FACULTY OF BIOSCIENCE ENGINEERING

Predicting trajectories of temperate forest understorey vegetation responses to global change

Bingbin Wen[1], Haben Blondeel[1] , Kris Verheyen[1], Dries Landuyt[1]
forestREplot, and PASTFORWARD

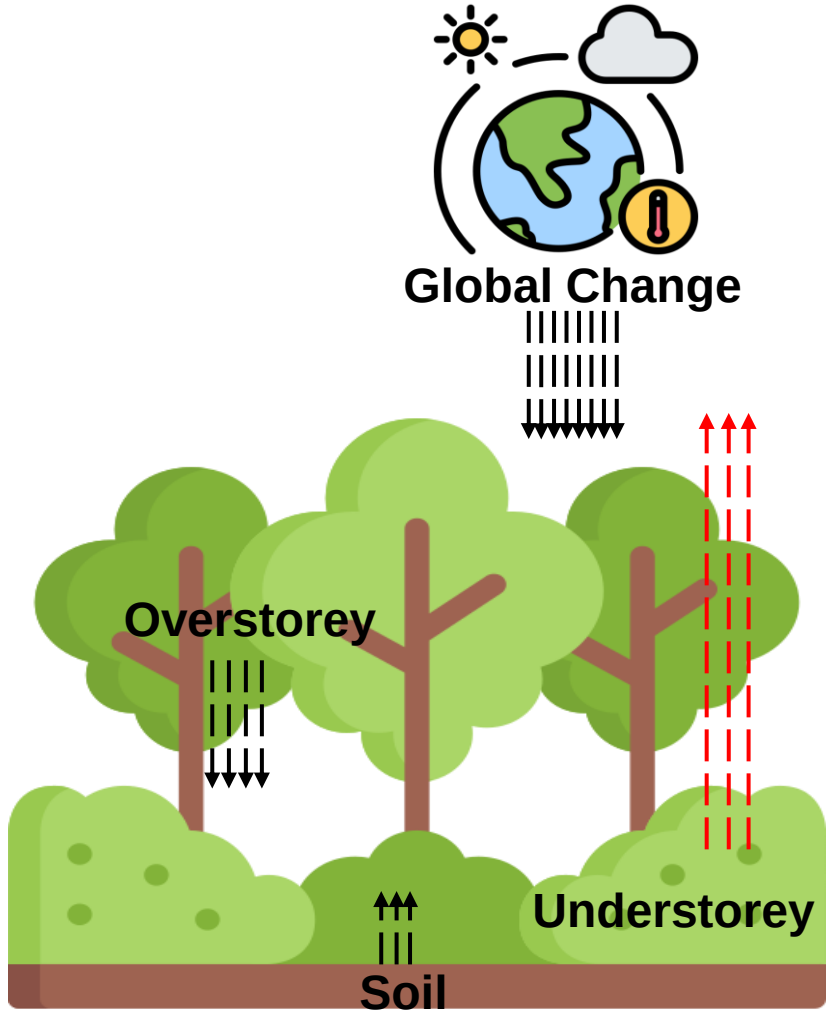
1 Forest and Nature Lab, Department of Environment, Ghent University

16/04/2024 EGU , Vienna, Austria

GHENT UNIVERSITY

RESEARCH GAP

1. Understorey communities response to global change are often context-dependent(Perring, et al., 2018) , driven by differences in soil characteristics and overstorey structure and composition.
2. Reliable predictive understorey models are still scarce (Landuyt et al., 2018).
3. Lack of information on site-specific environmental conditions(e.g. soil characteristics) in regional-scale datasets limits the potential of machine learning tools for the understorey predictive modelling.



