areas with a lot of snow (Dotterer and Bernhart, 1996; Mermod and Liberek, 2002). In addition, Mermod and Liberek (2002) and Klar et al. (2009) were able to show in their studies that wildcats relocate their home range higher up in summer, while in winter they move down to areas with less snow cover. These results combined with the fact, that in the Jura Mts. home ranges of wildcats can cover both the high altitudes and the vally bottom (Dotterer and Bernhart, 1996), it is likely that our predicted suitable winter habitat can be regarded as a minimum habitat area. This minimum area could be extended to higher altitues in the summer, if these areas are located within the home range of the cat.

In total, we analysed 26 different environmental variables that were considered important. In the habitat modelling studies by Klar et al. (2008) they used only "Distance to …" variables whereas Graf et al. (2013) supplemented these variables with the forest type, primary surface and elevation. With the exception of primary surfacec, we included the same variables in our study and completed them with further potential relevant predictor variables. From an intensive literature review we decided to include predictors such as Slope and Snow-variables (Mermod and Liberek, 2002), Fragmentation-variables (Hartmann et al., 2013; Pir et al., 2011) or human-influence variables (Pineiro et al., 2012). Unfortunately, it was not possible to include a variable for the prey density that would be important for a better habitat prediction (Litvaitis et al., 1986; Torres et al., 2008). There was also no variable for intra- and interspecific competition. As the study of Jerosch et al. (2017) shows, wildcats sometimes use the agricultural dominated landscapes. Together with observations of two wildcats with GPS-collars (BJÖRN and DUNJA) in the Fanel (unpublished results from KORA), these landscapes could play an important role in the habitat preferences if no optimal biotops are available - as it is true for most part of the Plateau - but reliable studies are missing. In addition, agrocultural areas underlie a yearly shift of the grown cultures (crop rotation) and therefore reliable spatial data is missing.

We skipped all correlated and weak predictors and used only those that had a significant influence on the modelling. A total of 15 variables could be skipped, resulting in total of 11 used predictor variables. In other habitat modelling studies, we observe that in most cases the number of predictor variables is smaller. Some studies used smaller set of environmental variable (Klar et al., 2008), while others modelled organisms with more specific habitat requirements than wildcats (Kuemmerle et al., 2018). Known as generalists (Büttner, 1988), wildcats can live in different environments (Yamaguchi et al., 2015) and need more predictor variables to account for different regions.

For the model extrapolation the raster resolution of 1km^2 would be most suitable, since the roughest variable resolution has the same extent (*Light_2010_2012* and *Snow_SWE*) and additionally the average wildcat home-range size include several square kilometers. But in view of the fine-spatial diversity of some areas (especially the Jura Mts. and the Pre-Alps) the

resolution of $1km^2$ is extremely rough. In addition, the calculation of distance-based variables become less accurate. In order to take these problems into account, the extrapolation to a 1ha grid shows more varied results despite the downsampling of the two variables mentioned.
We used the prediction values for the presence and background points as a basis for the classification and the color range of the prediction maps. In the range between the mean predictor values for presence points (0.46159) and absences (0.17662) there were presence and background points present. Therefore, we created this area as “little” and “moderate” suitable for potential wildcat occurrences which means that there may occur wildcats but the likelihood is low. There would be other possibilites for the scaling (e.g. ranges based on the prediction quantiles), but we think the used classification system is appropriate for this study.

Due to the data situation (predominant wildcat detections in the Jura Mts.) and the validation the strengths of the models lie in the biogeographical area of the Jura Mts. There, the accuracy was high whereas it decreases for the Pre-Alps (slightly) and for the Plateau (moderate). For the Pre-Alps it should be possible to identify potential distribution areas on a broader scale, as the landscape aspects are quite similar to the Jura Mts. For the Plateau, however, the model has to be adjusted as the landscape contains different aspects. This could be achieved by removing the variables *Elevation* and *Snow_SWE* and integrating a land-class variable that includes some agrocultural aspects. If we consider the variation of some predictor variables from one model to another, one could argue that some of them are not important or that one of the calibration data sets is not optimal and should be excluded. This could be verified in an additional study. For the future it would also be good to consider GPS-locations of collared wildcats as in other habitat modelling (Klar et al., 2008).

We belive that this study can improve future wildcat research and management projects in Switzerland. For example, it could be combined with other data sets like density estimations of deterministic wildcat trap studies to estimate the current population size of the Jura Mts. In addition, dispersal corridors from the Jura Mts. to the adjoining Plateau or the influence of global warming could be assessed based on this study.

References

Biro Z., Lanszki J., Szemethy L., Heltai M. and Randi E. 2005. Feeding habits of feral domestic cats (Felis catus), wild cats (Felis silvestris) and their hybrids: trophic niche overlap among cat groups in Hungary. 0952-8369

Biro Z., Szemethy L. and Heltai M. 2004. Home range sizes of wildcats (Felis silvestris) and feral domestic cats (Felis silvestris f. catus) in a hilly region of Hungary. 1616-5047

Breitenmoser U., Ryser-Degiorgis M. P., Vogt K. and Zimmermann F. 2010. Beobachtung zweier rehabilitierter Wildkatzen im Berner Jura.

