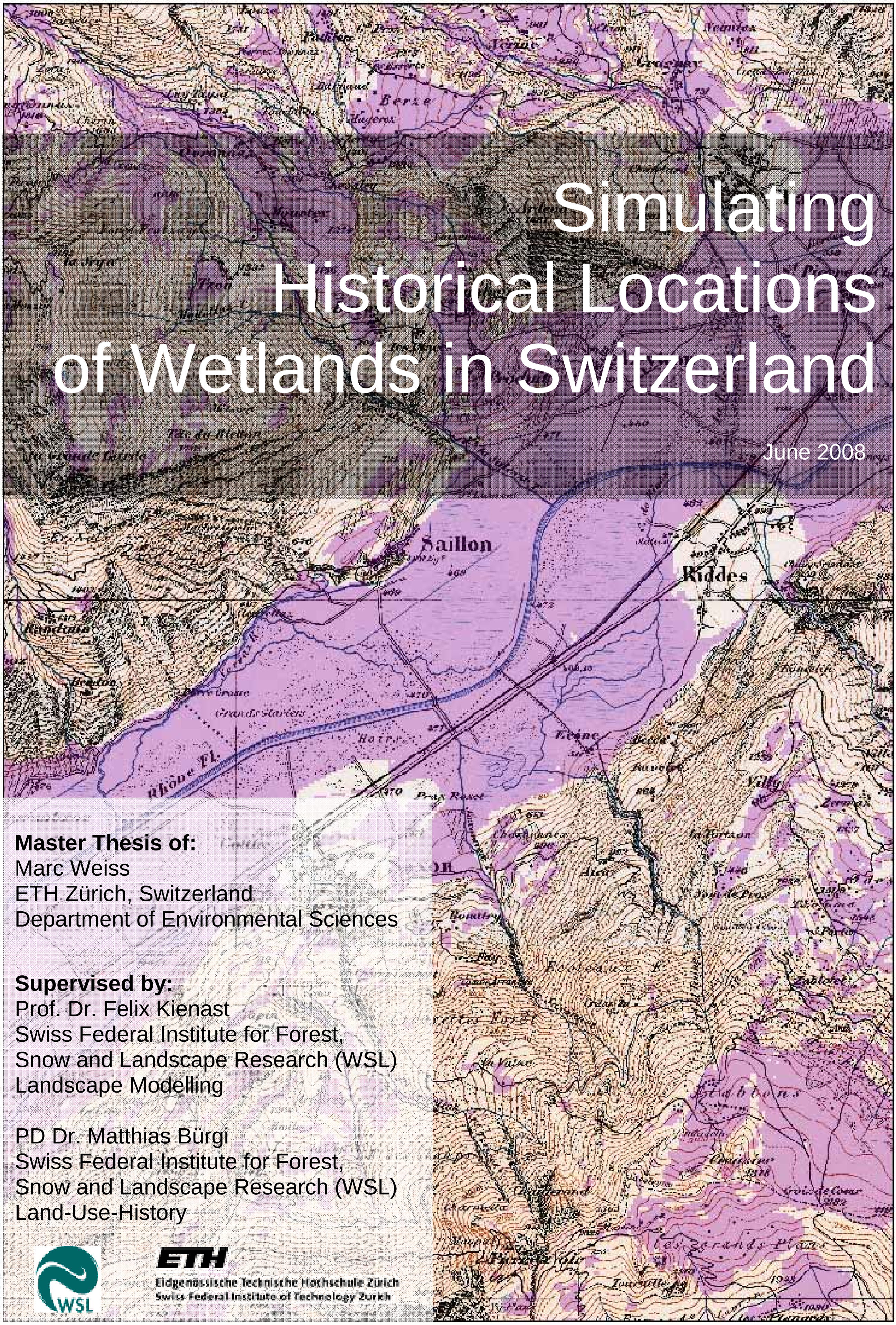
Simulating historical locations of wetlands in Switzerland



Simulating Historical Locations of Wetlands in Switzerland

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Master Thesis of:
Marc Weiss
ETH Zürich, Switzerland
Department of Environmental Sciences

Supervised by:
Prof. Dr. Felix Kienast
Swiss Federal Institute for Forest, Snow and Landscape Research (WSL)
Landscape Modelling

PD Dr. Matthias Bürgi
Swiss Federal Institute for Forest, Snow and Landscape Research (WSL)
Land-Use-History

WSL

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Ordering information:
Felix Kienast, WSL: felix.kienast@wsl.ch

Index

Summary

In this thesis we present a method for hindcasting the composite historical distribution of wetlands in Switzerland. Locations and extents of the wetland areas are simulated with the aid of predictive models relating historically documented wetland occurrences to climatic, topographic and soil data.

To simulate the composite historical distribution of wetlands, Switzerland was divided into four regions (Jura, Swiss Plateau, Northern Alps, Central-South) and for each region, seven statistical models were calibrated. They differ in the way the dependent and the predictor variables were selected. The dependent variables for calibration were one or a combination of the following layers: (a) recent inventory data on wetlands, namely the *Three federal inventorys for the protection of mires* (sic!) (1990s) and (b) the wetland map of *Früh and Schröter* (1904). One model predicts the location of wetland areas based on only one predictor, namely the potentially flooded areas, mimicked with the aid of a stream flow network. The other models were generalised linear models that used environmental descriptors such as slope or temperature and the information on wetness and permeability of the soil as independent variables.

The verification of the models was done in two steps: (a) Predictions on the randomly chosen calibration points (1000 presence, 1000 absence) were verified using different statistical measures and (b) the entire predicted area of wetland occurrence was verified with the composite layers of the *Three federal inventories for the protection of mires* and the map of *Früh and Schröter*. As a last step the predicted area of wetland occurrence was validated with the mapped wetlands of selected sheets of the *Siegfriedkarte* (1922) and a best model for each region was proposed. For the validation we used a selection of the earliest sheets of the *Siegfriedkarte* which date back to the 1870s.

For the prediction of wetlands slope and topography are of great importance, followed by temperature and degree days. The information of the *soil suitability map* improved the prediction of today's wetlands but reduced the performance of models calibrated with historical data only (i.e. layer of *Früh and Schröter)*.

Best predictions of the composite historical distribution of wetlands can be achieved if the presence and absence points are selected from as many historical maps as possible. This is due to the fact that the size of the calibration area is increased and the errors in historical data can be reduced.

According to our models, it is likely that the loss of historical wetlands up to today even exceeds[1] the 90% suggested by Grüning (1994). The loss in wetlands has been greatest in the regions Swiss Plateau and Central-South.

The approach used in this thesis represents a necessary new step in historical ecology, namely the simulation of large-scale past landscape conditions with numerical models calibrated with old maps. The latter are, however, still needed to calibrate and validate the models.

[1] The exceedance can be explained by the fact that we include flooded areas along rivers in our wetland definition and Grünig restricted wetlands to peat bogs, mires and fens.

1 Introduction

1.1 Definition and history

1.1.1 Definition of wetlands

We define wetlands as stated by the United States Environmental Protection Agency as "those areas that are inundated or saturated by surface or ground water at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soils. Wetlands generally include swamps, marshes, bogs, and similar areas" (EPA 1977).

Hence wetlands are strongly dependent on sufficient water influx either by rivers or by precipitation. In Switzerland with a high density of alpine rivers and regions like Ticino and Northern Alps with plenty of rainfall, the conditions for wetland occurrences are favourable. In addition large parts of Switzerland have an oceanic temperate climate which reduces evapotranspiration and favours water-locked soils.

1.1.2 The history of wetlands in Switzerland

In the middle of the 18th century the hitherto worthless peat has been discovered as a replacement for wood and coal particularly on the Swiss Plateau and in the Jura mountains. As a result the use of peat as energy source has been recognised and many peat bogs were exploited (Grünig 1994). Thus almost all of today's raised bogs show signs of peat cutting and the raised bogs listed in the *Three federal inventorys for the protection of mires* (sic!) are the remnants of once huge tracts of raised bogs.

During the second half of the 19th century fens were an important land use since they supplied the urgently needed litter for animals. Litter was rare since the first international transports allowed cheap wheat from overseas and Eastern Europe to be imported. Consequently many farmers changed from planting wheat to farming animals. Thus less straw was produced in Switzerland and a replacement was searched for. The litter of the fens was a welcome substitute and wet meadows were valued even higher than crop land (BUWAL 2002). This land use changed completely in the course of the 20th century with the intensification of agriculture where litter production was considered an "agricultural fossil" (BUWAL 2002). Therefore many fens were drained and used in a more profitable way like agriculture and grazing. In 1987, the Swiss people accepted the Rothenthurm-Initiative aiming at protecting the mires in Switzerland. As a consequence of this vote, a legally binding inventory of fens, peat bogs and mires was assembled.

1.2 The research framework

1.2.1 Predictive modelling

Predictive statistical modelling is a common tool for simulating spatially explicit species or community occurrence as a function of independent environmental factors. It combines upfront statistical techniques and geographical information technology (Guisan and Zimmermann 2000). According to Levins (1966) only two out of three model properties (generality, reality and precision) can be optimised at a time (See Fig. 1.2.1). All other model realisations deviate in one or more properties from the ideal (maximised) standard. Predictive models normally sacrifice generality to precision and reality and are therefore classified as empirical or statistical models (Levins 1966). They are mainly designed to condense empirical non-process oriented knowledge and are only partially capable of detecting new underlying ecological functions and mechanisms (Wissel 1992). In our search to quantitatively model the possible location of historical wetlands, reality and precision have more importance than generality. Therefore an empirical or statistical model is a sound approach to this task.

Generalised linear modelling (GLM) (Nelder and Wedderburn 1972) is commonly used for modelling species distribution based on presence/absence data. Although presence data are unambiguously verified in the field, true absence data are much harder to confirm, because it can just as well be that the place is not yet colonised, only temporarily absent or not detected (Lütolf et al. 2006).

Similarly to modelling species distributions, modelling of wetland occurrence has the same pitfalls in finding true absence data. With historical maps, wetlands can only be traced back a certain time and we will never know if at one place there has never been a wetland. Unfortunately this information is a prerequisite for true absence points. Considering the fact that nowadays not even 10% of the initial wetlands are still present (Grünig 1994), the chance is quite high that we assume absence when historically there once was a presence.

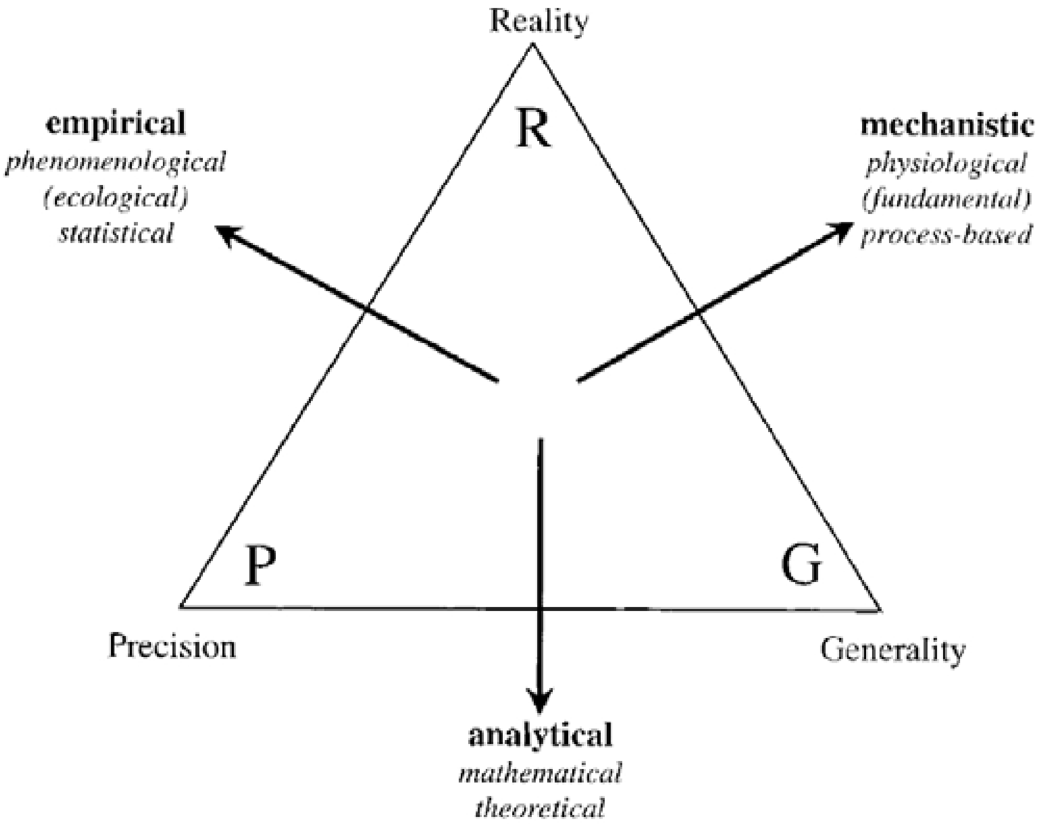

Fig. 1.2.1: A classification of models according to Levins (1966) and Sharpe (1990) based on their intrinsic properties.

1.2.2 Modelling of historical states

In historical ecology a variety of data sources are used to decipher historical states. Major sources are historical documents like management plans, land survey records, repeated photography and oral history interviews. Additional data can be drawn from biological archives like tree rings, pollen, diatoms and charcoal sediments, fire scars and bark peelings, archaeological evidence and ecosystem and landscape themselves (Russel 1997).

Historical documents are often the only source of information on past states of the landscape. The information does, however, not reach very far into the past. Unless cross-validated with independent information the accuracy of the gathered data is often low. Cross-validation is however very time-consuming and the information gained is frequently valid for smaller areas only and difficult to generalise.

The majority of the hindcasting activities simulate a phenomenon back to the time-step when the data was collected (e.g. Bromberg and Bertness 2005; Coops et al. 2005; Grossinger et al. 2007). We are aware of only few attempts that go beyond the historical states of the data collection or use a composite of historical layers (e.g. Aaviksoo 1995; Keane et al. 2002). Aaviksoo (1995) used Markov Models to reconstruct mire plant communities. In this study transition probabilities for fairly small time-steps are projected into the past to simulate the state of plant communities prior to observation.

1.2.3 Research questions

Historical extents of wetlands are an important source of information for nature protection strategies, vegetation history, climate history or carbon sequestration studies. For a thorough discussion of these issues see paragraph 1.3.

However assessing historical occurrences of wetlands in Switzerland is not an easy task at all. Despite the fact that historical maps show locations of wetlands at various levels of detail, there are serious limits in the use of these historical sources as exemplified below.

The first map focusing entirely on mires in Switzerland was published in the year 1904 by Früh and Schröter. On their map, many places were flagged as *former mires* simply because the local names suggested the occurrence of (former) mires. Since peat mining started already in the middle of the 18^{th} century one can assume that at the time when e.g. the *Siegfriedkarte* was generated (Siegfried 1922, in some areas back to 1870), many mires were already diminished or lost.

Even in cases where older historical maps exist, these maps probably do not provide an accurate picture either, at least for remote areas. Many places in the Alps were hardly accessible and many places were most likely never visited.

The aim of this thesis is to provide a composite map of historical wetlands in Switzerland of various time-steps. These predicted locations should not be derived directly from old maps, but simulated with the aid of predictive models relating wetland occurrence to climatic, topographic and soil data. The empirical relationships (environmental envelopes) shall be based on a composite of presence/absence data of current and historical inventories.

The following major question shall be answered in the course of the project:

i Is it possible to simulate potential locations of wetlands as reported by historical sources, by means of a predictive model relying entirely on climatic, topographic and soil data (i.e. modelling a composite of historical wetlands of various time-steps up to present)?

From the main question, the following sub-questions were derived:

Methodological questions:

i.i What environmental descriptors are significant factors for creating the predictive models?

i.ii What influence does the soil suitability map (BFS Geostat/BUWAL 2001) have on the quality of the models?

i.iii What selection of presence/absence data does improve the predictive models?

Content questions:

i.iv How big is the loss in wetland area compared to a composite of historical wetlands?

i.v In which areas was the degradation of the wetlands greatest?

1.2.4 Hypotheses

The research questions exemplified under 1.2.3 have been transformed into several hypotheses described in Table 1.2.1.

Table 1.2.1: Hypotheses of the presented research. The hypotheses are based on the research questions exemplified in paragraph 1.2.3.

No.	Hypothesis
Environmental descriptors of the model	
i.i	The importance of the predictors will greatly depend on the region considered. For all regions soil suitability parameters - aggregating many factors like permeability or wetness of the soil (see BFS Geostat/BUWAL 2001 for further details) - improve the model.
i.ia	For the Jura - with low altitudinal differences, streams in almost all valleys and dry conditions on the hilltops - the predictor altitude is of low significance. The predictors topography and amount of rainfall are much more important.
i.ib	On the Swiss Plateau with many river channels the predictors altitude and rainfall are not important. Temperature and topography are of highest significance.
i.ic	For the Northern Alps, rainfall, altitude and topography are most important predictors. Due to the large range in altitude, topography has a high significance.
i.id	In the Central and Southern Alps and the insubrian region of Ticino (henceforth called Central-South) temperature, topography and water budget are important. Due to high temperature and low rainfall in the area, water budget and topography strongly influence the model.
i.ii	Including the soil suitability map as a model predictor will improve model accuracy.
Empirical presence/absence data	
i.iii	The more historical presence/absence data are used the more accurate the data will be.
Wetland drainage and exploitation	
i.iv	The current extent of wetlands consists of 10% of the initial wetland area.
i.v	The loss of wetlands was greatest on the Swiss Plateau (intensive agriculture) and lowest in the region Central-South (lowest population density).

1.3 Relevance of the study

Wetlands play an important role in nature conservation. They are diverse habitats giving home to many red-list species. This was clearly shown during the monitoring of the effectiveness of mire protection in Switzerland where 108 species of the red-list of fern and flowering plants were found (Klaus 2007). Furthermore wetlands are able to store precipitation water and release it later in a more uniform way (CEC 1995). Due to these important ecological functions both wetland conservation and restoration play a crucial role in Swiss nature conservation policy. Restoration efforts are facilitated and costs are reduced if the historical location of wetlands is known.

Another reason to locate historical occurrence of wetlands is the fact that a wealth of historical data is stored in peat bogs. The acidic and wet environment of peat conserves pollen and macrofossils that can be identified even after thousands of years. Analysis of pollen sequences can answer questions concerning past vegetation changes. Knowing the historical location of wetlands can facilitate site selection for core drilling. Furthermore the analysis of peat layers also yields historical information about air pollutants (BUWAL 2002).

As already pointed out previously, mires regulate soil water and runoff. Drainage and exploitation of mires can therefore have another important impact on the environment as pointed out by Schneider and Eugster (2007). They show evidence that wetland exploitation and drainage led to an altered energy and moisture exchange in their research area (north-western part of the Swiss Plateau). The authors conclude that the primary cause of the observed change in the cloud coverage during the warm season is the drainage and exploitation of wetlands. They equal the removal to an average daytime cooling of up to 0.6°C and an average night-time warming of up to 0.34°C. Knowing the historical location of wetlands would provide the opportunity to perform similar research in different parts of Switzerland.

> On first sight, historical information might simply complicate studies on pattern and processes in ecosystems and landscapes – especially if the data is taken from historical sources do not fully correspond with the rigid requirements of traditional scientific analyses. However, the alternative to dealing with incomplete and qualitative information is to ignore the historical dimension – and consequently to run the risk of greatly misinterpreting the ecological data recorded today.
>
> -- Bürgi and Gimmi (2007)

Furthermore wetlands are assumed to have some influence on global warming. On the one hand, under anaerobic soil conditions in wetlands, carbon is stored in histosols. On the other hand, methane is emitted by wetlands. Therefore the balance of CH_4 and CO_2 exchange can provide information on the contribution of wetlands to the quantity of greenhouse gases in the atmosphere (Whiting and Chanton 2001). Knowing where historical wetlands were located can provide some information on how much CO_2 was released due to degradation of wetlands and how much impact this degradation had on the production of greenhouse gases and the capacity of peat bogs as CO_2 sinks. This information can be of particular interest as the Kyoto Protocol is implemented with the development of carbon sinks to offset greenhouse gas emissions. The conservation of peat-developing wetlands and the restoration and creation of other wetlands sequestering carbon may be considered for carbon credits (Whiting and Chanton 2001).

2 Methods and Material

2.1 Material

2.1.1 Maps and layers used

In this thesis, models were calculated for the whole area of Switzerland. Thus maps providing predictor (independent) variables were restricted to those available at a national level. Regional maps have not been considered. The following list presents an overview of all the data layers used in this study:

- BFS Geostat/BUWAL. Three federal inventorys for the protection of mires (sic!) [maps]:
    - BFS Geostat/BUWAL. Bundesinventar der Hoch- und Übergangsmoore von Nationaler Bedeutung [map]. Place of Production: GEOSTAT, 2003
    - BFS Geostat/BUWAL. Bundesinventar der Moorlandschaften von Nationaler Bedeutung [map]. Place of Production: GEOSTAT, 1996
    - BFS Geostat/BUWAL. Bundesinventar der Flachmoore von Nationaler Bedeutung [map]. Place of Production: GEOSTAT, 1998
- BFS Geostat/BUWAL. Bodeneignungskarte der Schweiz (Überarbeitete Version) [map]. Place of Production: GEOSTAT, 2001
- Früh, J. and Schröter, C. Die Moore der Schweiz, mit Berücksichtigung der Gesamten Moorfrage [map]. Place of Production: Stiftung Schnyder von Wartensee, Bern, 1904
- Schenker, J. Biogeographische Regionen der Schweiz (CH) [map]. Place of Production: BAFU, 2001
- Siegfried, H. Topografischer Atlas der Schweiz [map]. Place of Production: Swisstopo, 1922
- Swisstopo. Dhm25 Level2. Kartendaten: Gg25 © 2007 Swisstopo (Dv033492) [map]. Place of Production: Federal office of Topography, 2007
- Swisstopo. Primärflächen. Kartendaten: Vector25 @ 2007 Swisstopo [map]. Place of Production: Federal office of Topography, 2007
- WSL. Bioklimatische Karten der Schweiz© Auf Grundlage der Stationsdaten SMA-Meteoschweiz [map]. Place of Production: Eidg. Forschungsanstalt für Wald, Schnee und Landschaft (WSL), Birmensdorf, 1995

2.2 Methods

2.2.1 Dependent variables

One thousand presence and 1000 absence points were randomly selected for every Generalised Linear Model (GLM) (Nelder and Wedderburn 1972). We distinguished between several selections that differ in the way the historical and recent data layers of the dependent variables are combined. Later we refer to these selections as Models. The model abbreviations indicate what data layers were used to select the presence points. The combinations of data layers used are exhibited in Table 2.2.1.

From the *Three federal inventorys for the protection of mires* (sic!) (see paragraph 2.1.1) the layer *Mire landscapes* containing small scattered wetlands was not used because it contains a large amount of non-wetland areas. Furthermore from the layer on *Raised bogs and transition bogs* the polygons marked as *Raised bog environment* (Attribute HM-Typ = 3) were removed because they are not wetlands either.

From the polygons of *Früh and Schröter* (see paragraph 2.1.1) only the layer containing the raised bogs and transition bogs and the layer containing the fens were used because the layer of mires contained too many non-wetland areas.

Table 2.2.1: Overview of the data layers used for the selection of the dependent variables. Each selection is representative for one model.

Presence points selected from layer...	Model Abbreviation	Explanation
Flooded areas (separate calculation)	Fill	See paragraph 2.2.2
Three federal inventories	FMHM	Three federal inventorys for the protection of mires (sic!) in Switzerland containing the following inventories: • Raised bogs and transition bogs (BFS Geostat/BUWAL 1991) • Fens (BFS Geostat/BUWAL 1998)
Wetland polygons of Früh and Schröter	FS	Früh and Schröter (1904)
Three federal inventories and wetland polygon of Früh and Schröter	FMHM-FS	All above layers combined (except fill)

2.2.2 Independent variables

The independent variables were taken from the following data layers:

- Soil suitability map: *Bek200* (BFS Geostat/BUWAL 2001)
- Digital Elevation Model: *DHM25_Level2* (Swisstopo 2007)
- Degree-days : *DGD30_25a* (WSL 1995)
- Average temperature in July: *tjul_25m* (WSL 1995)
- Average precipitation in July: *njul_25m* (WSL 1995)
- Average precipitation per year: *njahr_25a* (WSL 1995)
- Average water budget in July: *wbjul_25a* (WSL 1995)
- Slope: *slope_dhm*, derived from DHM25
- Curvature: *topos*, derived from DHM25[1]
- Curvature tweened once: *twi25s*, derived from topos[1]
- Curvature tweened twice: *twi25ss*, derived from twi25s[1]
- *Flooded areas*: modelled with an own approach (see below)

For *Flooded areas* we developed a layer with an own stream flow model. The aim of this model was to find areas with more or less frequent river flooding. To do so, a potentially natural stream network was created from the *Digital Elevation Model* of Switzerland (DHM25) using the approach originally suggested by O' Callaghan and Mark. Using a potentially natural stream network rather than the existing one is necessary in a country like Switzerland since many riverbeds have been changed and the courses of the rivers have been altered by mankind.

For the stream flow model, the Digital Elevation Model (DHM25_Level2, Swisstopo 2007) was used in a two-step procedure (Fig. 2.2.1):

[1] For further Information on the function used to calculate this map refer to http://www.wsl.ch/staff/niklaus.zimmermann/programs/aml4_1.html

Step 1: Calculation of potentially natural stream network: A stream network can be created from a digital elevation model by using the GIS functions *flow direction* and *flow accumulation*[1]. This procedure is sensitive to pits, defined by O' Callaghan and Mark (1984) as "points which are lower than all of their neighbours". O' Callaghan and Mark (1984) mention several reasons why artefact pits are produced during the construction of a Digital Elevation Model. In the course of calculating a river network, artefact pits appear as isolated sinks causing a calculated river channel to virtually disappear. To get an appropriate river network, it is therefore crucial to detect and remove these artificial pits (O' Callaghan and Mark 1984).

Therefore in a first step (Fig. 2.2.1, upper part), all small scale sinks in the DHM25 (Swisstopo 2007) were removed in ArcGIS 9.2[2] using the Fill-Function[3]. The corrected Elevation Model was then used to calculate the flow direction and the flow accumulation.

The flow accumulation file represents grid cells of 25x25m. A number is calculated for every cell representing the number of cells draining into this cell. We decided that every cell having a flow accumulation of 100 cells or more is considered a river channel.

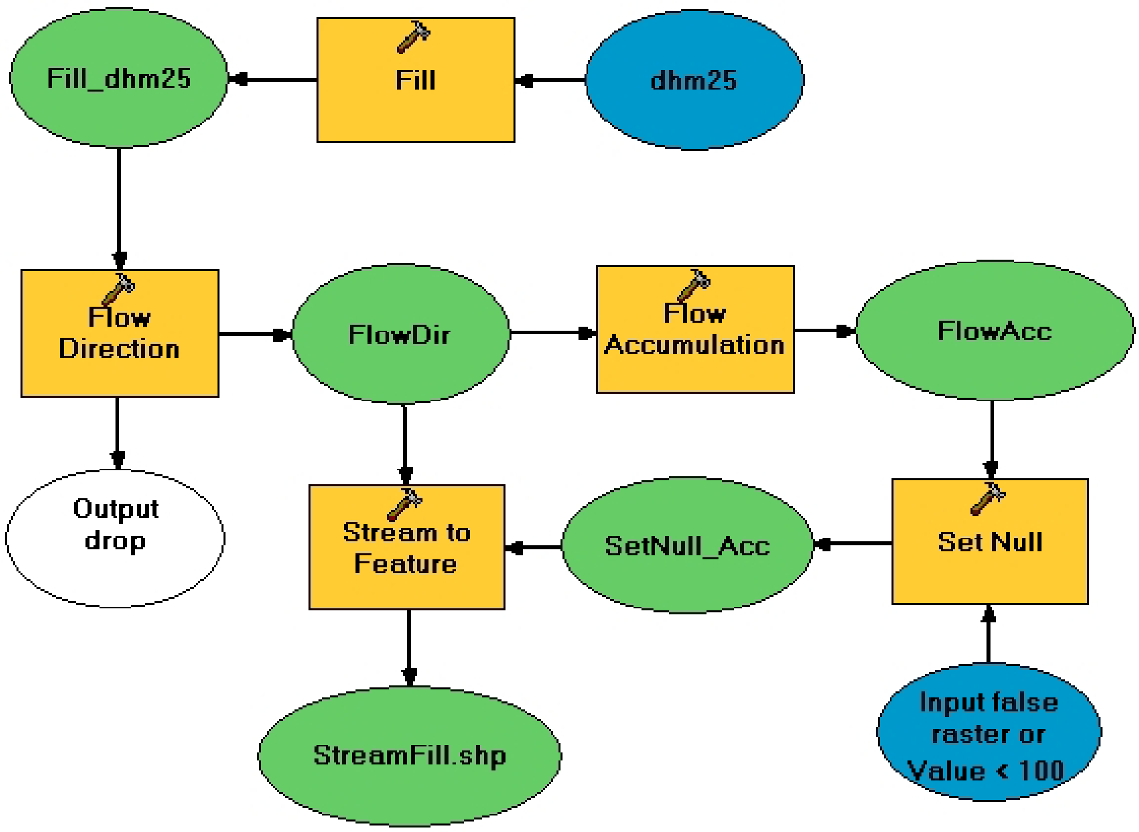

Fig. 2.2.1: Calculating flooded areas with a stream flow model using ArcGIS 9.2[2].

