Modelling the effect of changing snow cover regimes on alpine plant species distribution in Alpine context

Jean-Pierre DEDIEU [1], Christophe RANDIN [2], Massimiliano ZAPPA [3], Stefan DULLINGER [4]

[1] University of Grenoble Alpes, CNRS, LTHE (UMR 5564), F-38000 Grenoble, France
[2] UNIBAS, University of Basel, Schönbeinstrasse 6, CH-4056 Basel, Suisse.
[3] WSL-SLF, Swiss Federal Institute for Forest, Snow and Landscape, Birmensdorf, CH-8903, Suisse
[4] Dep. of Conservation Biology, Vegetation- and Landscape Ecology, Univie, Rennweg 14, 1030 Vienna, Austria.

ABSTRACT: Snow cover is a critical parameter for the distribution of plant species in alpine regions. Earlier snow melt and an elongation and/or shift of the snow-free period - as a result of increasing summer temperatures observed since the 1990's – might hence severely alter the spatial pattern of suitable habitats for many alpine plants. Here, we use two spatially-explicit and physically-based snow distribution models (PREVAH and SnowModel) to develop various snow cover maps (SCMs) at a 20m resolution for a high mountain landscape in Austria. We use four different mountain ranges in the North-eastern Calcareous Alps (Mt. Hochschwab, Mt. Rax, Mt. Schneealpe and Mt. Schneeberg; overall area of about 150 km^2). SCMs will first be evaluated with SPOT-HRVIR images. After successful evaluation, accordant SCMs will be simulated under various scenarios of temperature, precipitation and wind regime changes for the middle and the end of the 21st century (A2 IPCC scenario). These SCMs are finally used as additional predictor variables in species distribution models (SDMs) to assess potential modification in the area and connectivity of the habitats of a set of alpine plants, in particular those confined to sites with long-lasting snow cover ("snowbeds"). The main parameters analyzed are the timing and duration of the snow period to provide spatial projection of species distribution under current and future climate conditions. SDMs results indicate that changes on snowbeds species may be buffered (2050's) but then could become stronger at the end of the century.

KEYWORDS: Snow, Mountains, Climate Change, Alpine Ecology.

1 INTRODUCTION

Improving our understanding of interactions between climate, snow pack and alpine plant distribution at fine spatial resolutions (i.e. meters) is an enduring goal of alpine plant ecology. Quantifying these interactions is required to predict future changes in alpine plant species diversity and distribution given anticipated temperature and precipitation changes. Earlier snow melt and an elongation and/or shift of the snow-free period - as a result of increasing temperatures observed since the 1990's in some regions of the Alps (Marty 2008; Marty and Blanchet 2012) might hence severely alter the spatial pattern of suitable habitats of highly specialized plants of snowbed communities.

In recent years, species distribution models (SDMs) have become a powerful method for obtaining effective primary assessments of the potential ecological impact of rapid climatic change on alpine plant species (Engler *et al.* 2011). However, improvements are still required to provide robust projections of SDMs in complex landscapes such as mountain systems and these empirical models have reached their limits at fine scale and high resolution. Geographic projections of SDMs are mostly based on models which correlate only climatic data and topographical variables with current species distributions and thus implicitly assuming that this combination of site features adequately represent the factors that actually drive species occurrence in high-mountain landscapes. However, among these factors, snow depth is known to be one of the most important in temperate and boreal mountain ecosystems (Randin *et al.* 2009) as it is the main determinant of growing season length and additionally affects winter soil temperatures, thus controlling nutrient turnover rates and availability, as well as moisture conditions during the onset of plant growth. Although snow depth is certainly related to temperature, precipitation and topography, the usually simple and additive combination of these variables SDM is likely not an adequate representation of how these, and other, factors interact in driving the spatio-temporal pattern of snow depth in mountain ecosystems. In fact, sophisticated hydrological models exist which allow for predicting these patterns from various input parameters

Corresponding author adress: Jean-Pierre Dedieu, LTHE-CNRS Laboratory, University of Grenoble-Alpes, France.,tel: +33 4 56 52 09 77; fax: +33 4 76 63 58 87,
Email: jean-pierre.dedieu@ujf-grenoble.fr

via based algorithms. Obviously, the output of these models would deliver a highly appropriate input for predictions of current and future mountain species distributions but is has never been used in this context so far, probably because the links between hydrological and biodiversity modelers are poorly developed.

