



Short communication

Modeling sensitivity to climate change and estimating the uncertainty of its impact: A probabilistic concept for risk assessment in forestry

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ABSTRACT

Many uncertainties emerge dealing with future climate conditions and their possible impacts on forests. In this paper we suggest a probabilistic approach extending existing ensemble species distribution modeling concepts by addressing important sources of uncertainty. We exemplify our approach using European beech as the target tree species and bioclimatic predictors derived from WorldClim data. Model parameter uncertainty is represented by 1000 parameter samples from a Bayesian generalized linear model. Climate change impact (CCI) is based on 63 different climate model outputs using four RCP-scenarios (Representative Concentration Pathways) in addition to the parameter uncertainty. The proposed difference of the probability of occurrence p_{occ} to a predefined threshold, allows for evaluation of parameter uncertainty as well as for the uncertainty of future climate and describes the changing niche position. Further, we suggest the probability that the probability of occurrence exceeds a predefined threshold (p_{exc}) as a metric for the distance of a site to the niche edge. These metrics are unambiguously determinable, intuitive and evident. Stands at a central, a marginal and an intermediate niche position are taken to exemplify deduction and application of p_{occ} and p_{exc} . A regional exercise shows how a map of p_{exc} may support forest management planning and decision making under severe uncertainty. A key advantage of our novel metrics is the reformulation of common species distribution model (SDM) outputs in terms of risk thereby accounting for two important sources of uncertainty.

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1. Introduction

Forestry is particularly dependent of ambient climatic conditions, trees are long-lived organisms and their migration rates are often inadequate in relation to projected rates of climate change (CC). At large areas in Central Europe silviculture aims at close-to-nature stands derived from a range of regeneration methods (Brang et al., 2014). In the face of CC traditional concepts of tree species selection need supporting information about the climatic suitability of a tree species within a time-scale from several decades to about a century. After early applications (Booth and McMurtrie, 1988; Booth et al., 2014) species distribution models (SDM) have

recently gained attention in forest planning in Central Europe (Falk and Mellert, 2011; Mellert et al. 2011; Zimmermann et al., 2013; Hanewinkel et al., 2014). Along an environmental gradient, decreasing habitat suitability for a tree species is obviously associated with increasing problems such as, limited regeneration, reduced competitive strength, increased vulnerability to biotic hazards (Hanewinkel et al., 2014). In forest practice, a deterioration of habitat suitability due to CC infers risks for tree cultivation.

However, many uncertainties emerge dealing with future climate conditions and their possible influences on forests. Existing ensemble modeling approaches take these uncertainties into account. Araújo and New (2007) described a framework comprising initial conditions (1), model classes (2), model parameterization (3), boundary conditions (4), and different projections of climate scenarios (5) as elements of ensemble modeling (Fig. 1). Many approaches based on these principles have been published. For example BIOMOD is a widely used software package for ensemble modeling focusing on the variability of model classes (2) (Thuiller, 2003).

Instead, we suggest a probabilistic concept extending the framework described in Araújo and New (2007) (Fig. 1, step 5). As

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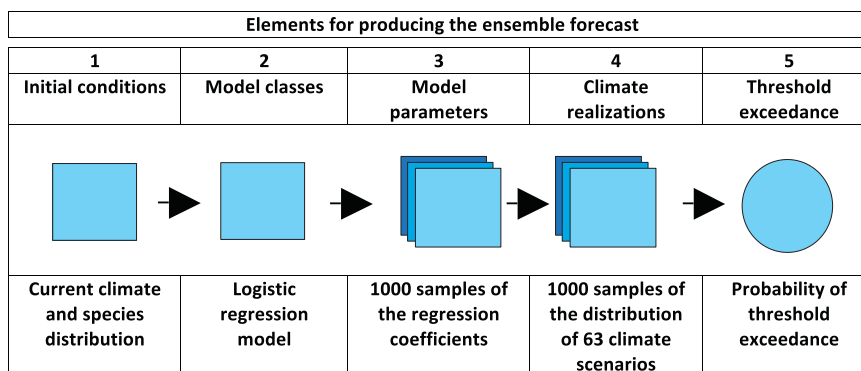


Fig. 1. Elements for ensemble forecasting (Step (1) to (3) c.f. Araújo and New, 2007). The presented example base on current climate (Step (1)) according to WorldClim (Hijmans et al., 2005), using logistic regression model as model class (Step (2)) with 1000 parameter samples (Step (3)) and samples from 63 future climate realizations available from WorldClim (Hijmans et al., 2005). Instead of producing multiple projections in step (5) (see Araújo and New, 2007), the suggested approach provides the probability for exceeding the threshold of occurrence as a single measure for the cultivation risk of a tree species at a site under future climate realizations. The squares represent different steps and the production of ensembles and circles represent the prediction from the model. (For interpretation of the references to color in figure legend, the reader is referred to the web version of the article.)