Burton A. C., Neilson E., Moreira D., Ladle A., Steenweg R., Fisher J. T., Bayne E. and Boutin S. 2015. Wildlife camera trapping: a review and recommendations for linking surveys to ecological processes. 0021-8901

Büttner K. 1988. Die Wiedereinbürgerung von Raubwild aus waldhygienischer Sicht.

Ceballos G. and Ehrlich P. R. 2002. Mammal population losses and the extinction crisis. 0036-8075

Chefaoui R. M. and Lobo J. M. 2008. Assessing the effects of pseudo-absences on predictive distribution model performance. 0304-3800

Crase B., Liedloff A. C. and Wintle B. A. 2012. A new method for dealing with residual spatial autocorrelation in species distribution models. 0906-7590

De'ath G. 2007. Boosted trees for ecological modeling and prediction. 0012-9658

Dietz M., Lang J., Rüth K., Krannich A. and Simon O. 2016. Wiederbesiedlung und Habitatpräferenzen der Europäischen Wildkatze im Rothaargebirge. 0940-6808

Dormann C. F., Elith J., Bacher S., Buchmann C., Carl G., Carre G., Marquez J. R. G., Gruber B., Lafourcade B., Leitao P. J., Munkemuller T., McClean C., Osborne P. E., Reineking B., Schroder B., Skidmore A. K., Zurell D. and Lautenbach S. 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. 0906-7590

Dormann C. F., McPherson J. M., Araújo M. B., Bivand R., Bolliger J., Carl G., Davies R. G., Hirzel A., Jetz W. and Kissling W. D. 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. 1600-0587

Dotterer M. and Bernhart F. 1996. The occurrence of wildcats in the southern Swiss Jura Mountains. 0001-7051

Duan R. Y., Kong X. Q., Huang M. Y., Fan W. Y. and Wang Z. G. 2014. The Predictive Performance and Stability of Six Species Distribution Models. 1932-6203

Elith J. and Leathwick J. 2017. Boosted Regression Trees for ecological modeling.

Elith J. and Leathwick J. R. 2009. Species distribution models: ecological explanation and prediction across space and time. 1543-592X

Elith J., Leathwick J. R. and Hastie T. 2008. A working guide to boosted regression trees. 1365-2656

Friedman J., Hastie T. and Tibshirani R. 2001. The elements of statistical learning. Springer series in statistics New York, NY, USA:.

Friedman J. H. and Meulman J. J. 2003. Multiple additive regression trees with application in epidemiology. 0277-6715

Fryxell J. M., Sinclair A. R. and Caughley G. 2014. Wildlife ecology, conservation, and management. John Wiley & Sons. 1118348192

Gonseth Y. and Buttler A. 2001. Die biogeographischen Regionen der Schweiz: Erläuterungen und Einteilungsstandard. OFEFP.

Graf R. F., Bitterlin L., Stoller S. and Bächtiger M. 2013. Habitatanalyse für die Wildkatze in der Region Albis und Umgebung. Zürcher Hochschule für Angewandte Wissenschaften ZHAW. Wädenswil.

Groombridge B. 1992. Global biodiversity: status of the earth's living resources. Chapman & Hall. 0412472406

Guisan A. 2017. Habitat suitability and distribution models : with applications in R. London : Cambridge University Press. 978-0-521-75836-9
978-0-521-76513-8

Guisan A. and Thuiller W. 2005. Predicting species distribution: offering more than simple habitat models. 1461-023X

Guisan A. and Zimmermann N. E. 2000. Predictive habitat distribution models in ecology. 0304-3800

Harrell F. E., Lee K. L. and Mark D. B. 1996. Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. 1097-0258

Hartmann S. A., Steyer K., Kraus R. H. S., Segelbacher G. and Nowak C. 2013. Potential barriers to gene flow in the endangered European wildcat (Felis silvestris). 1566-0621

Hinkle D. E., Wiersma W. and Jurs S. G. 1988. Applied statistics for the behavioral sciences.

Jerosch S., Gotz M. and Roth M. 2017. Spatial organisation of European wildcats (Felis silvestris silvestris) in an agriculturally dominated landscape in Central Europe. 1616-5047

Klar N. 2009. Anwendung eines Habitatmodells für die Wildkatze im Freistaat Bayern. ÖKO-LOG Freilandforschung.

Klar N., Fernandez N., Kramer-Schadt S., Herrmann M., Trinzen M., Buttner I. and Niemitz C. 2008. Habitat selection models for European wildcat conservation. 0006-3207

Klar N., Herrmann M. and Kramer-Schadt S. 2009. Effects and Mitigation of Road Impacts on Individual Movement Behavior of Wildcats. 0022-541X

KORA. 2018. Unpublizierte Daten. Muri.

Kuemmerle T., Levers C., Bleyhl B., Olech W., Perzanowski K., Reusch C. and Kramer-Schadt S. 2018. One size does not fit all: European bison habitat selection across herds and spatial scales. 0921-2973

Landolt E., Sigg H. and Hirzel R. 1992. Unsere alpenflora. Fischer Stuttgart. 3437204882

Liberek M. 1999. Eco-ethologie du chat sauvage Felis s. silvestris, Schreber 1777 dans le Jura Vaudois (Suisse): Influence de la couverture neigeuse.