As a first step into this direction, we first compare two hydrologically based models of snow distribution (PREVAH and Snowmodel) with respect to their ability to reliably predict attributes of the snow cover which are particularly relevant for plant species distribution, namely gradual reduction of snow depth during the melt-out period in spring. We then used the spatially-explicit and physically-based snow distribution model (Snowmodel) under the A2 IPCC scenario for the middle and the end of the 21st century to predict the combined effect of changing climate and snow cover on alpine plant species in the Alps. For this, we used four different mountain ranges in Austria as a model system and five SDMs techniques to assess potential modification in the area and connectivity of the habitats of a set of 58 alpine plants, in particular those confined to sites with long-lasting snow cover ("snowbeds").

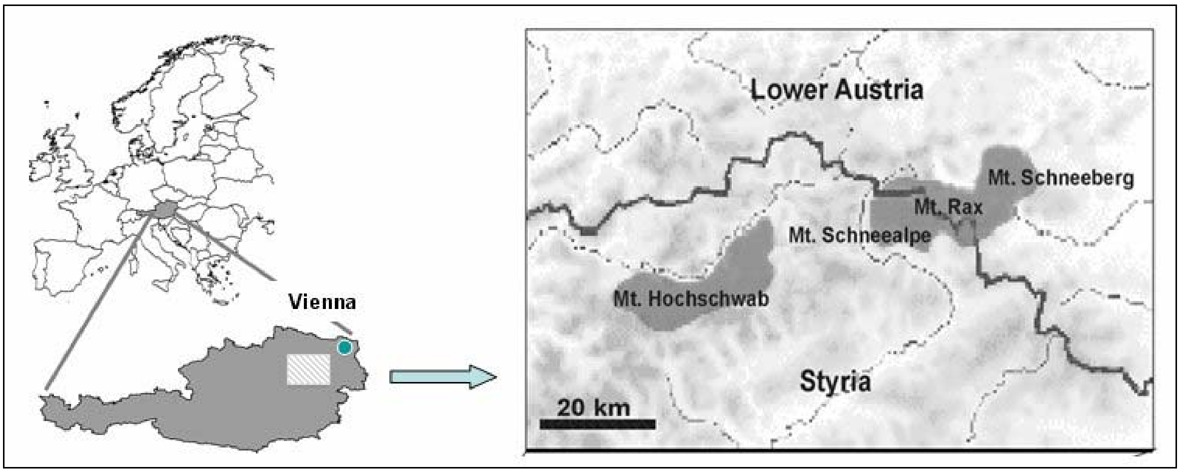

Figure 1: Study area location

2 METHODS

2.1 Study area

We used the alpine zone of four mountain ranges of the North-eastern Calcareous Alps (47° 40' N, 15° 30' E; Mts Schneeberg, Schneealpe, Rax and Hochschwab; as a model system (Figure 1). Summits vary between 1900 and 2300 m a.s.l. and are largely covered by snow in winter. The mountain system consists of mesozoic limestone and dolomites and is characterized by displaced plateaus of different altitudes. Climate conditions are temperate humid. Mean annual temperature approximates 6–8 °C in the valleys decreasing to c. 0–2 °C in the summit region. Annual precipitation averages 700 mm (valleys) and 1500–2500 mm (summits).

2.2 *Models of snow distribution*

The semi-distributed hydrological modelling system PREVAH (Gurtz *et al.* 1999, 2003 ; PREecipitation-Runoff-EVApotranspiration HRU Model) has been developed especially to suit conditions in mountainous environments with their highly variable environmental and climatic conditions (Viviroli et al. 2009). SnowModel (Liston & Elder 2006) is a spatially distributed snow-evolution model. It is an aggregation of four submodels: MicroMet (Liston & Elder 2006) defines meteorological forcing conditions, EnBal calculates surface energy exchanges, SnowPack simulates snow depth and water-equivalent evolution whereas SnowTran-3D (Liston & Sturm, 1998; Liston *et al.* 2007) accounts for snow redistribution by wind. Simulated processes include snow accumulation, blowing-snow redistribution and sublimation, vegetation canopy interception, unloading, and sublimation, snow-density evolution and snowpack melt. Simulations with the two models were run at a daily time step for the 1981-2000 time period. Data used as forcing climate parameters in the simulations came from two sources : a first set of eleven stations were provided by the national meteorological office of Austria (ZAMG) and three additional stations located along a transect were obtained on Schneeberg from the Wiener-Wasser-Werke (WWW) and Technical University of Vienna (TU-Wien).