Step 2: Calculation of potentially flooded areas: In this step potentially flooded areas were calculated. To do so we first calculated the slope of all 25x25m pixels based on the DHM25. Potentially flooded areas were defined as areas with a slope below 3°.

[1] For further information refer to ArcGIS Desktop Help: http://webhelp.esri.com/arcgisdesktop/9.2/
[2] For further information of ArcGIS refer to http://www.esri.com/software/arcgis/
[3] For further information refer to ArcGIS Desktop Help: http://webhelp.esri.com/arcgisdesktop/9.2/

For the purpose of the simple model we considered these flat areas as locations where water movement is slow and therefore imply a potential for flooding. Finally we checked whether the flat terrain has some connection to the river channel. Consequently, in this very simple model, the potential flooded areas are all polygons with a slope lower than 3° and a connection to a stream (calculated as in Step 1).

The graphical representation of all potentially flooded areas in Switzerland is given in Fig. 2.2.2. Note that these are the major areas that have been channelized during the second half of the 19th century with an enormous technological effort (Rohde 2004). Recently, remnants of the once large wetlands are being restored as a result of various concerted restoration efforts.

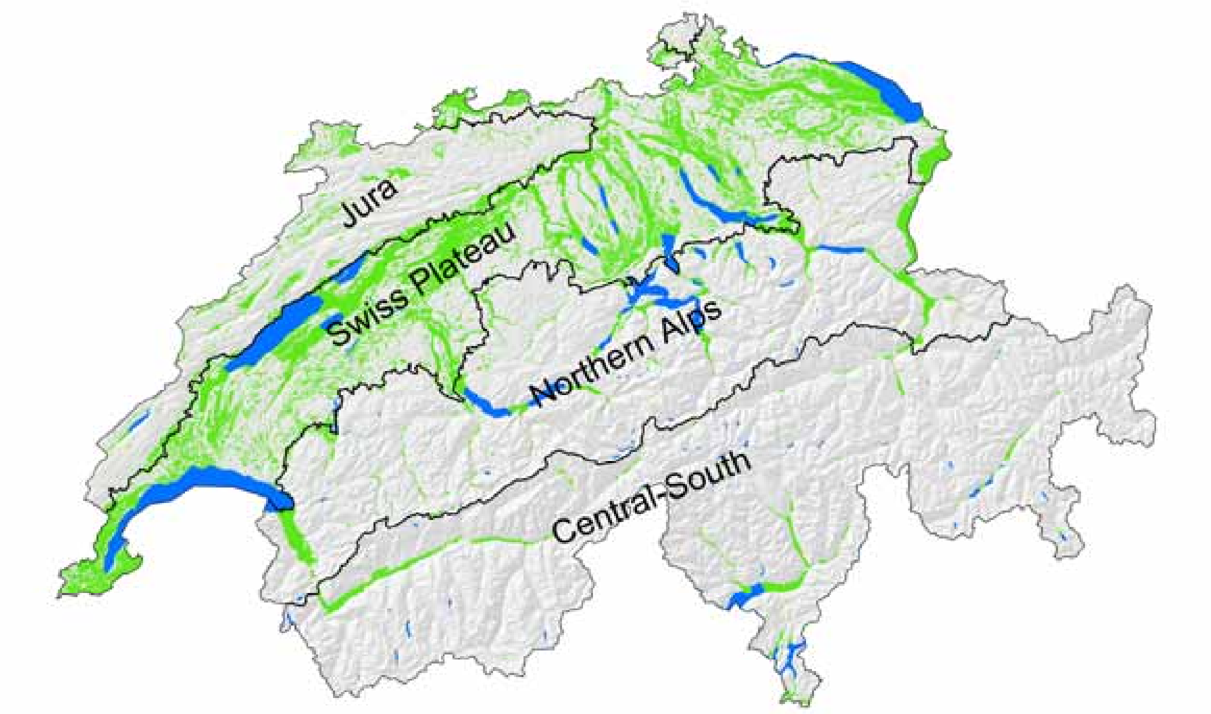

Fig. 2.2.2: Results of the simple flood model yielding potentially flooded areas. The model uses a potentially natural stream network based on a Digital Elevation Model. The green areas represent the simulated potential wetlands along larger rivers.

2.3 Statistical models

We calculated a set of region-specific Generalised Linear Models (GLMs) that differ in both the input (independent) and the dependent variables. Paragraph 2.3.1 describes the regions used and paragraph 2.3.2 elucidates the different sets of input and dependent parameters.

2.3.1 Regionalisation

For all region-specific GLMs, Switzerland was divided into four regions (see Fig. 2.2.2) based on the biogeographical regions of Switzerland (Schenker 2001). The original six biogeographical regions were collapsed to the following four regions:

- Jura (Query: BIOGREG_R6 = “Jura”)
- Swiss Plateau (Query: BIOGREG_R6 = “Mittelland”)
- Northern Alps (Query: BIOGREG_R6 = “Alpennordflanke”)
- Central-South (Query: BIOREG_R6 = “Östliche Zentralalpen” | BIOREG_R6 = “Westliche Zentralalpen” | BIOREG_R6 = “Alpensüdflanke” | BIOREG_R6 = “Altiplano”)

2.3.2 Model calibration

GLMs were fitted on the selected data points (see paragraphs 2.2.1 and 2.2.2) for each region using R[1]. Prior to running the GLMs, highly correlated independent variables were removed (see Paragraph A.2.1, Appendix). The predictors remaining in the final models were selected using the R-function STEP, a function considering stepwise forward and backward selection based on the Akaike information Criterion (AIC).

Simulated presence/absence was optimised by using different thresholds for the probability of occurrence. We optimised for κ using an R routine. As a last step the probability maps were displayed with ArcInfo V9.1[2].

For each region, seven different models were calculated (see Table 2.3.1). They differ in the way the presence points were selected and whether the information on wetness and permeability of the soil (provided by the *soil suitability map*) was included as independent variables in each of the GLMs (see paragraphs A.2.2 to A.2.7, Appendix). The first model (Fill) does not use presence data at all and is based on flooded areas only. The next models use information of the *Three federal inventories* only. Subsequent models only use the information of *Früh and Schröter*. The last models use both *Früh and Schröter* and the *Three federal inventories* for the selection of presence points.

Table 2.3.1: Overview of the models calculated and the layers used for calibration.

Model Abbreviation	Presence points selected from...	Independent Variables	
		Set of least intercorrelated biophysical data (Table 3.1.1)	Soil Suitability Map
Fill	Flooded areas (separate calculation)	No	No
FMHM	Three federal inventories	Yes	No
FMHM-Soil	Three federal inventories	Yes	Yes
FS	Wetland polygon of Früh and Schröter	Yes	No
FS-Soil	Wetland polygon of Früh and Schröter	Yes	Yes
FMHM-FS	Three federal inventories Wetland polygon of Früh and Schröter	Yes	No
FMHM-FS-Soil	Three federal inventories Wetland polygon of Früh and Schröter	Yes	Yes

2.4 Model evaluation

2.4.1 Verification

For the verification procedure a number of presumptions have been made:

First, we assumed that the area of wetlands in Switzerland generally only decreases since centuries. Second it is a widely recognised fact that nowadays not even 10% of the historical wetlands of Switzerland still exist (Grünig 1994). This has implications for the presence/absence points used in our models. Whilst we know where wetlands are located today, we do not know where they have been in the past. Thus we are in a similar situation as biologists building a distribution model with a rare species that once had a wide distribution. Con-

[1] For further Information on R refer to http://stat.ethz.ch/~statsoft/stat.programme/R.html
[2] For further Information on ArcInfo refer to http://www.esri.com/software/arcgis/arcinfo/about/features.html

sequently the presence data have a high accuracy whereas we do not have information on the accuracy of the absence points. The chance is quite high that an absence point as we detect it today is a pseudo-absence and formerly was a wetland.

		Observed	
		Presence	**A**bsence
Simulated	P	**a** [1] correct True positive	**b** [2] incorrect False positive
Simulated	A	**c** [3] incorrect False negative	**d** [4] correct True negative

Fig. 2.4.1: 2x2 Confusion matrix.

The verification procedure was twofold: (a) we verified the models with the randomly chosen calibration points (1000 presence, 1000 absence) using different statistical measures, (b) we verified the models on the entire calibration area. An important indicator for model performance was the κ-value that was calculated for each GLM as proposed by Monserud and Leemans (1992).

Model calibration on individual sample points used a 10-fold cross validation and a resubstitution test as well as the values for the correct classification rate (PCC), the specificity (SPEC), the sensitivity (SENS) and the κ-values. Additionally the receiver operating characteristic plot (AUC) was drawn (for further information on these values refer to Fielding and Bell 1997). PCC, SPEC, SENS and κ-values were calculated according to Table 2.4.1.

Model verification on the entire calibration area used the whole area of the combined layers of the *Three federal inventories* and the polygon layers of *Früh and Schröter* as presence area. This map composition provided the largest composite area of wetlands in Switzerland. All models were evaluated against this data set. Because the individual GLMs provided a probability map, a threshold was calculated, optimising for κ.

The false negative rate (FNR), the misclassification rate (MCR), the κ-value and the false positive rate (FPR) were calculated for each GLM (for further information on these values

Table 2.4.1: Test parameters derived from a 2x2 cross table (from Fielding and Bell 1997). N is the sum of a+b+c+d (see Fig. 2.4.1).

Test parameter	Formula	Acronym
Correct classification rate	$(a+d)/N$	CCR
Sensitivity	$a/(a+c)$	Sens
Specificity	$d/(b+d)$	Spec
Misclassification rate	$(b+c)/N$	MCR
False positive rate	$b/(b+d)$	FPR
False negative rate	$c/(a+c)$	FNR
Total misclassification	$\frac{c}{a+c}+\frac{b}{b+d}$	TMC
Odds ration	$(ad)/(cb)$	OR
Kappa statistics	$\frac{(a+d)-\frac{(a+c)*(a+b)+(b+d)*(c+d)}{N}}{N-\frac{(a+c)*(a+b)+(b+d)*(c+d)}{N}}$	κ

refer to Fielding and Bell 1997; Forbes 1995). Because of the uncertainty of the absence points, we decided to put special emphasis on both κ and the FNR for the model evaluation. Hence models with high κ-values and low FNR were considered as the best ones. However due to the reasons stated above, we expected rather low κ-values and high misclassification rates for all models considered.

2.4.2 Validation

The modelled wetlands were checked against mapped wetlands of selected sheets of the *Siegfriedkarte* (Siegfried 1922) of Switzerland mapped 1870. The maps were selected in a way that all regions were represented. Again the κ-value, the misclassification rate (MCR), the false positive rate (FPR) and the false negative rate (FNR) was calculated for each model.

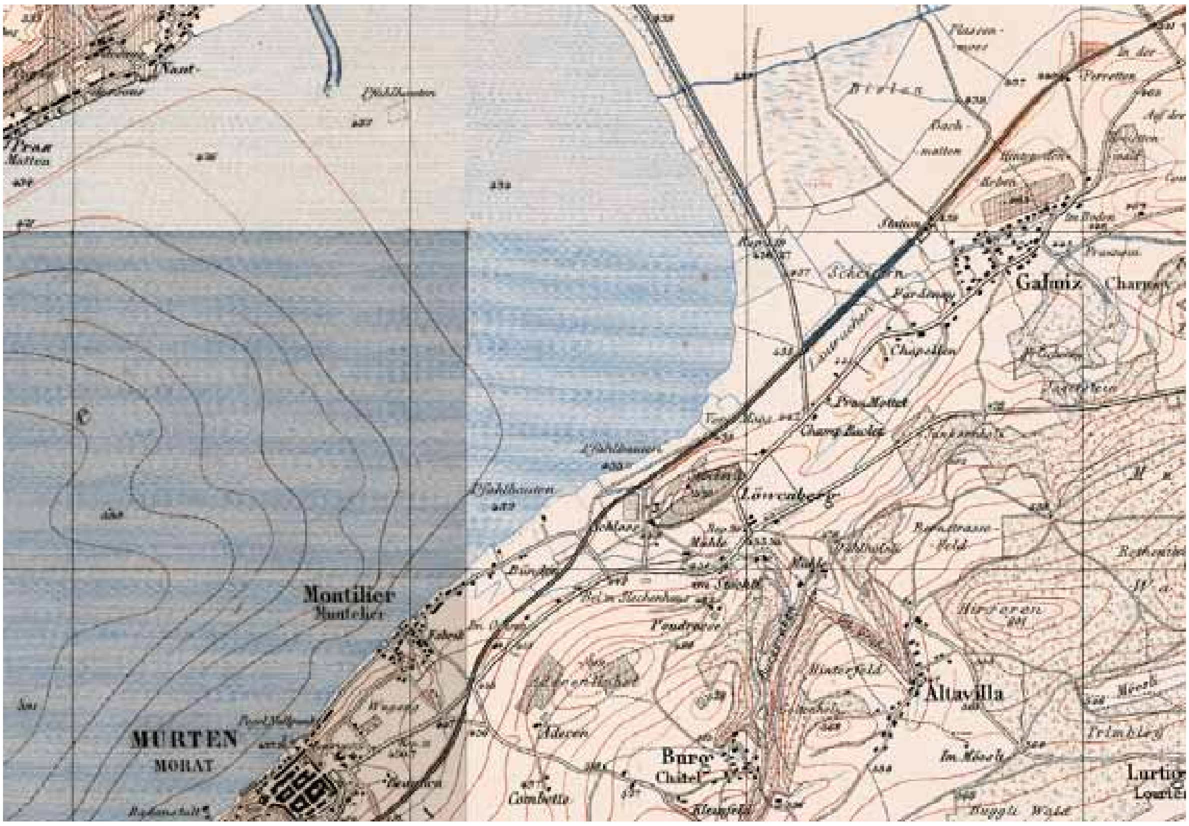

Fig. 2.4.2: Segment of the *Siegfriedkarte* (first edition) showing the region of Murten. In the upper part four different map sheets merge. Note the various blue tones aggravating automated assessment of wet areas particularly.

Once more we want to stress the point of uncertainty of historical data. Despite the fact that the *Siegfriedkarte* is one of the most accurate representations of the past, many uncertainties can still arise. Even in flat regions (e.g. Murten as seen in Fig. 2.4.2) where the data collection can be assumed to be well done, the definition of what is a wetland and where its boundary is strongly depends on the cartographer. Furthermore distortion errors and yellowing of the old paper might decrease the accuracy of the digitalisation process (Leyk and Zimmermann 2007).

3 Results

3.1 Final models

The GLMs with automated selection of independent variables yielded important insight into the predicting power of these variables. As can be seen in Table 3.1.1 an important factor in all models was slope (slope_dhm) as well as topography (topos). Factors that were rarely selected are annual rainfall (njahr_25a) and water budget in July (wbjul_25a). This result is surprising since from the point of view of hydrology, rainfall related drivers play an important role for wetland formation. Not used at all was elevation (dhm25_l2). If information of the soil suitability map (bek200) was included, wetness of soil (verna) was more frequently selected than soil permeability (durchl).

For the region Jura the variables slope, topography and temperature in July were significant descriptors in most models, while rainfall, water budget and degree days were rarely selected.

In the region of the Swiss Plateau the variables degree days, slope and the first tween of topography (twi25s) were good predictors for most models. No significant influence was found for temperature in July and annual rainfall.

Wetlands of the northern Alps were best correlated with slope and rainfall in July. Annual rainfall, water budget and elevation were seldom selected.

In the region Central-South most models had topography, temperature in July, slope and annual rainfall as major driving variables. Degree days, elevation and water budget had no or only low predictive power in this region.

Table 3.1.1: Environmental descriptors with statistically significant predictive power used in the different models. FMHM: Layer of *Three federal inventories*, FS: Layer of *Früh and Schröter*; Soil: Information of the *soil suitability map* is included; ju: Jura, mi: Swiss Plateau, al: Northern Alps, cs: Central-South; independent variables: See paragraph 2.2.2.

	FMHM				FMHM-Soil				FS				FS-Soil				FMHM-FS				FMHM-FS-Soil			
	ju	mi	al	cs	ju	mi	al	cs	ju	mi	al	cs	ju	mi	al	cs	ju	mi	al	cs	ju	mi	al	cs
dgd30_25a		X	X			X	X			X				X				X				X		
dhm25_l2																								
njahr_25a	X							X				X				X							X	X
njul_25m		X	X	X			X	X		X	X				X			X	X			X		
slope_dhm	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X
tjul_25m					X			X	X		X	X	X		X	X	X			X	X			X
topos	X	X		X	X	X		X	X		X	X	X		X	X	X		X	X	X		X	X
twi25s		X				X				X								X	X			X	X	
twi25ss							X		X			X	X				X				X			
wbjul_25a						X			X					X						X				
durchl							X									X							X	
verna					X	X		X					X	X	X						X	X		X

3.2 Model performance

3.2.1 Verification on calibration points

Verification on the calibration points showed a range of D^2 between 22% and 72% with a median of 40-50%. Including the soil suitability map increased D^2 in all GLMs and they appeared to be quite robust towards the resubstitution and cross-validation test. The AUC values ran between 0.78 and 0.98. The indicator values for the resubstitution test were generally very similar to the indicator values for the cross-validation (see chapter A.3, Appendix).

The best model fits were found in the region Jura. The model FMHM-Soil had an impressively high κ-value of 0.86 and a D^2 of 0.72. Generally the models using the information of the *Three federal inventories* provided the best values in D^2 (see Table 3.2.1).

Table 3.2.1: Verification of the mathematical models on the calibration points. All values are given as percentage. Highest values within a region are highlighted with yellow. PCC: Correct Classification Rate, SPEC: Specificity, SENS: Sensitivity, AUC: Area under the curve of operating characteristic plot; Ju: Jura, Mi: Swiss Plateau, Al: Northern Alps, Cs: Central-South.

				Resubstitution					Cross-validation				
		D^2	κ	pcc	spec	sens	κ	auc	pcc	spec	sens	κ	auc
Ju	FMHM	70	86	93	94	92	86	97	93	94	92	86	97
	FMHM-Soil	72	86	93	93	93	86	98	93	92	93	85	98
	FS	37	65	82	86	79	65	89	82	85	79	64	89
	FS-Soil	42	61	81	86	75	61	89	80	85	75	60	89
	FMHM-FS	37	60	60	83	77	60	88	79	83	76	58	88
	FMHM-FS-Soil	45	63	81	83	80	63	90	81	82	79	61	90
Mi	FMHM	42	67	83	81	86	66	90	83	80	86	66	90
	FMHM-Soil	49	71	85	81	90	71	92	85	81	89	70	92
	FS	22	50	75	78	72	50	81	74	77	71	48	80
	FS-Soil	28	53	77	85	69	54	83	76	84	68	52	83
	FMHM-FS	25	51	76	77	75	51	82	76	77	76	51	82
	FMHM-FS-Soil	29	50	77	81	74	55	84	77	80	74	54	84
Al	FMHM	29	54	78	65	88	54	83	77	66	88	53	83
	FMHM-Soil	43	64	82	73	90	63	90	81	73	90	63	90
	FS	21	43	71	63	80	43	80	71	63	80	42	79
	FS-Soil	29	47	75	72	79	50	84	74	71	78	49	83
	FMHM-FS	20	44	72	64	80	44	78	72	64	80	44	78
	FMHM-FS-Soil	31	53	77	70	83	53	85	76	70	83	52	85
Cs	FMHM	43	67	83	78	88	67	89	83	78	89	66	89
	FMHM-Soil	57	77	88	84	92	77	94	88	84	92	76	94
	FS	60	80	90	96	85	81	95	90	96	84	80	95
	FS-Soil	64	82	91	96	86	82	96	91	96	86	81	86
	FMHM-FS	45	68	84	83	85	68	91	84	82	85	67	91
	FMHM-FS-Soil	53	73	87	82	92	73	94	86	81	91	73	93

3.2.2 Verification on entire calibration areas

Verification on the entire calibration area is necessary due to the fact that the absence points have such a low reliability (see paragraph 2.4.1). For each model and region a plot was generated exhibiting all important statistical indicators (see paragraph A.4.2 to A.4.5, Appendix). This plot was one of the major sources for selecting the best models.

For the region Jura the model FS produced the lowest false negative rate of 21.45%. An almost similar false negative rate (FNR) was found in the model FMHM-FS-Soil (22.08%). The worst false negative rate in the region Jura was found for the model FMHM.

On the Swiss Plateau the simple flood model was the model with the lowest false negative rate (21.59%). All GLM-models in this region showed a similar FNR (between 26.25% and 31.38%).

For the region Northern Alps the lowest FNR was found for the model FMHM-FS-Soil (19.65%). Nonetheless all GLM-models showed similar false negative rates. Only the simple flood model did not perform well (FNR: 77.92%).

The model with the lowest false negative rate in the region Central-South was FMHM-FS-Soil (8.70%). Low FNRs were found for the models FMHM, FMHM-Soil and FMHM-FS ranging between 11.14% and 16.06%.

Table 3.2.2: Verification on entire calibration area. All values are given as percentage. Best values within a region are highlighted with yellow. FNR: False Negative Rate, MCR: Misclassification Rate, FPR: False Positive rate; Ju: Jura, Mi: Swiss Plateau, Al: Northern Alps, Cs: Central-South.

Region	Model	FNR	MCR	κ-Value	FPR
Ju	Flood Model	34.35	87.68	9.55	11.68
	FMHM	48.04	91.03	10.22	8.46
	FMHM-Soil	33.72	88.42	10.37	10.92
	FS	21.45	83.43	8.45	15.82
	FS-Soil	29.54	80.57	5.99	18.82
	FMHM-FS	26.2	81.02	6.58	18.32
	FMHM-FS-Soil	22.08	80.2	6.7	19.11
Mi	Flood Model	21.59	63.84	7.41	34.74
	FMHM	30.85	77.29	12.33	21.15
	FMHM-Soil	31.38	79.94	14.35	18.43
	FS	27	74.33	11.29	24.08
	FS-Soil	32.7	82.68	16.7	15.64
	FMHM-FS	26.25	73.68	11.07	24.72
	FMHM-FS-Soil	26.84	78.21	14.13	20.07
Al	Flood Model	77.92	94.75	12.42	4.75
	FMHM	22	64.33	6.72	34.41
	FMHM-Soil	21.57	71.49	9.73	27.02
	FS	20.25	61.39	6.07	37.38
	FS-Soil	24.25	69.56	8.32	29.09
	FMHM-FS	19.85	61.85	6.27	36.9
	FMHM-FS-Soil	19.65	69.82	9.28	28.68
Cs	Flood Model	51.05	97.59	9.92	2.28
	FMHM	11.6	77.29	1.64	22.52
	FMHM-Soil	11.14	83.14	2.42	16.65
	FS	48.29	94.79	4.87	5.08
	FS-Soil	47.88	94.56	4.7	5.3
	FMHM-FS	16.06	81.84	2.05	17.97
	FMHM-FS-Soil	8.7	79.21	1.93	20.59

As expected the κ-values were very low in all regions (between 1.64% in model FMHM Central-South and 14.35% in model FMHM-Soil Swiss Plateau). These low values are due to the fact that the calibration area for "wetland absence" is far too large compared with the composite historical situation. Consequently the Misclassification Error was quite high ranging between 61.39% (FS Northern Alps) and 97.59% (Simple flood model Central-South).

Inclusion of the soil suitability map generally lowered the false negative rate of the models and therefore improved model performance in all regions. This is not the case when the layer of *Früh and Schröter* was used for the extraction of the presence and absence points.

When comparing the models calculated on the basis of the *Three federal inventories* and the models based on the layers of *Früh and Schröter*, the historical database of *Früh and Schröter* provided models with lower false negative rates except for the region of the Central-South, where the false negative rate and the overall misclassification rate increased drastically. In general the best result was achieved when the combined layer of *Früh and* Schröter and the *Three federal inventories* was used for the selection of presence and absence points (see Table 3.2.2 for details).

3.2.3 Validation with wetland areas of the *Siegfriedkarte*

For the region Jura, the model FS had the worst false negative rate being more than 25%. Generally the other GLM-models performed quite well with FNR ranging between 3.83% (FMHM-FS-Soil) and 13.61%.

In the region Swiss Plateau, the simple flood model showed the best false negative rate (14.39%) with only a small difference to the model FMHM (15.73%). The highest value for FNR was found in model FS-Soil (32.20%).

The models where the soil suitability map was not included (FMHM; FS; FMHM-FS) performed much better in the region Northern Alps. Nonetheless the FNR of these three models had a range of 19.19% (FMHM-FS) to 22.48% which still is quite a high rate.

In the region Central-South the overall best false negative rates were found. The models FMHM, FMHM-Soil, FMHM-FS and FMHM-FS-Soil all showed a FNR between 1.57% and 2.64%. Although the other models performed worse, the false negative rates were quite low as well (11.07% - 15.46%) (see Fig. 3.2.1 and chapter A.5, Appendix).

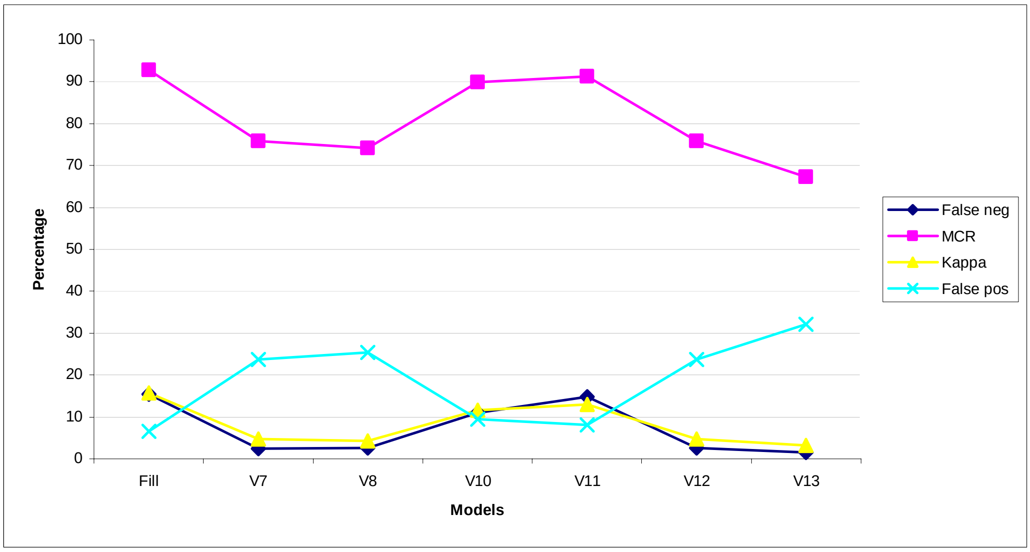

Fig. 3.2.1: Example of a validation of simulated areas with selected sheets of the *Siegfriedkarte* for the region Central-South. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil. For more examples see chapter A.5.

3.2.4 Best models

After the extensive evaluation (Verification on calibration points, verification on full area, validation) we came up with the best available models per region.

Table 3.2.3: Best models per region providing the best composite map of historical time-steps.

Region	Best fitting calibration points selected from:	Soil suitability map	Abbreviation
Jura	Früh and Schröter	No	FS
Swiss Plateau	Simple Flood Model	No	Fill
Northern Alps	Three federal inventories Früh and Schröter	Yes	FMHM-FS-Soil
Central-South	Three federal inventories Früh and Schröter	Yes	FMHM-FS-Soil

Table 3.2.3 exhibits the selection of the best models for a composite map of historical time-steps (see 4.1 for thorough discussion). The associated map can be seen in Fig. 3.2.2.