GHENT UNIVERSITY

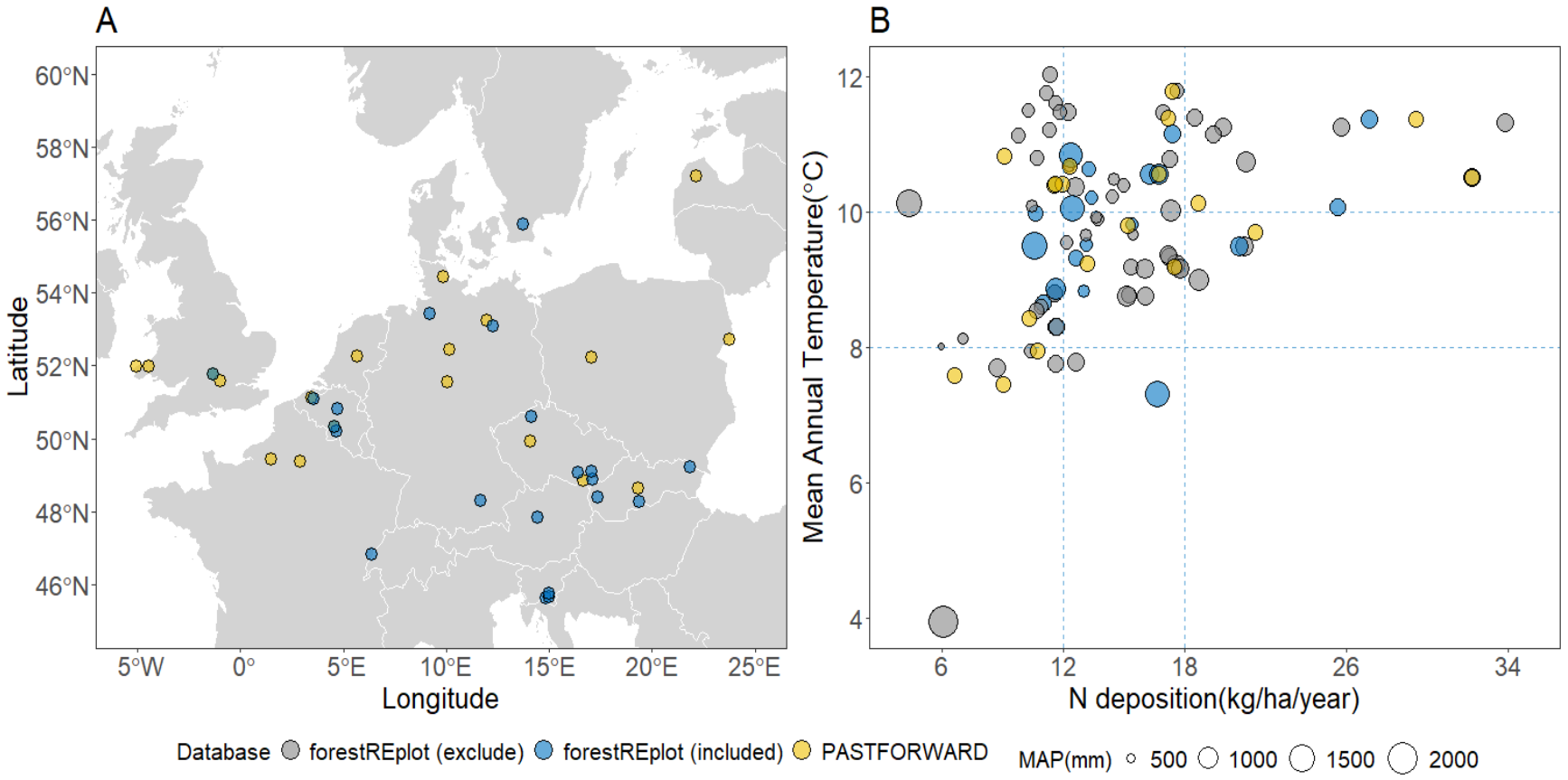
Landuyt, D.,et al., 2018. Perspect. Plant Ecol. Evol. Syst. 31, 44–54. https://doi.org/10.1016/J.PPEES.2018.01.002;
Perring, M.P., et al, 2018. Environ. Pollut. 242, 1787–1799. https://doi.org/10.1016/J.ENVPOL.2018.07.089

1. RESEARCH OBJECTIVES

- Developing plot-level predictive models of the trajectories of temperate forest understorey properties in response to global change and forest management.
- Applying these predictive models to identify important environmental drivers.
- Predicting trajectories of temperate understorey vegetation responses to climate change, N deposition and forest management at specific forest sites.

