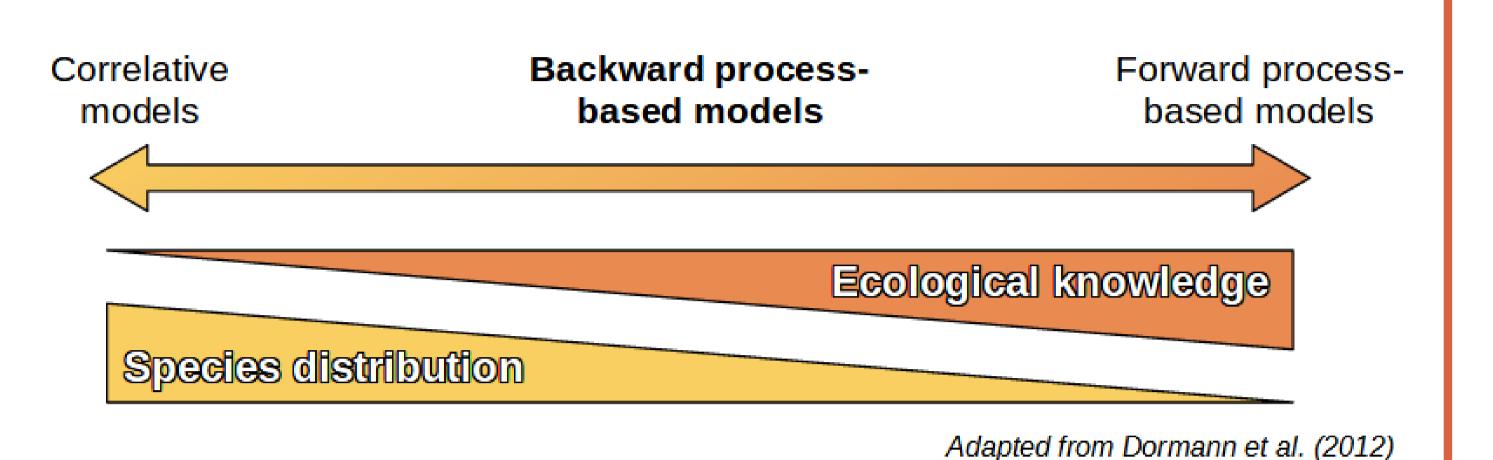
A novel method to estimate process-based model parameters from species distribution data

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1. Introduction

- Two types of species distribution models (SDMs): **correlative niche-based models** and **process-based models**¹
- Process-based models aim to translate into mathematical equations our knowledge about the physiological and ecological processes
- They take more time to develop: in particular, calibration is challenging and timeconsuming



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We explored the feasibility and interests of calibrating process-based models using species occurrence data as correlative SDMs do (using the geographic distributions of species), i.e. backward calibration

2. Data and models

Tree occurrence data

- EU-Forest dataset
- Completed with records from GBIF, filtered with Atlas Flora Europeae and EuroVegMap species ranges
- For Quercus ilex, added records from WOODIV database

Climate and soil data

- Climatic variables were derived from ERA5-Land (1970-2000), 0.1° resolution
- Soil variables were extracted from EU-SoilHydroGrids and SoilGrids250m

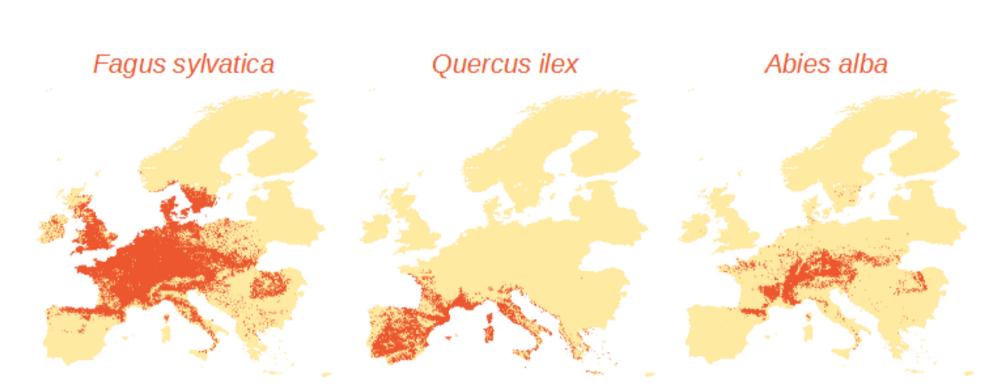


Fig. 3: Species distribution

Process-based models

- **PHENOFIT**²: focuses on phenology and simulates the fitness (survival and reproductive success) of an average individual
- CASTANEA³: simulates carbon and water fluxes in forest, with several processes (photosynthesis, stomatal conductance, respiration...)

3. Covariance matrix adaptation, evolution strategy

CMA-ES in a nutshell

- Robust optimization algorithm for nonlinear optimization problems in continuous domain developped by Nikolaus Hansen⁴
- Inspired by evolutionary biology: recombination, mutation and selection

In practice

- Parallel implementation on two computing clusters (40 to 100 CPUs)
- Runtime :
- PHENOFIT: ~ 24 hours
- CASTANEA: ~ 20 days

References

- 1. Dormann, C. F. et al. 2012. *Correlation and process in species distribution models: Bridging a dichotomy*. Journal of Biogeography 39: 2119–2131.
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- 4. Dufrêne, E. et al. 2005. *Modelling carbon and water cycles in a beech forest: Part I: Model description and uncertainty analysis on modelled NEE*. Ecological Modelling 185: 407–436.
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PHENOFIT Forward calibration AUC = 0.79 AUC = 0.86 AUC = 0.92 AUC = 0.72 AUC = 0.93 AUC = 0.93 AUC = 0.93 AUC = 0.94 AUC = 0.95

Fig. 4: Species distribution maps obtained with PHENOFIT and CASTANEA forward and backward parametrization. Optimal threshold to dichotomize model outputs is the Youden Index-based cut-off point.