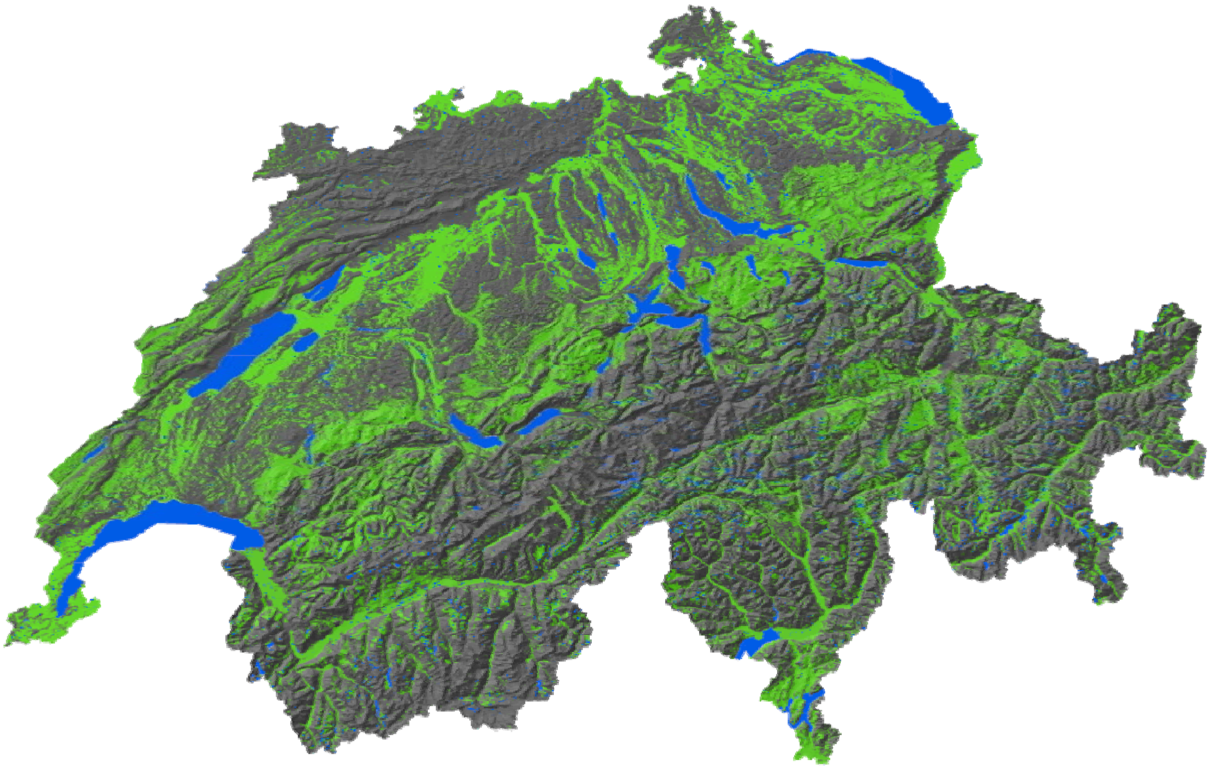

Fig. 3.2.2: A composite map of the potential wetland areas of Switzerland based on the best available models, i.e. models with the lowest false negative rate on the entire calibration area per region. The simulated wetlands are displayed in green.

3.3 Wetland loss

The range of loss depends on the selected models. If models with the smallest predicted area of wetlands for each region are considered, about 88% of the historical wetlands in Switzerland have been lost. On the other hand, if models are considered that predict the largest area of wetlands, more than 98% of all historical wetlands have already disappeared (see Table 3.3.1). If the models with the best performance on the calibration area are selected (Fig. 3.2.2), the total of remaining wetlands is estimated to be approximately 2% of the initial wetland area. For a discussion of these values see chapter 4.

Although the overall drainage and exploitation of wetlands seems to be higher than expected, the high loss of wetlands in the region of the Swiss Plateau (99%) is not a big surprise. We also expected that the loss is lowest in the region Northern Alps with 96%. Somewhat unexpected is the very high loss in the region Central-South (99.5%).

Table 3.3.1: Upper: Comparison of simulated (Sim) wetland area (in km^2) and the observed area in the layers of the *Three federal inventories* (FMHM) and *Früh and Schröter* (FS). Lower: The same information as in the upper part, but values are given as percentages. Ju: Jura, Mi: Swiss Plateau, Al: Northern Alps, Cs: Central-South; Fill: Simple flood model, FMHM: Layer of *Three federal inventories*, FS: Layer of *Früh and Schröter*; Soil: Information of the *soil suitability map* is included.

		Fill	FMHM	FMHM-Soil	FS	FS-Soil	FMHM-FS	FMHM-FS-Soil
Sim	Ju	529	385	497	712	834	815	850
	Mi	3682	2312	2041	2614	1763	2680	2218
	Al	588	3993	3191	4322	3407	4271	3378
	Cs	342	3223	2391	740	771	2577	2949
FMHM	Ju	9	9	9	9	9	9	9
	Mi	34	34	34	34	34	34	34
	Al	144	144	144	144	144	144	144
	Cs	19	19	19	19	19	19	19
FS	Ju	44	44	44	44	44	44	44
	Mi	305	305	305	305	305	305	305
	Al	207	207	207	207	207	207	207
	Cs	22	22	22	22	22	22	22
Sim-CH		5142	9914	8120	8387	6775	10343	9395
FHMH-CH		206	206	206	206	206	206	206
FS-CH		578	578	578	578	578	578	578

		Fill	FMHM	FMHM-Soil	FS	FS-Soil	FMHM-FS	FMHM-FS-Soil
FMHM	Ju	1.65%	2.26%	1.75%	1.22%	1.04%	1.07%	1.02%
	Mi	0.93%	1.48%	1.67%	1.31%	1.94%	1.27%	1.54%
	Al	24.53%	3.61%	4.52%	3.34%	4.23%	3.38%	4.27%
	Cs	5.44%	0.58%	0.78%	2.52%	2.42%	0.72%	0.63%
FS	Ju	8.31%	11.40%	8.85%	6.18%	5.27%	5.39%	5.17%
	Mi	8.27%	13.17%	14.92%	11.65%	17.28%	11.37%	13.73%
	Al	35.17%	5.18%	6.48%	4.79%	6.07%	4.84%	6.12%
	Cs	6.50%	0.69%	0.93%	3.01%	2.89%	0.86%	0.75%
FMHM-CH		4.00%	2.08%	2.53%	2.45%	3.04%	1.99%	2.19%
FS-CH		11.23%	5.83%	7.11%	6.89%	8.53%	5.58%	6.15%

Calculated loss when using best models (lowest FNR)

Region	Loss	Best model
Ju	98.8%	FS
Mi	99.1%	Fill
Al	95.7%	FMHM-FS-Soil
Cs	99.4%	FMHM-FS-Soil
CH	98.1%	

4 Discussion

Prior to drawing final conclusions a number of critical aspects and shortcomings of the current research need to be assembled and discussed. The discussion loosely follows the hypotheses listed in Table 1.2.1.

4.1 Dependent variables

The selection of the dependent calibration data was explained in detail in paragraph 2.2.1 and proved to be a major step forward in improving model performance. There is one critical aspect in the layer of *Früh and Schröter* that has to be mentioned:

For reasons of consistency only the larger polygons of *Früh and Schröter* have been used and not the point information (too large error in the location of these wetlands).This approach is appropriate for regions with big wetland areas. For regions like the Northern Alps or Central-South with many little wetlands, it might present a problem because much additional information is lost. Fortunately the information on scattered small wetlands was retrieved from the polygon layer of the *Three federal inventories*. Thus the models including these layers for calibration generally performed better.

In general our models have large simulated wetland areas, and we are well aware that this is not a specific historical distribution but rather a composite of various historical time-steps up to present. We have evidence, that wetlands have been simulated in regions where previously no wetland ever existed naturally. This is especially true in regions with heavy cattle grazing, where the soil has been compacted and new wetlands appeared, e.g. in some regions of the *Entlebuch* (M. Bürgi, personal communication, 19 May 2008). Due to the method applied in this thesis (use of a composite of historical calibration points; i.e. 1904-1998), these manmade "new" wetlands have been simulated as well. For the research topics listed in paragraph 1.3, this model characteristic is rather an improvement than a disadvantage.

The models generally improved when the data was drawn from the historical map of *Früh and Schröter*. This is no big surprise because the wetland locations on this map are much closer to the composite historical occurrences than the *Three federal inventories* alone, and the area covered with data points is much larger. There is one exemption from this rule, namely the region Central-South, where the model fit declined when the map of *Früh and Schröter* was used. We assume that this is due to the quality of the provided map in the mountainous part of Switzerland. *Früh and Schröter* collected information on wetland occurrence using archives, oral information and field expeditions (Früh and Schröter 1904). Presumably it was quite difficult to get information on wetlands in this region because it had a low accessibility and the population density was very low as well. Therefore we assume that wetlands close to accessible points had a higher chance of being mapped. As a matter of fact most of the wetlands mapped in the region Central-South are very close to major roads (see Fig. 4.1.1). Furthermore there is a high chance that small wetlands were not detected during the digitising process of the map of *Früh and Schröter*. Overall the combined layer (*Früh and Schröter* and the *Three federal inventories*) seems to be the best data source for modelling wetlands.

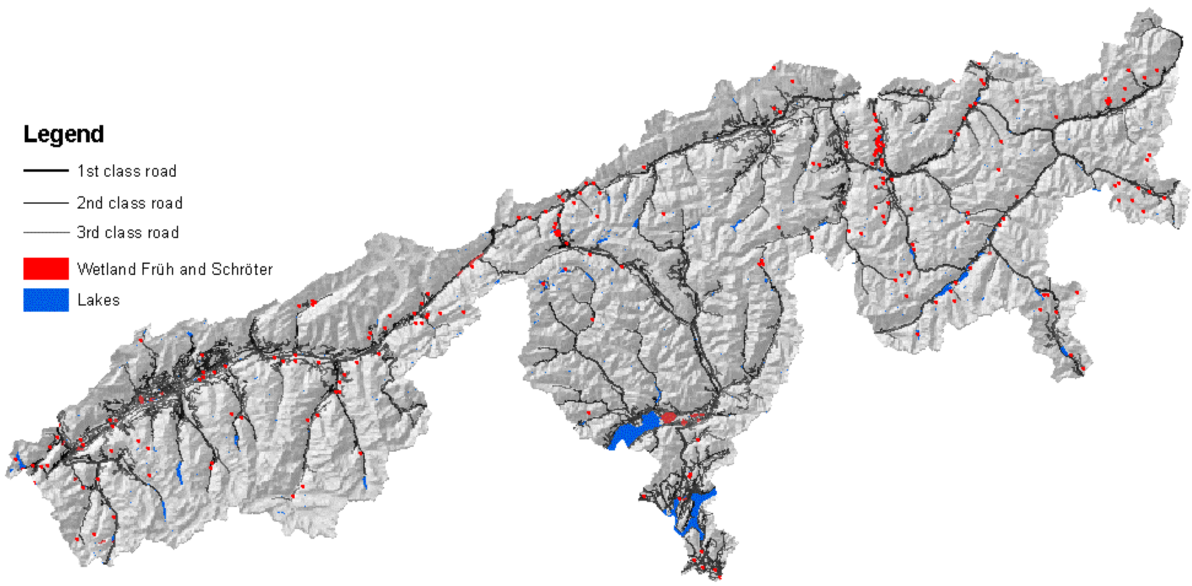

Fig. 4.1.1: Map of the region Central-South presenting the wetlands of *Früh and Schröter* and the road network in the region.

4.2 Selection of environmental descriptors

The selection of the environmental descriptors merits some thoughts. The selection was two-fold, namely (a) conceptually driven and (b) a result of a stepwise selection. The conceptual selection was assisted by a correlation analysis where highly intercorrelated input variables were eliminated. Nonetheless we cannot completely exclude a certain dependency of the variables (see paragraph A.2.1, Appendix).

The information on elevation was not used in any of the models. This is a conceptually satisfactory finding since altitude is an indirect factor. According to Austin and Smith (1989), an indirect factor is a combination of direct and resource gradients. This combination is, however, not constant in space and only valid for a limited geographical extent. It was shown that in different regions, the same elevation reveals a different combination of direct and resource gradients (Guisan and Zimmermann 2000). The elevation per se does, according to our studies, not imply information on wetland occurrence and is therefore not used in the models. However we acknowledge that altitude is a dominant driver for many of the independent layers (temperature, degree days) where it was used for spatial extrapolation of the meteo data.

Because standing water is an important factor in wetlands, slope is an important predictor in all the models. The same applies to the topography variables. Although both, slope and topography are indirect gradients, they are able to provide specific information relevant to wetlands and therefore differ from the information provided by the elevation.

A bit surprising was the finding that water budget and annual rainfall were not used frequently as a predictor in the models. We suppose that this was due to the fact that these predictors were often highly correlated with other predictors and therefore were well described by a set of other significant predictors.

As expected, the topography was an important predictor for the wetlands in the region Jura. A bit unexpected was the absence of the predictor "rainfall". Owing to the fact that this region has the strongest oceanic influence, the rainfall pattern was probably not a discriminating factor.

For the region Swiss Plateau the topography (in this case the first tween twi25s and the slope) was, as expected a main predictor due to the fact that the wetlands of this region predominantly occur in basins. Degree days were selected in all models together with either the water budget in July or the rainfall in July. We stress the fact that the information on the amount of rainfall was more important than expected in the hypothesis (Table 1.2.1).

In the Northern Alps, slope and rainfall in July had strong influence. Topography on the other hand was a factor with a low predictive ability, which is not surprising given the high amount of rainfall in this region.

Topographical properties (slope and topography) were, as expected, important factors for the region Central-South. Furthermore temperature in July and rainfall in July or annual rainfall and in one case even water budget were useful predictors as well, which is not a surprise because of the insubrian climate: water supply is short during the hot season and therefore an important discriminating factor for the existence of wetlands.

Finally we stress the fact that the presently used variables yield only a limited set of descriptors. One could imagine that more detailed soil variables (e.g. on the 1:25000 soil maps) or information on historical land use would improve the prediction. However this information is only available locally and not nationwide, which was one of the premises to include a data set in this study.

4.3 Statistical indicators for model performances

Our proposed indicators for model performance are suitable measures to determine model quality. Most measures are derived from the confusion matrix (Table 2.4.1) and serve different purposes. Each selected measure should clearly reflect its intended use (Fielding and Bell 1997). In the present research we therefore put strong emphasis on two measures: κ and false negative rate. The κ-value represents the proportion of agreement after chance agreement is removed (Cohen 1960). It optimises for a good fit on presence and absence points.

Since our absence points are not true absences we put strong emphasis on a second indicator: the false negative rate. Optimising for the false negative rate favours models where the simulated wetland area is large (see Table 2.4.1). The chance of an observed wetland being simulated as wetland is higher when more wetland is simulated. Therefore models with large simulated areas of wetland lower the FNR. We found that the two-step procedure (1. optimisation for κ; 2. optimisation for FNR) yielded the best model evaluation.

When selecting large numbers of geographically referenced sample points, there is always a risk that spatial autocorrelation causes a bias in the results. For the Swiss National Forest Inventory (Brassel and Brändli 1999), points being 1km apart or further are known to have negligible autocorrelation in Switzerland (F. Kienast, personal communication, 19 May 2008). In our random sample (2000 points) taken from the *Three federal inventories* only about 20% of the points are less than 1km apart. Therefore the risk of a bias due to spatial autocorrelation is quite low. The sample points taken from *Früh and Schröter* are much more clustered and about one third of the points are less than 1km apart. In this data set we cannot exclude an effect of spatial autocorrelation, but it is still of minor importance.

4.4 Model performance

4.4.1 Verification

The simple flood model reflects a simple model and fits the region Swiss Plateau really well. According to Früh and Schröter (1904) the region Swiss Plateau was studded with wetlands. With the extended network of rivers and streams, the simple flood model works well for this region. In the other regions, the simple flood model does not work as well, because e.g. bogs normally shouldn't have any access to streams and are therefore not detected using this simple method.

The combined layers (*Früh and Schröter* and *Three federal inventories*) performed best in the regions Northern Alps and Central-South. Because these regions are quite diverse, it is important to have as many different wetland occurrences as possible. This might be the reason for the good performance of the models using the combined layers. In these regions the soil suitability improved the model because it provided another set of information not correlated with topography and/or temperature.

However the inclusion of the soil suitability map is somehow ambiguous. For some models it improved performance for some it didn't. For all models calibrated with the wetlands of *Früh and Schröter*, inclusion of the soil suitability map lowered the performance, i.e. increased the false negative rate. This is due to the fact that two different time-steps are combined: The soil suitability map represents the current situation of soil permeability and wetness, *Früh and Schröter* the conditions at the beginning of the 20th century.

The problem of combining different time-steps is most pronounced in the soil suitability map. In contrast to the more gradually changing variables climate, rainfall and topography, soil suitability changes more stochastically depending on the use of the soil (e.g. agriculture, forestry, stock grazing …).

4.4.2 Validation with the *Siegfriedkarte*

Model validation with the *Siegfriedkarte* yields a slightly different picture of the optimum models and its driving variables. The inclusion of the soil suitability map in the models led to a decrease in accuracy in the regions Swiss Plateau and Northern Alps. These regions perceived the biggest change due to changing land use. While in the Swiss Plateau the agriculture was heavily intensified during the last century, in the region Northern Alps the grazing was intensified resulting in great changes in the soil and consequently also in the soil suitability (Grünig 1994). This might be the reason for the decrease in accuracy when the soil suitability map was included, since the soil suitability map represents recent soil characteristics, whereas the *Siegfriedkarte* characterises the situation in the middle of the 19th century.

For the region Jura, a surprisingly high false negative rate was found for the model FS which had the best FNR in the verification on the calibration area (see paragraph A.5.1, Appendix). It could be that there was already a shift in the location of the wetlands between 1870 and 1904 and therefore the wetland model calibrated with *Früh and* Schröter had such a high false negative rate. If this was the case, the soil suitability map was able to correct this estimate because the model FS-Soil performed much better. Another explanation might be the selection of the validation maps. Selecting only a small area for validation implies the chance of choosing an area that is not representative. To be sure on this case, all the maps from the *Siegfriedkarte* would have been needed for validation.

Most manmade changes in wetlands probably occurred in the region Swiss Plateau. River channels were changed and wetlands were drained to be used as agricultural land. This might be the reason why the soil suitability map (representing today's situation) does lower the simulation accuracy of the models in this region (see paragraph A.5.2, Appendix). Therefore it is plausible that the simple flood model calculated only on topographic information that did not change much in the past performs best in this region.

Most models in the region Northern Alps did not reach a low false negative rate when checked against the *Siegfriedkarte*. In the set of maps published in 1870, only areas with few wetlands were contained. Therefore already a small false positive value (value b in Fig. 2.4.1) results in a significant increase in the value of the false negative rate. Including the soil suitability map in the prediction generally caused a decrease in the accuracy of all models in this region (see paragraph A.5.3, Appendix) which again might be a sign for the high inhomogeneity of this region.

For the region Central-South extremely low false negative rates were found. It seems that, although the region is quite inhomogeneous concerning topography, climate and rainfall, the wetlands are represented quite well with these models. A strange effect can be seen as the κ-value seems closely linked to the false negative rate (see paragraph A.5.4, Appendix). However since the area of wetlands is so low in this region, the κ-Value is negatively dependent on the false positive rate and therefore falls on the same curve as the false negative rate in this case.

5 Conclusion

In this thesis we present a method suitable for hindcasting the composite of historical distribution of wetlands. Due to the calibration method employed in this study the maps cannot be related to one time-step but rather to a composite of various historical time-steps. It therefore represents the largest possible area ever covered with wetlands.

When evaluating the best available models with parts of the *Siegfriedkarte* (Siegfried 1922; sheets from the 1870s), the wetland areas in the regions Jura and Central-South were predicted with great accuracy. In the region Northern Alps, where the climatic and topographic diversity is quite high and the microclimate plays an important role, our models do still provide reasonably good results.

For the prediction of wetlands slope and topography are of great importance, followed by temperature and degree days. Including the information of the *soil suitability map* is somewhat ambiguous. It improved the simulations for today's wetlands. However it lowered the performance of models calibrated with historical data (i.e. wetlands of *Früh and Schröter*). We conclude that merging two different time-steps in the predictor variables lowers model quality. This phenomenon is most pronounced in the case of the *soil suitability map*. The latter should only be included if the calibration points contain recent occurrence data.

Using and merging different time-steps for the selection of presence/absence data entails several advantages: (a) the area to collect presence data from is larger and therefore the risk of a bias due to autocorrelation can be reduced; (b) the chance of selecting real absence points is increased due to the fact that more true wetland locations are used; (c) errors in historical sources can be reduced, because repeated mapping efforts increase correct identification of objects. Consequently we favour the idea of including as many time-steps as possible in the selection process of presence and absence points.

Although a composite map of various historical time-steps overestimates the area of historical wetlands for specific time-steps, some conclusions can be drawn in respect to the historical loss of wetlands. According to our models it is quite likely that the loss of historical wetlands up to today even exceeds the 90% suggested by Grünig (1994). The exceedance can be explained by the fact that we included flooded areas along rivers in our wetland definition and Grünig restricted wetlands to peat bogs, mires and fens. Furthermore it is quite surprising that the largest loss in wetland areas is not, as expected, on the Swiss Plateau but in the region Central-South.

To improve the accuracy of the present models, one should find a consistent technique to deal with the locational errors of *Früh and Schröter*. This could e.g. include removal of all locations where the physical conditions would, to best of our knowledge, never have occurred. Furthermore the accuracy of the prediction for the region Northern Alps should be improved by creating smaller regions to achieve a better model fit.

The approach used in this thesis represents a necessary new step in historical ecology, namely the simulation of large-scale past landscape conditions with numerical models calibrated with old maps. The latter are, however, still needed to calibrate and validate the models. The maps that were produced can be used as an important source of information for nature protection strategies, vegetation history, climate history or carbon sequestration studies.

6 References

Aaviksoo, K. (1995). Simulating Vegetation Dynamics and Land Use in a Mire Landscape Using a Markov Model. Landscape and Urban Planning **31**(1-3): 129-142.

Austin, M. P. and Smith, T. M. (1989). A New Model for the Continuum Concept. Vegetatio **83**(1-2): 35-47.

BFS Geostat/BUWAL. Bundesinventar der Hoch- und Übergangsmoore von Nationaler Bedeutung [map]. Place of production: GEOSTAT, 1991

BFS Geostat/BUWAL. Bundesinventar der Flachmoore von Nationaler Bedeutung [map]. Place of production: GEOSTAT, 1998

BFS Geostat/BUWAL. Bodeneignungskarte der Schweiz (Überarbeitete Version) [map]. Place of production: GEOSTAT, 2001

Brassel, P. and Brändli, U.-B., Eds. (1999). Swiss National Forest Inventory. Results of the Second Inventory 1993-1995. Bern, Stuttgart, Wien, Bundesamt für Umwelt, Wald und Landschaft (BUWAL) and Eidg. Forschungsanstalt für Wald, Schnee und Landschaft (WSL).

Bromberg, K. D. and Bertness, M. D. (2005). Reconstructing New England Salt Marsh Losses Using Historical Maps. Estuaries **28**(6): 823-832.

Bürgi, M. and Gimmi, U. (2007). Three Objectives of Historical Ecology: The Case of Litter Collecting in Central European Forests. Landscape Ecology **22**: 77-87.

BUWAL, Ed. (2002). Moore und Moorschutz in der Schweiz, Bundesamt für Umwelt, Wald und Landschaft (BUWAL) and Eidg. Forschungsanstalt für Wald, Schnee und Landschaft (WSL).

CEC (1995). Wise Use and Conservation of Wetlands. Communication from the Commission to the Council and the European Parliament. Brussels, Commission of the European Communities (CEC).

Cohen, J. (1960). A Coefficient of Agreement for Nominal Scales. Educational and Psychological Measurement **20**(1): 37-46.

Coops, N. C., Waring, R. H. and Law, B. E. (2005). Assessing the Past and Future Distribution and Productivity of Ponderosa Pine in the Pacific Northwest Using a Process Model, 3-Pg. Ecological Modelling **183**(1): 107-124.

EPA (1977). 40 Cfr 116.3: Definitions, U.S. Environmental Protection Agency.

Fielding, A. H. and Bell, J. F. (1997). A Review of Methods for the Assessment of Prediction Errors in Conservation Presence/Absence Models. Environmental Conservation **24**(1): 38-49.

Forbes, A. D. (1995). Classification-Algorithm Evaluation: Five Performance Measures Based on Confusion Matrices. Journal of Clinical Monitoring and Computing **11**(3): 189-206.

Früh, J. and Schröter, C. (1904). Die Moore der Schweiz, mit Berücksichtigung der Gesamten Moorfrage, Stiftung Schnyder von Wartensee, Bern.

Früh, J. and Schröter, C. Die Moore der Schweiz, mit Berücksichtigung der Gesamten Moorfrage [map]. Place of production: Stiftung Schnyder von Wartensee, Bern, 1904

Grossinger, R. M., et al. (2007). Historical Landscape Ecology of an Urbanized California Valley: Wetlands and Woodlands in the Santa Clara Valley. Landscape Ecology **22**: 103-120.

Grünig, A., Ed. (1994). Mires and Man: Mire Conservation in a Densely Populated Country - the Swiss Experience: Excursion Guide and Symposium Proceedings of the 5th Field Symposium of the International Mire Conservation Group (Imcg) to Switzerland 1992. Birmensdorf, Swiss Federal Institute for Forest, Snow and Landscape Research.

Guisan, A. and Zimmermann, N. E. (2000). Predictive Habitat Distribution Models in Ecology. Ecological Modelling **135**(2-3): 147-186.

Keane, R. E., Parsons, R. A. and Hessburg, P. F. (2002). Estimating Historical Range and Variation of Landscape Patch Dynamics: Limitations of the Simulation Approach. Ecological Modelling **151**(1): 29-49.

Klaus, G. (2007). Zustand und Entwicklung der Moore in der Schweiz. Ergebnisse der Erfolgskontrolle Moorschutz. V. Eidg. Departement Für Umwelt, Energie und Kommunikation, Bundesamt für Umwelt BAFU.

Levins, R. (1966). Strategy of Model Building in Population Biology. American Scientist **54**(4): 421-431.

Leyk, S. and Zimmermann, N. (2007). Improving Land Change Detection Based on Uncertain Survey Maps Using Fuzzy Sets. Landscape Ecology **22**(2): 257-272.

Lütolf, M., Kienast, F. and Guisan, A. (2006). The Ghost of Past Species Occurrence: Improving Species Distribution Models for Presence-Only Data. Journal of Applied Ecology **43**(4): 802-815.

Monserud, R. A. and Leemans, R. (1992). Comparing Global Vegetation Maps with the Kappa Statistic. Ecological Modelling **62**(4): 275-293.

Nelder, J. A. and Wedderburn, R. W. M. (1972). Generalized Linear Models. Journal of the Royal Statistical Society Series a-General **135**(3): 370-&.

O' Callaghan, J. F. and Mark, D. M. (1984). The Extraction of Drainage Networks from Digital Elevation Data. Computer Vision, Graphics, and Image Processing **28**(3): 323-344.

Rohde, S. (2004). River Restoration: Potential and Limitations to Re-Establish Riparian Landscapes. Assessment & Planning. Zürich, Diss., Eidgenössische Technische Hochschule ETH Zürich, Nr. 15496, 2004.

Russel, E. (1997). People and the Land through Time: Linking Ecology and History. New Haven, Yale University Press.

Schenker, J. Biogeographische Regionen der Schweiz (Ch) [map]. Place of production: BAFU, 2001

Schneider, N. and Eugster, W. (2007). Climatic Impacts of Historical Wetland Drainage in Switzerland. Climatic Change **80**(3-4): 301-321.

Sharpe, P. J. A. (1990). Forest Modeling Approaches: Compromises between Generality and Precision. In: R. K. Dixon, R. S. Meldahl, G. A. Ruark and W. G. Warren, Process Modeling of Plants to Multiple Stress. Timber Press, Portland, OR**:** 180-190.

Siegfried, H. Topografischer Atlas der Schweiz [map]. Place of production: Swisstopo, 1922

Swisstopo. Dhm25 Level2. Kartendaten: Gg25 © 2007 Swisstopo (Dv033492) [map]. Place of production: Federal office of Topography, 2007

Whiting, G. J. and Chanton, J. P. (2001). Greenhouse Carbon Balance of Wetlands: Methane Emission Versus Carbon Sequestration. Tellus B **53**(5): 521-528.

Wissel, C. (1992). Aims and Limits of Ecological Modeling Exemplified by Island Theory. Ecological Modelling **63**(1-4): 1-12.

WSL. Bioklimatische Karten der Schweiz© auf Grundlage der Stationsdaten SMA-Meteoschweiz [map]. Place of production: Eidg. Forschungsanstalt für Wald, Schnee und Landschaft (WSL), Birmensdorf, 1995

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Ruedi Boesch, WSL prepared selected sheets of the Siegfried Atlas for model validation.

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Last but not least I want to thank all the friends who were always open for discussion and gave their input if needed. Special thanks in this respect goes to Ana Sesartic and Golo Stadelmann.