2.3 Validation of SDSEMs with SPOT images

We evaluated prediction of snow cover by PREVAH and Snowmodel with SPOT-HRVIR images. With spectral bands in the visible, near and middle infrared, the SPOT sensors are used to retrieve snow cover at a 20-m resolution. For our study, twelve relatively cloud free SPOT images were available for the years 1998-2000.

The relationships between PREVAH and SnowModel predictions and SPOT observations of snow cover were tested with linear regressions (N = 257'338 pixels). Snow cover predicted by PREVAH and SnowModel were compared together with a Spearman rank correlation test.

2.4 Simulations with PREVAH and SnowModel under climate change

We used one dataset of climate projections for the 2041-2050 period derived from the regional circulation model (RCM) MM5 (Dudhia *et al.* 1986), and another one for the 2081-2100 period derived from the global circulation model (GCM) HadCM3 (Carson 1999) developed by the UK Hadley Center for Climate Prediction and Research. Simulations of the two models were based on the A2 socio-economic scenario of the IPCC (Intergovernmental Panel on Climate Change; Nakicenovic & Swart 2000).

2.5 Species distribution modeling i

We used five techniques of species distribution models to provide spatial projections of the potential distribution of 58 plant species under current and future climate conditions: generalised linear models (GLM; McCullagh & Nelder, 1989), generalised additive models (GAM; Hastie & Tibshirani, 1986), the gradient boosting machine (GBM; Ridgeway 1999), the random forest technique (RF; Breiman 2001) and artificial neural networks (ANN ; Ripley 1996). SDMs were first calibrated with a set of five topo-climatic predicting variables (TC models) composed of growing degree-days with a 0-°C threshold, moisture index of the growing season, slope, curvature and global solar radiation of the growing season. Growing degree-days and moisture index were calculated for current and future climate conditions. Three snow-based predicting variables (SB ; Number of snow days, frost risk during snow-free days and final snow accumulation day) were derived from the daily simulations of Snowmodel under current and future climate conditions. Such predicting variables allowed for tracking spatial patterns of snowbed habitats or analysing whether emerging gaps or corridors could prohibit, respectively facilitate, adaptive migration of plants in the future. The predictive power of TC models and TC models including SB variables (TC+SB) was evaluated by running a 10-fold cross-validation (Van Houwelingen & Le Cessie 1990) on the calibration data set. During this cross-validation procedure, the original prevalence of the species presences and absences was maintained in each of the 10 runs. The true skill statistic (TSS; Allouche *et al.*, 2006) was used as a metric to assess the agreement between predicted and observed values. TSS evaluation value varies between 0 (random model) and 1 (perfect agreement).

An index was developed to compare the connectivity between projections of suitable habitats of the TC+SB models under current and future climate change conditions. Let CS_i be the number of cells predicted suitable in a 3x3 moving window of cells around a suitable focus cell i. Let CT_i be the total number of cells in the 3x3 cell window around the focus cell i. CT_i reaches a maximum of 8 if cells have not been removed by the mask. We calculated a connectivity index CI as follows:

$$\frac{\left(\sum_{i=1}^{N} \frac{CS_i}{CT_i}\right)}{N} \qquad (1)$$

The connectivity index reaches a maximum value of 1 when all cells surrounding the focus suitable cell are also suitable. We also developed an index of persistence to assess the remaining potential suitable surfaces for each species under climate change. This index is the ratio of the sum of surfaces potentially occupied and colonized under future climate conditions divided by the surface potentially occupied under current conditions. Species were classified into three categories of habitats (snowbed, ridge and non-specialized species). Comparisons of SDM predictive power, connectivity and persistence were performed among these three categories.

3 RESULTS

3.1 Validations of PREVAH and Snowmodel projections with SPOT images

The three linear regressions of snow cover (SC) showed all significant relationships (SC PREVAH ~ SC SPOT images; 0.97, SC SnowModel ~ SC SPOT images; 0.98, SC PREVAH ~ SC SnowModel; 0.97, all P-values < 0.05).

3.2 Snow-based predicting variables

An example of snow-based predicting variable (yearly averaged snow cover duration) is provided on Figure 2 for current and future climate conditions. The spatial pattern of snow cover duration was not necessarily correlated with elevation (as for other standard climatic variables) and was mostly driven by the topography and the dominant wind direction.

