Spatio-Temporal Analysis of Forest Inventories: Challenges and Approaches for Modelling Ingrowth Dynamics

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Swiss national forest inventory (NFI)

Important properties

- permanent plots.
- based on regular 1.4*km* grid.
- roughly 5′500 plots.
- since 1983.
- NFI1, ..., NFI4 complete.
- NFI5 on-going.

Swiss NFI plot distribution with respect to production regions.

Ingrowth in the context of the Swiss NFI

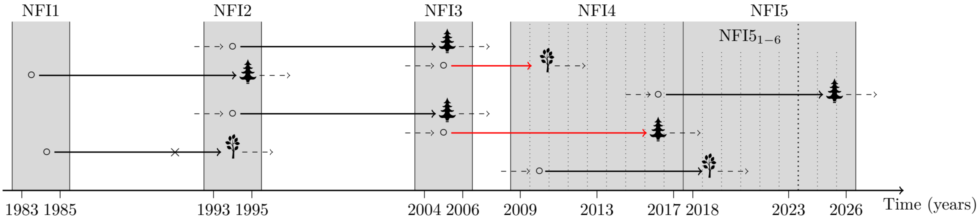
Definition (Ingrowth)

- new tree between two consecutive NFI campaigns, e.g. NFI1-2.
- surpassing caliper threshold of $12cm$.

Context

- focus is on the **number of ingrowth per plot** – for spruce (*Picea abies*) and beech (*Fagus sylvatica*).
- assessing trends in time and space.
- no predictions or extrapolation.

Swiss NFI sampling design



Examplified ingrowth per plots between two NFI campaigns; adapted from Flury et al. (2024).

Ingrowth across NFI campaigns

- Consider number of ingrowth trees per years or vegetation periods (vegper) between plot visits.

Remark

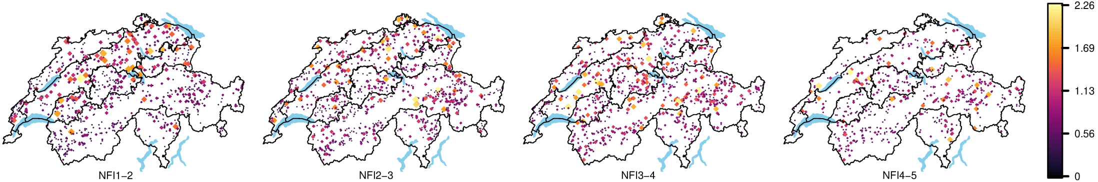
- ingrowth does not follow a linear behaviour over time.
- the probability of ingrowth depends on the number of visits per time.

interpolating ingrowth to specific time points, potentially bias the results.

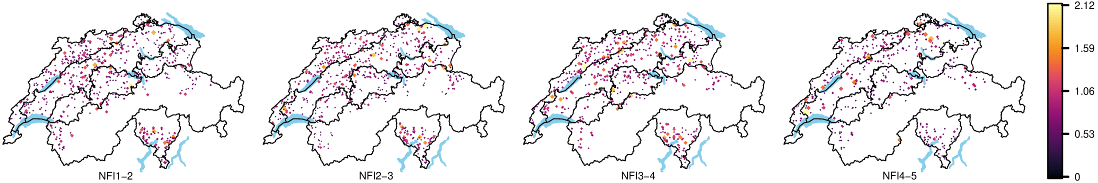
Adding the spatial dimensions

Where does ingrowth change across NFI campaigns?

Where does ingrowth change?



The number of spruce ingrowth per vegper across NFI campaigns.

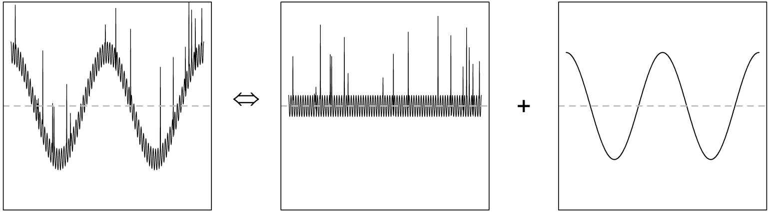


The number of beech ingrowth per vegper across NFI campaigns.