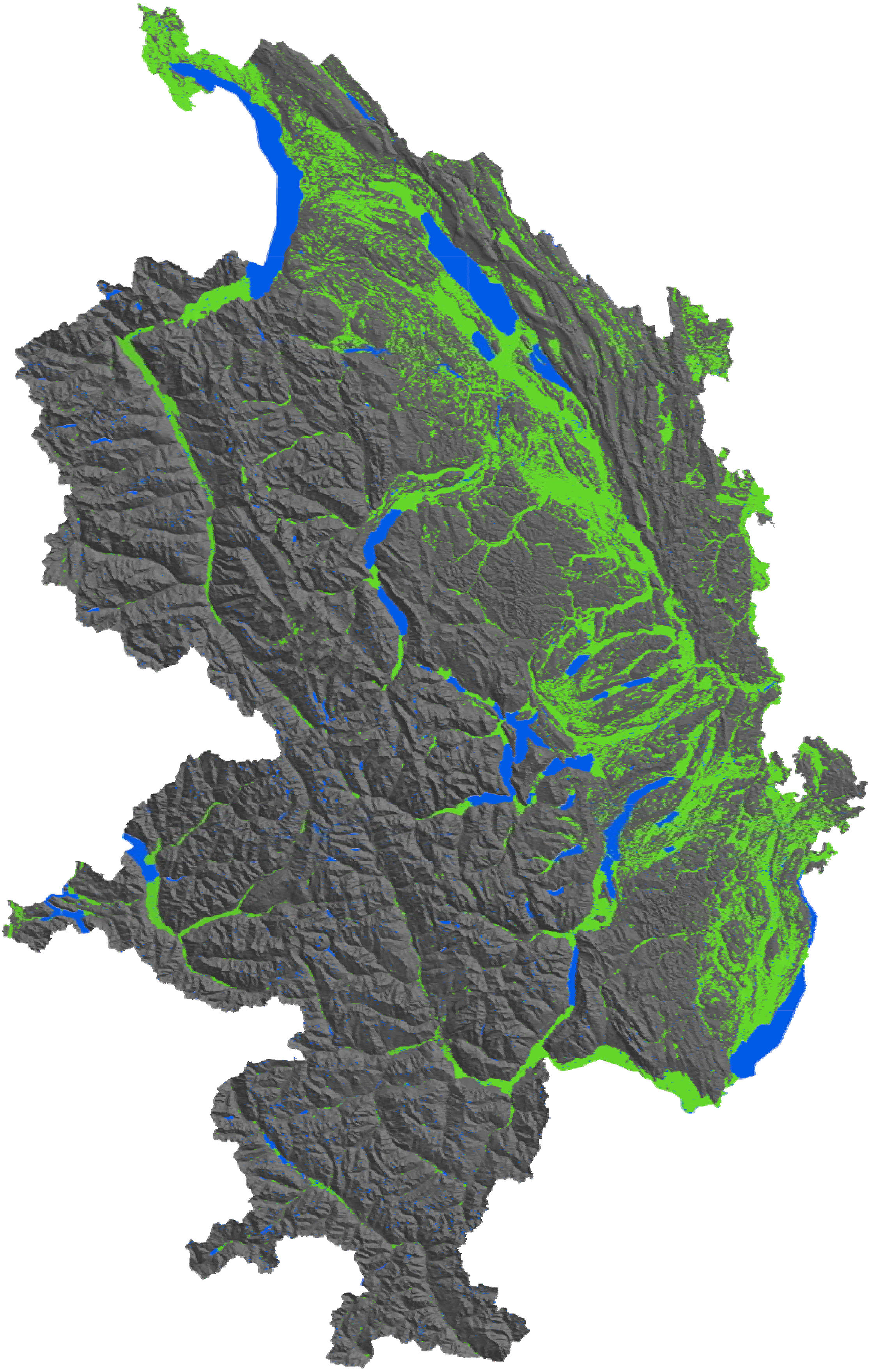
A Appendix

A.1 Maps

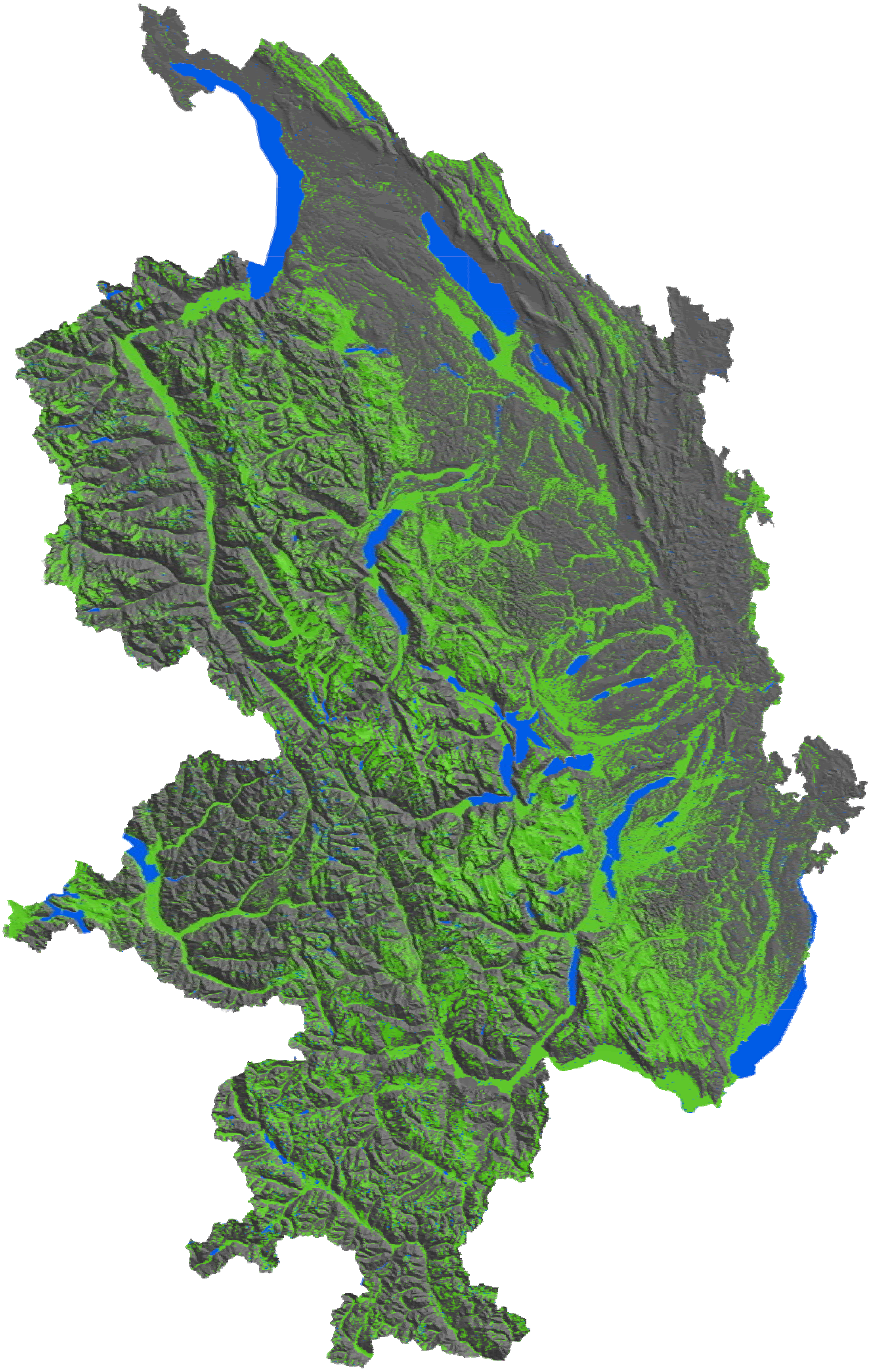
The following colour code was used for all maps:

- Blue colour: Lakes
- Green colour: Simulated wetlands

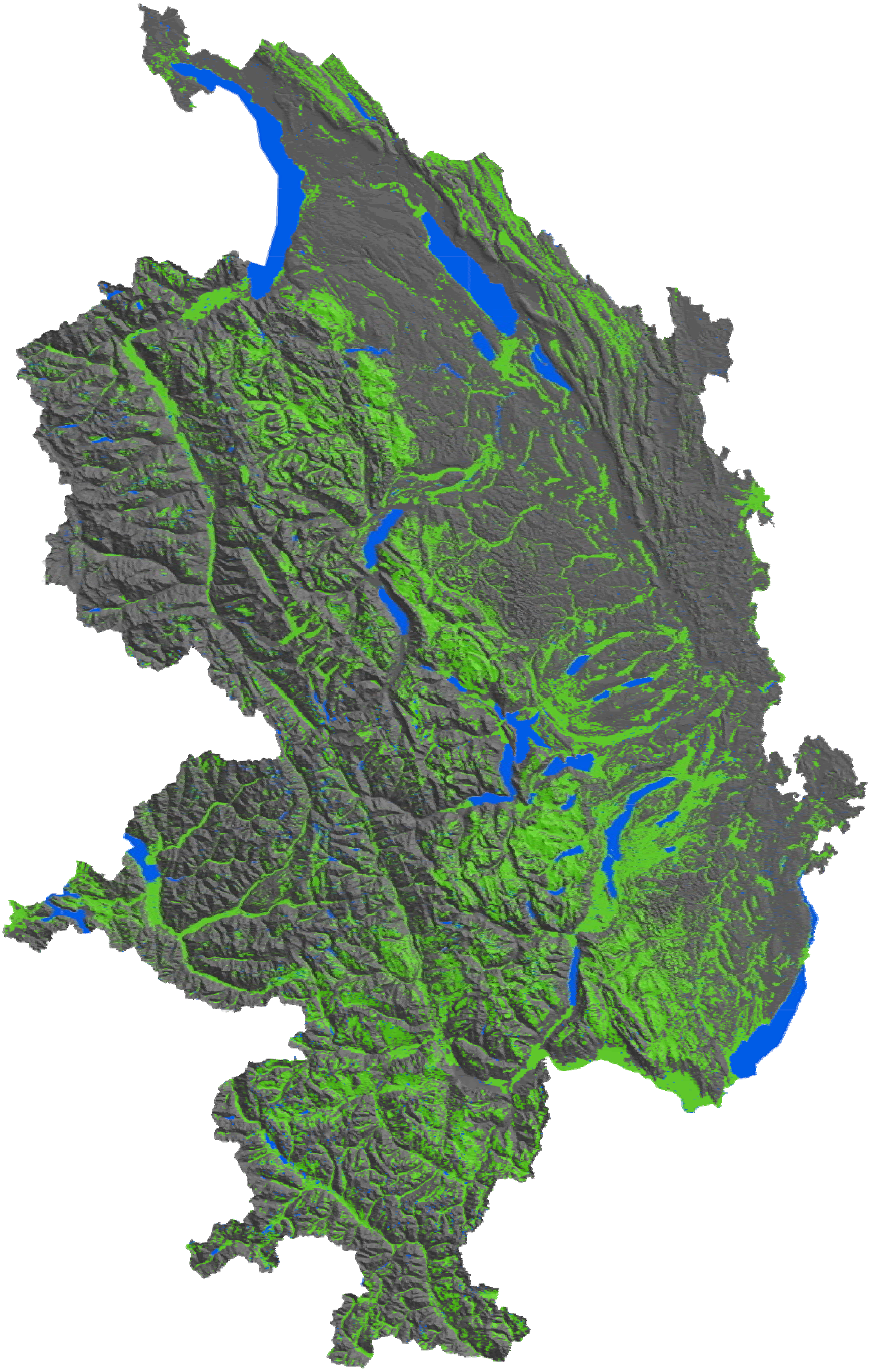
A.1.1 Simple Flood Model



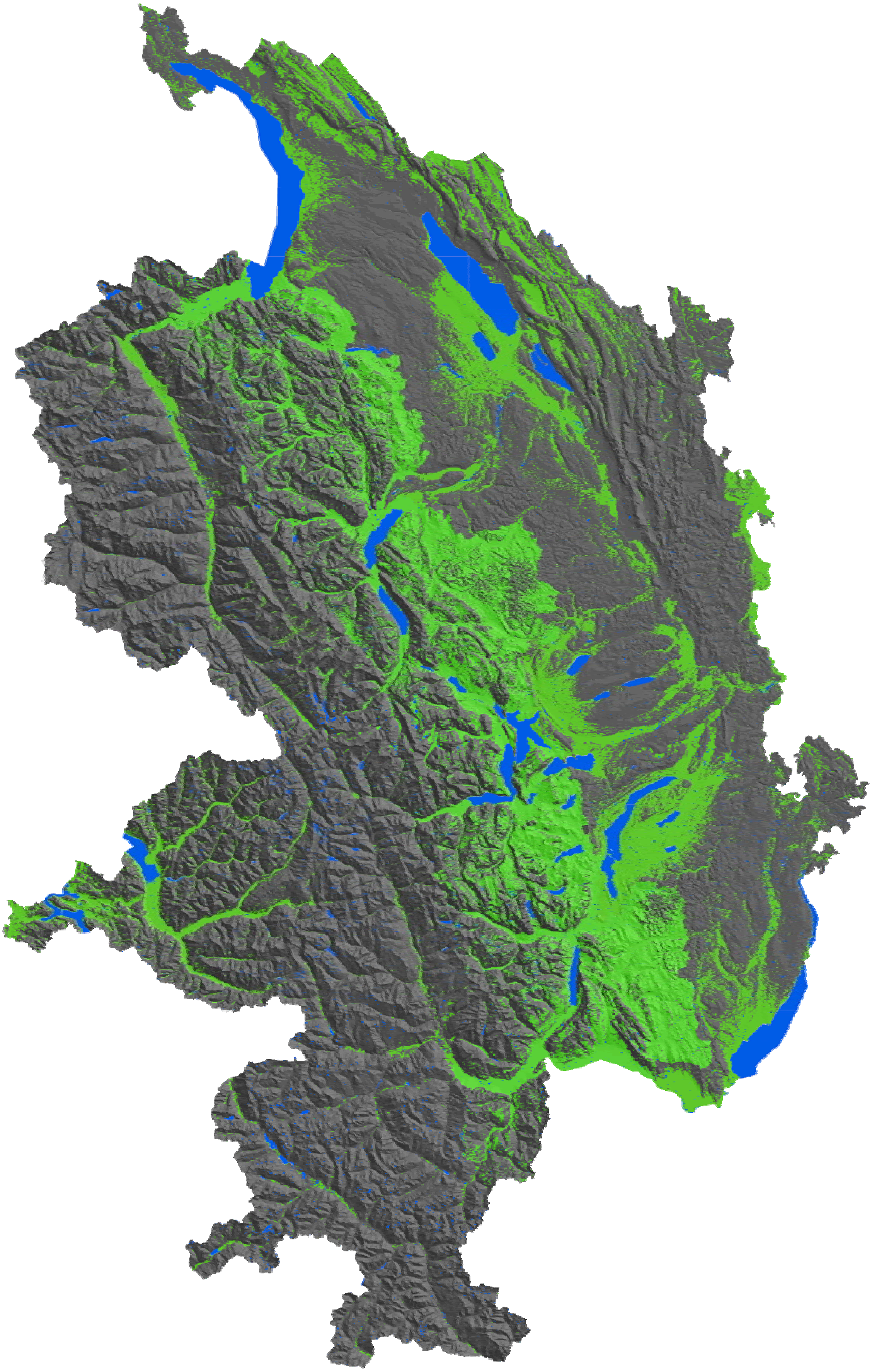
A.1.2 Model with layer of *Three federal inventories* (FMHM)



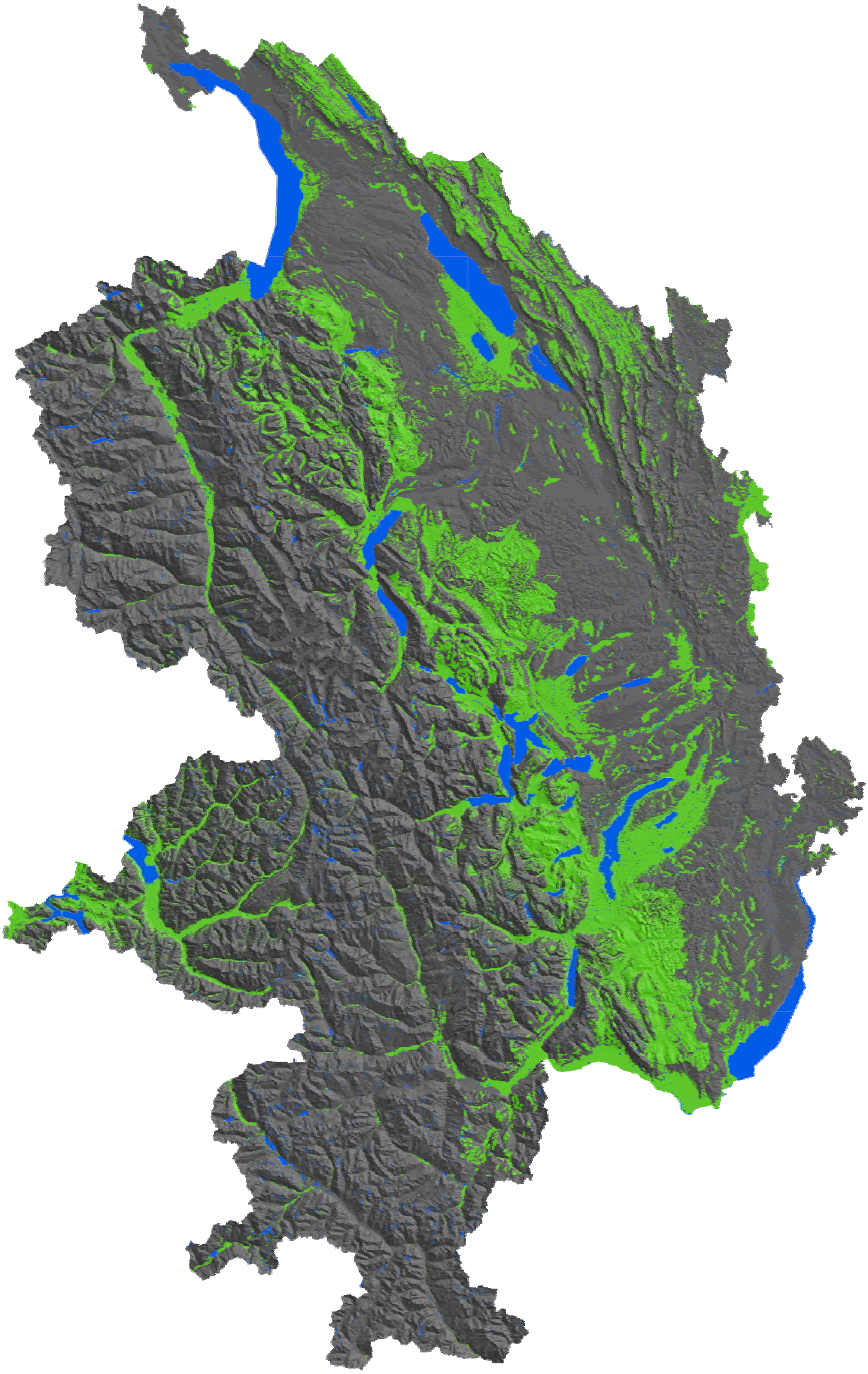
A.1.3 Model with layer of *Three federal inventories* and soil suitability map (FMHM-Soil)



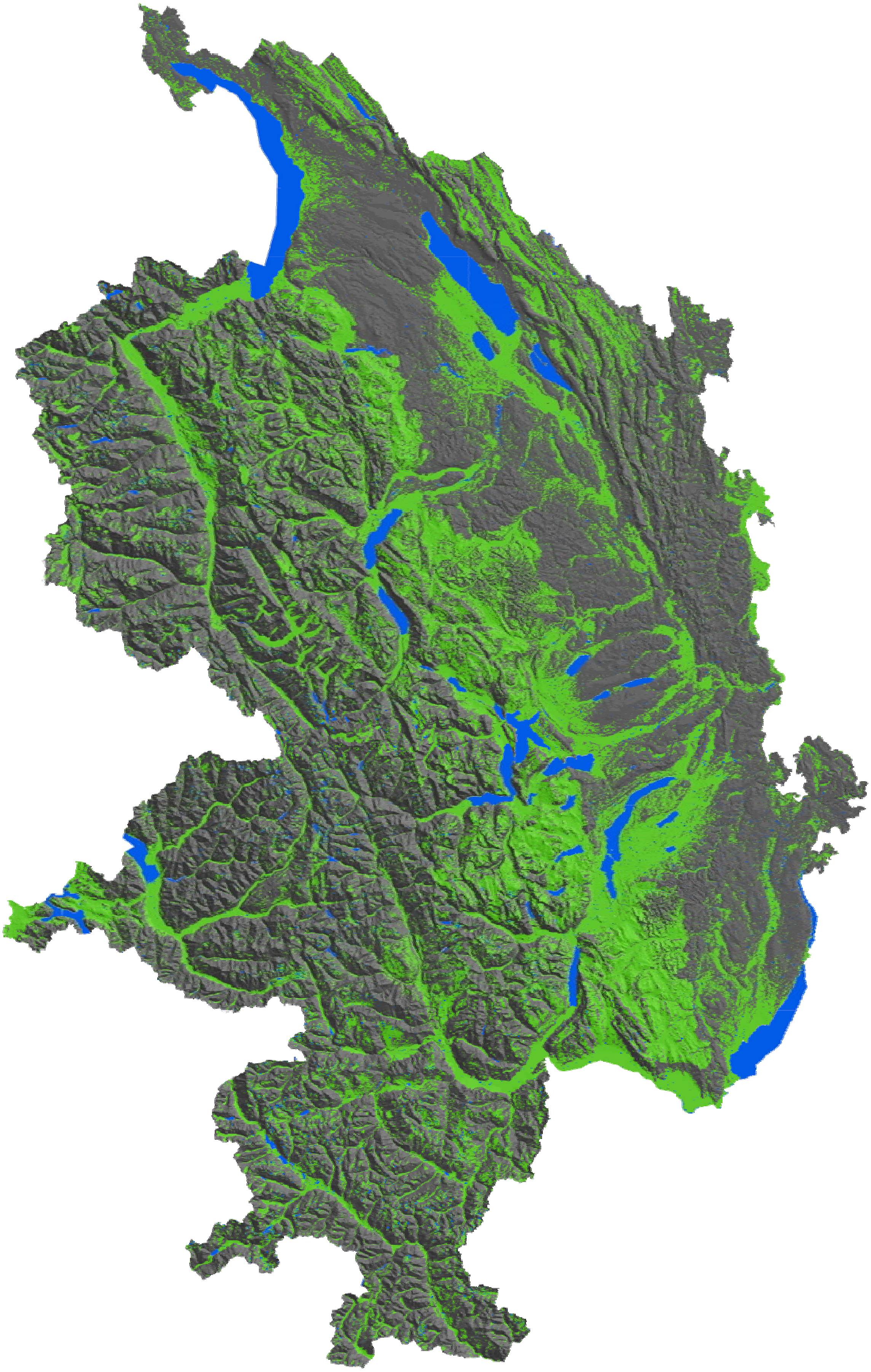
A.1.4 Model with layer of *Früh and Schröter* (FS)



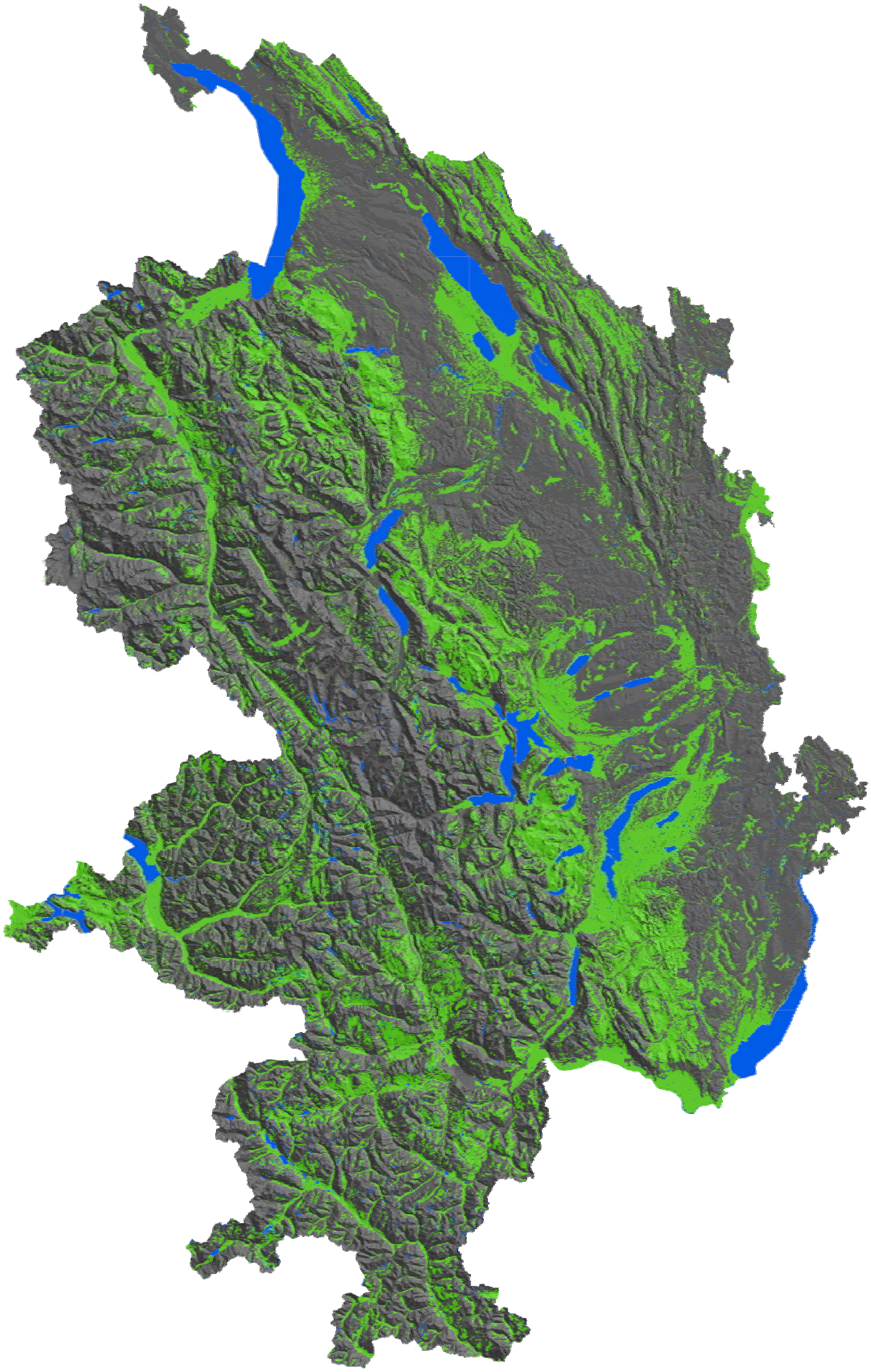
A.1.5 Model with layer of *Früh and Schröter* and soil suitability map (FS-Soil)



A.1.6 Model with the combined layers (FMHM-FS)



A.1.7 Model with the combined layers and soil suitability map (FMHM-FS-Soil)



A.2 Models

A.2.1 Correlation Tables

A.2.1.1 Three federal inventories for the protection of mires (Model FMHM and FMHM-soil)

Correlation Jura

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.90775	1											
njahr_2	-0.90302	0.972681	1										
njul_25	-0.73234	0.776391	0.817869	1									
slope_d	0.164699	-0.1662	-0.169	0.046687	1								
tjul_25	0.933815	-0.99037	-0.9685	-0.81018	0.17005	1							
topos	-0.12035	0.114503	0.117452	0.382584	0.249818	-0.13579	1						
twi25s	-0.10995	0.114576	0.120398	-0.09113	-0.66998	-0.11001	-0.45506	1					
twi25ss	-0.1118	0.116369	0.125995	-0.09357	-0.71161	-0.11363	-0.47613	0.91529	1				
wbjul_2	-0.50341	0.529096	0.586658	0.921249	0.283505	-0.57472	0.444242	-0.26269	-0.27842	1			
wet	-0.40417	0.43238	0.446926	0.192044	-0.60115	-0.43659	-0.35361	0.570555	0.619449	-0.02577	1		
durchl	0.01252	0.013917	-0.00067	0.06805	0.4125	0.009832	0.235581	-0.35712	-0.41268	0.132134	-0.43216	1	
verna	-0.28874	0.206502	0.249266	0.141931	-0.42842	-0.23664	-0.17625	0.377588	0.447479	0.018847	0.573004	-0.49111	1

Correlation Swiss Plateau

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.75067	1											
njahr_2	-0.58825	0.700551	1										
njul_25	-0.50709	0.493541	0.91086	1									
slope_d	-0.3562	0.402307	0.21577	0.122317	1								
tjul_25	0.782945	-0.94588	-0.76304	-0.62491	-0.40406	1							
topos	-0.27781	0.376266	0.243973	0.157863	0.216626	-0.37246	1						
twi25s	0.385945	-0.42859	-0.22753	-0.1362	-0.68953	0.432384	-0.36596	1					
twi25ss	0.444324	-0.4949	-0.27798	-0.17712	-0.72087	0.503552	-0.38051	0.926059	1				
wbjul_2	-0.46262	0.402105	0.866996	0.991545	0.110365	-0.56182	0.126165	-0.11256	-0.14987	1			
wet	0.245549	-0.248	0.086514	0.200737	-0.47443	0.193415	-0.2194	0.523484	0.553221	0.228501	1		
durchl	0.045241	-0.07032	-0.20389	-0.2199	0.032112	0.103214	-0.01274	-0.00328	0.026826	-0.22148	-0.12666	1	
verna	0.045463	-0.07061	-0.20381	-0.21966	0.03172	0.103397	-0.01295	-0.00286	0.027298	-0.2212	-0.126	0.999999	1

Fig. A.2.1: Correlation tables of variables used in Model FMHM and FMHM-Soil for regions Jura and Swiss Plateau. Correlations >0.7 are highlighted.