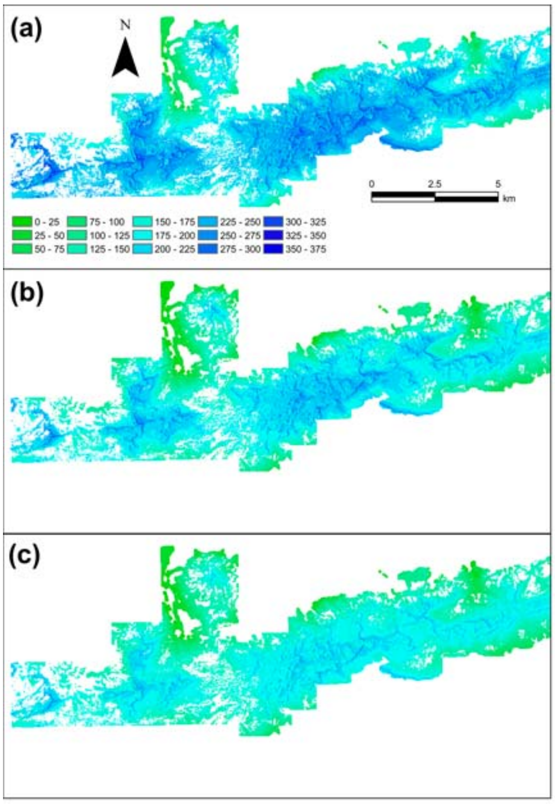

Figure 2: Snow cover duration (in days) under current conditions (a ; 1981-2000) and under the A2 scenarios for 2041-2050 (b : MM5 RCM) and 2081-2100 (c ; HadCM3 GCM).

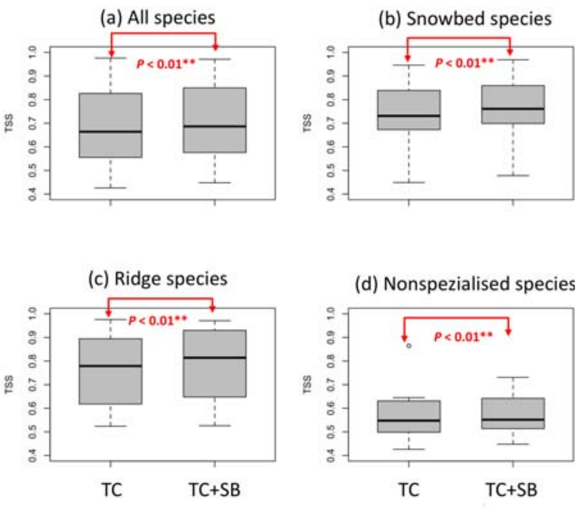

Figure 3: Predictive power (TSS) of species from different habitats (a: all species; b: snowbed; c: ridge and d: nonspecialized). TSS are provided for the best modeling technique (GBM) among the five techniques used.

3.3 Predictive power of TC and TC+SB models

The predictive power was significantly higher (Paired Wilcoxon tests; $P < 0.01$) when snow-based variables were included into topo-climatic models for the entire set of species (Figure 3a) and for species of the different habitats (Figure 3b-d):

3.4 Evolution of potential habitat connectivity

The connectivity was predicted to significantly decrease (Paired Wilcoxon tests; $P < 0.001$) under future climate conditions at the end of the century for the entire set of species (Figure 4a) and for specialized species of snowbeds and ridges (Figure 4b-c). Interestingly, no significant differences ($P > 0.05$) were found for non specialized species (Figure 4d).

3.5 Persistence of plant species under climate change

We showed that ridge species might become rapidly exposed to the effect of climate change (2050; Figure 5c). Impacts on snowbed species may be buffered (Figure 5b) but then could become stronger at the end of the century (Figure 5f). Non-specialized species may be less affected than specialized species in terms of persistence (Figure 5 d and h).

4

4. CONCLUSION

We were first able to successfully predict the sptatio-temporal pattern of snowcover in the complex terrain of a mountain region with the semi-distributed hydrological modelling system PREVAH and the spatially distributed snow-evolution Snowmodel. In a second step, we used species distribution modeling techniques to predict the combined effect of changing climate and snow cover on alpine plant species in the Alps under the A2 IPCC scenario for the end of the 21st century (2081-2100).

Snowmodel was used to derive snow-based predicting variables that significantly improved the predictive power of SDM compared to commonly-used topo-climatic variables. SDMs allowed for tracking spatial patterns of specialized habitats (i.e. ridges and snowbeds) and analysing whether emerging gaps or corridors could prohibit, respectively facilitate, adaptive migration of plants in the future.