Litvaitis J. A., Sherburne J. A. and Bissonette J. A. 1986. Bobcat habitat use and home range size in relation to prey density. 0022-541X

Loiselle B. A., Howell C. A., Graham C. H., Goerck J. M., Brooks T., Smith K. G. and Williams P. H. 2003. Avoiding pitfalls of using species distribution models in conservation planning. 0888-8892

Lüps P. 1981. Nachweis der Wildkatze Felis s. silvestris Schreber, 1777 im Berner Jura.

Mermod C. P. and Liberek M. 2002. The role of snowcover for European wildcat in Switzerland. 0044-2887

Molinari-Jobin A. 2003. The pan-Alpine conservation strategy for the lynx. Council of Europe. 9287151113

Pearce J. L. and Boyce M. S. 2006. Modelling distribution and abundance with presence-only data. 1365-2664

Peterson J. T. and Dunham J. 2003. Combining inferences from models of capture efficiency, detectability, and suitable habitat to classify landscapes for conservation of threatened bull trout. 0888-8892

Piechocki R. 1990. Die Wildkatze: Felis silvestris. Ziemsen. 3740302267

Piechocki R. 2001. Lebensräume-Die Verbreitung der Wildkatze in Europa.

Pierpaoli M., Biro Z. S., Herrmann M., Hupe K., Fernandes M., Ragni B., Szemethy L. and Randi E. 2003. Genetic distinction of wildcat (Felis silvestris) populations in Europe, and hybridization with domestic cats in Hungary. 0962-1083

Pineiro A., Barja I., Silvan G. and Illera J. C. 2012. Effects of tourist pressure and reproduction on physiological stress response in wildcats: management implications for species conservation. 1035-3712

Pir J. B., Schauls R., Dietz M. and Simon O. 2011. Bedeutung von Wildbrücken zur Vernetzung von Wanderkorridoren für die Europäische Wildkatze (Felis silvestris silvestris Schreber, 1777) am Beispiel von Pettingen/Mersch (Luxemburg).

Say L., Devillard S., Leger F., Pontier D. and Ruette S. 2012. Distribution and spatial genetic structure of European wildcat in France. 1367-9430

Schubarth C. and Weibel F. 2013. Land use in Switzerland: Results of the Swiss land use statistics. Swiss Federal Statistical Office (FSO). Neuchâtel.

Slotta-Bachmayr L., Meikl M. and Hagenstein I. 2016. Aktueller Status der Europäischen Wildkatze (Felis silvestris silvestris, Schreber, 1777) in Österreich.

Stahl P. and Artois M. 1994. Status and conservation of the wildcat (Felis silvestris) in Europe and around the Mediterranean rim. Council of Europe. 928712499X

Streif S., Kraft S., Veith S., Kohnen A. and Suchant R. 2012. Monitoring and research of the European wildcat (Felis silvestris) in Baden-Württemberg.

Swets J. A. 1988. Measuring the accuracy of diagnostic systems. 0036-8075

Torres L. G., Read A. J. and Halpin P. 2008. Fine-scale habitat modeling of a top marine predator: do prey data improve predictive capacity. 1939-5582

VanDerWal J., Shoo L. P., Graham C. and Williams S. E. 2009. Selecting pseudo-absence data for presence-only distribution modeling: How far should you stray from what you know? 0304-3800

Weber D., Roth T. and Huwyler S. 2010. Die aktuelle Verbreitung der Wildkatze (Felis silvestris silvestris Schreber, 1777) in der Schweiz. Ergebnisse der systematischen Erhebungen in den Jurakantonen in den Wintern 2008/09 und 2009/10. Hintermann & Weber AG.

Wollschläger D. 2015. Grundlagen der Datenanalyse mit R: eine anwendungsorientierte Einführung. Springer-Verlag. 3662455072

Yamaguchi N., Kitchener A., Driscoll C. and Nussberger B. 2015. Felis silvestris. The IUCN Red List of Threatened Species 2015.

Zimmermann F. 2004. Conservation of the Eurasian Lynx (Lynx Lynx) in a Fragmented Landscape: Habitat Models, Dispersal and Potential Distribution.

Supplement material

S1 – Spatial and temporal autocorrelation of data points

Moran's Index describe the amount of autocorrelation between data points (e.g. the wildcat monitoring grids contain multiple and spatially close positive detection points in contrast to the lynx monitoring grids with less spatial collection of positive detections). The wildcat grids lead to a positive autocorrelation whereas the lynx grids push the value towards negativity. This is also true for the temporal sampling. Some locations had over 30 detections in a time frame of two month whereas others have only one detections in the same time frame.

The subsampling was made to take down the initial high z-score close to a random distribution (with z-value around 0-5).

The autocorrelation index was calculated for all subsamples made with Moran's Index in ArcGIS. Table 1 shows a selection. In total, 5 spatial and 10 temporal subsampling's were made with all combinations between them.

Table 1 Overview of the temporal and spatial subsampling with the amount of presence and absence points and the autocorrelation values. The bold green ones are two of the chosen final models (WC2_pseudo is equal to the Wh_Ps model and WC2_fofa equal to Wh_Fo).