Correlation Northern Alps

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.97127	1											
njahr_2	-0.40672	0.339101	1										
njul_25	-0.00066	-0.09466	0.83609	1									
slope_d	-0.31784	0.350809	0.033398	-0.1433	1								
tjul_25	0.976576	-0.99084	-0.40074	0.005717	-0.34403	1							
topos	-0.26584	0.271615	0.18963	0.072127	0.148803	-0.27577	1						
twi25s	0.27571	-0.2817	-0.13886	-0.00122	-0.63896	0.282483	-0.41792	1					
twi25ss	0.327253	-0.33175	-0.15605	0.002288	-0.6819	0.333134	-0.43868	0.910497	1				
wbjul_2	-0.08612	0.007497	0.835182	0.962818	0.010643	-0.1051	0.084727	-0.07534	-0.07801	1			
wet	-0.03239	-0.03713	0.161959	0.213719	-0.50664	0.030744	-0.0354	0.304581	0.336583	0.082175	1		
durchl	0.32698	-0.34586	-0.19869	-0.02598	0.054275	0.340097	-0.12695	-0.03261	-0.04268	-0.07455	-0.18479	1	
verna	0.220988	-0.26892	-0.03047	0.094845	-0.43488	0.273627	-0.07853	0.210821	0.256588	-0.03136	0.500472	-0.20878	1

Correlation Central-South

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.95869	1											
njahr_2	-0.01057	0.112784	1										
njul_25	-0.0495	0.10768	0.609363	1									
slope_d	-0.159	0.192226	0.174983	-0.03367	1								
tjul_25	0.966226	-0.97743	-0.03435	-0.09034	-0.14837	1							
topos	-0.12581	0.19218	0.163718	0.15355	0.22888	-0.16795	1						
twi25s	0.186537	-0.22817	-0.16785	-0.03755	-0.74296	0.186973	-0.43551	1					
twi25ss	0.224942	-0.26491	-0.19664	-0.03752	-0.76981	0.223021	-0.44931	0.927137	1				
wbjul_2	-0.24708	0.317386	0.554686	0.931783	0.113017	-0.31185	0.174436	-0.14409	-0.14897	1			
wet	0.077201	-0.12434	-0.15039	0.122238	-0.65638	0.05737	-0.17604	0.567444	0.596455	-0.00454	1		
durchl	0.297191	-0.39982	-0.11161	-0.17766	-0.06811	0.371477	-0.14825	0.070242	0.070202	-0.32884	0.129878	1	
verna	0.101771	-0.17573	-0.28296	0.016306	-0.45915	0.112298	-0.19689	0.402537	0.431157	-0.08271	0.541839	0.20122	1

Fig. A.2.2: Correlation tables of variables used in Model FMHM and FMHM-Soil for regions Northern Alps and Central-South. Correlations >0.7 are highlighted.

A.2.1.2 Früh and Schröter (Models FS and FS-Soil)

Correlation Jura

	dgd30_2	*dhm25_l*	*njahr_2*	*njul_25*	*slope_d*	*tjul_25*	*topos*	*twi25s*	*twi25ss*	*wbjul_2*	*wet*	*durchl*	*verna*
dgd30_2	1												
dhm25_l	-0.953141	1											
njahr_2	-0.929985	0.963243	1										
njul_25	-0.84356	0.869383	0.920492	1									
slope_d	-0.04888	0.049477	0.083305	0.197113	1								
tjul_25	0.964746	-0.992277	-0.966921	-0.895085	-0.059395	1							
topos	-0.190768	0.219432	0.209418	0.29876	0.183217	-0.21169	1						
twi25s	0.120784	-0.132328	-0.169247	-0.253627	-0.655523	0.145268	-0.407515	1					
twi25ss	0.143511	-0.152762	-0.195321	-0.286592	-0.685179	0.168282	-0.427516	0.937664	1				
wbjul_2	-0.696555	0.709986	0.792383	0.94836	0.368251	-0.74941	0.325815	-0.369092	-0.4109	1			
wet	-0.154257	0.173068	0.116984	-0.007299	-0.490971	-0.1535	-0.249092	0.471286	0.525855	-0.168311	1		
durchl	-0.118344	0.127155	0.113352	0.120871	0.356719	-0.108247	0.227291	-0.307122	-0.344889	0.149362	-0.304834	1	
verna	0.00387	-0.028593	-0.021443	-0.060912	-0.464312	0.01994	-0.251464	0.486647	0.543803	-0.13049	0.525929	-0.536871	1

Correlation Swiss Plateau

	dgd30_2	*dhm25_l*	*njahr_2*	*njul_25*	*slope_d*	*tjul_25*	*topos*	*twi25s*	*twi25ss*	*wbjul_2*	*wet*	*durchl*	*verna*
dgd30_2	1												
dhm25_l	-0.815474	1											
njahr_2	-0.448327	0.512916	1										
njul_25	-0.303349	0.261345	0.902813	1									
slope_d	-0.431204	0.437875	0.254315	0.134592	1								
tjul_25	0.859332	-0.935006	-0.631719	-0.452058	-0.471572	1							
topos	-0.293469	0.358624	0.240845	0.135765	0.211498	-0.376109	1						
twi25s	0.458287	-0.463766	-0.233195	-0.111599	-0.686464	0.492292	-0.342944	1					
twi25ss	0.511024	-0.517548	-0.269871	-0.13732	-0.723525	0.54946	-0.363442	0.938224	1				
wbjul_2	-0.247239	0.162585	0.85789	0.99159	0.12044	-0.380088	0.103927	-0.085623	-0.107497	1			
wet	0.364048	-0.331391	0.023872	0.155665	-0.356533	0.305203	-0.112359	0.357894	0.400817	0.17603	1		
durchl	-0.016613	-0.009135	-0.074209	-0.086872	-0.007212	0.030479	-0.005501	0.031355	0.046983	-0.087657	-0.013485	1	
verna	-0.015815	-0.010006	-0.073942	-0.086191	-0.007999	0.03113	-0.0059	0.032276	0.047996	-0.086881	-0.012437	0.999996	1

Fig. A.2.3: Correlation tables of variables used in Model FS and FS-Soil for regions Jura and Swiss Plateau. Correlations >0.7 are highlighted.

Correlation Northern Alps

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.972882	1											
njahr_2	-0.59365	0.534412	1										
njul_25	-0.153952	0.0457	0.80636	1									
slope_d	-0.537875	0.552598	0.246122	-0.025732	1								
tjul_25	0.978842	-0.993232	-0.584994	-0.125634	-0.549511	1							
topos	-0.265423	0.280808	0.192768	0.055238	0.152304	-0.280687	1						
twi25s	0.525525	-0.503739	-0.303029	-0.075557	-0.700517	0.505306	-0.382851	1					
twi25ss	0.579582	-0.55529	-0.336866	-0.089334	-0.741086	0.557838	-0.376124	0.938775	1				
wbjul_2	-0.23103	0.145043	0.816956	0.96228	0.107566	-0.229827	0.071977	-0.129549	-0.147762	1			
wet	0.299822	-0.346811	-0.08053	0.095219	-0.481234	0.34384	-0.043084	0.338942	0.381466	0.006	1		
durchl	0.216528	-0.260414	-0.164446	-0.007742	0.092806	0.257066	-0.118767	-0.103432	-0.114056	-0.07708	-0.177062	1	
verna	0.314636	-0.362007	-0.136199	0.053828	-0.447791	0.354545	-0.095728	0.291615	0.331305	-0.045739	0.457808	-0.106103	1

Correlation Central-South

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.980659	1											
njahr_2	0.038753	0.026214	1										
njul_25	0.246568	-0.177205	0.809231	1									
slope_d	-0.672145	0.677215	0.026414	-0.144518	1								
tjul_25	0.989302	-0.991842	0.037493	0.230931	-0.66993	1							
topos	-0.10354	0.167657	0.118224	0.162078	0.160514	-0.1441	1						
twi25s	0.652975	-0.666821	-0.058951	0.074811	-0.834517	0.655365	-0.310029	1					
twi25ss	0.696323	-0.710268	-0.065586	0.07805	-0.864557	0.699756	-0.303996	0.957798	1				
wbjul_2	0.032126	0.046961	0.771333	0.952518	0.041629	0.002072	0.211973	-0.091374	-0.097184	1			
wet	0.698254	-0.723198	0.066318	0.134876	-0.726598	0.716063	-0.187487	0.697881	0.751085	-0.043848	1		
durchl	0.460163	-0.530623	-0.141324	-0.103888	-0.266493	0.506552	-0.185075	0.27904	0.306042	-0.273246	0.389771	1	
verna	0.488314	-0.511442	0.157938	0.289591	-0.435493	0.504336	-0.167155	0.406561	0.441876	0.139998	0.416695	0.372157	1

Fig. A.2.4: Correlation tables of variables used in Model FS and FS-Soil for regions Northern Alps and Central-South. Correlations >0.7 are highlighted.

A.2.1.3 *Combined Layer of Früh and Schröter* and the *Three federal inventories for the protection of mires*

Correlation Jura

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.94526	1											
njahr_2	-0.92546	0.964448	1										
njul_25	-0.82903	0.856922	0.907552	1									
slope_d	-0.02565	0.027699	0.057731	0.188117	1								
tjul_25	0.959561	-0.99144	-0.96687	-0.88532	-0.03896	1							
topos	-0.15766	0.178792	0.172723	0.286659	0.194202	-0.17514	1						
twi25s	0.092236	-0.10004	-0.13289	-0.24006	-0.65648	0.116806	-0.40356	1					
twi25ss	0.106755	-0.11525	-0.15251	-0.2627	-0.69184	0.132921	-0.42203	0.932223	1				
wbjul_2	-0.67323	0.687718	0.768698	0.945353	0.365152	-0.73057	0.31596	-0.36215	-0.39452	1			
wet	-0.18207	0.202719	0.153299	0.006999	-0.49517	-0.18173	-0.28115	0.496171	0.549773	-0.16144	1		
durchl	-0.07772	0.096596	0.080526	0.0838	0.345864	-0.07344	0.23684	-0.30515	-0.34894	0.1145	-0.32397	1	
verna	-0.06633	0.032315	0.041264	-0.00513	-0.46103	-0.04435	-0.24984	0.465881	0.524814	-0.08428	0.554129	-0.55437	1

Correlation Swiss Plateau

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.80719	1											
njahr_2	-0.49416	0.558192	1										
njul_25	-0.34364	0.295657	0.896459	1									
slope_d	-0.42854	0.444019	0.258509	0.139278	1								
tjul_25	0.850326	-0.9369	-0.66783	-0.47874	-0.47411	1							
topos	-0.26547	0.329778	0.211866	0.113154	0.174299	-0.34293	1						
twi25s	0.4613	-0.45838	-0.26836	-0.15844	-0.69158	0.495634	-0.33047	1					
twi25ss	0.513156	-0.51561	-0.28883	-0.1647	-0.7244	0.552568	-0.34699	0.938748	1				
wbjul_2	-0.28628	0.194723	0.848803	0.991205	0.125436	-0.40531	0.083228	-0.13399	-0.13633	1			
wet	0.361401	-0.32196	0.008516	0.133613	-0.39634	0.31142	-0.14076	0.401291	0.447398	0.151988	1		
durchl	0.007832	-0.02532	-0.08605	-0.09497	0.013969	0.047207	-0.01547	0.029689	0.04686	-0.09517	-0.01348	1	
verna	0.008522	-0.02612	-0.08582	-0.09436	0.013244	0.047798	-0.01584	0.030517	0.047795	-0.09446	-0.01248	0.999997	1

Fig. A.2.5: Correlation tables of variables used in Model FMHM-FS and FMHM-FS-Soil for regions Jura and Swiss Plateau. Correlations >0.7 are highlighted.

Correlation Northern Alps

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.97347	1											
njahr_2	-0.56857	0.515095	1										
njul_25	-0.15395	0.05687	0.823096	1									
slope_d	-0.48927	0.499785	0.230874	-0.00182	1								
tjul_25	0.97875	-0.99253	-0.56705	-0.13883	-0.49975	1							
topos	-0.25526	0.26998	0.198825	0.081448	0.147639	-0.2707	1						
twi25s	0.457575	-0.44064	-0.2861	-0.10231	-0.69975	0.445872	-0.3991	1					
twi25ss	0.525252	-0.50264	-0.32062	-0.11554	-0.73396	0.509157	-0.40029	0.930004	1				
wbjul_2	-0.22504	0.148108	0.826513	0.962464	0.135155	-0.23621	0.093917	-0.16636	-0.18041	1			
wet	0.20644	-0.24954	-0.0357	0.094038	-0.47516	0.249121	-0.02315	0.34724	0.371243	-0.01163	1		
durchl	0.247589	-0.30098	-0.16795	0.0046	0.053739	0.294984	-0.12325	-0.05812	-0.06376	-0.05995	-0.15605	1	
verna	0.272518	-0.32537	-0.09088	0.079346	-0.43714	0.320942	-0.09241	0.270947	0.29991	-0.03536	0.484179	-0.17107	1

Correlation Central-South

	dgd30_2	dhm25_l	njahr_2	njul_25	slope_d	tjul_25	topos	twi25s	twi25ss	wbjul_2	wet	durchl	verna
dgd30_2	1												
dhm25_l	-0.97774	1											
njahr_2	0.061088	0.011212	1										
njul_25	0.172685	-0.10297	0.730491	1									
slope_d	-0.51469	0.524978	0.061687	-0.11806	1								
tjul_25	0.985633	-0.98939	0.054746	0.14585	-0.50481	1							
topos	-0.13087	0.186374	0.126174	0.153281	0.174999	-0.16508	1						
twi25s	0.521811	-0.54	-0.09227	0.032161	-0.7954	0.518372	-0.35268	1					
twi25ss	0.577996	-0.59666	-0.09002	0.037629	-0.82378	0.577284	-0.35485	0.946793	1				
wbjul_2	-0.04823	0.127575	0.679217	0.942925	0.064035	-0.09079	0.196779	-0.12466	-0.13108	1			
wet	0.44199	-0.47201	-0.01561	0.127496	-0.68482	0.441018	-0.16414	0.626544	0.65988	-0.02624	1		
durchl	0.437152	-0.51267	-0.09523	-0.11316	-0.19813	0.488182	-0.1632	0.209437	0.238973	-0.2843	0.273538	1	
verna	0.302655	-0.33409	-0.03201	0.201402	-0.43866	0.304629	-0.16127	0.382138	0.406478	0.067696	0.490995	0.262119	1

Fig. A.2.6: Correlation tables of variables used in Model FMHM-FS and FMHM-FS-Soil for regions Northern Alps and Central-South. Correlations >0.7 are highlighted.

A.2.2 GLM FMHM

A.2.2.1 Jura

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.3415	-0.1216	0.0068	0.3318	3.9209

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-1.13E+01	8.16E-01	-13.83	<2e-16	***
njahr_2	9.12E-04	5.55E-05	16.43	<2e-16	***
slope_d	-5.89E-01	3.42E-02	-17.21	<2e-16	***
topos	-3.51E-02	2.77E-03	-12.69	<2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.59 on 1999 degrees of freedom
Residual deviance: 838.05 on 1996 degrees of freedom
AIC: 846.05

Number of Fisher Scoring iterations: 7

A.2.2.2 Swiss Plateau

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.11303	-0.59136	0.02739	0.69136	3.5042

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-1.29E+01	1.13E+00	-11.363	< 2e-16	***
dgd30_2	2.93E-03	3.43E-04	8.542	< 2e-16	***
njul_25	5.09E-03	3.19E-04	15.993	< 2e-16	***
slope_d	-3.16E-01	3.04E-02	-10.411	< 2e-16	***
twi25s	5.33E-03	6.62E-04	8.054	7.99E-16	***
topos	-1.58E-02	3.48E-03	-4.534	5.79E-06	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1606.2 on 1994 degrees of freedom
AIC: 1618.2

Number of Fisher Scoring iterations: 6

A.2.2.3 Northern Alps

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.69636	-0.7591	0.08748	0.83471	2.16369

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	2.7727304	0.4114675	6.739	1.60E-11	***
dgd30_2	-0.0013985	0.0001295	-10.799	< 2e-16	***
njul_25	0.0011682	0.0001762	6.629	3.37E-11	***
slope_d	-0.1568718	0.0079234	-19.799	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1958.8 on 1996 degrees of freedom
AIC: 1966.8

Number of Fisher Scoring iterations: 5

A.2.2.4 Central-South

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.84298	-0.49378	0.07239	0.66348	2.46961

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.6494165	0.3923982	1.655	0.09793	.
njul_25	0.0020051	0.0003034	6.609	3.88E-11	***
slope_d	-0.1830172	0.0083496	-21.919	< 2e-16	***
topos	-0.0022486	0.000687	-3.273	0.00106	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1587.9 on 1996 degrees of freedom
AIC: 1595.9

Number of Fisher Scoring iterations: 6

A.2.3 GLM FMHM-Soil

A.2.3.1 Jura

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.49763	-0.141137	0.004514	0.261271	3.945097

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	21.3137075	1.561704	13.648	< 2e-16	***
slope_d	0.4918031	0.033876	14.518	< 2e-16	***
tjul_25	0.0131453	0.000951	13.826	< 2e-16	***
topos	0.0339683	0.002875	11.813	< 2e-16	***
as.factor(verna)1	0.0418001	0.488704	-0.086	0.932	
as.factor(verna)2	0.1019995	0.557612	-0.183	0.855	
as.factor(verna)3	0.6103562	0.522288	1.169	0.243	
as.factor(verna)4	2.2954721	0.587591	3.907	9.36E-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 782.8 on 1992 degrees of freedom
AIC: 798.8

Number of Fisher Scoring iterations: 7

A.2.3.2 Swiss Plateau

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.19585	-0.45591	0.03165	0.54611	3.25103

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	6.063087	1.228026	-4.937	7.92E-07	***
dgd30_2	0.0020171	0.000384	5.251	1.52E-07	***
slope_d	0.2238594	0.030086	-7.441	1.00E-13	***
topos	0.0095046	0.003664	-2.594	0.009488	**
twi25s	0.005616	0.000718	7.825	5.07E-15	***
wbjul_2	0.0394137	0.00307	12.839	< 2e-16	***
as.factor(verna)0	0.2051152	0.574583	-0.357	0.721106	
as.factor(verna)1	2.0275698	0.560212	-3.619	0.000295	***
as.factor(verna)2	2.6257828	0.584222	-4.494	6.97E-06	***
as.factor(verna)3	1.2339218	0.553411	-2.23	0.02577	*
as.factor(verna)4	0.1609034	0.563402	-0.286	0.77519	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1417.7 on 1989 degrees of freedom
AIC: 1439.7

Number of Fisher Scoring iterations: 6

A.2.3.3 Northern Alps

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.63141	-0.52369	0.04841	0.60695	2.72275

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.2589665	0.496228	0.522	0.60176	
dgd30_2	-0.0018746	0.000161	11.673	< 2e-16	***
njul_25	0.0013451	0.000206	6.529	6.60E-11	***
slope_d	-0.136416	0.01067	12.785	< 2e-16	***
twi25ss	0.0024777	0.000794	3.121	0.0018	**
as.factor(durchl)2	4.6725445	0.335459	13.929	< 2e-16	***
as.factor(durchl)3	3.2589271	0.314	10.379	< 2e-16	***
as.factor(durchl)4	2.5975127	0.308021	8.433	< 2e-16	***
as.factor(durchl)5	1.9491019	0.326073	5.977	2.27E-09	***
as.factor(durchl)6	1.0000109	0.563418	1.775	0.07591	.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1578.5 on 1990 degrees of freedom
AIC: 1598.5

Number of Fisher Scoring iterations: 6

A.2.3.4 Central-South

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.13167	-0.29562	0.03732	0.44909	2.65216

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	2.86E+00	6.67E-01	-4.29	1.79E-05	***
tjul_25	7.47E-04	2.11E-04	-3.536	0.000406	***
njahr_2	7.27E-05	3.11E-05	-2.34	0.019261	*
njul_25	3.53E-03	4.40E-04	8.015	1.10E-15	***
slope_d	1.97E-01	1.07E-02	18.342	< 2e-16	***
topos	2.31E-03	8.54E-04	-2.704	0.006852	**
as.factor(verna)1	3.62E+00	3.08E-01	11.755	< 2e-16	***
as.factor(verna)2	4.75E+00	3.64E-01	13.072	< 2e-16	***
as.factor(verna)3	5.00E+00	3.80E-01	13.162	< 2e-16	***
as.factor(verna)4	3.82E+00	3.95E-01	9.684	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1200.3 on 1990 degrees of freedom
AIC: 1220.3

Number of Fisher Scoring iterations: 6

A.2.4 GLM FS

A.2.4.1 Jura

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.807	-0.632	0.1058	0.6682	3.9325

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	19.4091481	1.3941241	13.922	< 2e-16	***
tjul_25	-0.0102102	0.0007201	-14.179	< 2e-16	***
wbjul_2	-0.063598	0.0072573	-8.763	< 2e-16	***
slope_d	-0.1136055	0.0140439	-8.089	6.00E-16	***
topos	-0.0096174	0.0016696	-5.76	8.40E-09	***
twi25ss	0.0062277	0.000748	8.325	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1736.8 on 1994 degrees of freedom
AIC: 1748.8

Number of Fisher Scoring iterations: 5

A.2.4.2 Swiss Plateau

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.39674	-0.92801	0.04124	0.88758	2.61511

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-1.22E+01	8.89E-01	-13.735	< 2e-16	***
dgd30_2	3.68E-03	2.96E-04	12.455	< 2e-16	***
njul_25	2.77E-03	2.24E-04	12.367	< 2e-16	***
slope_d	-9.74E-02	1.51E-02	-6.475	9.48E-11	***
twi25s	1.80E-03	4.96E-04	3.634	0.000279	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 2149.5 on 1995 degrees of freedom
AIC: 2159.5

Number of Fisher Scoring iterations: 4

A.2.4.3 Northern Alps

Deviance Residuals:

Min	1Q	Median	3Q	Max	
	-2.0768	-0.8997	0.2028	0.8987	2.6837

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-1.7928763	0.4946898	-3.624	0.00029	***
njul_25	0.0008684	0.0001788	4.857	1.19E-06	***
slope_d	-0.0793903	0.005315	-14.937	< 2e-16	***
tjul_25	0.0012163	0.0002161	5.629	1.82E-08	***
topos	0.0015418	0.0005891	2.617	0.00887	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 2189.1 on 1995 degrees of freedom
AIC: 2199.1

Number of Fisher Scoring iterations: 4

A.2.4.4 Central-South

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.58232	-0.4099298	0.0007047	0.2867683	3.2284091

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-5.07E+00	4.22E-01	-12.02	< 2e-16	***
njahr_2	1.37E-04	2.02E-05	6.79	1.12E-11	***
tjul_25	2.34E-03	1.78E-04	13.099	< 2e-16	***
topos	-1.99E-03	8.89E-04	-2.243	0.0249	*
twi25ss	1.09E-02	6.60E-04	16.467	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1099.3 on 1995 degrees of freedom
AIC: 1109.3

Number of Fisher Scoring iterations: 6

A.2.5 GLM FS-Soil

A.2.5.1 Jura

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.046	-0.69552	0.02168	0.46219	3.29936

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	6.0695086	0.8694307	6.981	2.93E-12	***
slope_d	-0.0967981	0.0128688	-7.522	5.40E-14	***
tjul_25	-0.0041814	0.0004667	-8.96	< 2e-16	***
topos	-0.0083721	0.0015323	-5.464	4.66E-08	***
twi25ss	0.0045367	0.0007411	6.122	9.26E-10	***
as.factor(verna)1	0.696364	0.4276614	1.628	0.1035	
as.factor(verna)2	-0.2379043	0.48024	-0.495	0.6203	
as.factor(verna)3	1.1392389	0.467444	2.437	0.0148	*
as.factor(verna)4	3.6503277	0.5158366	7.077	1.48E-12	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1610.3 on 1991 degrees of freedom
AIC: 1628.3

Number of Fisher Scoring iterations: 6

A.2.5.2 Swiss Plateau

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.74302	-0.81485	-0.02795	0.70039	2.58166

Coefficients:

	Estimate	Std.Error	zvalue	Pr(>|z|)	
(Intercept)	-1.05E+01	1.10E+00	-9.556	< 2e-16	***
dgd30_2	3.44E-03	3.09E-04	11.12	< 2e-16	***
slope_d	-9.60E-02	1.25E-02	-7.653	1.97E-14	***
wbjul_2	2.58E-02	2.25E-03	11.447	< 2e-16	***
as.factor(verna)0	4.95E-01	6.38E-01	0.775	0.438486	
as.factor(verna)1	6.47E-01	6.31E-01	1.026	0.304865	
as.factor(verna)2	1.96E-01	6.32E-01	0.31	0.75694	
as.factor(verna)3	-9.78E-02	6.32E-01	-0.155	0.877029	
as.factor(verna)4	2.23E+00	6.38E-01	3.501	0.000464	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1983.1 on 1991 degrees of freedom
AIC: 2001.1

Number of Fisher Scoring iterations: 5

A.2.5.3 Northern Alps

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.52697	-0.76494	0.09642	0.79513	2.61534

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-3.5063387	0.5803843	-6.041	1.53E-09	***
njul_25	0.0011387	0.000193	5.899	3.65E-09	***
slope_d	-0.0610719	0.0058608	-10.42	< 2e-16	***
tjul_25	0.0013315	0.0002565	5.19	2.10E-07	***
topos	0.0017482	0.0006367	2.746	0.00604	**
as.factor(verna)1	0.0241753	0.2323765	0.104	0.91714	
as.factor(verna)2	1.0835327	0.2361314	4.589	4.46E-06	***
as.factor(verna)3	0.3964718	0.2701584	1.468	0.14223	
as.factor(verna)4	2.1667552	0.2472611	8.763	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1974.8 on 1991 degrees of freedom
AIC: 1992.8

Number of Fisher Scoring iterations: 5

A.2.5.4 Central-South

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.04983	-0.32545	0.06049	0.38554	3.07737

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-5.01E+00	5.30E-01	-9.452	< 2e-16	***
njahr_2	1.42E-04	2.18E-05	6.517	7.17E-11	***
slope_d	-1.25E-01	7.47E-03	-16.666	< 2e-16	***
tjul_25	1.99E-03	2.00E-04	9.96	< 2e-16	***
topos	-5.89E-03	9.77E-04	-6.028	1.66E-09	***
as.factor(durchl)2	-1.50E+01	1.23E+03	-0.012	0.99	
as.factor(durchl)3	-1.45E+01	5.41E+02	-0.027	0.979	
as.factor(durchl)4	5.69E-01	4.18E-01	1.362	0.173	
as.factor(durchl)5	1.57E+00	3.40E-01	4.627	3.71E-06	***
as.factor(durchl)6	2.51E+00	3.28E-01	7.66	1.86E-14	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 999.9 on 1990 degrees of freedom
AIC: 1019.9

Number of Fisher Scoring iterations: 16

A.2.6 GLM FMHM-FS

A.2.6.1 Jura

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.93545	-0.68705	0.08137	0.62475	3.40893

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	9.7230138	0.6788098	14.324	< 2e-16	***
tjul_25	-0.0058871	0.0004285	-13.739	< 2e-16	***
slope_d	-0.1210391	0.0133049	-9.097	< 2e-16	***
topos	-0.0122774	0.0015847	-7.748	9.36E-15	***
twi25ss	0.0075081	0.0007351	10.213	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1737.6 on 1995 degrees of freedom
AIC: 1747.6

Number of Fisher Scoring iterations: 5

A.2.6.2 Swiss Plateau

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.5074	-0.891	0.0553	0.861	3.0566

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-1.19E+01	9.27E-01	-12.873	< 2e-16	***
dgd30_2	3.50E-03	3.03E-04	11.568	< 2e-16	***
njul_25	2.97E-03	2.41E-04	12.347	< 2e-16	***
slope_d	-1.24E-01	1.71E-02	-7.208	5.66E-13	***
twi25s	2.64E-03	5.20E-04	5.084	3.70E-07	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 2074.7 on 1995 degrees of freedom
AIC: 2084.7

Number of Fisher Scoring iterations: 5

A.2.6.3 Northern Plains

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.1181	-0.9193	0.1736	0.9247	3.2038

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.3204667	0.2987156	1.073	0.28335	
njul_25	0.0008112	0.0001698	4.777	1.78E-06	***
slope_d	-0.0904442	0.0066733	-13.553	< 2e-16	***
topos	0.0017762	0.0006284	2.827	0.00471	**
twi25s	0.0011589	0.0005509	2.104	0.03541	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 2217.5 on 1995 degrees of freedom
AIC: 2227.5

Number of Fisher Scoring iterations: 4

A.2.6.4 Central-South

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.6119	-0.5498	0.1047	0.4967	3.2678

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.9459507	0.3206648	2.95	0.003178	**
tjul_25	0.0008408	0.0001657	5.075	3.88E-07	***
slope_d	-0.1411711	0.0067634	-20.873	< 2e-16	***
wbjul_2	0.0047653	0.0022778	2.092	0.036433	*
topos	-0.0022852	0.0006823	-3.349	0.000811	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1533.2 on 1995 degrees of freedom
AIC: 1543.2

Number of Fisher Scoring iterations: 5

A.2.7 GLM FMHM-FS-Soil

A.2.7.1 Jura

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.13573	-0.64762	0.02237	0.40886	3.07292

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	6.5415164	0.9088984	7.197	6.15E-13	***
slope_d	-0.0861336	0.0129599	-6.646	3.01E-11	***
tjul_25	-0.0047915	0.0004763	-10.06	< 2e-16	***
topos	-0.0098653	0.0015659	-6.3	2.98E-10	***
twi25ss	0.0057464	0.0007631	7.531	5.04E-14	***
as.factor(verna)1	0.9343359	0.485812	1.923	0.054449	.
as.factor(verna)2	0.4794204	0.5155412	0.93	0.352404	
as.factor(verna)3	1.7497288	0.5191933	3.37	0.000751	***
as.factor(verna)4	3.9282483	0.5632129	6.975	3.06E-12	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1535.2 on 1991 degrees of freedom
AIC: 1553.2

Number of Fisher Scoring iterations: 6

A.2.7.2 Swiss Plateau

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.630954	-0.821938	-0.003414	0.754041	2.938914

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-1.23E+01	1.22E+00	-10.058	< 2e-16	***
dgd30_2	3.40E-03	3.25E-04	10.473	< 2e-16	***
njul_25	2.93E-03	2.60E-04	11.286	< 2e-16	***
slope_d	-1.04E-01	1.69E-02	-6.148	7.86E-10	***
twi25s	1.84E-03	5.37E-04	3.42	0.000625	***
as.factor(verna)0	4.77E-01	6.48E-01	0.736	0.461506	
as.factor(verna)1	4.13E-01	6.39E-01	0.645	0.518829	
as.factor(verna)2	3.35E-01	6.42E-01	0.522	0.601377	
as.factor(verna)3	1.15E-01	6.40E-01	0.18	0.857484	
as.factor(verna)4	1.94E+00	6.48E-01	2.995	0.002745	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1959.1 on 1990 degrees of freedom
AIC: 1979.1

Number of Fisher Scoring iterations: 5

A.2.7.3 Northern Alps

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.59723	-0.75118	0.07518	0.76441	2.81349

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-1.51E+00	4.64E-01	-3.248	0.00116	**
njahr_2	6.97E-05	2.32E-05	2.998	0.00271	**
slope_d	-7.60E-02	7.50E-03	-10.126	< 2e-16	***
topos	2.17E-03	7.28E-04	2.976	0.00292	**
twi25s	1.91E-03	6.16E-04	3.095	0.00197	**
as.factor(durchl)2	3.55E+00	2.95E-01	12.044	< 2e-16	***
as.factor(durchl)3	2.36E+00	2.69E-01	8.778	< 2e-16	***
as.factor(durchl)4	1.61E+00	2.62E-01	6.153	7.59E-10	***
as.factor(durchl)5	1.16E+00	2.75E-01	4.22	2.44E-05	***
as.factor(durchl)6	-1.34E+00	7.88E-01	-1.705	0.08812	.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1901.0 on 1990 degrees of freedom
AIC: 1921

Number of Fisher Scoring iterations: 6

A.2.7.4 Central-South

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.84658	-0.41982	0.06577	0.4821	3.39993

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-2.08E+00	4.64E-01	-4.483	7.34E-06	***
njahr_2	9.38E-05	2.07E-05	4.537	5.70E-06	***
slope_d	-1.44E-01	8.00E-03	-18.016	< 2e-16	***
tjul_25	3.98E-04	1.77E-04	2.248	0.02458	*
topos	-2.48E-03	7.79E-04	-3.184	0.00145	**
as.factor(verna)1	2.61E+00	2.78E-01	9.395	< 2e-16	***
as.factor(verna)2	3.52E+00	3.27E-01	10.751	< 2e-16	***
as.factor(verna)3	4.28E+00	3.62E-01	11.816	< 2e-16	***
as.factor(verna)4	3.08E+00	3.79E-01	8.12	4.65E-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2772.6 on 1999 degrees of freedom
Residual deviance: 1306.7 on 1991 degrees of freedom
AIC: 1324.7

Number of Fisher Scoring iterations: 6

A.3 Verification Tables

A.3.1 Verification of GLMs

Table A.3.1: Verification measures of the different GLMs considering the selected data points only. All the values are given as percentage. The following abbreviations are used: Ju: Jura, Mi: Swiss Plateau, Al: Northern Alps, Cs: Central-South; spec: specificity, sens: sensitivity, auc: area under the curve; Fill: Simple flood model, FMHM: Layer of *Three federal inventories*, FS: Layer of *Früh and Schröter*; Soil: Information of the *soil suitability map* is included.