We showed that ridge species might become rapidly exposed to the effect of climate change (2050[1]s). Impacts on snowbed species may be buffered (2050[1]s) but then could become stronger at the end of the century.

Non specialized species may be less affected than specialized species (i.e. ridge and snowbed species) in terms of persistence and connectivity of future suitable areas.

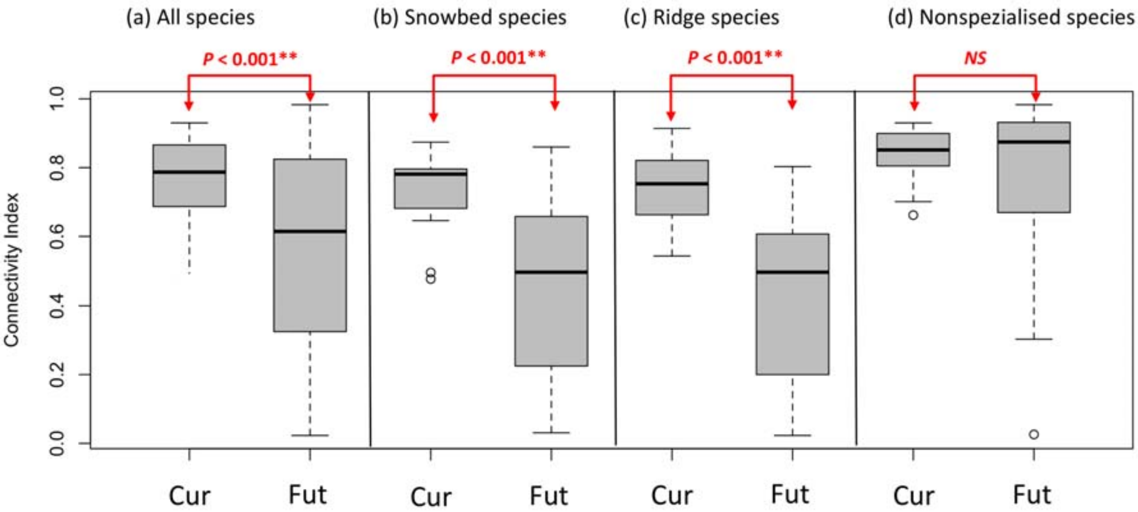

Figure 4: Connectivity index for the species of different habitats under current conditions (Cur) for the 1981-2000 period, and under the A2 scenario for 2081-2100 (Fut) driven by the HadCM3 GCM.

