COST
EUROPEAN COOPERATION
IN SCIENCE & TECHNOLOGY

SHORT TERM SCIENTIFIC MISSION (STSM) SCIENTIFIC REPORT

This report is submitted for approval by the STSM applicant to the STSM coordinator

Action number: CA18201
STSM title: Quantifying the effect of climate change on threatened forest plant species by incorporating microclimatic data into species distribution models.
STSM start and end date: 27/09/2021 to 15/10/2021
Grantee name: Stef Haesen

PURPOSE OF THE STSM

The overall goal of this Short Term Scientific Mission (STSM) was to model the effects of climate change on threatened forest plant species using SDMs. We recently developed gridded microclimatic temperature products at 25 m resolution across Europe (Haesen et al., 2021), which – for the first time – enable us to more accurately model the effects of climate change on the distribution of near-surface forest plant species. Within this STSM, we layed the foundation of (i) using SDMs to identify red-listed forest plant species that could potentially lose all of their habitat with suitable climatic conditions within certain European countries and (ii) evaluate the potential of microclimates to mitigate species loss and extinctions of threatened forest plant species induced by climate change. Furthermore, the results of this STSM can be used by policy makers and conservation managers in order to align regional and national nature conservation policy and practices with the problem of climate change.

DESCRIPTION OF WORK CARRIED OUT DURING THE STSMS

With this STSM, I further developed my skills within this field of ecological modelling. Due to the state-of-the-art knowledge offered by dr. Jonathan Lenoir, I am now able to build state-of-the-art SDMs. We considered *Actaea spicata* as our species of interest for this STSM, as it is listed as an endangered species within the Red List for Flanders. Upon return to the home institution, SDMs can be performed for additional red-listed species.

We opted to build species distribution models based on presence-only data in order to increase the amount of occurrence points (i.e. presence-absence data is less available). Therefore, we queried GBIF (Global Biodiversity Information Facility), which contains well sampled information over a large spatial area. We opted to use the MaxEnt (Maximum Entropy) algorithm, which is the most commonly used tool for species distribution modeling based on presence-only data (Merow, Smith, & Silander, 2013). These SDMs combine species' presence-only data with our macroclimatic/microclimatic predictor data to model the environmental suitability for *Actaea spicata*. Background data were generated by sampling equal amount of background point as occurrence points with a spatial density of the background points proportional to the spatial density of occurrence points. This approach has recently been suggested (Lake, Briscoe Runquist & Moeller, 2020; Vollering, Halvorsen, Auestad & Rydgren, 2019) and accounts for remaining spatial bias in the occurrence records (after thinning). To deal with common issues in SDMs, including spatial bias and bad model performance, we implemented MaxEnt in the R package ENMeval (Kass et al., 2021; Muscarella et al., 2014). Spatial autocorrelation issues are handled in ENMeval by using block cross-validation to validate the models (Roberts et al., 2017), which is certainly necessary as the SDMs are built upon spatially structured occurrence data. Model performance can be improved by tuning the model settings (e.g. feature classes = "Linear", "Product" and "Quadratic" and regularization multipliers = "0.5", "1", "2", "3", "4" and "5") in ENMeval rather than working with the default settings. Model performance was evaluated using the Continuous Boyce Index (CBI) rather than the commonly used AUC as it has recently been shown that the latter is subjected to bias in presence-only models (Jiménez-Valverde, 2012; Jiménez & Soberón, 2020). The CBI represents the correlation between predicted habitat suitability and the distribution of occurrence records (Hirzel, Le Lay, Helfer, Randin & Guisan, 2006) and ranges between -1 and 1, where values > 0 denote that the model is better than random. Finally, we calculated sensitivity for the model on an independent 20% dataset in order to quantify how good our model is able to distinguish between true positives and false negatives.

DESCRIPTION OF THE MAIN RESULTS OBTAINED

We found that our models for *Actaea spicata* performed well (CBI > 0.7) and that sensitivity was high (> 90%) under both macroclimatic and microclimatic conditions. Visually we can observe clear differences in the potential range of *Actaea spicata* (Figure 1).

