Improved species distribtion models with explicit modelling of spatial autocorrelation: challenges and perspectives using INLA and SPDE

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Content

- Species distribution models and tree species suitability
- Spatial effects in SDMs
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Species distribution models and tree species suitability

- Tree species adapted to future climate conditions?

→ Practical: Field trials

→ Modelling: landscape models, vegetation models, single-tree growth models, etc. … Species Distribution Models (SDMs)

How good are SDMs in reflecting the ecophysiological potential of a tree species (fundamental niche)?

… epigenetic effect and local adaptions?

… phenology?

… biotic interactions?

… competition and facilitation?

→ Booth (2018), Garzón et al. (2019)

Spatial effects in SDMs

- Tree species occurrence and associated climate- and soil data are not independent from another

→ Spatial Autocorrelation (SAC) may bias model results

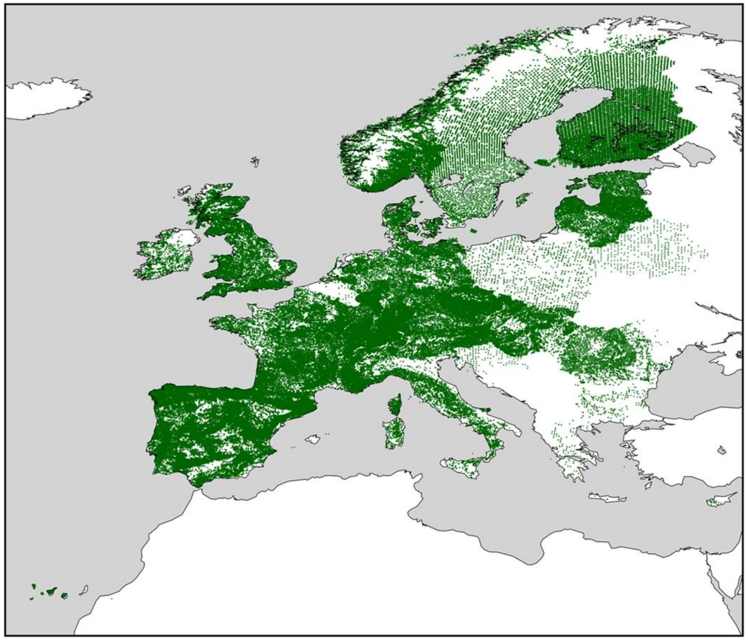


Fig. 1: Species distributions in Mauri et al. (2017)

Possible causes:
- Inventory design
- Historical processes
- Biotic processes

etc.

Dealing with SAC?
- Remove SAC effects(Wavelet Revised Models (Carl & Kühn, 2010))
- Estimate residual spatial autocorrelation (Dormann et al., 2007)

Bayes-modelling approach with INLA and SPDE

- Estimating the spatial dependency of tree species occurrences with a covariance function

→ Computational expensive: changing covariance into precision matrices

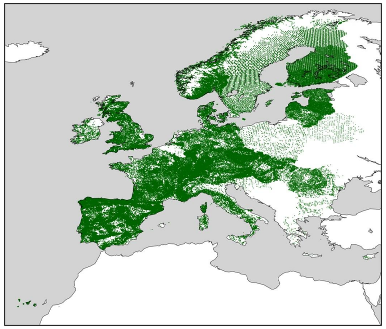
→ Approximation of the convariance function with Stochastic Partial Differential Equations (SPDE) and the finite-element method (Lindgren et al. 2011)

→ Model inference with Integrated Nested Laplace Approximation INLA, Rue et al. (2009)

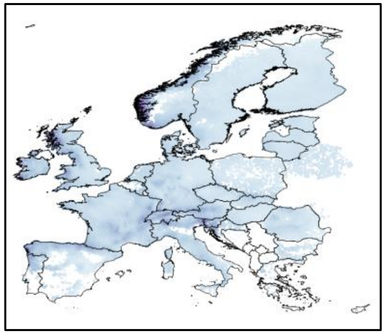
Bayes-modelling approach with INLA and SPDE

- R software with package R-INLA (Rue et al. 2009) and mgcv (Wood 2017)
- Constructing a SPDE-smooth in GAMs possible (Miller et al. 2019)
- Matérn basis-penalty SPDE smoother with hyperparameters κ and τ