GHENT UNIVERSITY

2. METHOD- DATA COLLECTION



(40 individual resurvey vegetation studies:1363 plots=1171 plots from forestREplot+ 192 plots from PASTFORWARD)

a) Time interval between two surveys ranged between 12 and 83 years (37.88 ± 12.47[1 SD] years on average);

b) *Regional-scale global-change drivers: mean annual temperature(MAT), mean annual precipitation(MAP), Nitrogen(N) deposition,*

c) *Site-specific drivers:* ***field-collected soil pH and total carbon-to-nitrogen(CN) ratio,*** *tree cover, overstorey shade-casting ability score(SCA) and litter quality score (LQ)*

GHENT UNIVERSITY

forestReplot: https://forestreplot.ugent.be/ ; PASTFORWARD: https://pastforward.ugent.be/

2.METHOD- MODELLING

Predictor variables

(Regional-scale)

MAP/MAT /N deposition (initial and resurveys)

(Site-specific)

pH/ CN ratio

Tree cover/ overstorey SCA, and LQ (initial and resurvey)

Understorey properties (initial)

Machine learning models

Response variables (resurvey)

Understorey properties:
Species richness
Total vegetation cover
Proportion of woody species
Proportion of forest specialists

GHENT UNIVERSITY

2.METHOD-MODELLING

The absolute change between two surveys

Value at Initial Survey

Value at Resurvey

Value at resurvey

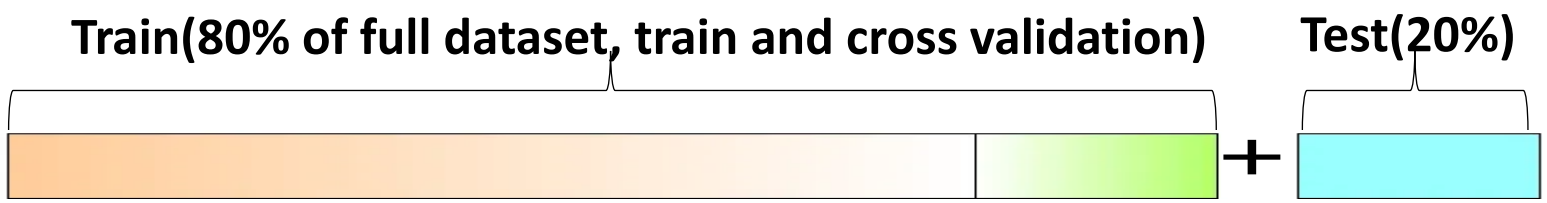
Constant over time

Value at Initial Survey

Understory property = **MAP** **MAT** **N deposition** Tree cover Overstorey SCA Overstorey LQ + **MAP** **MAT** **N deposition** Tree cover Overstorey SCA Overstorey LQ + pH CN ratio + **Plot size** (only used in richness) + **Understory property**

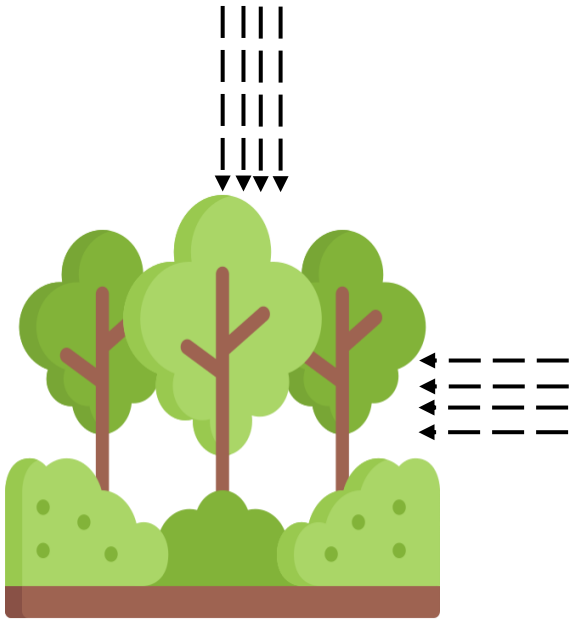
Using global-change, soil, overstorey layer and understory variable itself in the past to predict understory variable in the present.

Gradient boosting regression model (GBM)



2.METHOD- PREDICTING TRAJECTORIES

Climate change scenarios
(two MAT, two N deposition)



Forest management
(Three Tree cover scenarios)

Case study: Applying the final GBM models at 8 forest sites in Austria

1. **Hindcast** understorey trajectories from the year 1993 to 2017
2. **Forecast** understorey trajectories from the year 2017 to 2030 with twelve scenarios.