Model	Region	D^2	κ	Resubstitution					Cross-validation				
				pcc	spec	sens	κ	auc	pcc	spec	sens	κ	auc
FMHM	Ju	70	86	93	94	92	86	97	93	94	92	86	97
	Mi	42	67	83	81	86	66	90	83	80	86	66	90
	Al	29	54	78	65	88	54	83	77	66	88	53	83
	Cs	43	67	83	78	88	67	89	83	78	89	66	89
FMHM-Soil	Ju	72	86	93	93	93	86	98	93	92	93	85	98
	Mi	49	71	85	81	90	71	92	85	81	89	70	92
	Al	43	64	82	73	90	63	90	81	73	90	63	90
	Cs	57	77	88	84	92	77	94	88	84	92	76	94
FS	Ju	37	65	82	86	79	65	89	82	85	79	64	89
	Mi	22	50	75	78	72	50	81	74	77	71	48	80
	Al	21	43	71	63	80	43	80	71	63	80	42	79
	Cs	60	80	90	96	85	81	95	90	96	84	80	95
FS-Soil	Ju	42	61	81	86	75	61	89	80	85	75	60	89
	Mi	28	53	77	85	69	54	83	76	84	68	52	83
	Al	29	47	75	72	79	50	84	74	71	78	49	83
	Cs	64	82	91	96	86	82	96	91	96	86	81	86
FMHM-FS	Ju	37	60	60	83	77	60	88	79	83	76	58	88
	Mi	25	51	76	77	75	51	82	76	77	76	51	82
	Al	20	44	72	64	80	44	78	72	64	80	44	78
	Cs	45	68	84	83	85	68	91	84	82	85	67	91
FMHM-FS-Soil	Ju	45	63	81	83	80	63	90	81	82	79	61	90
	Mi	29	50	77	81	74	55	84	77	80	74	54	84
	Al	31	53	77	70	83	53	85	76	70	83	52	85
	Cs	53	73	87	82	92	73	94	86	81	91	73	93

A.3.2 AUC Graphs of GLMs

A.3.2.1 FMHM

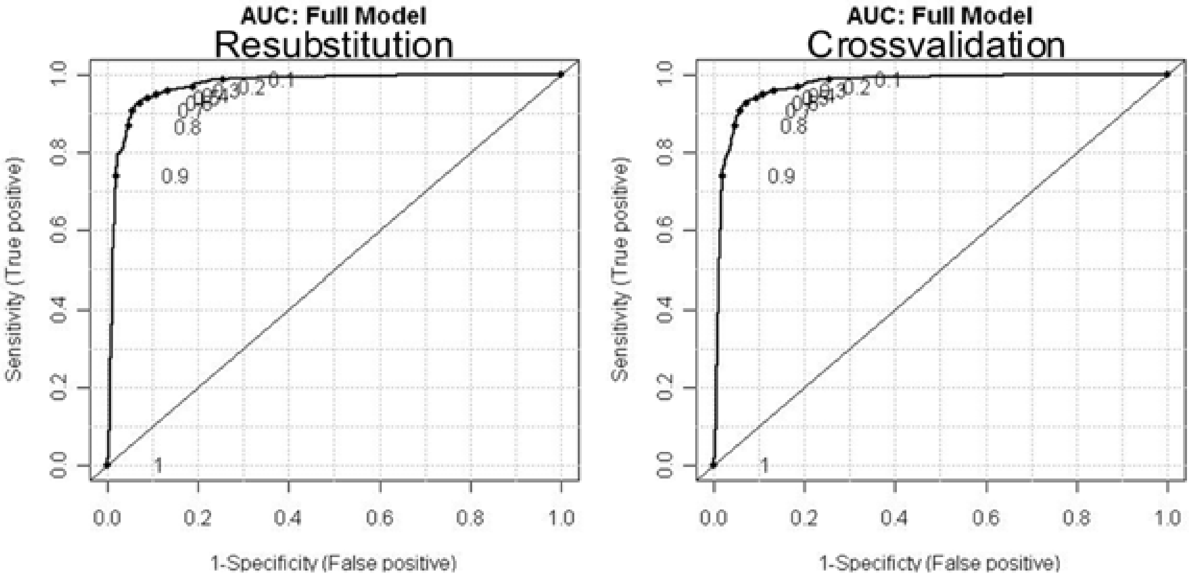


Fig. A.3.1: AUC of model FMHM for region Jura.

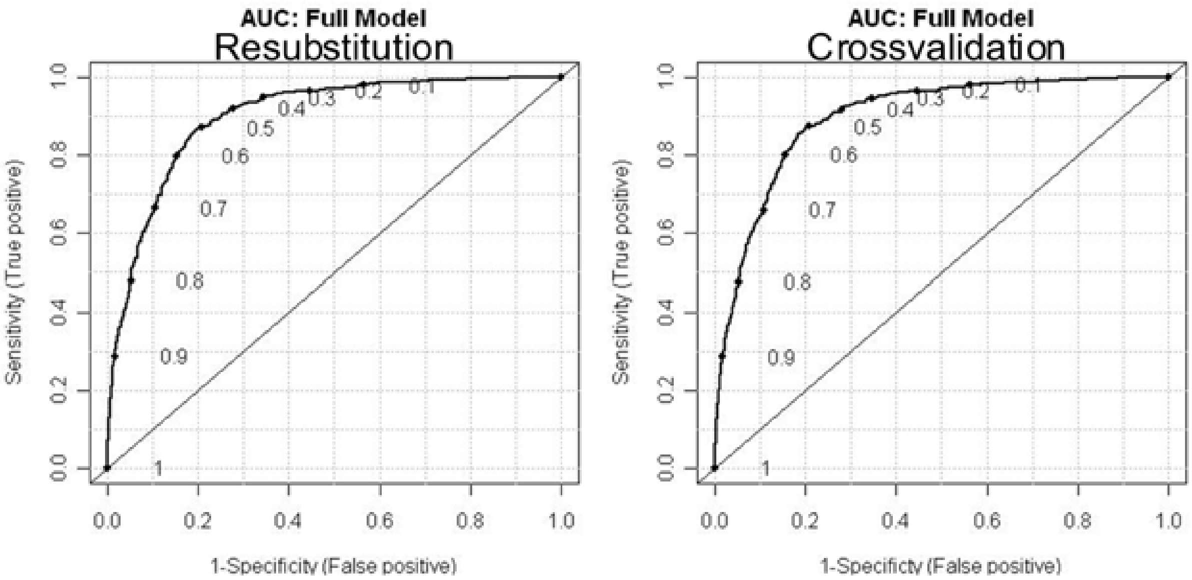


Fig. A.3.2: AUC of model FMHM for region Swiss Plateau.

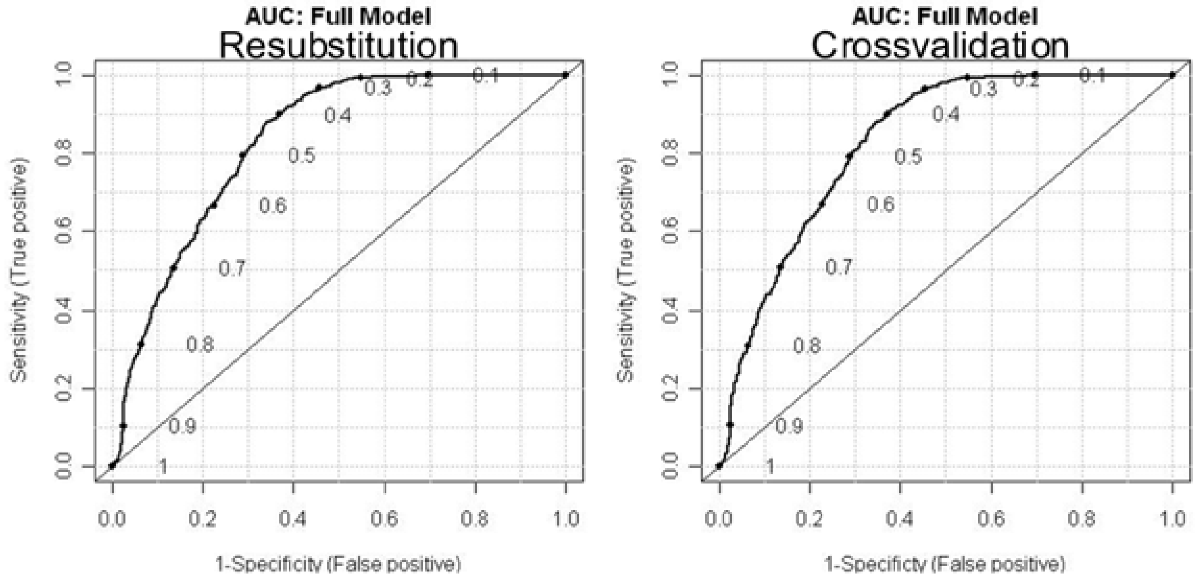


Fig. A.3.3: AUC of model FMHM for region Northern Alps.

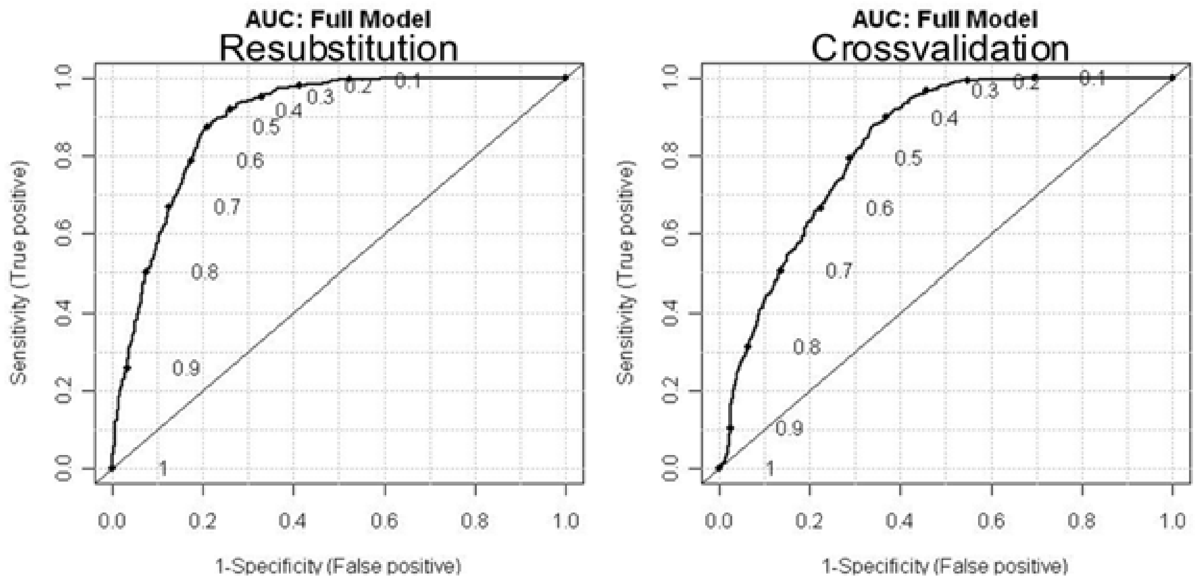


Fig. A.3.4: AUC of model FMHM for region Central-South.

A.3.2.2 FMHM including information from Soil Suitability Map

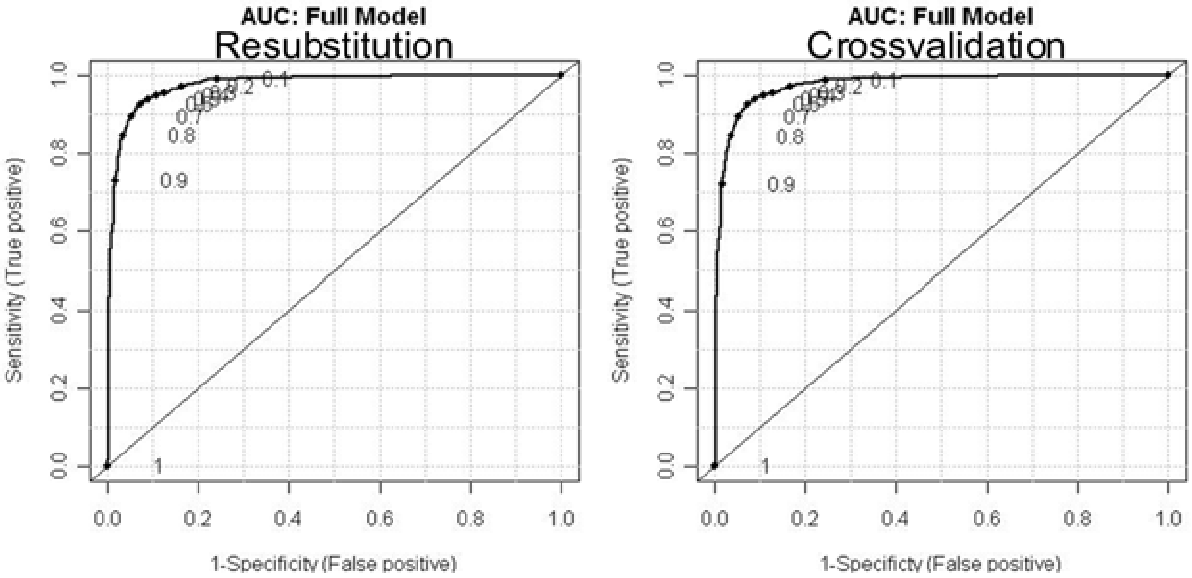


Fig. A.3.5: AUC of model FMHM-Soil for region Jura.

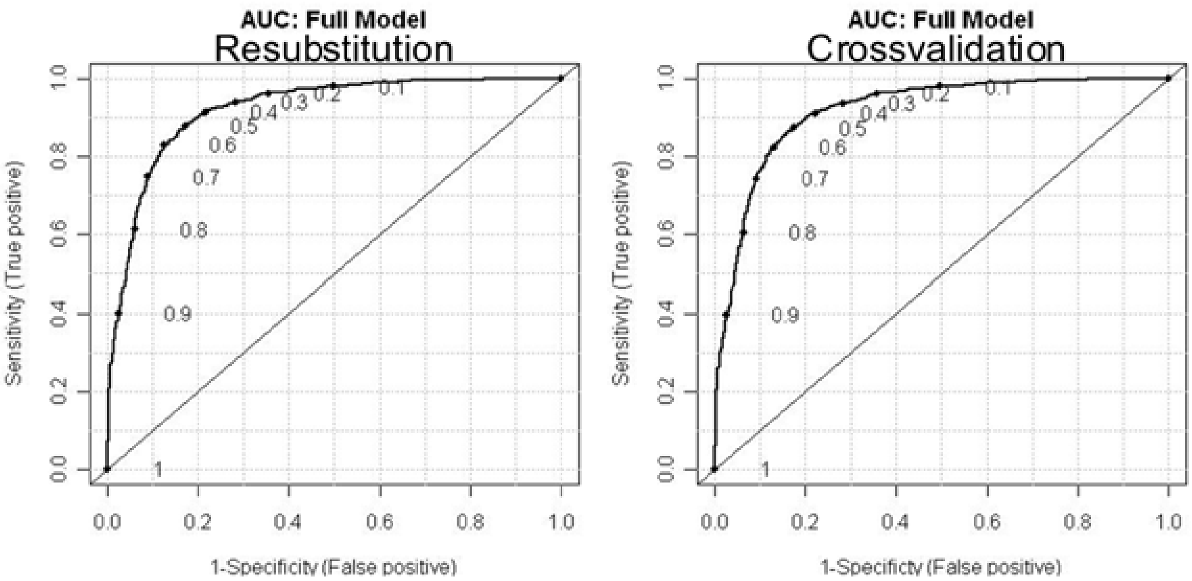


Fig. A.3.6: AUC of model FMHM-Soil for region Swiss Plateau.

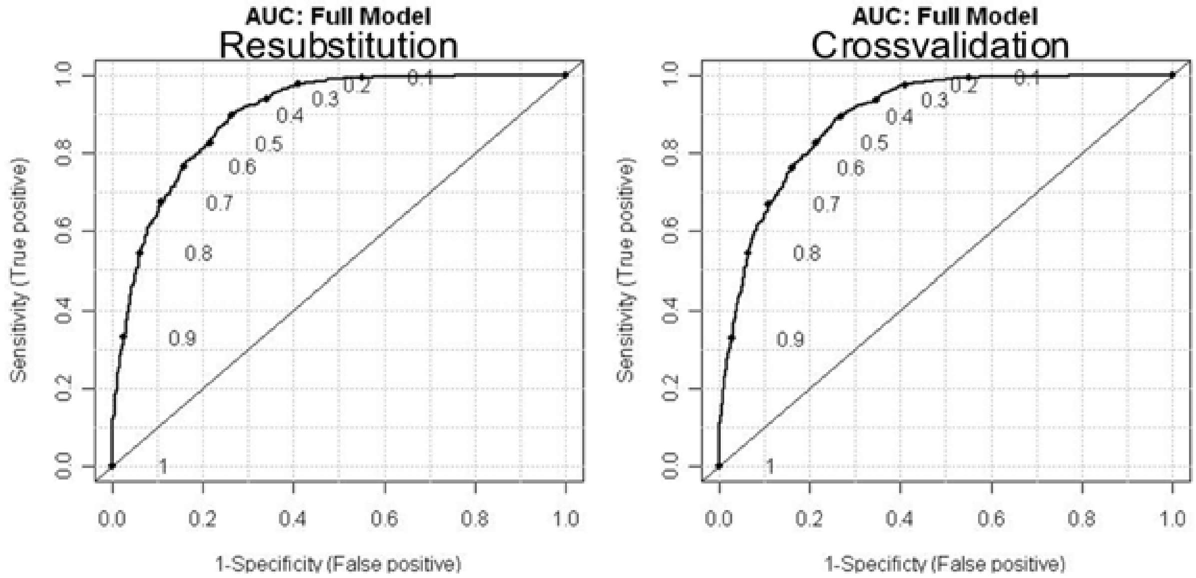


Fig. A.3.7: AUC of model FMHM-Soil for region Northern Alps.

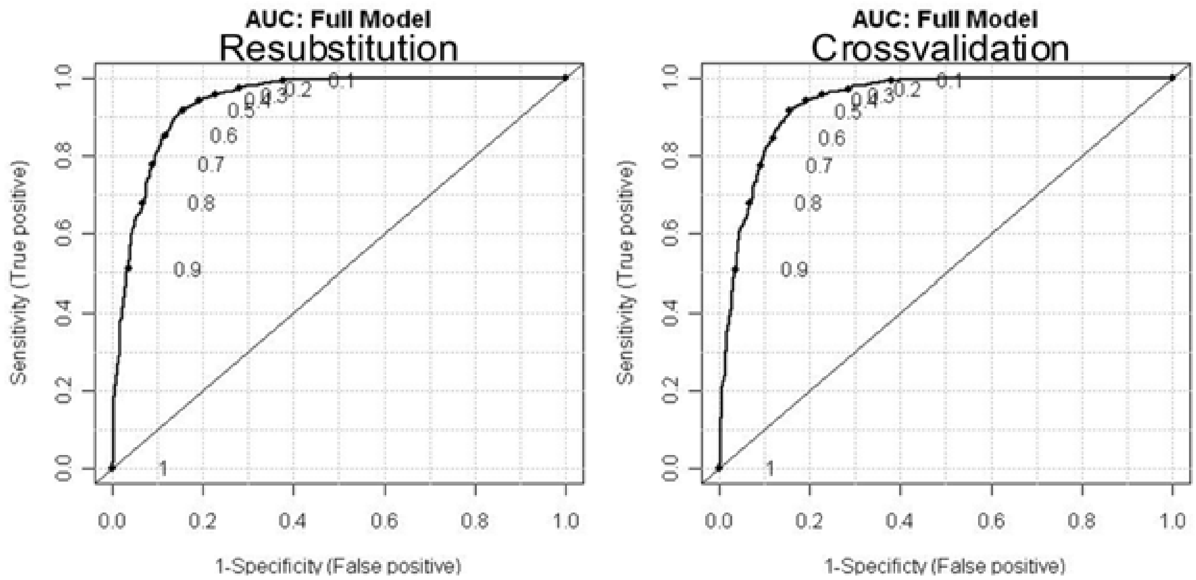


Fig. A.3.8: AUC of model FMHM-Soil for region Central-South.

A.3.2.3 Früh and Schröter

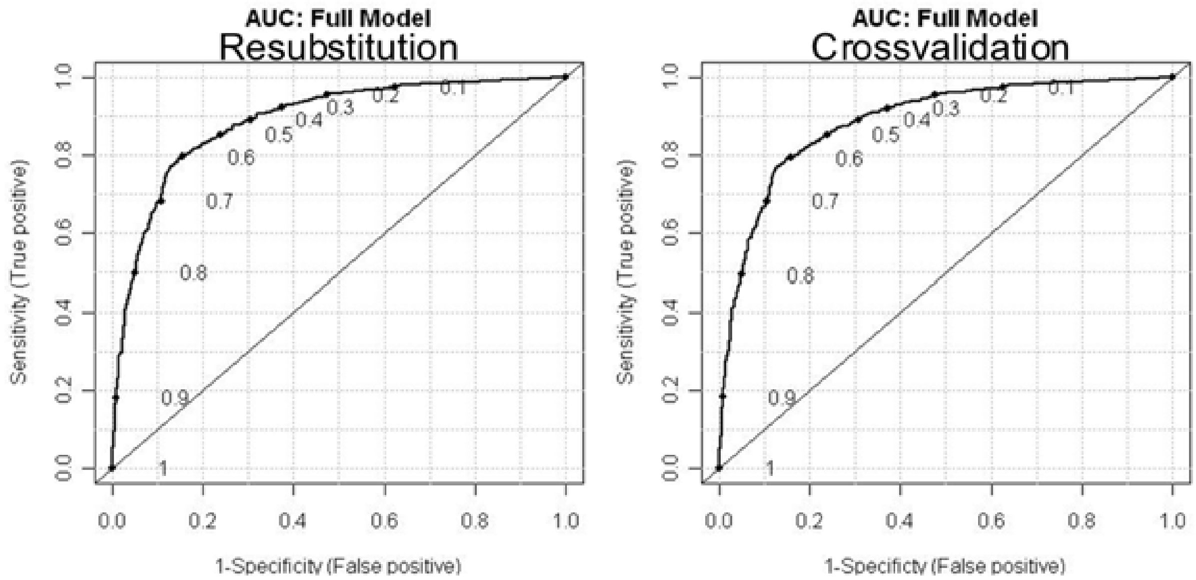


Fig. A.3.9: AUC of model FS for region Jura.

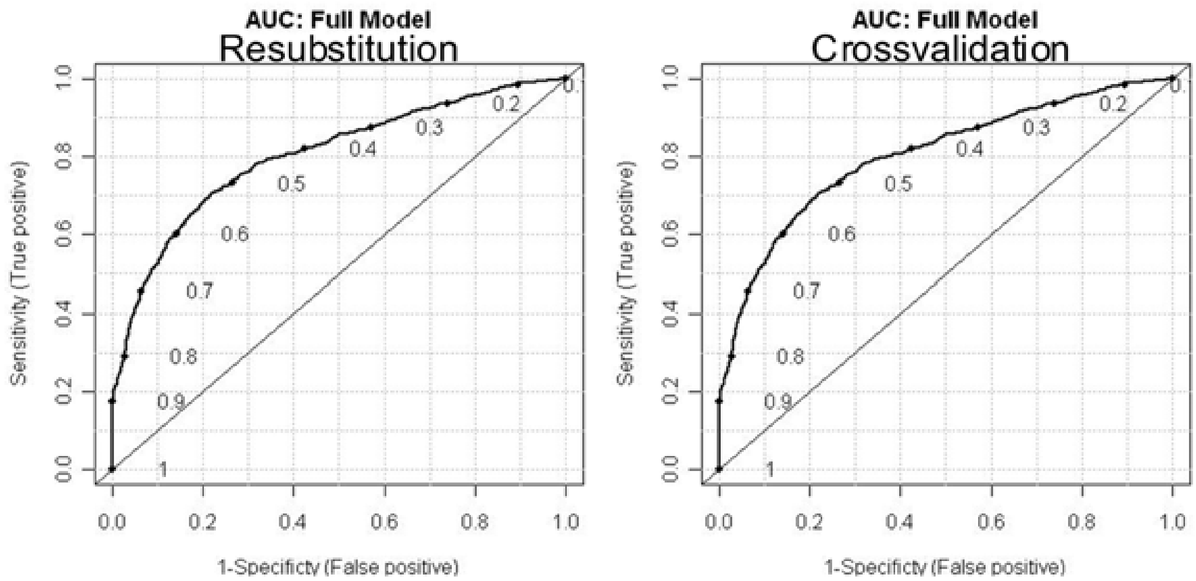


Fig. A.3.10: AUC of model FS for region Swiss Plateau.