5. Non-identifiability of parameters

• We focus here on the leaf unfolding submodel in PHENOFIT. We found a high variability in the parameter estimates

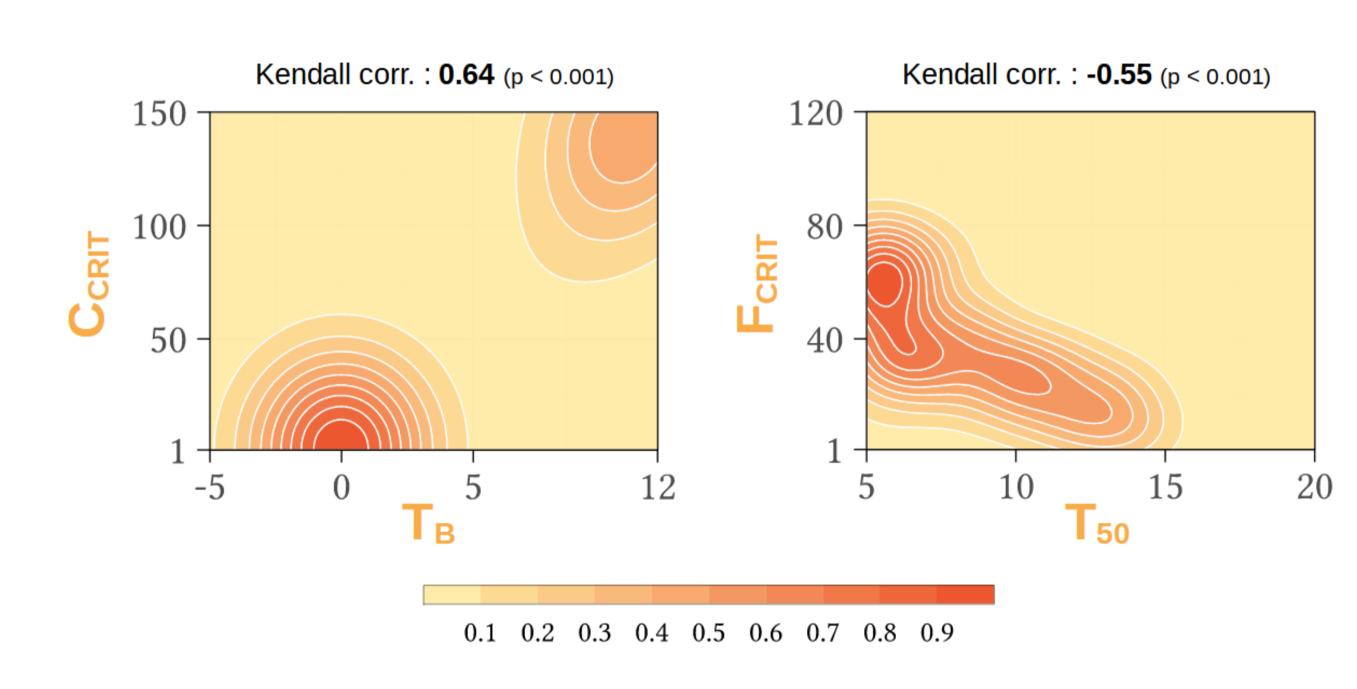


Fig. 2: Leaf unfolding submodel parameter density, after 100 calibrations with F. sylvatica

• Parameters are strongly dependent because of **structural correlations**. Thus, parameter values are **not necessarily ecologically relevant**

6. Advantages of CMA-ES

Comparison with ABC

CMA-ES slighty **outperforms** a widely used approximate bayesian computation (ABC) optimization method

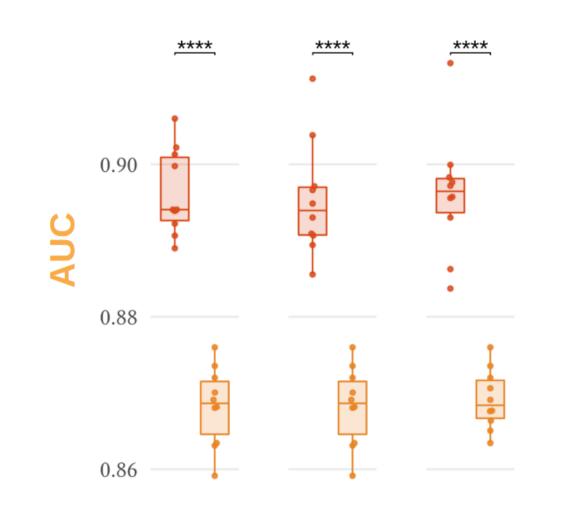


Fig. 5: Comparison of CMA-ES (red) and ABC-rejection (orange) methods, with F. sylvatica

Calibration performance

- AUC is sharply improved compared to classical (forward) parametrization
- Easy to use: does not require an extensive tuning
- Efficient to deal with ill-conditioned and non-separable problems
- CMA-ES backward optimization can be a **powerful technique** to calibrate submodels whose parameter values can hardly be experimentally measured