

# MoGLI: Potential Distribution Maps for Swiss Woody Species

a summary of methods and results

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We used Swiss National Forest Inventory (NFI) data to model the potential distribution of the most common woody species for the forested area of Switzerland and provide potential distribution maps that fulfill minimal quality criteria with regard to predicting performance. Distribution maps were produced based on the principles of species distribution modeling, where the known occurrence of species from the NFI is statistically related to environmental predictors. The potential distribution was then predicted for the entire forested area of Switzerland using the derived statistical relationship. Apart from traditional predictors such as climate or topography, MoGLI developed new predictors that describe forest structure using LiDAR (light detection and ranging; a method that scans the earth surface using laser-technology), and also used soil property maps to improve the accuracy of the spatial projections.

**The resulting maps can be viewed in a simple web-GIS application available at:  
<https://www.lfi.ch/produkte/mogli/mogli-en.php>**

## Methods

The exact procedure is divided into three steps: occurrence and environmental data processing, statistical modelling, and spatial prediction.

### Occurrence and Environmental Data

On the one hand, we used occurrence data of woody species from the Swiss National Forest Inventory (NFI). On the other hand, the project used information on environmental conditions available over the entire forested area of Switzerland. In addition to information on climate, topography and soil pH, satellite and LiDAR data were used for modelling. We used NDVI (normalized difference vegetation index) satellite data from the LANDSAT mission because they provide information on forest productivity. LiDAR data have been used to derive information on the vertical forest structure and can serve as a proxy to describe light conditions in forest stands. It has been shown that such structural features can especially improve the model quality for (shrub) species that require light such as the common juniper (*Juniperus communis* L. subsp. *communis*) and the blackthorn (*Prunus spinosa* L.), see Wüest et al. (2020) for more details.

### Modeling Procedure

Five different statistical models (GLMs, GAMs, MaxEnt, random Forests, artificial neural networks) were used to explain the presence (or absence) of species at the NFI sampling locations. The quality of the models was checked by cross-validating for each species how well the models predict the occurrence (or absence) for the respective species. In cross-validation, the NFI data set was randomly divided into 70% training and 30% test data. All five models were then generated with the training data, and the predictions of these models were compared with the actual observed occurrences/absences in the test data. The quality of the predictions was assessed using the True Skills Statistics (*TSS*). This procedure was repeated a hundred times, and an average *TSS* value was calculated for each species. *TSS* values can vary between zero (worst possible model) and one

(perfect model). Maps for species with insufficient model quality ( $TSS_{CV} < 0.5$ ) have not been published to ensure that only reliable species maps are available for download.

## Creating Maps

In the final step, the statistical models were used to predict the occurrence of the woody species for the entire Swiss forest area. The MoGLI project provides three products. The first product, the so-called ensemble map, is the average predicted probability of occurrence of a species. For this, the predicted values from the five statistical models were averaged, resulting in values between zero and one (the ensemble probability maps are provided in percent ranging from 0% to 100%). The second product provides information on how much the models differ in their predictions. This was calculated as the standard deviation across the five models, with large values indicating high discrepancies between the models (the standard deviation maps are provided as standard deviations multiplied by 100). The third product, so-called consensus maps, provides information about both the probability of occurrence and the uncertainty associated with the forecast. This was achieved by providing three classes, whereby two classes are assigned low uncertainty and indicate either the occurrence or absence of a species, while the third class does not provide any information on the potential current occurrence due to too much uncertainty. The consensus maps contain values ranging from one to three that indicate:

- 1 := occurrence unlikely
- 2 := occurrence uncertain
- 3 := occurrence likely

## Results

### Prediction Quality

Table 1 gives Details on the number of presences ( $N_{\text{presences}}$ ) that were observed in the NFI. It also indicates how many climate ( $N_{\text{clim}}$ ), terrain attribute ( $N_{\text{terat}}$ ), linear feature ( $N_{\text{lin}}$ ), and remotely sensed predictor variables ( $N_{\text{rs}}$ ) were used.  $N_{\text{total}}$  declares the total number of predictor variables that the models used.  $TSS_{CV}$  indicates the average  $TSS_{CV}$  value in cross validation (where  $TSS_{CV} = 0$  would indicate the worst possible model and  $TSS_{CV} = 1$  would indicate a perfect model).

**Table 1** Modeled species for which the model quality was above the given threshold ( $TSS_{cv} > 0.5$ ). For all of these species potential distribution maps are available (<https://www.envidat.ch/dataset/mogli-sdm>). The table further includes the number of presences of each species in the NFI data ( $N_{\text{presences}}$ ), the total number of variables used for modeling the species ( $N_{\text{total}}$ ) the number of variables used per category (climate:  $N_{\text{clim}}$ ; terrain attributes:  $N_{\text{terat}}$ ; linear distance features:  $N_{\text{lin}}$ ; remote sensing:  $N_{\text{rs}}$ ), and the average TSS of all cross-validation runs across all models ( $TSS_{CV}$ ).