Name	Spatial distance between points	Temporal distance between points	Nr of presence points	Nr of absence points	Moran's Index	z-score	p-value
WC1_pseudo	0m	0d	1181	545	0.461473	38.233	0.000000
WC1_fofa	0m	0d	1181	482	0.329092	28.185	0.000000
WC2_pseudo	**0m**	**365d**	**445**	**445**	**0.999903**	**4.990**	**0.000001**
WC2_fofa	**0m**	**365d**	**445**	**482**	**-0.238270**	**-2.450**	**0.014269**
WC3_pseudo	800m	0d	576	576	0.466449	21.419	0.000000
WC3_fofa	800m	0d	576	302	0.321052	13.325	0.000000
WC4_pseudo	800m	365d	244	244	0.999962	3.643	0.000270
WC4_fofa	800m	365d	244	362	-0.224081	-1.576	0.114996
WC5_pseudo	1'600m	0d	379	379	0.448306	19.526	0.000000
WC5_fofa	1'600m	0d	379	293	0.325707	16.225	0.000000
WC6_pseudo	1'600m	365d	183	183	-0.276755	-3.836	0.000125
WC6_fofa	1'600m	365d	183	293	-0.983662	-3.508	0.000452

S2 – Partial dependence plots (PDP)

For all 11 final predictor variables, PDP were generated and interpreted. The most eye-catching fact, is that for all PDP the two whole year models and the two winter models show similar progress (Fig. 1, 2 & 3).

Regarding the predictor variable *Near_Buildings* which has high differences in the predictor value between the models we see that for the fofa-absence models the influence is almost zero for the whole span whereas for the pseudo-absence models the influence of distance is negative until 250m (second graph in Fig. 2).

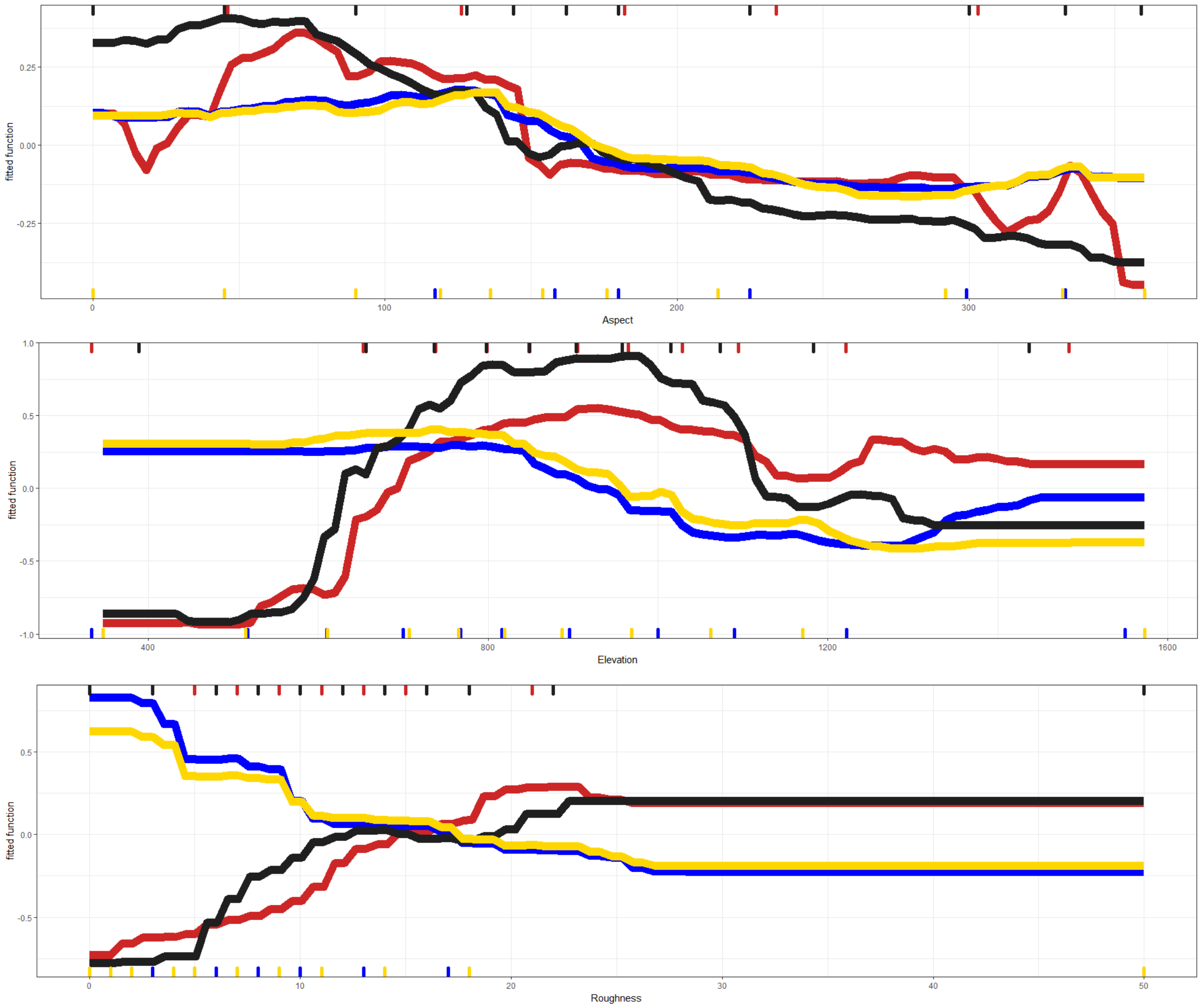


Fig. 1 Partial dependence plot for the variables *Aspect* (first graph), *Elevation* (second graph) and *Aspect* (third graph). The red line symbolize the Wh_Ps model, the black line the Wi_Ps model, the blue line the Wh_Fo model and the yellow line the Wi_Fo model.