- Two MAT scenarios from CMIP6 : SSP1, SSP5
- Two Nitrogen deposition scenarios:
  Business as usual (BAU) and Current legislation scenario (CLE)
- Three Forest management scenarios: representing by tree cover: open(25%), intermediate(50%), closed(100%)

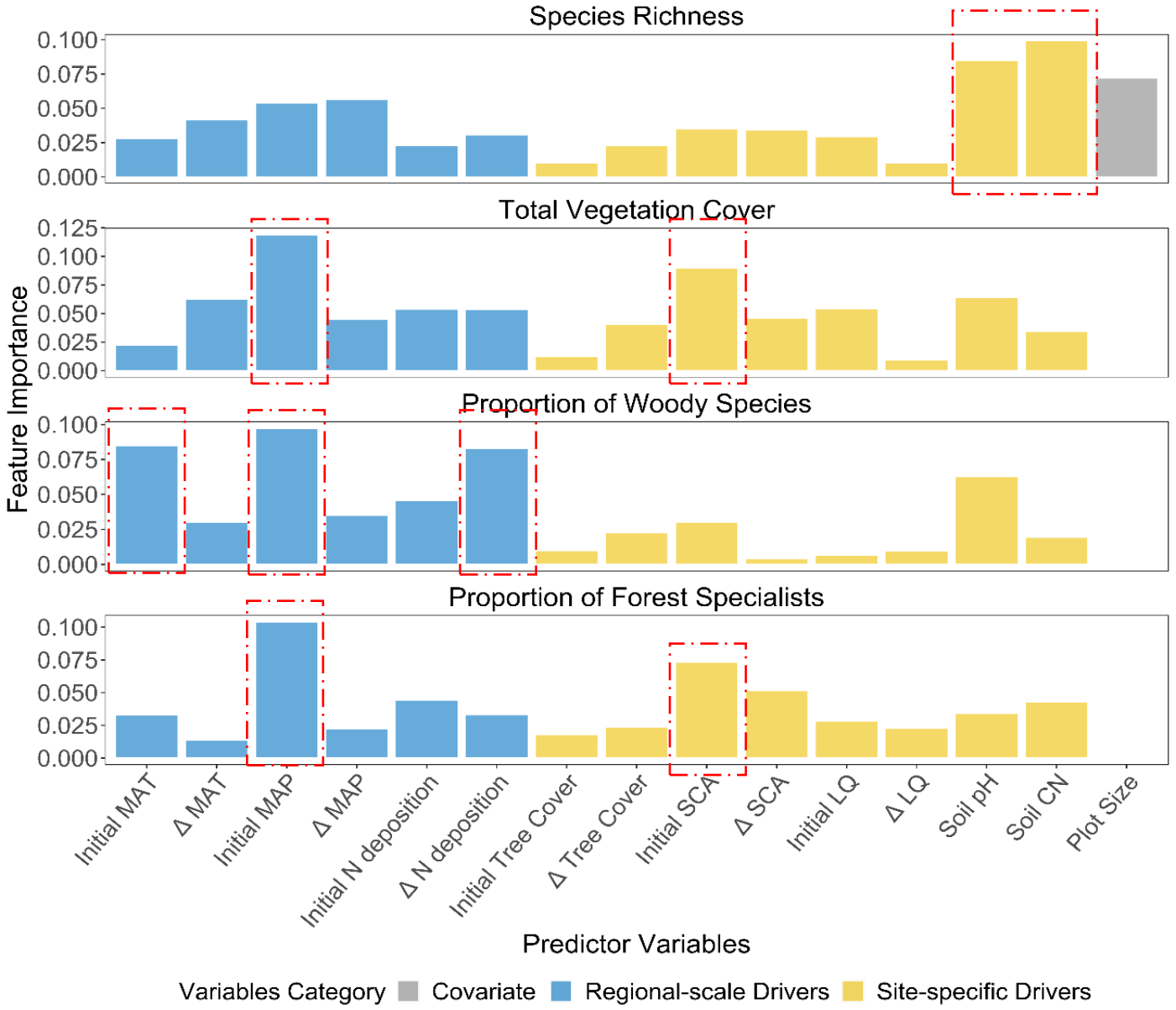
Scenarios set as resurvey state of variables in the models

3 RESULTS-MODEL PERFORMANCE

Table 1 Performance of the final GBM models that predict forest understorey trajectories based on the gradient boosting regression algorithm. R^2_{train} is the coefficient of determination of the final GBM model fitted with the training dataset (n = 942), R^2_{test} is the coefficient of determination of the final GBM model fitted with the test dataset (n = 236), R^2_{full} is the coefficient of determination of the final GBM model fitted with the full dataset (n = 1178). Pearson's r values represent coefficients of correlation between predictions and observations of the Austrian sites (dataset 27, n = 32).