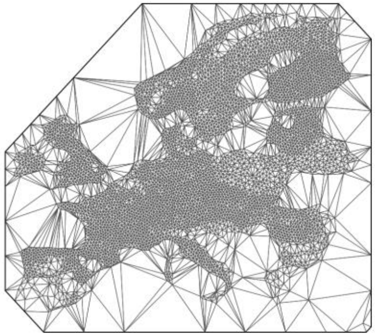
Species occurrences based on Mauri et al. (2017)



Bioclimatic variables based on Karger et al. (2017)



Use SPDE-smooth in GAM



- Binomial GAMs with logit-link, REML and INLA estimation (Wood 2019)
- Variable selection (Marra & Wood 2011), Concurvity reduction (Wood 2017)

Model results

Species	AUC (without/with SPDE)		AIC (without/with SPDE)		TSS (without/with SPDE)	
Picea abies (L.) Karst.	0.87	0.91	154.533	133.100	0.61	0.67
Abies alba Mill.	0.89	0.94	51.451	42.478	0.63	0.75
Pinus sylvestris L.	0.79	0.86	196.928	168.672	0.41	0.54
Fagus sylvatica L.	0.83	0.89	138.772	115.724	0.49	0.59
Quercus robur L.	0.84	0.90	125.075	105.425	0.49	0.63

Model results

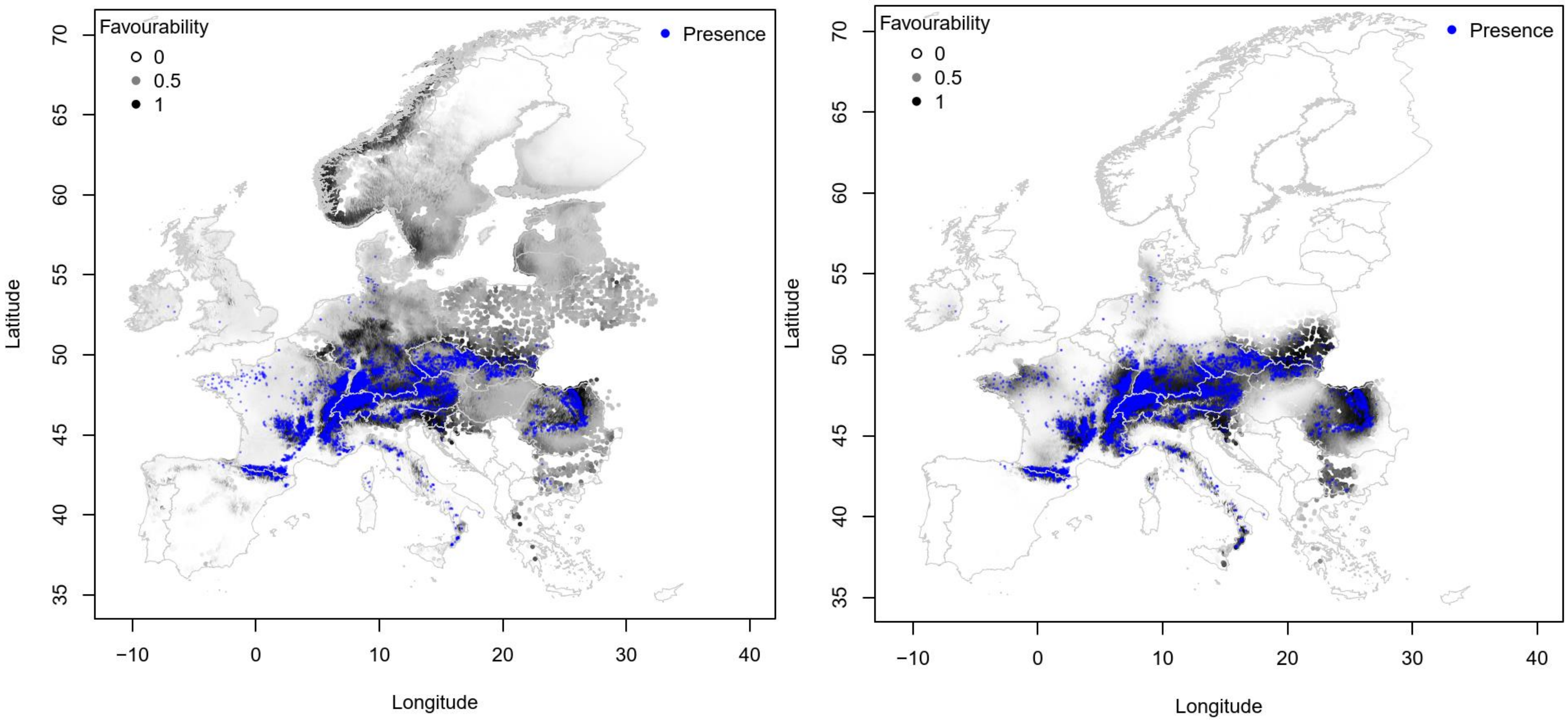


Fig. 2: Species favourability prediction for Abies alba Mill. Without (left) and with (right) SPDE-smooth in the model.