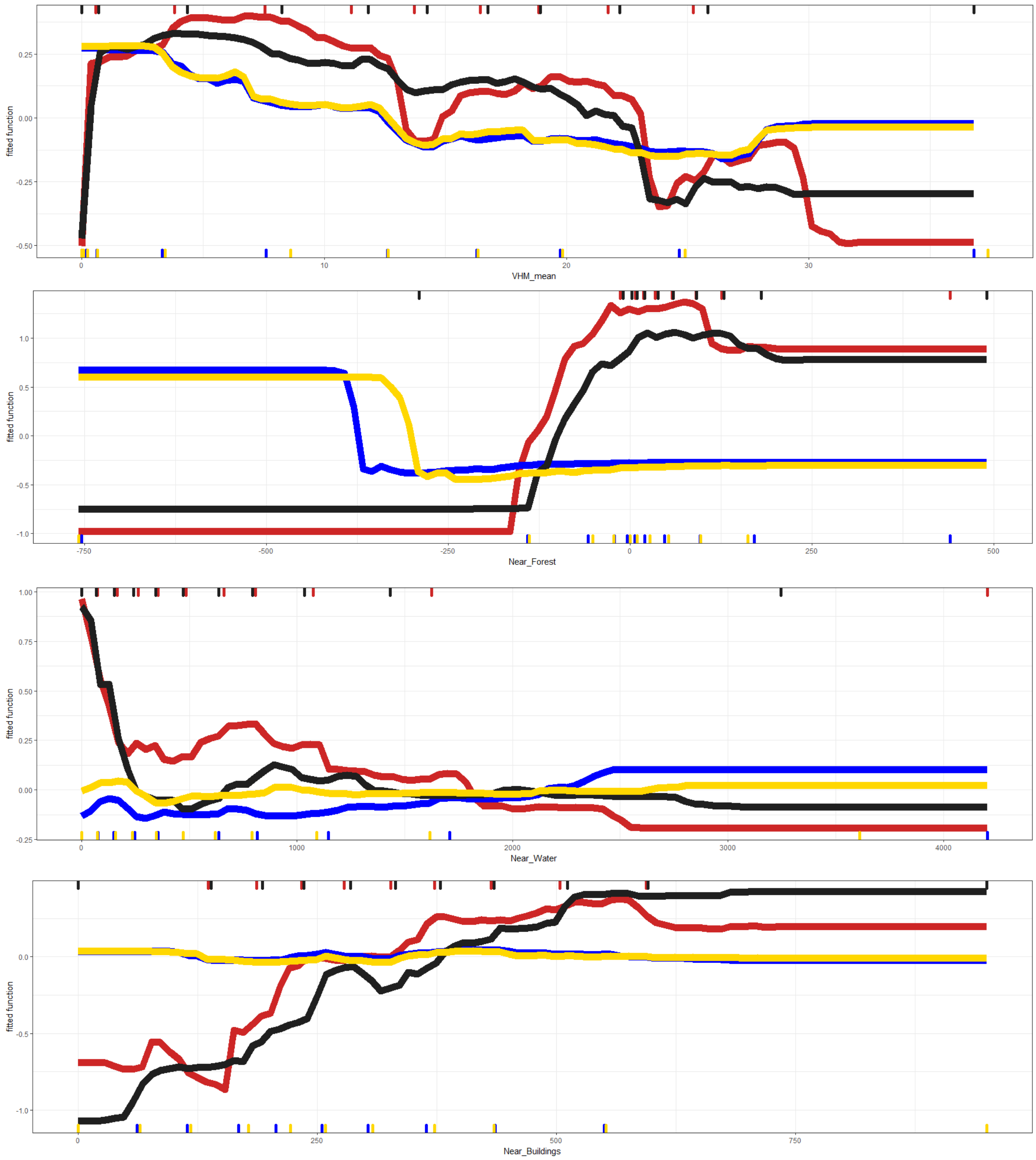


Fig. 2 Partial dependence plot for the variables *VHM_mean* (first graph), *Near_Forest* (second graph), *Near_Water* (third graph) and *Near_Buildings* (fourth graph). The red line symbolize the Wh_Ps model, the black line the Wi_Ps model, the blue line the Wh_Fo model and the yellow line the Wi_Fo model.