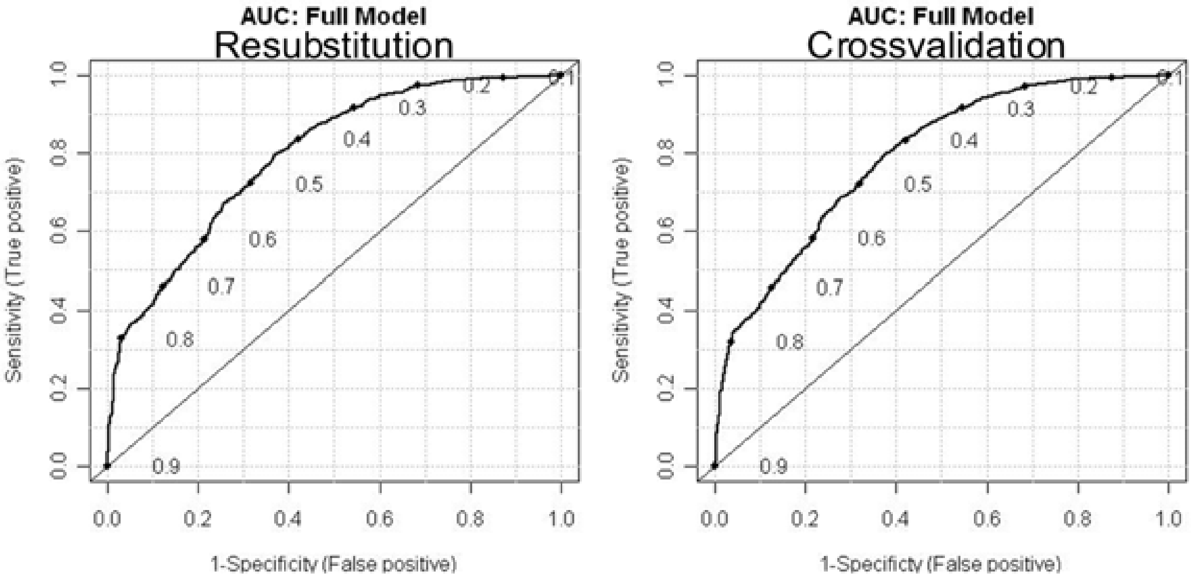


Fig. A.3.11: AUC of model FS for region Northern Alps.

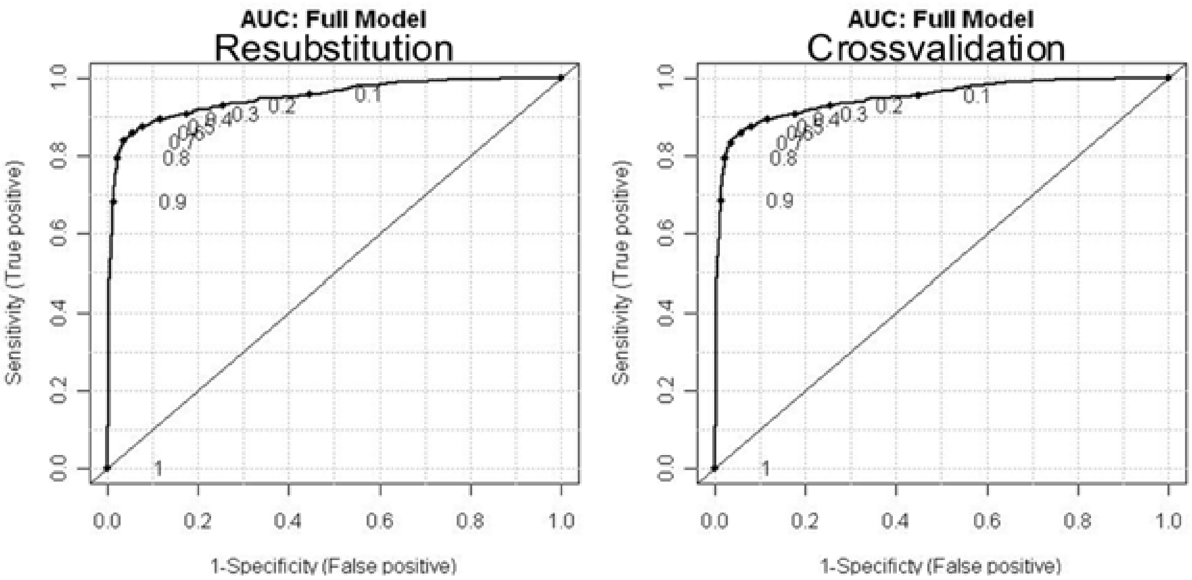


Fig. A.3.12: AUC of model FS for region Central-South.

A.3.2.4 Früh and Schröter including information of Soil Suitability Map

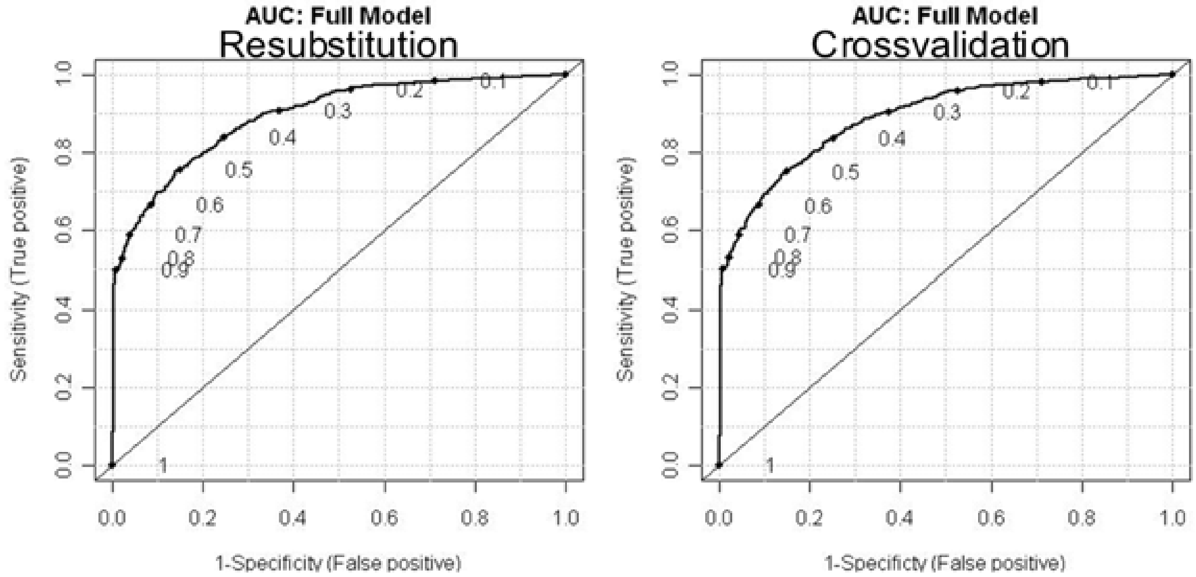


Fig. A.3.13: AUC of model FS-Soil for region Jura.

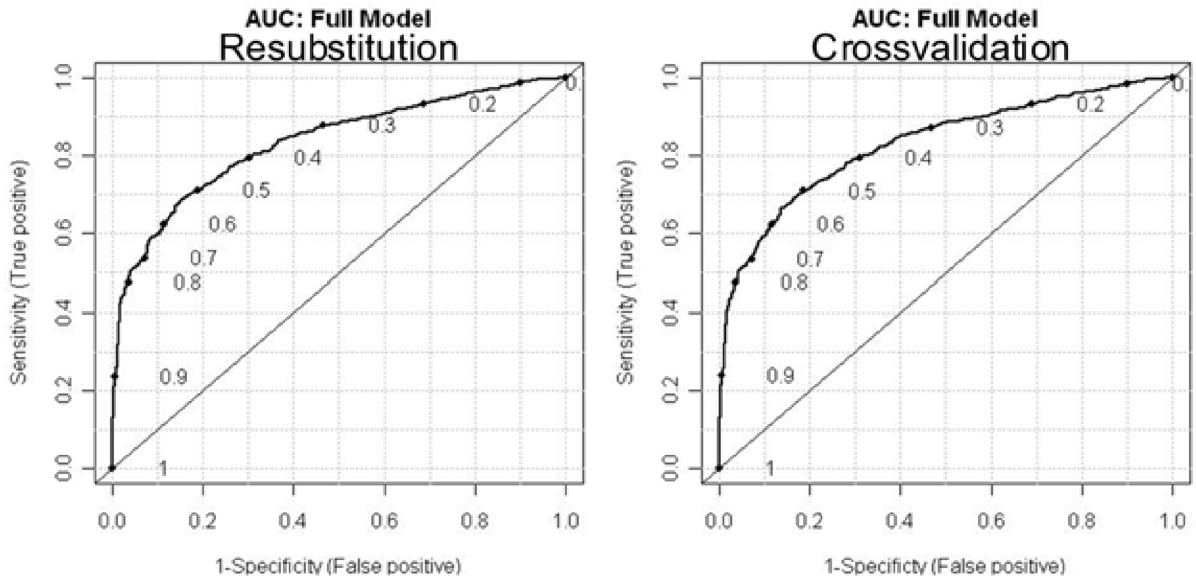


Fig. A.3.14: AUC of model FS-Soil for region Swiss Plateau.

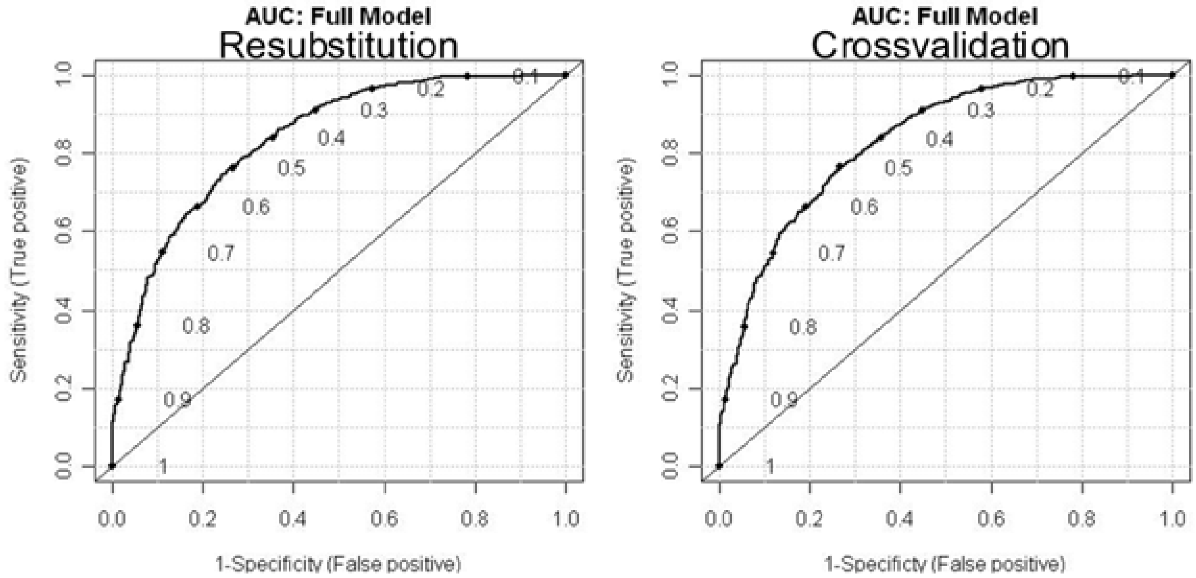


Fig. A.3.15: AUC of model FS-Soil for region Northern Alps.

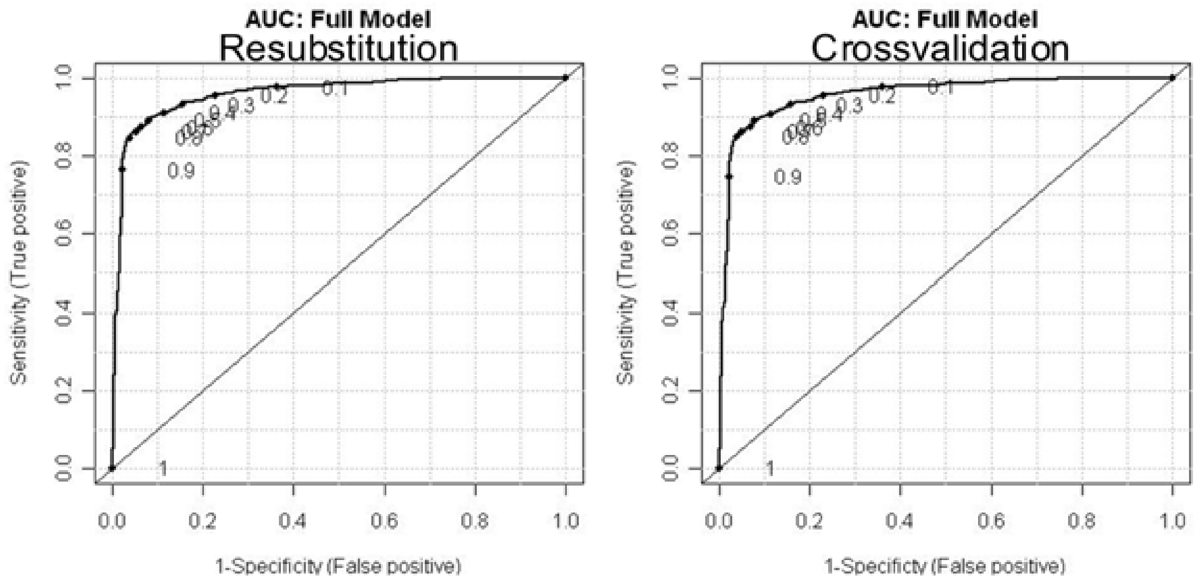


Fig. A.3.16: AUC of model FS-Soil for region Central-South.

A.3.2.5 Combined Layer

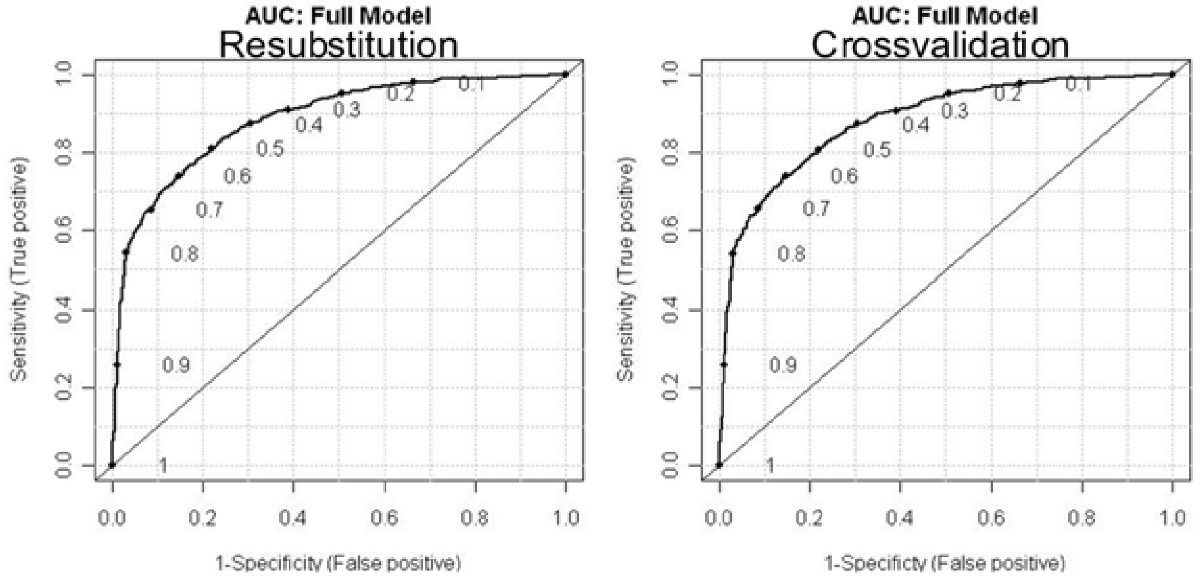


Fig. A.3.17: AUC of model FMHM-FS for region Jura.

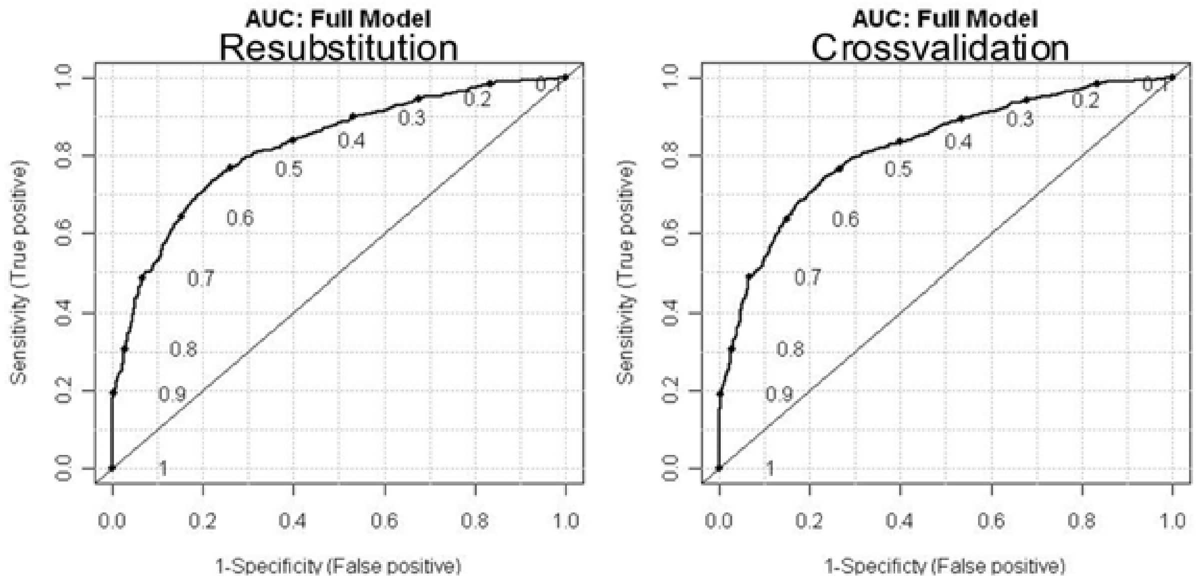


Fig. A.3.18: AUC of model FMHM-FS for region Swiss Plateau.

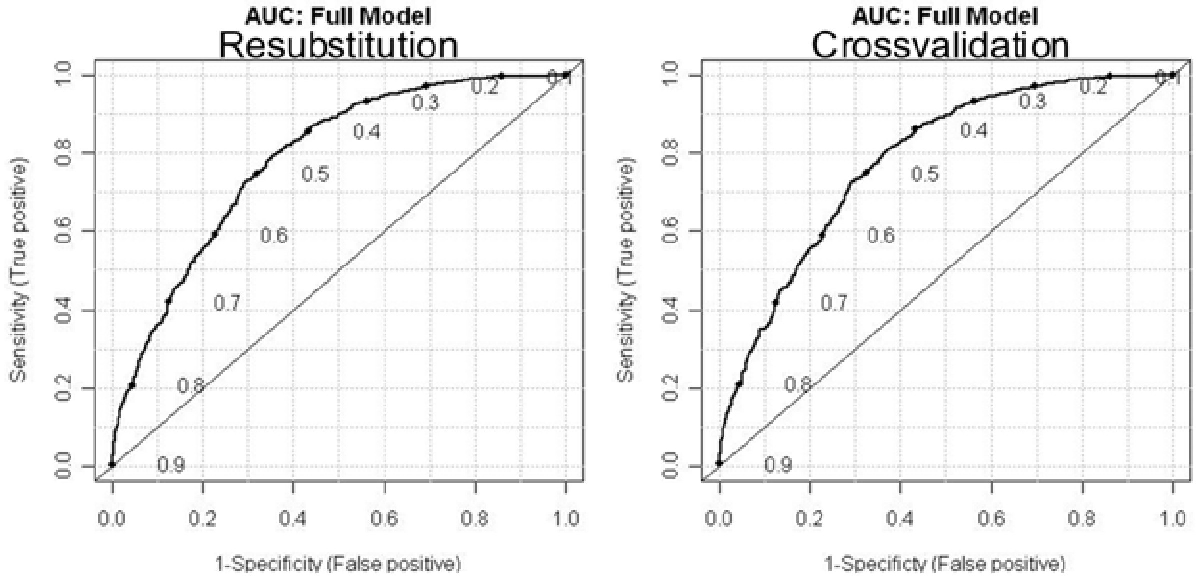


Fig. A.3.19: AUC of model FMHM-FS for region Northern Alps.

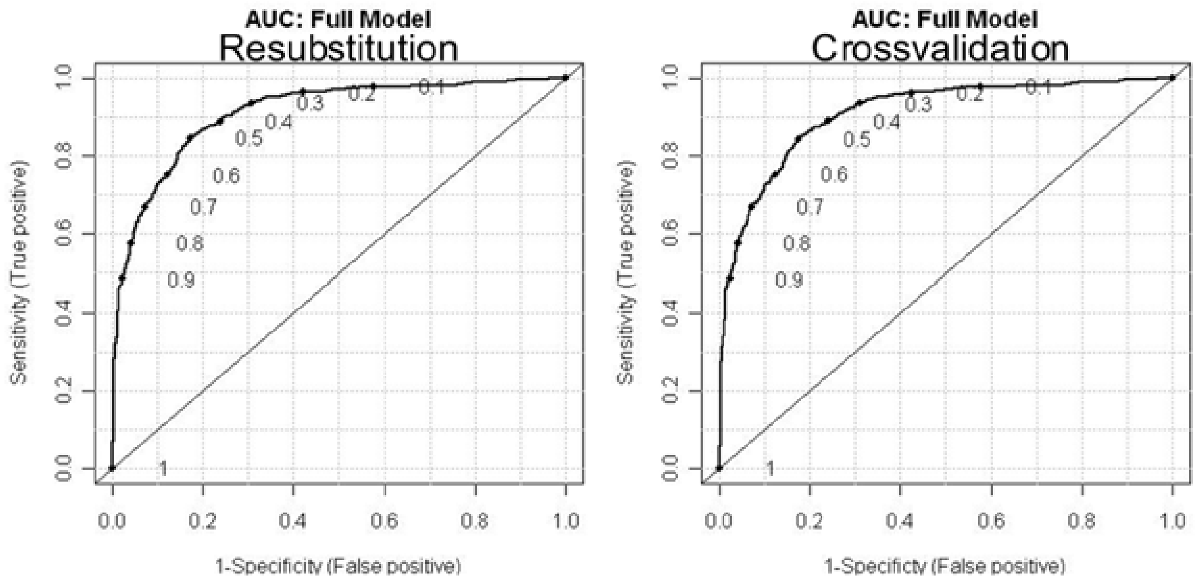


Fig. A.3.20: AUC of model FMHM-FS for region Central-South.

A.3.2.6 Combined Layer including information from Soil Suitability Map

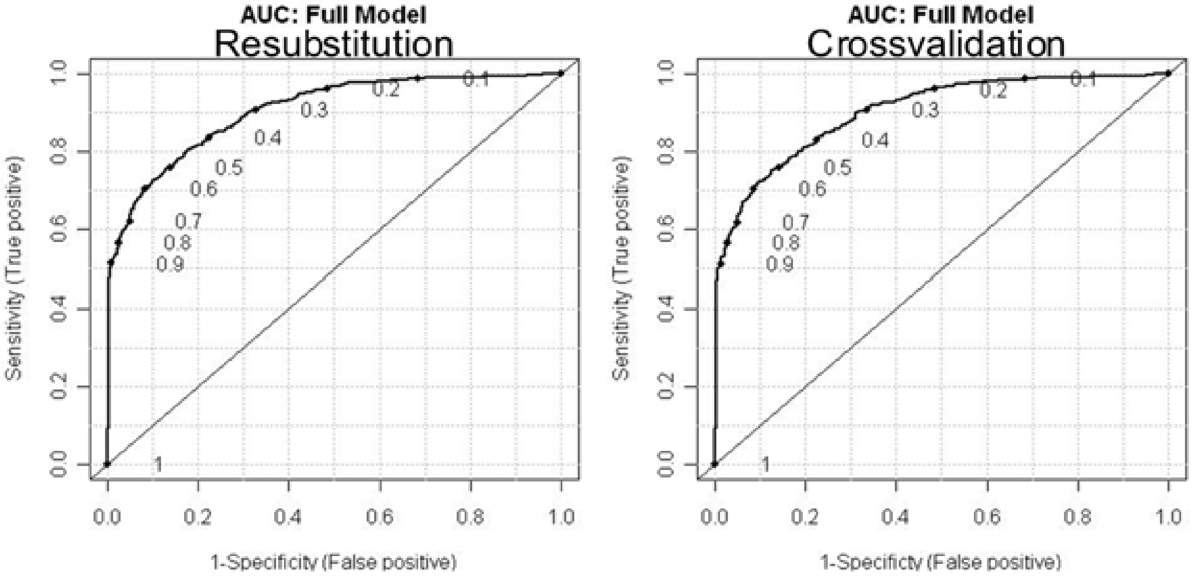


Fig. A.3.21: AUC of model FMHM-FS-Soil for region Jura.

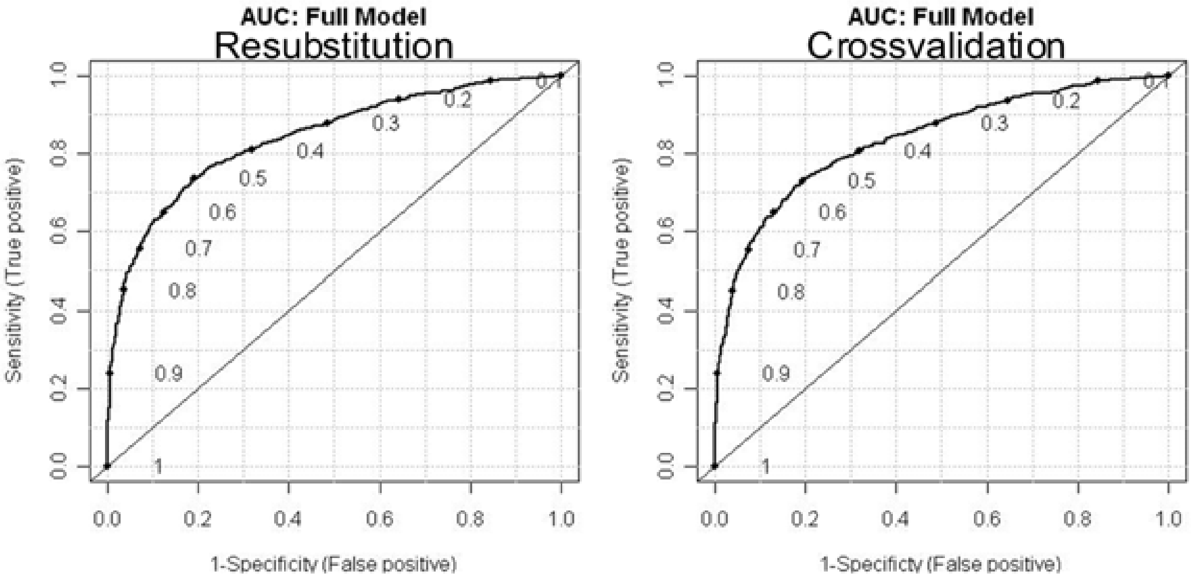


Fig. A.3.22: AUC of model FMHM-FS-Soil for region Swiss Plateau.

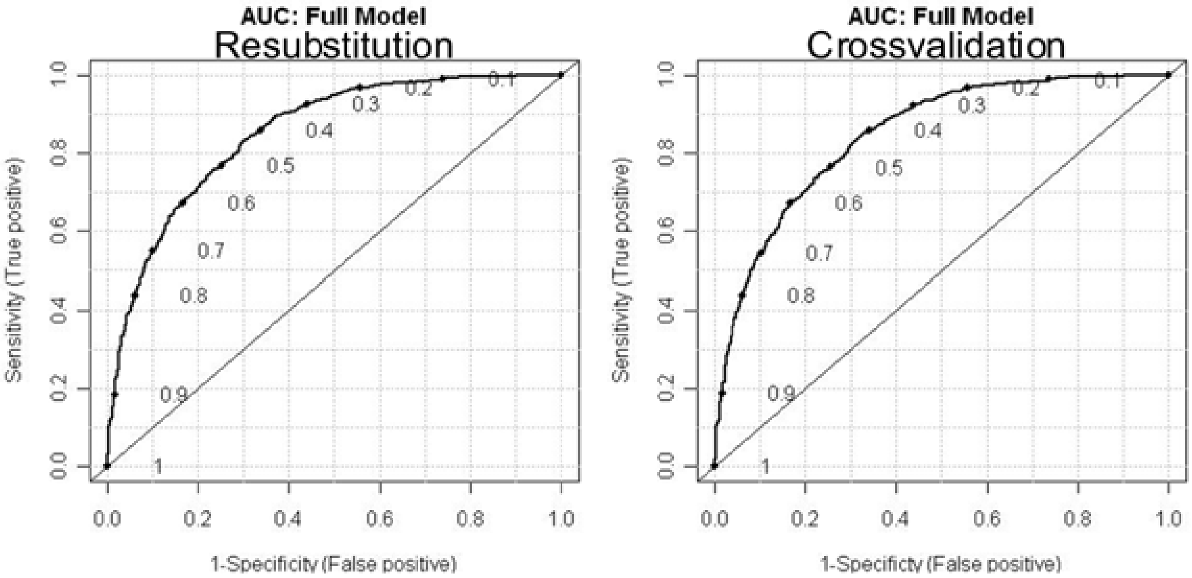


Fig. A.3.23: AUC of model FMHM-FS-Soil for region Northern Alps.