Improved tree species suitability with conditional predictions?

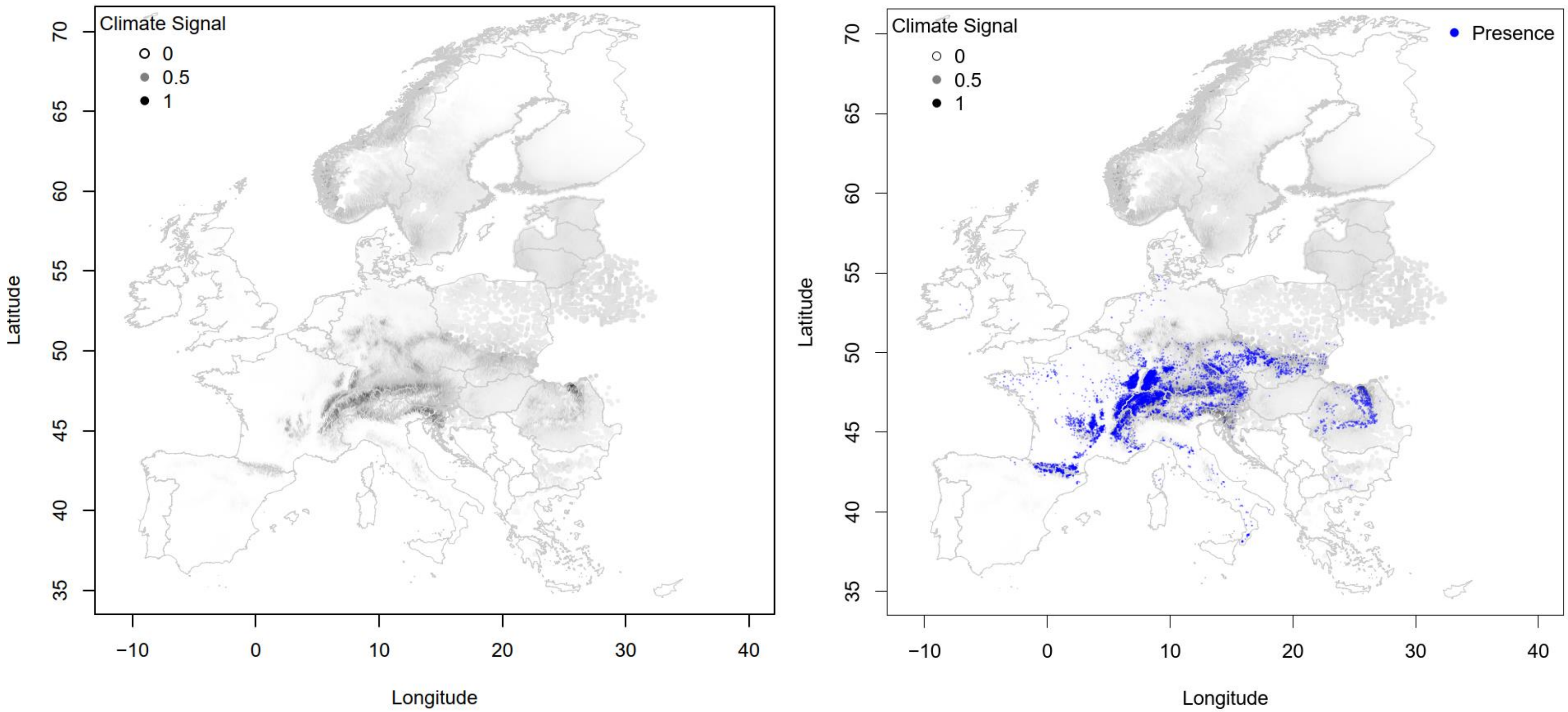


Fig. 3: Climate signal of the conditonal predictions for Abies alba Mill.

Summary

- INLA and SPDE enable computational effective estimation of spatial effects in SDMs
- Variable selection is still of high importance
- Harmonization of heterogenous data sets possible with INLA und SPDE
- Conditional predictions can remove spatial effects

→ Improved identification of core and marginal ecological ranges of a species

→ Better approximation fo the fundamental niche of a species

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