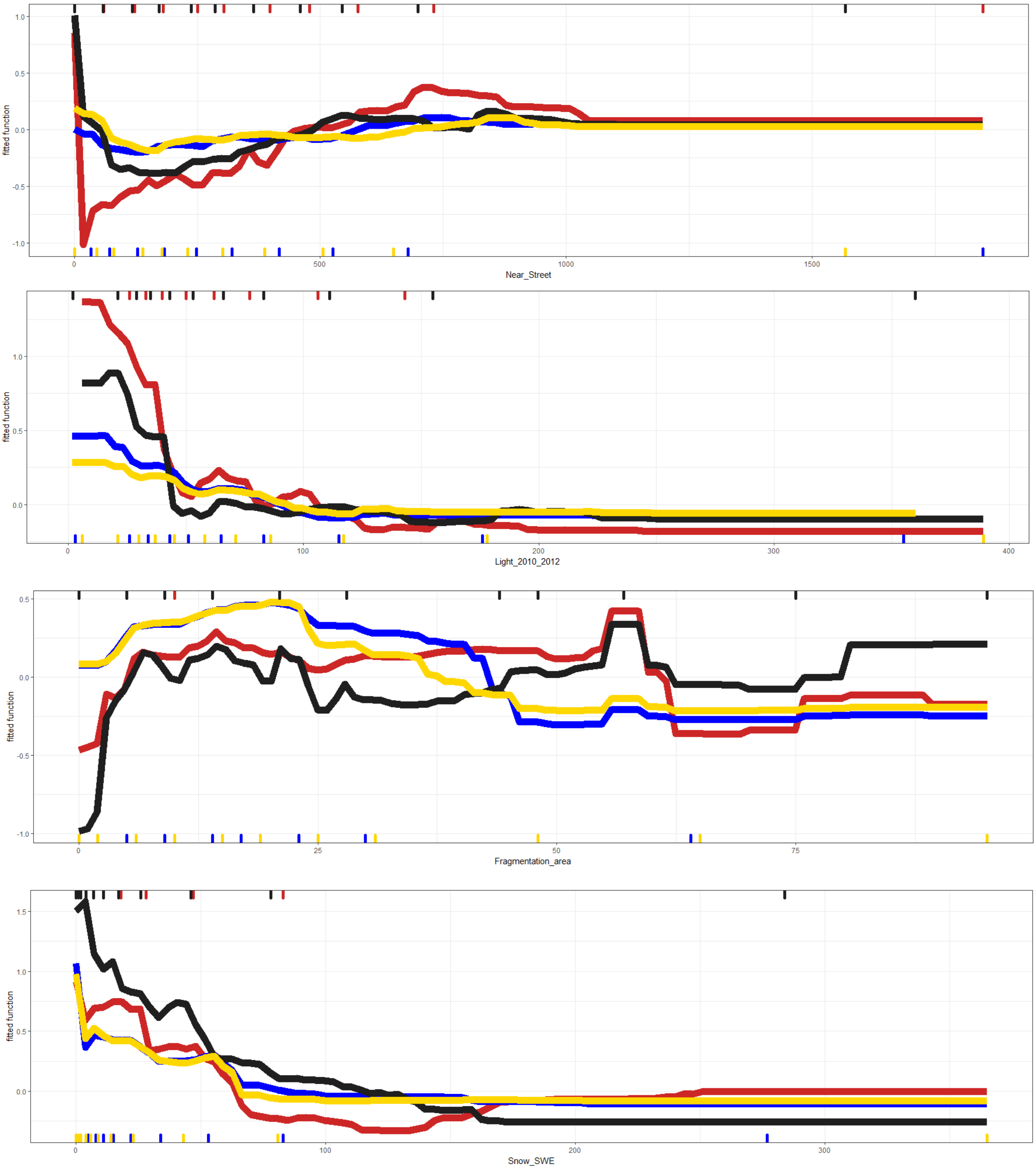


Fig. 3 Partial dependence plot for the variables *Near_Street* (first graph), *Light_2010_2012* (second graph), *Fragmentation_area* (third graph) and *Snow_SWE* (fourth graph). The red line symbolize the Wh_Ps model, the black line the Wi_Ps model, the blue line the Wh_Fo model and the yellow line the Wi_Fo model.

S3 – Prediction maps

Here are more prediction maps illustrated. As an addition to the prediction map (Wh_Ps) for the whole study are shown in the paper, here is the prediction map for the winter model (Fig. 4). Apart the different resolution (1km^2 and 1ha), the results are really similar. Between the whole-year models and the winter models the differences are also small (Fig. 5 & Fig. 6). This can also be seen in larger sections (Fig. 7 & Fig. 8). The differences for these insights are more obvious for the 1ha resolution than for the resolution with 1km^2.