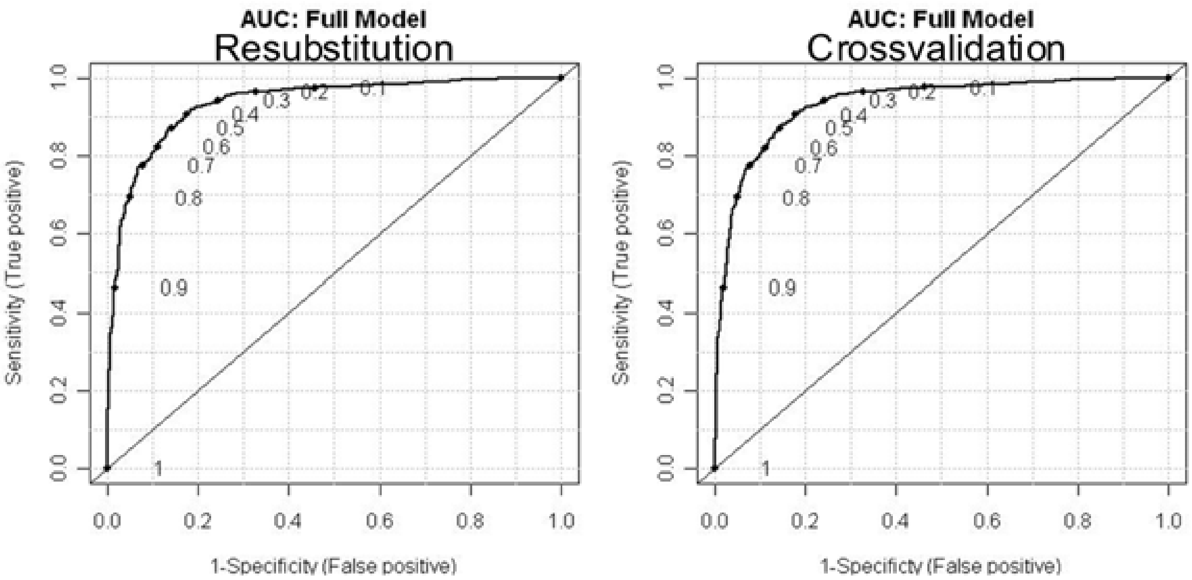


Fig. A.3.24: AUC of model FMHM-FS-Soil for region Central-South.

A.4 Verification on calibration area

A.4.1 Overview

Table A.4.1: Verification of the GLMs with the area of the combined layers of *Three federal inventories* and *Früh and Schröter*. The following abbreviations are used: Ju: Jura, Mi: Swiss Plateau, Al: Northern Alps, Cs: Central-South; FNR: False negative rate, MCR: Misclassification rate, FPR: False positive rate; Fill: Simple flood model, FMHM: Layer of *Three federal inventories*, FS: Layer of *Früh and Schröter*; Soil: Information of the *soil suitability map* is included. All values are given as percentage.

Model	Region	FNR	MCR	κ-Value	FPR
Flood Model	Ju	34.35	87.68	9.55	11.68
	Mi	21.59	63.84	7.41	34.74
	Al	77.92	94.75	12.42	4.75
	Cs	51.05	97.59	9.92	2.28
FMHM	Ju	48.04	91.03	10.22	8.46
	Mi	30.85	77.29	12.33	21.15
	Al	22.00	64.33	6.72	34.41
	Cs	11.60	77.29	1.64	22.52
FMHM-Boden	Ju	33.72	88.42	10.37	10.92
	Mi	31.38	79.94	14.35	18.43
	Al	21.57	71.49	9.73	27.02
	Cs	11.14	83.14	2.42	16.65
FS	Ju	21.45	83.43	8.45	15.82
	Mi	27.00	74.33	11.29	24.08
	Al	20.25	61.39	6.07	37.38
	Cs	48.29	94.79	4.87	5.08
FS-Boden	Ju	29.54	80.57	5.99	18.82
	Mi	32.70	82.68	16.70	15.64
	Al	24.25	69.56	8.32	29.09
	Cs	47.88	94.56	4.70	5.30
FMHM-FS	Ju	26.20	81.02	6.58	18.32
	Mi	26.25	73.68	11.07	24.72
	Al	19.85	61.85	6.27	36.90
	Cs	16.06	81.84	2.05	17.97
FMHM-FS-Boden	Ju	22.08	80.20	6.70	19.11
	Mi	26.84	78.21	14.13	20.07
	Al	19.65	69.82	9.28	28.68
	Cs	8.70	79.21	1.93	20.59

A.4.2 Jura

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	33.35	26.39	33.66	39.89	35.78	37.48	39.57
	nonwetsim	17.45	24.40	17.13	10.89	15.00	13.31	11.21
nonwet	wetsim	495.67	359.05	463.16	671.64	798.14	777.66	810.23
	nonwetsim	3748.62	3885.26	3777.43	3572.67	3442.45	3466.65	3430.36

	Fill	V7	V8	V10	V11	V12	V13
False neg	34.35	48.04	33.72	21.45	29.54	26.20	22.08
MCR	87.68	91.03	88.42	83.43	80.57	81.02	80.20
Kappa	9.55	10.22	10.37	8.45	5.99	6.58	6.70
False pos	11.68	8.46	10.92	15.82	18.82	18.32	19.11

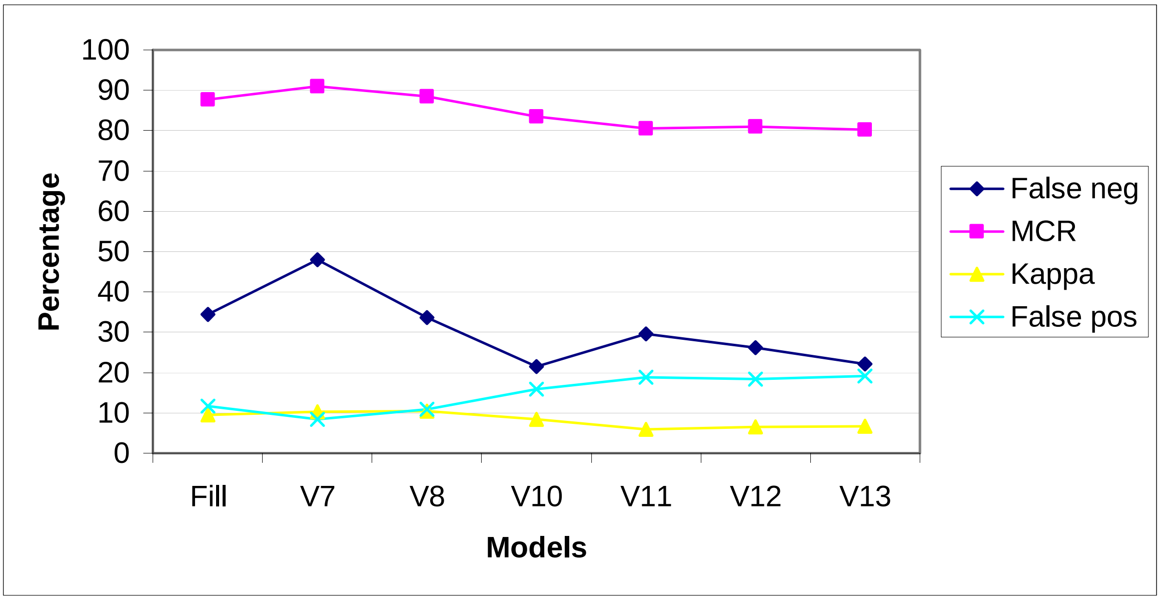


Fig. A.4.1: Comparison of different Models for the region Jura. Simulated areas are in km^2 and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.

A.4.3 Swiss Plateau

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	259.56	228.78	227.01	241.54	222.65	244.02	242.04
	nonwetsim	71.45	102.07	103.82	89.31	108.19	86.84	88.80
nonwet	wetsim	3422.74	2083.47	1814.44	2372.25	1540.58	2436.04	1976.10
	nonwetsim	6429.31	7769.46	8032.78	7480.69	8306.64	7416.90	7871.12
	False neg	21.59	30.85	31.38	27.00	32.70	26.25	26.84
	MCR	63.84	77.29	79.94	74.33	82.68	73.68	78.21
	Kappa	7.41	12.33	14.35	11.29	16.70	11.07	14.13
	False pos	34.74	21.15	18.43	24.08	15.64	24.72	20.07

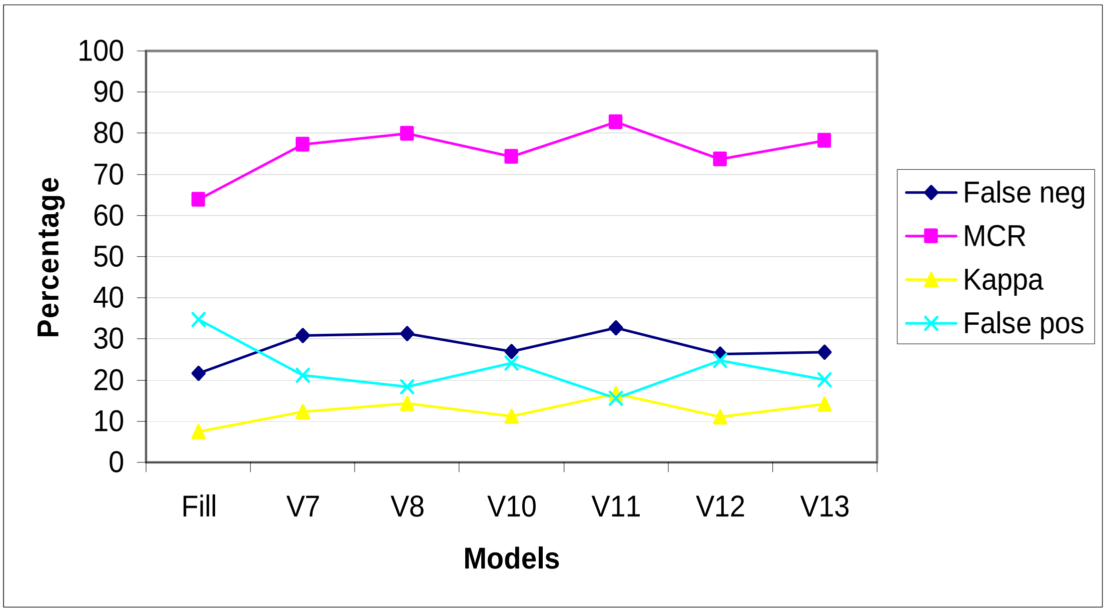


Fig. A.4.2: Comparison of different Models for the region Swiss Plateau. Simulated areas are in km² and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.

A.4.4 Northern Alps

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	71.60	253.01	254.40	258.69	245.71	259.96	260.62
	nonwetsim	252.73	71.36	69.97	65.67	78.65	64.40	63.74
nonwet	wetsim	516.54	3740.29	2936.27	4063.46	3161.53	4010.77	3117.08
	nonwetsim	10351.94	7129.86	7931.72	6806.70	7706.46	6859.39	7750.91

	Fill	V7	V8	V10	V11	V12	V13
False neg	77.92	22.00	21.57	20.25	24.25	19.85	19.65
MCR	94.75	64.33	71.49	61.39	69.56	61.85	69.82
Kappa	12.42	6.72	9.73	6.07	8.32	6.27	9.28
False pos	4.75	34.41	27.02	37.38	29.09	36.90	28.68

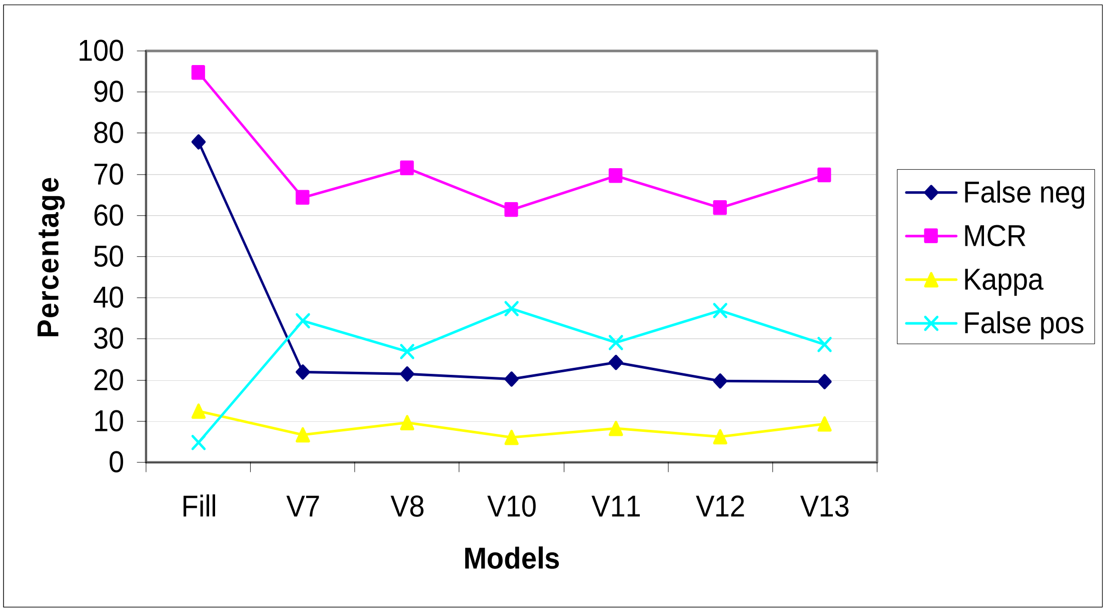


Fig. A.4.3: Comparison of different Models for the region Northern Alps. Simulated areas are in km^2 and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.

A.4.5 Central-South

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	19.89	35.91	36.10	21.01	21.17	34.10	37.09
	nonwetsim	20.74	4.71	4.52	19.62	19.45	6.53	3.53
nonwet	wetsim	322.56	3187.56	2355.37	718.71	749.86	2543.31	2912.35
	nonwetsim	13829.97	10963.93	11790.23	13432.78	13395.74	11608.18	11233.25
	False neg	51.05	11.60	11.14	48.29	47.88	16.06	8.70
	MCR	97.59	77.29	83.14	94.79	94.56	81.84	79.21
	Kappa	9.92	1.64	2.42	4.87	4.70	2.05	1.93
	False pos	2.28	22.52	16.65	5.08	5.30	17.97	20.59

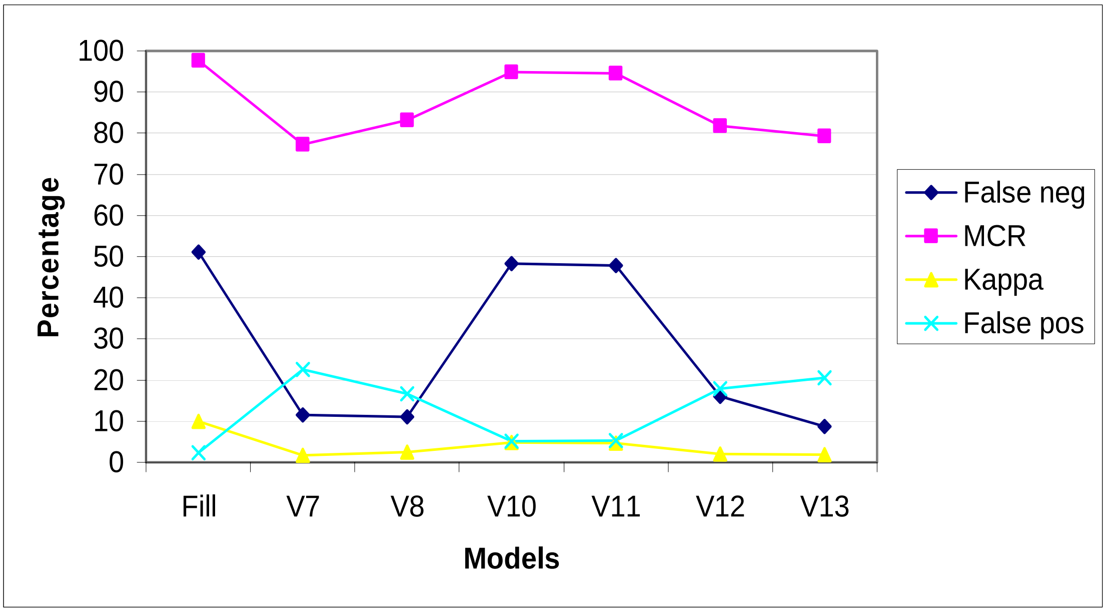


Fig. A.4.4: Comparison of different Models for the region Central-South. Simulated areas are in km² and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.

A.5 Validation with selected sheets of the Siegfriedkarte

A.5.1 Jura

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	1.40	1.55	1.64	1.32	1.71	1.67	1.73
	nonwetsim	0.40	0.24	0.15	0.47	0.08	0.13	0.07
nonwet	wetsim	17.51	32.06	38.92	24.36	59.41	47.76	54.14
	nonwetsim	138.06	123.52	116.66	131.22	96.17	107.82	101.44
	False neg	22.18	13.61	8.43	26.43	4.49	6.96	3.83
	MCR	87.98	78.64	74.23	83.68	61.16	68.59	64.50
	Kappa	11.67	6.74	5.70	7.64	3.31	4.42	3.86
	False pos	11.26	20.61	25.01	15.66	38.18	30.70	34.80

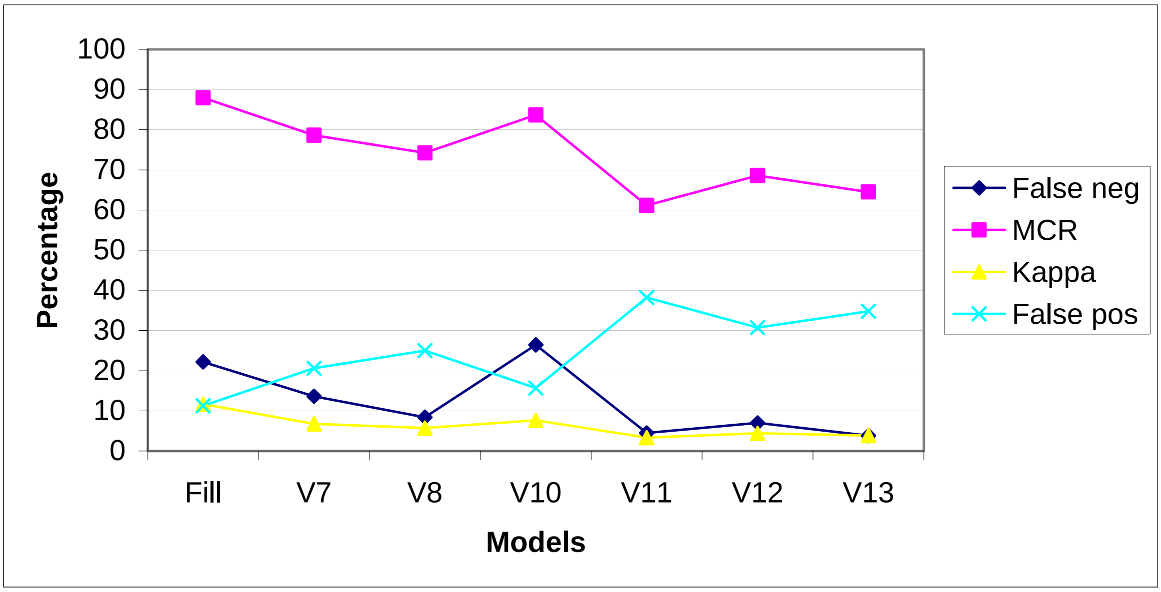


Fig. A.5.1: Verification on area with selected sheets of the Siegfriedkarte for the region Jura. Simulated areas are in km^2 and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. The model framed in blue is the model with the lowest FNR on the calibration area. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.

A.5.2 Swiss Plateau

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	1.27	1.26	1.19	1.12	1.01	1.19	1.12
	nonwetsim	0.21	0.24	0.30	0.37	0.48	0.30	0.38
nonwet	wetsim	29.33	23.14	21.99	17.62	11.04	20.33	15.61
	nonwetsim	74.03	80.21	81.36	85.73	92.31	83.02	87.74
	False neg	14.39	15.73	20.33	25.01	32.20	20.20	25.22
	MCR	70.81	76.72	77.89	82.12	88.51	79.47	84.04
	Kappa	5.37	7.23	7.16	8.66	12.75	7.91	9.91
	False pos	28.38	22.39	21.28	17.05	10.68	19.67	15.11

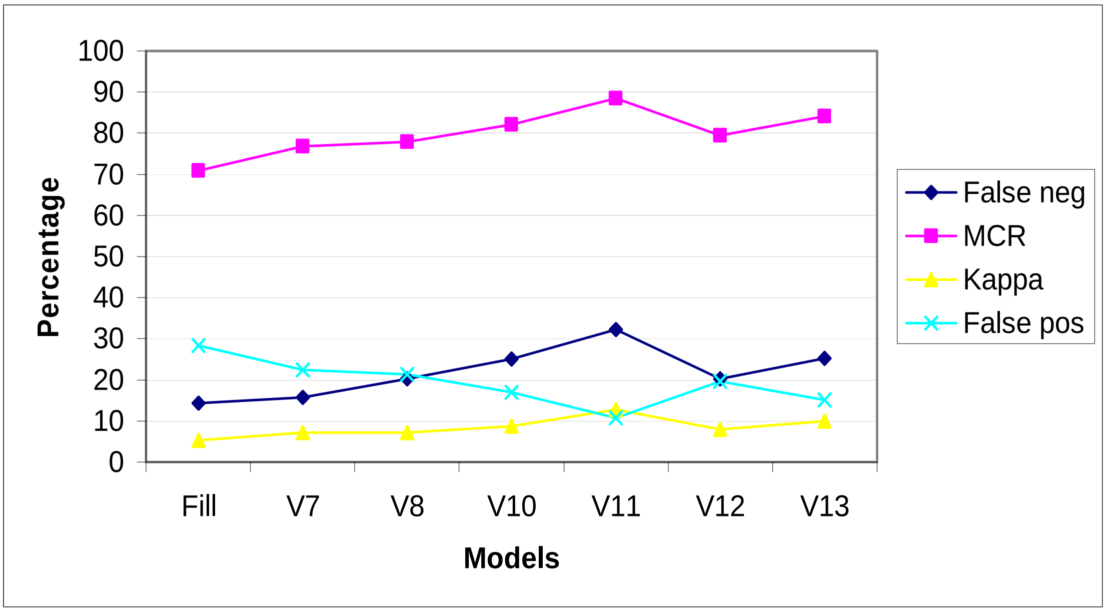


Fig. A.5.2: Verification on area with selected sheets of the *Siegfriedkarte* for the region Swiss Plateau. Simulated areas are in km^2 and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. The model framed in blue is the model with the lowest FNR on the calibration area. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.

A.5.3 Northern Alps

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	0.12	0.47	0.42	0.46	0.33	0.48	0.39
	nonwetsim	0.48	0.12	0.17	0.13	0.26	0.11	0.20
nonwet	wetsim	11.27	184.82	134.98	146.40	86.05	168.53	103.00
	nonwetsim	505.62	332.10	381.94	370.52	430.87	348.39	413.92
	False neg	80.44	20.15	29.48	22.48	44.22	19.19	34.68
	MCR	97.80	64.20	73.84	71.62	83.31	67.34	80.02
	Kappa	1.72	0.28	0.39	0.39	0.53	0.34	0.52
	False pos	2.18	35.75	26.11	28.32	16.65	32.60	19.92

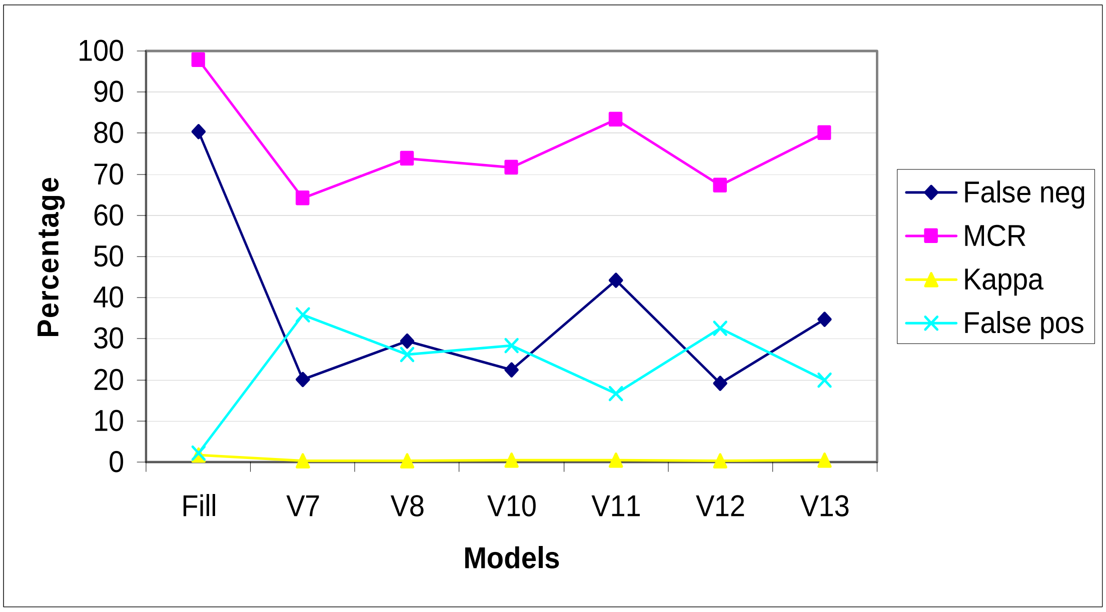


Fig. A.5.3: Verification on area with selected sheets of the *Siegfriedkarte* for the region Northern Alps. Simulated areas are in km^2 and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. The model framed in blue is the model with the lowest FNR on the calibration area. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.

A.5.4 Central-South

		Fill	V7	V8	V10	V11	V12	V13
wet	wetsim	2.83	3.26	3.26	2.97	2.85	3.26	3.29
	nonwetsim	0.52	0.08	0.08	0.37	0.49	0.09	0.05
nonwet	wetsim	27.24	98.48	105.49	39.57	33.54	98.49	134.04
	nonwetsim	389.01	318.08	311.08	376.99	383.02	318.07	282.52

	Fill	V7	V8	V10	V11	V12	V13
False neg	15.46	2.37	2.52	11.07	14.79	2.64	1.57
MCR	92.83	75.77	74.10	89.87	91.33	75.77	67.29
Kappa	15.73	4.74	4.34	11.66	13.07	4.73	3.17
False pos	6.54	23.64	25.32	9.50	8.05	23.64	32.18

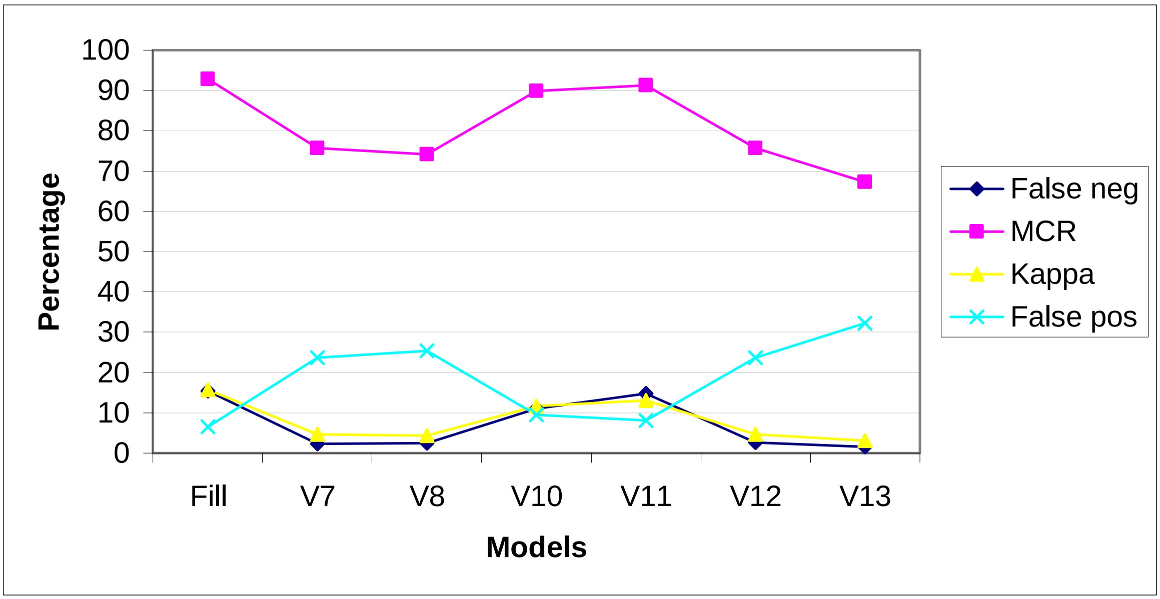


Fig. A.5.4: Verification on area with selected sheets of the *Siegfriedkarte* for the region Central-South. Simulated areas are in km^2 and indicator values are given as percentage. The model with the lowest false negative value is highlighted in yellow. The model framed in blue is the model with the lowest FNR on the calibration area. Fill: Simple flood model, V7: FMHM, V8: FMHM-Soil, V10: FS, V11: FS-Soil, V12: FMHM-FS, V13: FMHM-FS-Soil.