Plot vs regional scale

Assumption: high plot variation, since plots are not representative for a forest and local phenomenas/outlier potentially disturb the picture.

Idea: analyze different spatial scales individually



1-dimensional conceptual idea.

Spatial decomposition (Holmström et al., 2011; Flury et al., 2021)

- Smooth the spatial data $\boldsymbol{y}$ on different scales using $\boldsymbol{S}_\lambda := (\boldsymbol{I}_n + \boldsymbol{Q}_\lambda)^{-1}$
  - $\boldsymbol{Q} \in \mathbb{R}^{n \times n}$ is the precision matrix modeling dependencies between locations of $\boldsymbol{y}$
  - $\lambda \in \mathbb{R}^+$ the smoothing scale, such that $0 = \lambda_1 < \lambda_2 < \ldots < \lambda_L = \infty$

- decompose the vectorized spatial data $\boldsymbol{y}$ as sum of differences of smooths

$$\boldsymbol{y} = \underbrace{\boldsymbol{S}_{\lambda_1}\boldsymbol{y} - \boldsymbol{S}_{\lambda_2}\boldsymbol{y}}_{=:\boldsymbol{z}_1} + \underbrace{\boldsymbol{S}_{\lambda_2}\boldsymbol{y} - \boldsymbol{S}_{\lambda_3}\boldsymbol{y}}_{=:\boldsymbol{z}_2} \ldots - \boldsymbol{S}_\infty\boldsymbol{y} + \boldsymbol{S}_\infty\boldsymbol{y}$$

$$\boldsymbol{y} = \sum_{\ell=1}^{L} \boldsymbol{z}_\ell$$

Formalization of ingrowth example

Let $\boldsymbol{n}_{\text{in},i} \in \mathbb{R}^{m_i}$ be the vector containing the number of ingrowth trees per plot for all m_i plots. Where $i \in \{\text{NFI1-2}, \dots, \text{NFI4-5}\}$. Then

$$\boldsymbol{y}_i := \left(\frac{\boldsymbol{n}_{\text{in},i}}{\text{vegper}} \right)$$

Center $\boldsymbol{y}_i$ wit respect to the mean across all NFI campaigns.

Then decompose $\boldsymbol{y}_i$ with an *a priori* fixed λ_2 such that:

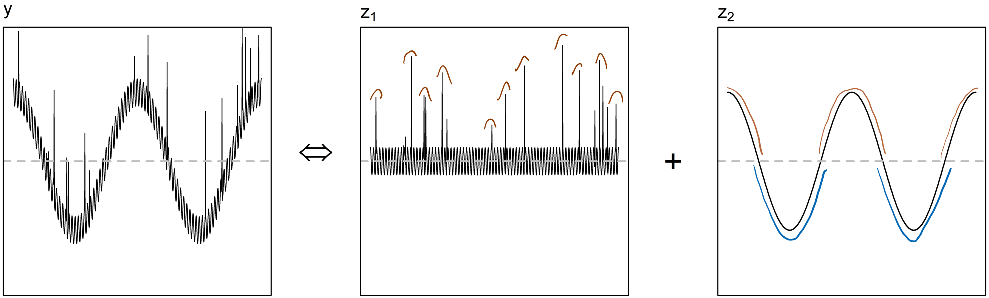
$$\boldsymbol{z}_{1,i} = \boldsymbol{y}_i - \boldsymbol{S}_{\lambda_2}\boldsymbol{y}_i, \quad \boldsymbol{z}_{2,i} = \boldsymbol{S}_{\lambda_2}\boldsymbol{y}_i - \boldsymbol{S}_{\infty}\boldsymbol{y}_i \quad \text{and} \quad \boldsymbol{z}_{\infty,i} = \boldsymbol{S}_{\infty}\boldsymbol{y}_i$$