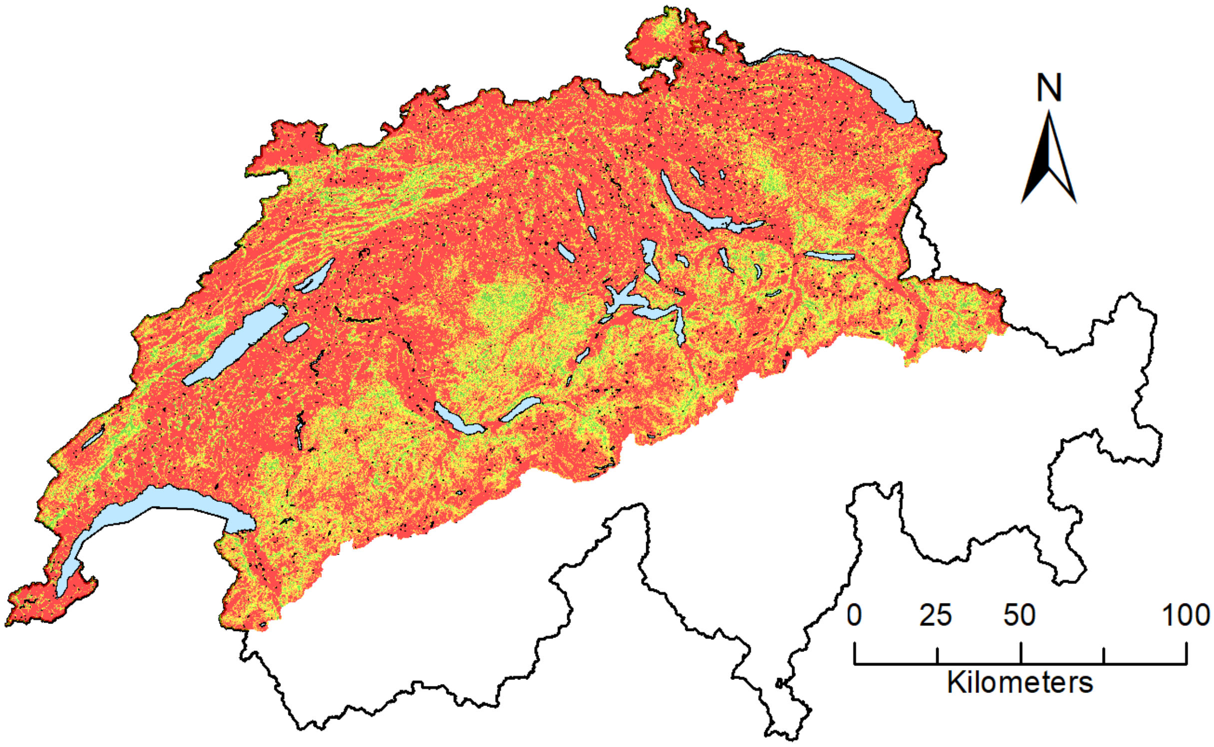


Fig. 4 1ha prediction map for the winter model (Wi_Ps).

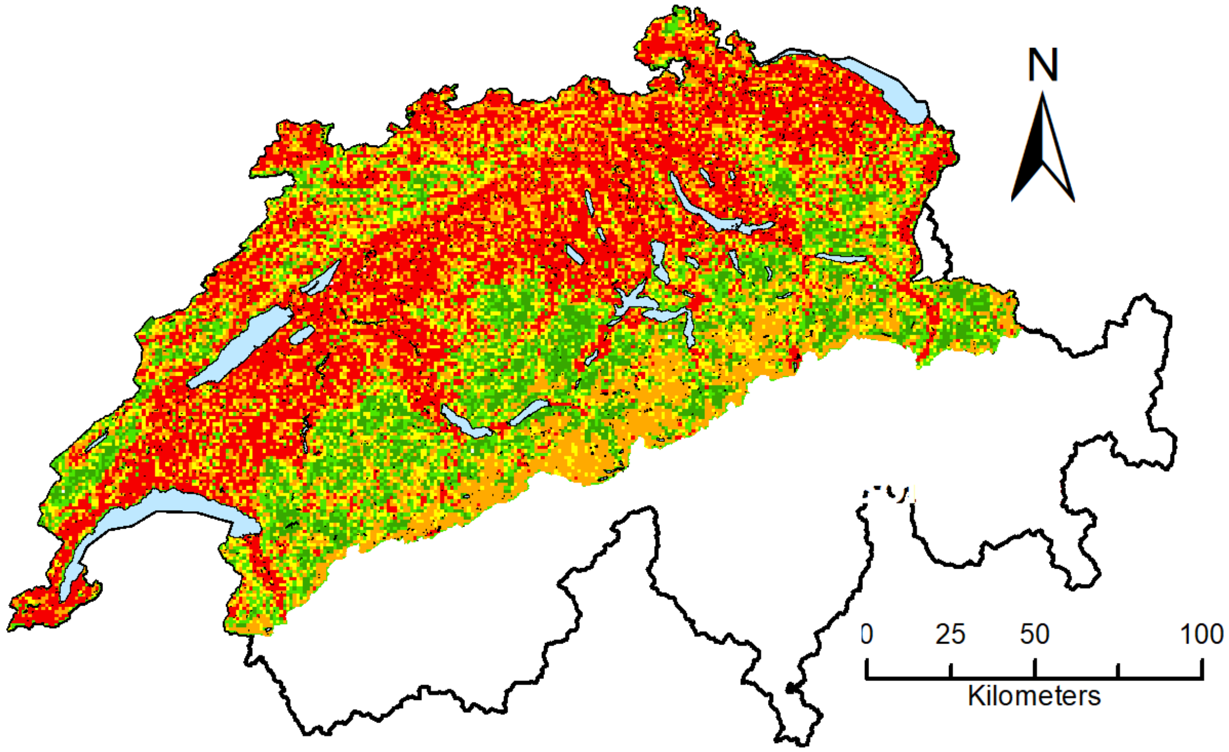


Fig. 5 1km² prediction map for the whole-year model (Wh_Ps).