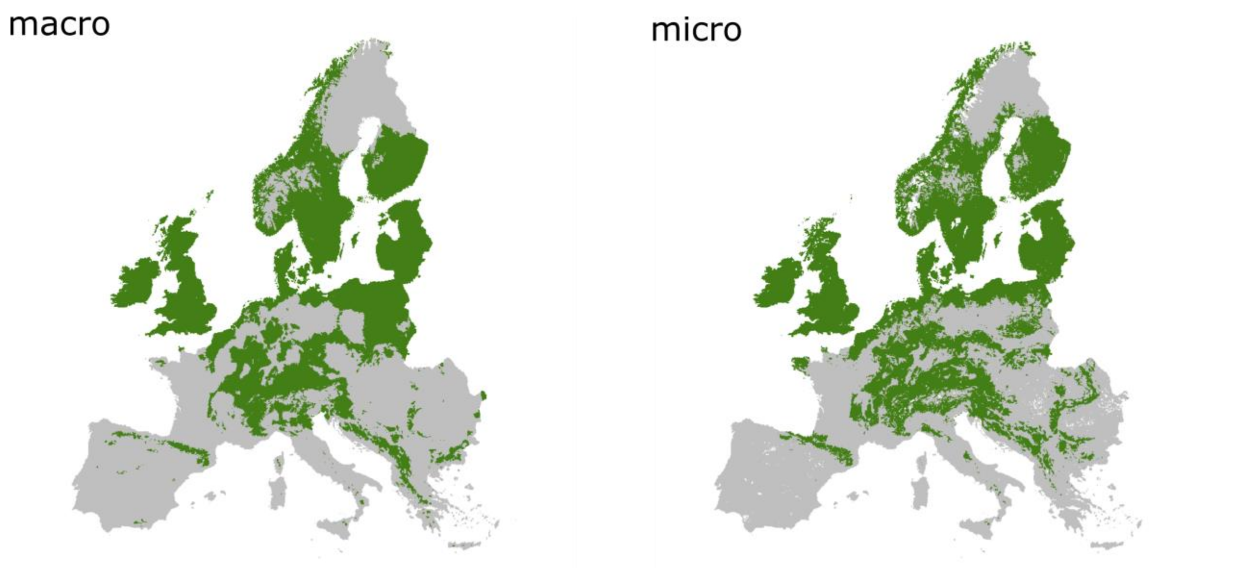

Figure 1: Binary maps for the potential range distribution of Actaea spicata at a spatial resolution of 4 km x 4 km. These maps indicate where the macroclimatic conditions (left) and microclimatic conditions (right) are suitable (green) or unsuitable (gray) for the species. Binary maps were constructed using the 10th percentile training presence as a threshold.

We also found differences in the optimal temperature for Actaea spicate, being 8.7°C under macroclimatic conditions and 7.1°C under microclimatic conditions. Furthermore, maximum thermal tolerance (95th percentile; macro = 11.7 °C; micro = 11.2 °C) and minimum thermal tolerance (5th percentile; macro = 3.9 °C; micro = 2.4 °C) differed under both conditions (Figure 2).

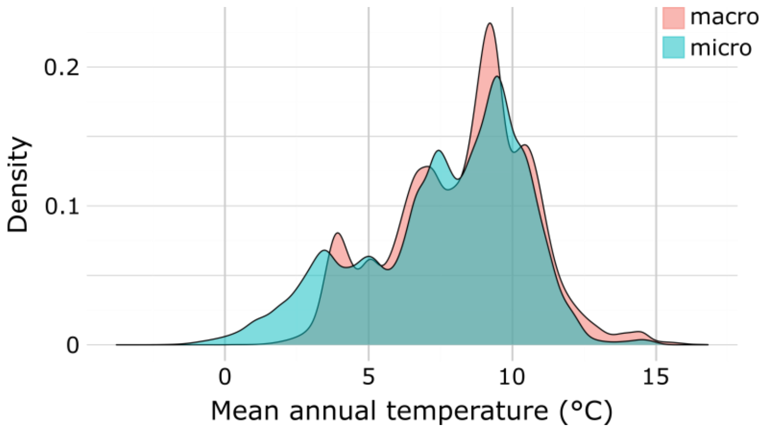

Figure 2: Thermal response curves for Actaea spicata under macroclimatic conditions (red) and microclimatic conditions (blue), which were derived based on the binary maps presented in Figure 1.

FUTURE COLLABORATIONS (if applicable)

This STSM has certainly strengthened the bonds between our two labs and further collaborations are inevitable. Certainly due to the great overlap in research interests (i.e. microclimate, species distribution modelling…) future combined endeavors are already planned within the upcoming chapters of my PhD. Finally, also interactions are possible within the framework of the PhD from Eva Gril, who works around modelling species distributions at a smaller extent but higher spatial resolution.

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