close-to-nature silviculture is widely applied in Central Europe (Brang et al., 2014), we aim at modeling the biotically reduced niche. We take *Fagus sylvatica* as the naturally dominating tree species in Central Europe at zonal site conditions as an example. Our species data comprise observed and potential species occurrences at Level-I monitoring plots (Fischer et al., 2010; Bohn et al., 2003). Our proposed extension refers to two of the five ensemble modeling elements: the uncertainty of model parameters (3) is involved through the posterior distribution of parameters; instead of producing multiple projections in step (5) of Araújo and New (2007) we suggest including the variation in the climate change signal provided by 63 future climate realizations according to Hijmans et al. (2005) by using the probability for exceeding a threshold of occurrence (Peterson et al., 2011, p. 119) as a single measure for the suitability of a site cultivating a tree species. The resulting climate change impact (CCI) is subject to the joint uncertainty in modeling and in climate development.

The discrepancy between the probability of occurrence under the current climate and the threshold resulting from applying the steps (1)–(3) indicates the distance of a site to the niche edge. This distance metric can be considered as the site marginality M (Mellert et al., 2015).

2. Material and methods

We used the presence/absence data from the Level I monitoring program of ICP Forests (Fischer et al., 2010), which involves 7569 plots in a 16×16 km grid throughout Europe (Fig. 2). Level I data were supplemented with information from the map of Natural Vegetation in Europe (Bohn et al., 2003). Each occurrence of beech (1014 cases) was considered as a presence, irrespective of stand history (natural occurrence or plantation). Additionally, the absences in Level I plots were converted to the presences (1364 cases) when located in the natural distribution area of the tree species according to Bohn et al. (2003). This procedure avoids fallacious absences of the species e.g. in landscapes where natural forests have been largely removed (Mellert et al., 2015). As *F. sylvatica* natural habitats are considered to be in equilibrium with current climate (Huntley et al., 1989), this data set allows for modeling the biotically reduced (bioclimatic) niche (Peterson et al., 2011, p. 30). Level I plot examples were taken from sites involved in the BioDiv and BioSoil project (Canullo et al., 2011; De Vos and Cools, 2011).

As bioclimatic predictors we used three BIOCLIM variables (Booth et al., 2014), the minimum temperature of the coldest month (T_{min}), the mean temperature of warmest quarter (T_{wq})

and the precipitation sum of the warmest quarter (P_{wq}) estimated by Hijmans et al. (2005) acting as proxies for the limitation due to chilliness and frost (T_{min}) as well as for summer heat (T_{wq}) and drought (P_{wq}). A quarter is a period of three consecutive months.

For the future climate we used 63 climate model outputs down-scaled to the 30 arc seconds resolution (Hijmans et al., 2005). The future climate data are climate projections from general circulation models (GCMs) for the four representative concentration pathways RCP 2.6, RCP 4.5, RCP 6 and RCP 8.5. These are the most recent GCM climate projections that are used in the Fifth Assessment IPCC report (IPCC, 2013). We used the GCM output which was downscaled and calibrated (bias corrected) using WorldClim 1.4 as baseline current climate. Further methodological details see www.worldclim.org/downscaling. Applied to our 7569 plots the mean changes between the current and the future climate are $\Delta T_{min} = +3.532^\circ\text{C}$, $\Delta T_{wq} = +3.529^\circ\text{C}$ and $\Delta P_{wq} = -6.871\text{mm}$.

The ecological niche of a tree species describes the environmental conditions which are suitable for the occurrence of the tree species (Peterson et al., 2011, p. 30). Using the probability of occurrence of a site as a simple measure for the description of its position in the ecological niche avoids having to deal with multidimensional environmental conditions.

The probability of occurrence $p_{occ}(s)$ of a tree species at site s depends on several conditions of this site, $C(s)$, including for example climatic and soil conditions. In the following we describe this association with the function f . However, local conditions, especially future conditions, are not fixed but fraught with uncertainty. Since the function f has to be estimated from data, also f is uncertain. Hence, the probability of occurrence depends in addition to the site also on the climatic conditions and on the parameters θ_f determining the function f , representing a two-dimensional random variable: $p_{occ}(\theta_f, C(s)) = f(C(s))$. The probability of occurrence for the present, fixed conditions at site s , $C_0(s)$, is given by the one-dimensional random variable $p_{occ}^0(\theta_f, C_0(s)) = f(C_0(s))$.

Using a threshold of occurrence t for the definition of the edge of a niche and for the conversion of predicted occurrence probabilities into the presence (1) and absence (0) is a basic principle in species distribution modeling (Peterson et al., 2011, p. 118). Such a threshold marks the cut-off value above which values indicate the presence and below which a species is assumed to be absent. In this sense the threshold of occurrence is an important inflection point in niche space.

There are several methods for thresholding available (Peterson et al., 2011, p. 119). When the proportions of the presences and absences are not equal within the sample, the logistic regression

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