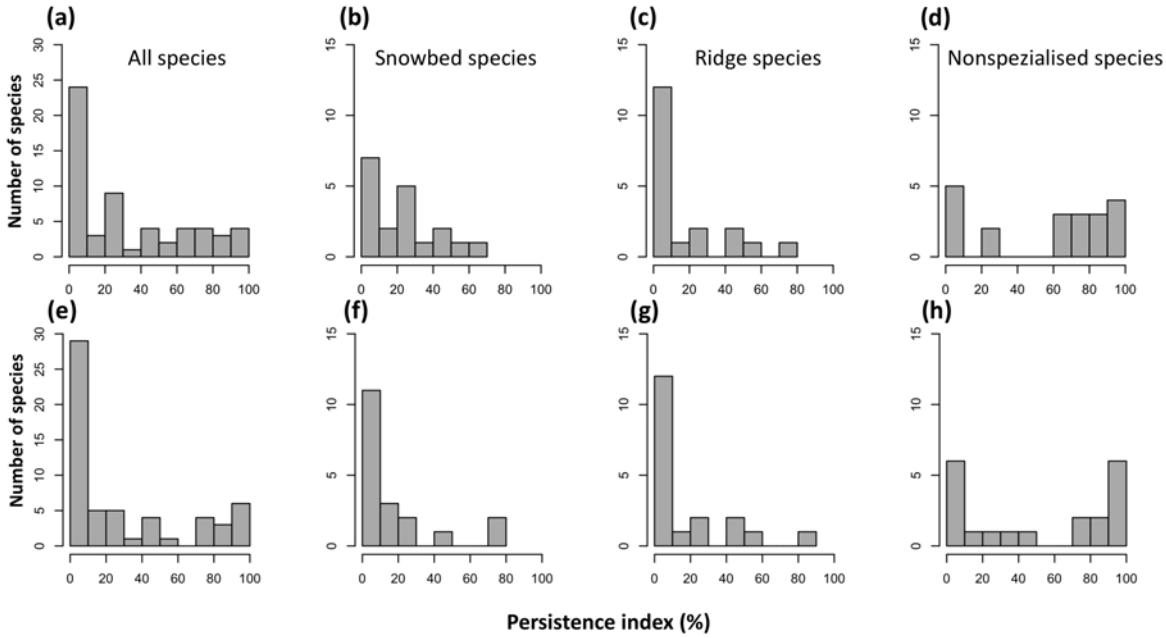

Figure 5: Persistence index for species of different habitats for the 2041-2050 period (a-d ; MM5 RCM) and for the 2081-2100 period (e-h ; HadCM3 GCM).

5 REFERENCES

Allouche, O., Tsoar, A. & Kadmon, R. (2006) Assessingthe accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology*, **43**, 1223-1232.

Breiman, L. (2001) Random Forests. *Machine Learning*, **45**, 5-32.

Carson, D.J. (1999) Climate Modelling: achievements and prospects. *Quarterly Journal of the Royal Meteorological Society*, **125**, 1:27.

Dudhia J., Gill D., Mannin K., Wang W. and Bruyere, C. (1986). PSU/NCAR Mesoscale Modeling System Tutorial class Notes and Users' Guide.

Engler, R., Randin, C.F., Thuiller, W., Dullinger, S., Zimmermann, N.E., Araújo, M.B., Pearman, P.B., Le Lay, G., Piédallu, C., Albert, C.H., Choler, P., Coldea, G., de Lamo, X., Dirnböck, T., Gégout,J.-C., Gómez-García, D., Grytnes, J.-A., Heegard, E., Høistad, F., Nogues-Bravo, D., Puscas, M., Sebasià, M.-T., Stanisci, A., Theurillat, J.-P., Trivedi, M.R., Vittoz, P. & Guisan, A. (2011) 21st century climate change threatens mountain flora unequally across Europe. *Global Change Biology*,

Gurtz, J., Baltensweiler, A. & Lang, H. (1999) Spatially distributed hydrotope-based modelling of evapotranspiration and runoff in mountain basins. *Hydrological Processes*, **13**, 2751-2768.

Gurtz, J., Zappa, M., Jasper, K., Lang, H., Verbunt, M., Badoux, A. & Vitvar, T. (2003) A comparative study in modelling runoff and its components in two mountainous catchments. *Hydrological Processes*, **17**

Hastie, T. & Tibshirani, R. (1986) Generalized Additive Models. *Statistical Sciences*, **1**, 297-318.

Liston, G.E. & Elder, K. (2006) A distributed snow-evolution modeling system (SnowModel). *Journal of Hydrometeorology*, **7**, 1259-1276.

Liston, G.E., Haehnel, R.B., Sturm, M., Hiemstra, C.A., Berezovskaya, S. & Tabler, R.D. (2007) Simulating complex snow distributions in windy environments using SnowTran-3D. *Journal of Glaciology*, **53**, 241-256.

Liston, G.E. & Sturm, M. (1998) A snow-transport model for complex terrain. *Journal of Glaciology*, **44**, 498-516.

Marty, C. (2008) Regime shift of snow days in Switzerland. *Geophysical research letters*, **35**

Marty, C. & Blanchet, J. (2012) Long-term changes in annual maximum snow depth and snowfall in Switzerland based on extreme value statistics. *Climatic Change*, **111**, 705-721.

McCullagh, P. & Nelder, J.A. (1989) *Generalized Linear Models. 2nd edition*. Chapman and Hall, London.

Nakicenovic, N. & Swart, R. (2000) *Emissions Scenarios: A Special Report of Working Group III of the Intergovermental Panel on Climate Change*. Cambridge University Press, Cambridge.

Randin, C.F., Vuissoz, G., Liston, G.E., Vittoz, P. & Guisan, A. (2009) Introduction of Snow and Geomorphic Disturbance Variables into Predictive Models of Alpine Plant Distribution in the Western Swiss Alps. *Arctic Antarctic and Alpine Research*, **41**, 347-361.

Ridgeway, G. (1999) The state of boosting. *Computing Science and Statistics*, **31**, 172-181.

Ripley, B.D. (1996) *Pattern Recognition and Neural Networks*. Cambridge Uuniversity Press, Cambridge.

Van Houwelingen, J.C. & Le Cessie, S. (1990) Predictive value of statistical models. *Statistics in Medicine*, **9**, 1303-1325.