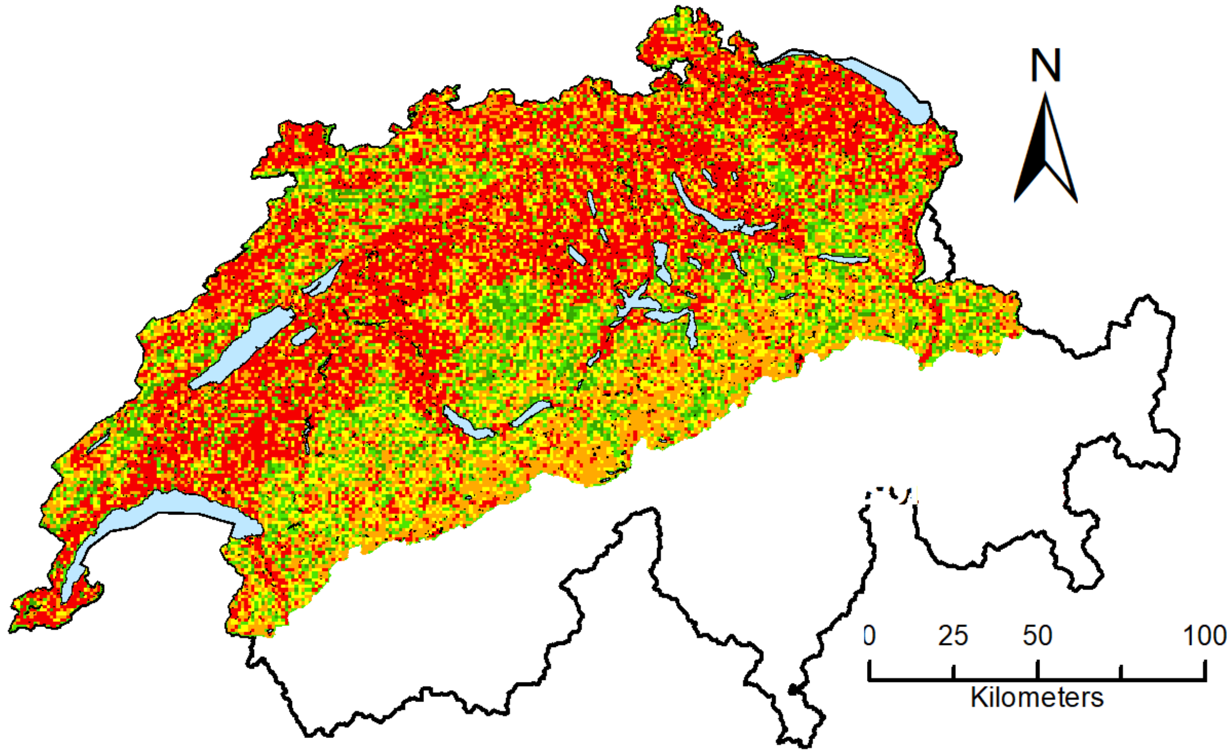


Fig. 6 1km2 prediction map for the winter model (Wi_Ps).

Fig. 7 Only small differences between the Wh_Ps (left map) and the Wi_Ps model (right map) in the area of the deterministic wildcat monitoring 2015/16 and 2016/17. White are the presence dots and black the pseudo-absences.

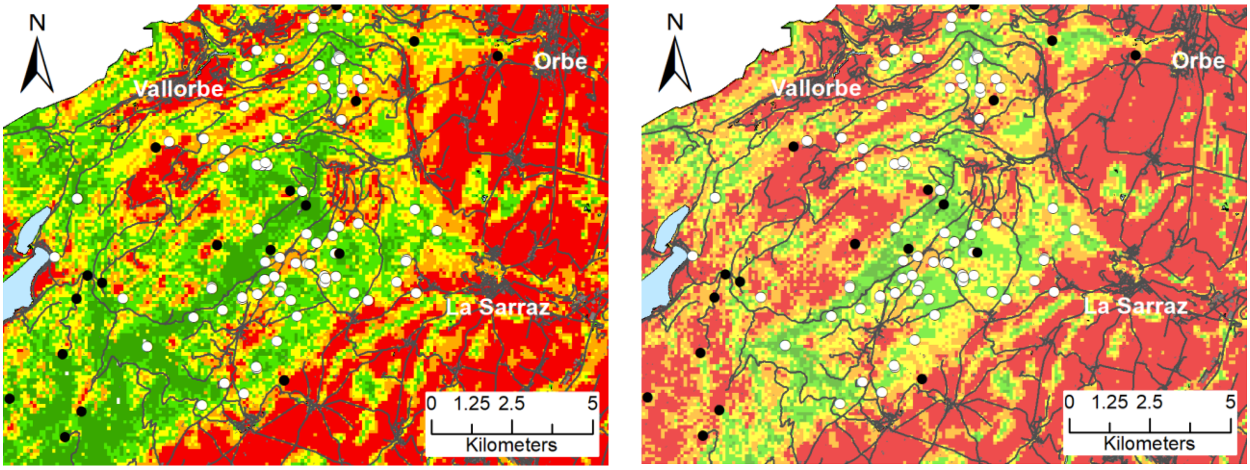


Fig. 8 Also in the 1ha prediction for the area of the deterministic wildcat monitoring area 2017/18 the differences between the whole-year (Wh_Ps) and the winter model (Wi_Ps) are small. The whole-year model has slightly higher potential usable wildcat areas.

ETH

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Titel der Arbeit (in Druckschrift):

Habitat model of the European wildcat (Felis silvestris silvestris) for the Swiss Jura Mountains, Plateau and near Pre-alpine regions

Verfasst von (in Druckschrift):
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