Credibility analysis

We resample $\boldsymbol{y}_i$ with a (parametric) bootstrap or Bayesian model

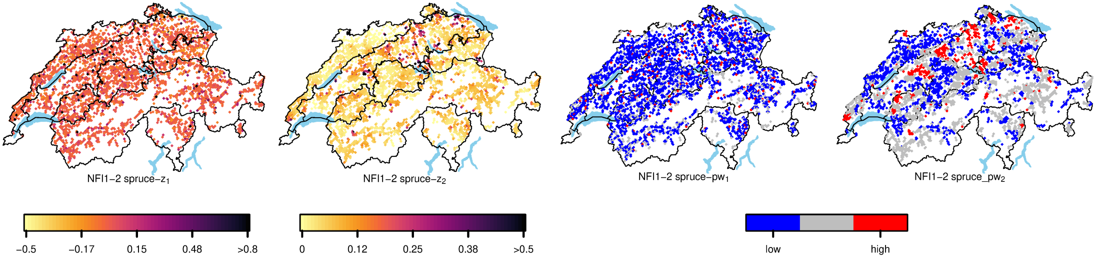
- to enable a credibility analysis.
- to identify hotspot areas, i.e., areas which are exceeding the mean over all NFI campaigns on a 95% credibility level.

Intuition



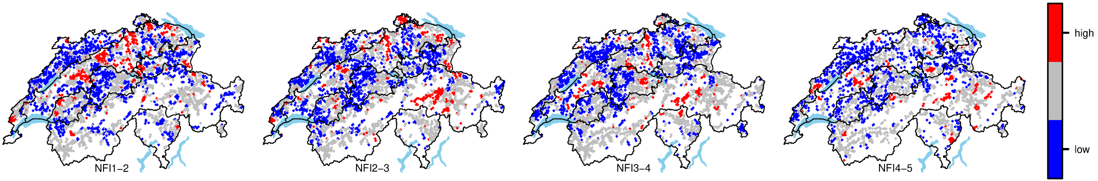
1-dimensional conceptual idea.

Spatial decomposition of NFI ingrowth

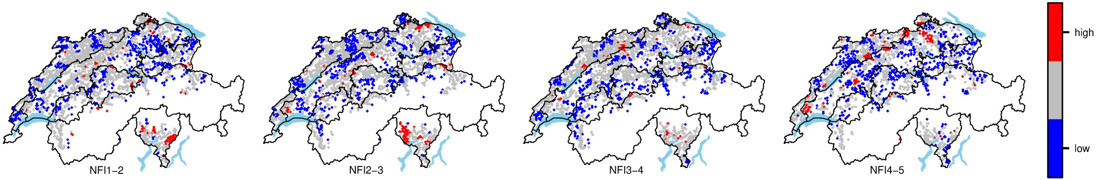


The number of spruce ingrowth/vegper for the NFI campaigns.

Results – mean exceedence areas/hotspots at the regional scale z_2



Credible areas that exceed the overall mean of the number of spruce ingrowth/vegper across NFI campaigns.



Credible areas that exceed the overall mean of the number of beech ingrowth/vegper across NFI campaigns.