Species	$N_{\text{presences}}$	$N_{\text{clim}}$	$N_{\text{terat}}$	$N_{\text{lin}}$	$N_{\text{rs}}$	$N_{\text{total}}$	$TSS_{CV}$
<i>Abies alba</i> Mill.	2307	20	33	6	9	68	0.524
<i>Acer campestre</i> L.	275	13	5	7	2	27	0.642
<i>Acer opalus</i> Mill.	73	5	1	0	1	7	0.787
<i>Acer platanoides</i> L.	236	12	3	5	3	23	0.508
<i>Alnus glutinosa</i> (L.) Gaertn.	85	5	3	0	0	8	0.600
<i>Alnus incana</i> (L.) Moench	275	7	17	0	3	27	0.528
<i>Alnus viridis</i> (Chaix) DC.	325	12	11	5	4	32	0.677
<i>Amelanchier ovalis</i> Medik.	33	2	0	0	1	3	0.639
<i>Berberis vulgaris</i> L.	175	12	2	0	3	17	0.622

<i>Carpinus betulus</i> L.	282	12	10	5	1	28	0.720
<i>Castanea sativa</i> Mill.	211	13	3	0	5	21	0.872
<i>Clematis vitalba</i> L.	230	12	5	4	2	23	0.563
<i>Cornus sanguinea</i> L.	389	14	15	6	3	38	0.636
<i>Cotoneaster tomentosus</i> Lindl.	53	3	0	0	2	5	0.603
<i>Crataegus monogyna</i> Jacq.	336	13	9	6	5	33	0.555
<i>Crataegus laevigata</i> (Poir.) DC.	207	13	3	4	0	20	0.557
<i>Cytisus scoparius</i> (L.) Link	57	5	0	0	0	5	0.887
<i>Daphne laureola</i> L.	61	4	2	0	0	6	0.704
<i>Euonymus europaeus</i> L.	245	9	8	7	0	24	0.657
<i>Fagus sylvatica</i> L.	3142	20	34	7	10	71	0.669
<i>Fraxinus excelsior</i> L.	2006	17	36	8	9	70	0.542
<i>Hedera helix</i> L.	907	15	35	6	10	66	0.622
<i>Hippocrepis emerus</i> (L.) Lassen	32	2	1	0	0	3	0.606
<i>Ilex aquifolium</i> L.	359	13	11	5	6	35	0.548
<i>Juglans regia</i> L.	189	11	3	4	0	18	0.563
<i>Juniperus communis</i> L. subsp. <i>communis</i>	151	8	3	0	4	15	0.615
<i>Juniperus communis</i> subsp. <i>alpina</i> Celak.	130	5	1	3	4	13	0.746
<i>Laburnum alpinum</i> (Mill.) Bercht. & J. Presl	36	2	1	0	0	3	0.551
<i>Laburnum anagyroides</i> Medik.	41	4	0	0	0	4	0.643
<i>Larix decidua</i> Mill.	1019	19	35	8	10	72	0.605
<i>Ligustrum vulgare</i> L.	294	12	7	7	3	29	0.669
<i>Lonicera caerulea</i> L.	62	5	0	1	0	6	0.504
<i>Lonicera xylosteum</i> L.	1179	15	33	7	10	65	0.509
<i>Ostrya carpinifolia</i> Scop.	32	3	0	0	0	3	0.853
<i>Picea abies</i> (L.) H. Karst.	4175	18	36	8	10	72	0.528
<i>Pinus cembra</i> L.	186	12	1	3	2	18	0.874
<i>Pinus mugo</i> subsp. <i>uncinata</i> (DC.) Domin	92	5	0	1	3	9	0.696
<i>Pinus mugo</i> Turra subsp. <i>mugo</i>	50	3	0	0	2	5	0.790
<i>Pinus sylvestris</i> L.	490	13	21	6	9	49	0.529
<i>Prunus avium</i> L.	610	14	31	6	10	61	0.510
<i>Prunus padus</i> L.	157	8	6	1	0	15	0.612
<i>Prunus spinosa</i> L.	153	9	2	4	0	15	0.551
<i>Pseudotsuga menziesii</i> (Mirb.) Franco	84	3	5	0	0	8	0.638
<i>Quercus petraea</i> Liebl.	295	15	5	5	4	29	0.581
<i>Quercus pubescens</i> Willd.	69	6	0	0	0	6	0.783
<i>Quercus robur</i> L.	344	10	18	6	0	34	0.607
<i>Rhododendron ferrugineum</i> L.	369	10	14	6	6	36	0.782
<i>Ribes alpinum</i> L.	83	6	2	0	0	8	0.579
<i>Robinia pseudoacacia</i> L.	36	3	0	0	0	3	0.681
<i>Sorbus chamaemespilus</i> (L.) Crantz	36	3	0	0	0	3	0.614
<i>Taxus baccata</i> L.	96	5	3	0	1	9	0.529
<i>Tilia cordata</i> Mill.	237	14	2	2	5	23	0.525

<i>Ulmus glabra</i> Huds.	476	16	18	6	7	47	0.526
<i>Vaccinium myrtillus</i> L.	369	14	9	5	8	36	0.575
<i>Viburnum lantana</i> L.	378	11	13	6	7	37	0.532
<i>Viburnum opulus</i> L.	240	10	8	6	0	24	0.531

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## References

Wüest, R. O., Bergamini, A., Bollmann, K., & Baltensweiler, A. (2020). LiDAR data as a proxy for light availability improve distribution modelling of woody species. *Forest Ecology and Management*, 456, 117644. <https://doi.org/10.1016/j.foreco.2019.117644>