Associations to predictor variables

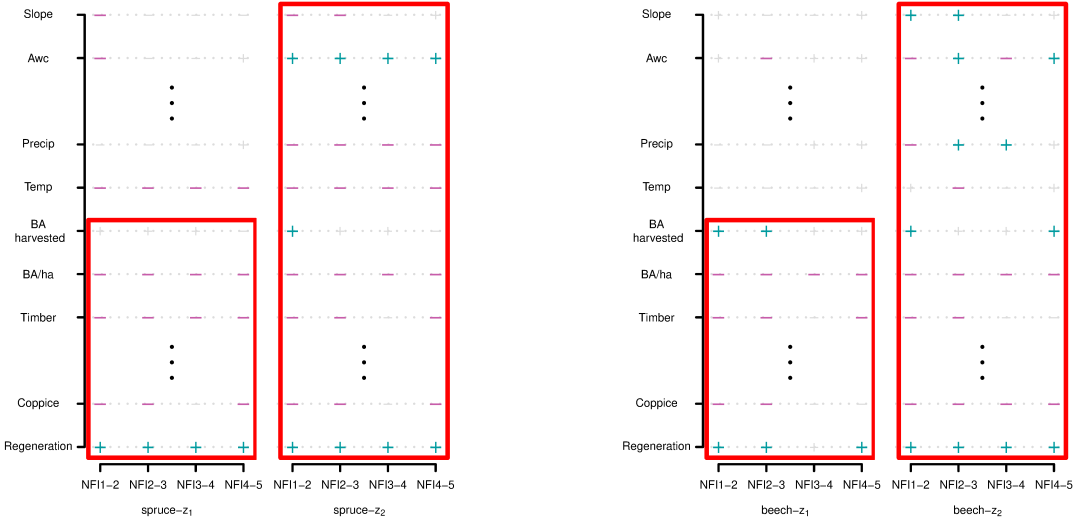
Plot-scale $\boldsymbol{z}_1$

- follows a Gaussian distribution.
- associations to predictor variables can be modelled with a regression model.

Regional-scale $\boldsymbol{z}_2$

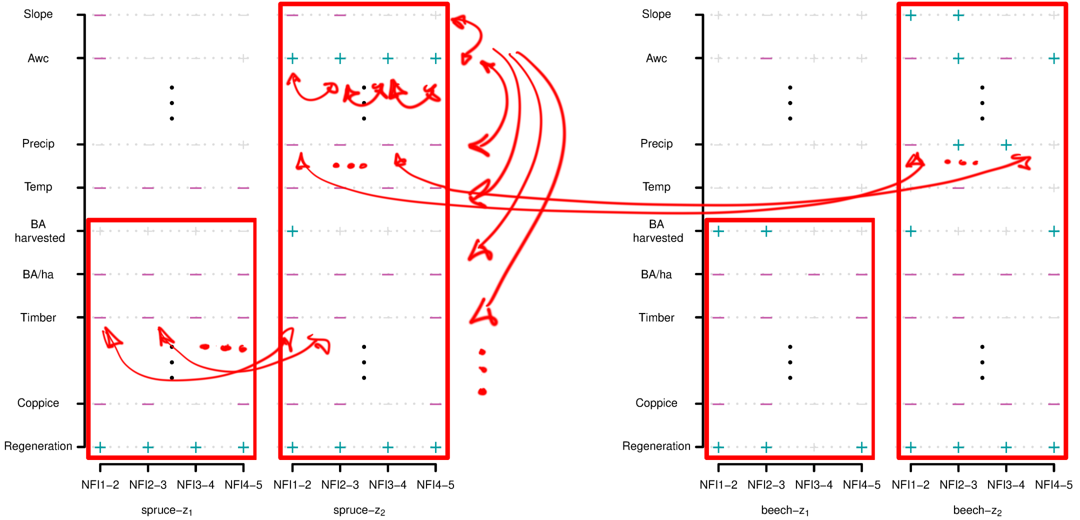
- is right skewed, since it is based on positive counts divided by number of vegetation periods.
- can be modelled with a gamma regression model to find associations to predictor variables.

Results - Associations to predictor variables



Associations of selected predictor variables to $\boldsymbol{z}_1$ and $\boldsymbol{z}_2$ across the NFI campaigns - for spruce and beech.

Results - Associations to predictor variables

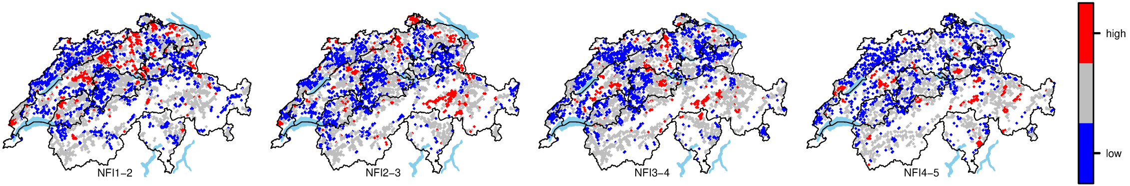


Associations of selected explanatory variables to z_1 and z_2 across the NFI campaigns - for spruce and beech.

Conclusions

Spatial decomposition enables

- the identification of mean exceedance areas on a forest representative regional-scale.
- the comparison of associations to predictor variables at plot and regional-scale.
- the comparison of associations to predictor variables across NFI campaigns with respect to the overall mean.



Credible areas that exceed the overall mean of the number of spruce ingrowth/vegper between the NFI campaigns.

References

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