Response Variables	**R^2_{train}**	**R^2_{test}**	**R^2_{full}**	**Pearson's r**
Resurvey species richness	0.729	0.626	0.707	0.414
Resurvey total vegetation cover	0.652	0.591	0.642	0.497
Resurvey proportion of woody species	0.707	0.663	0.698	0.358
Resurvey proportion of forest specialists	0.729	0.611	0.707	0.728

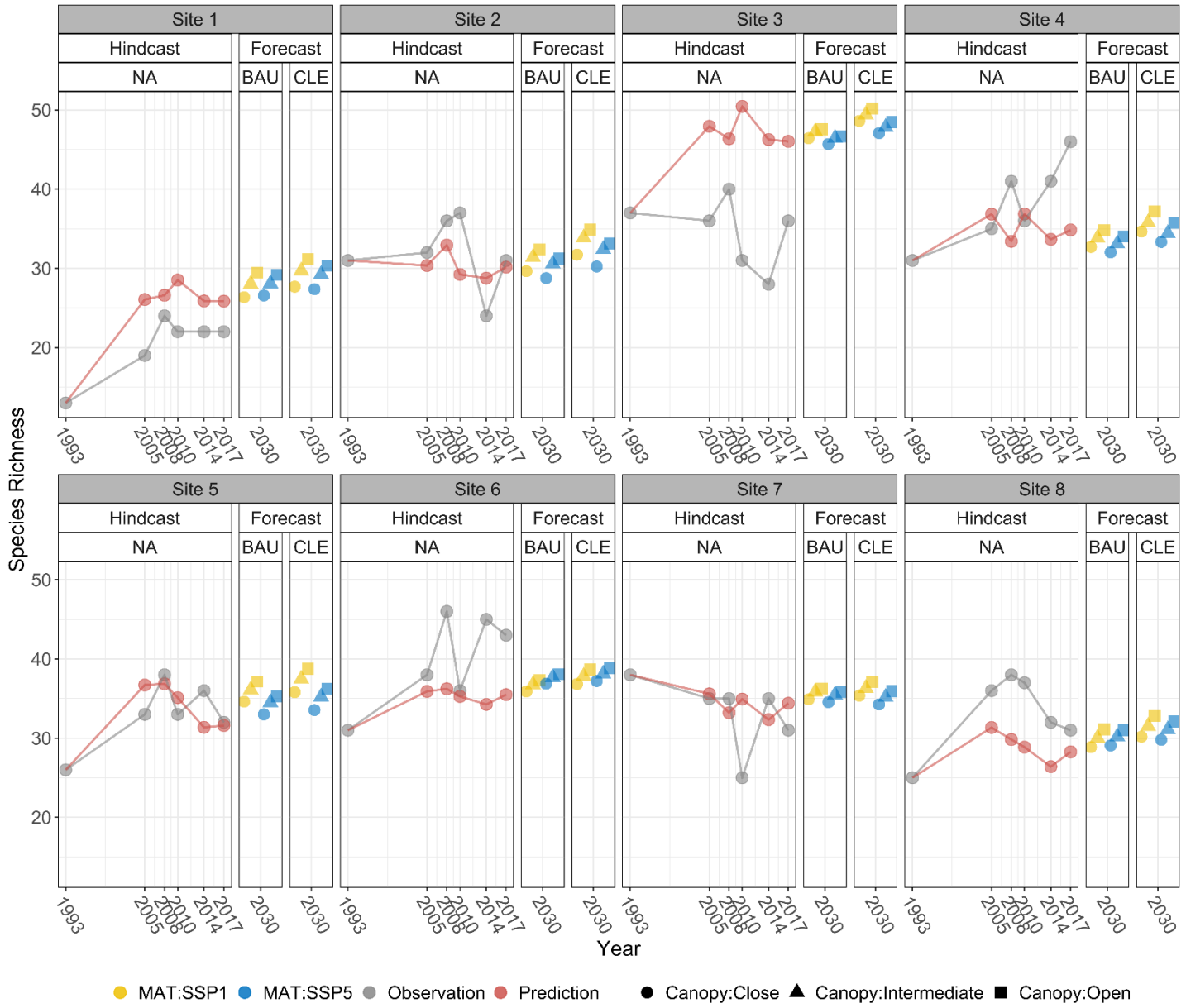
3 RESULTS-IMPORTANT DRIVERS



Important drivers:

- Species richness- soil pH and CN ratio
- Total vegetation cover: MAP, SCA
- Proportion of woody species: MAT, MAP,N deposition
- Proportion of forest specialists: MAP, SCA

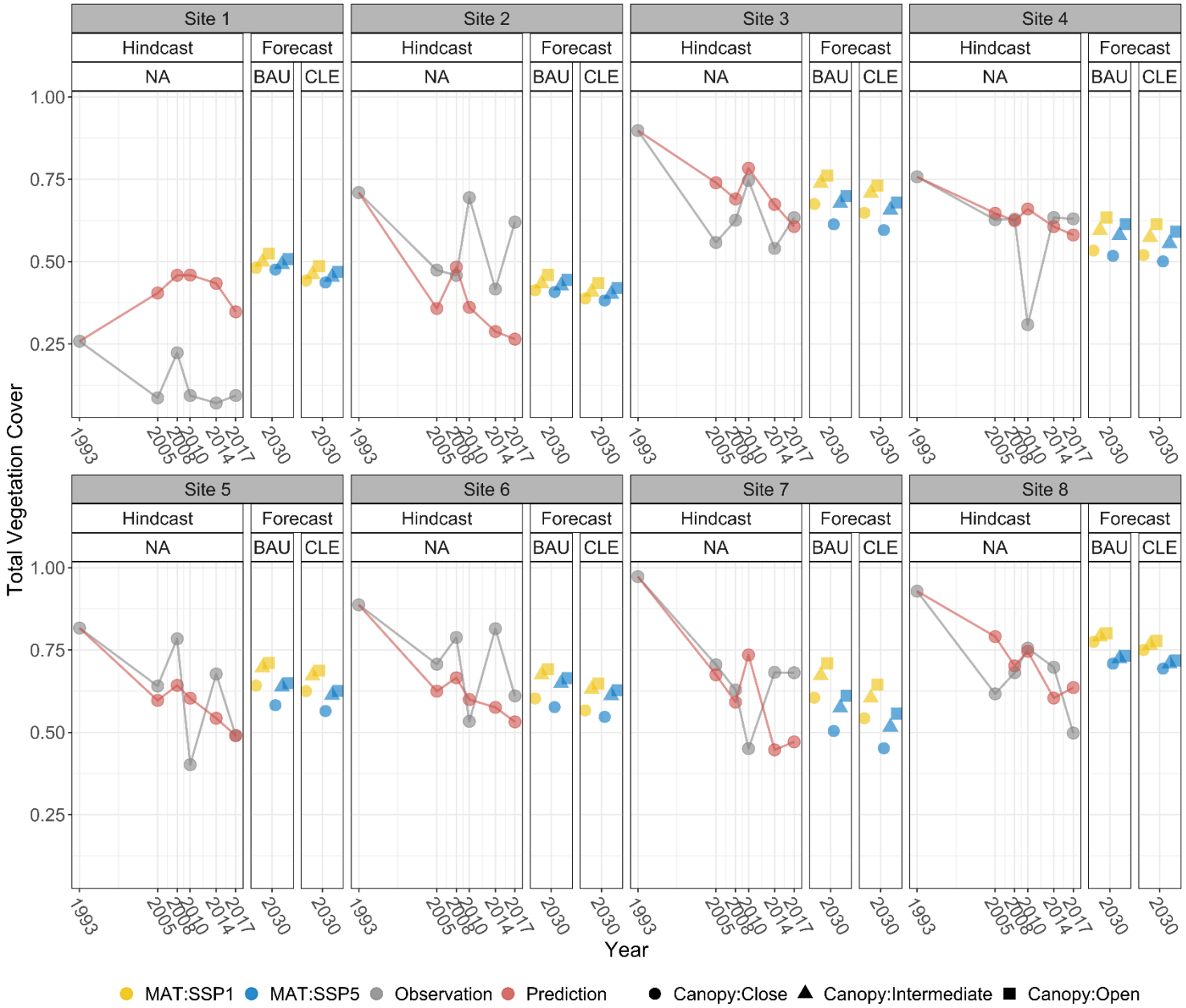
3 RESULTS-PREDICTING (CASE STUDY IN AUSTIRA)



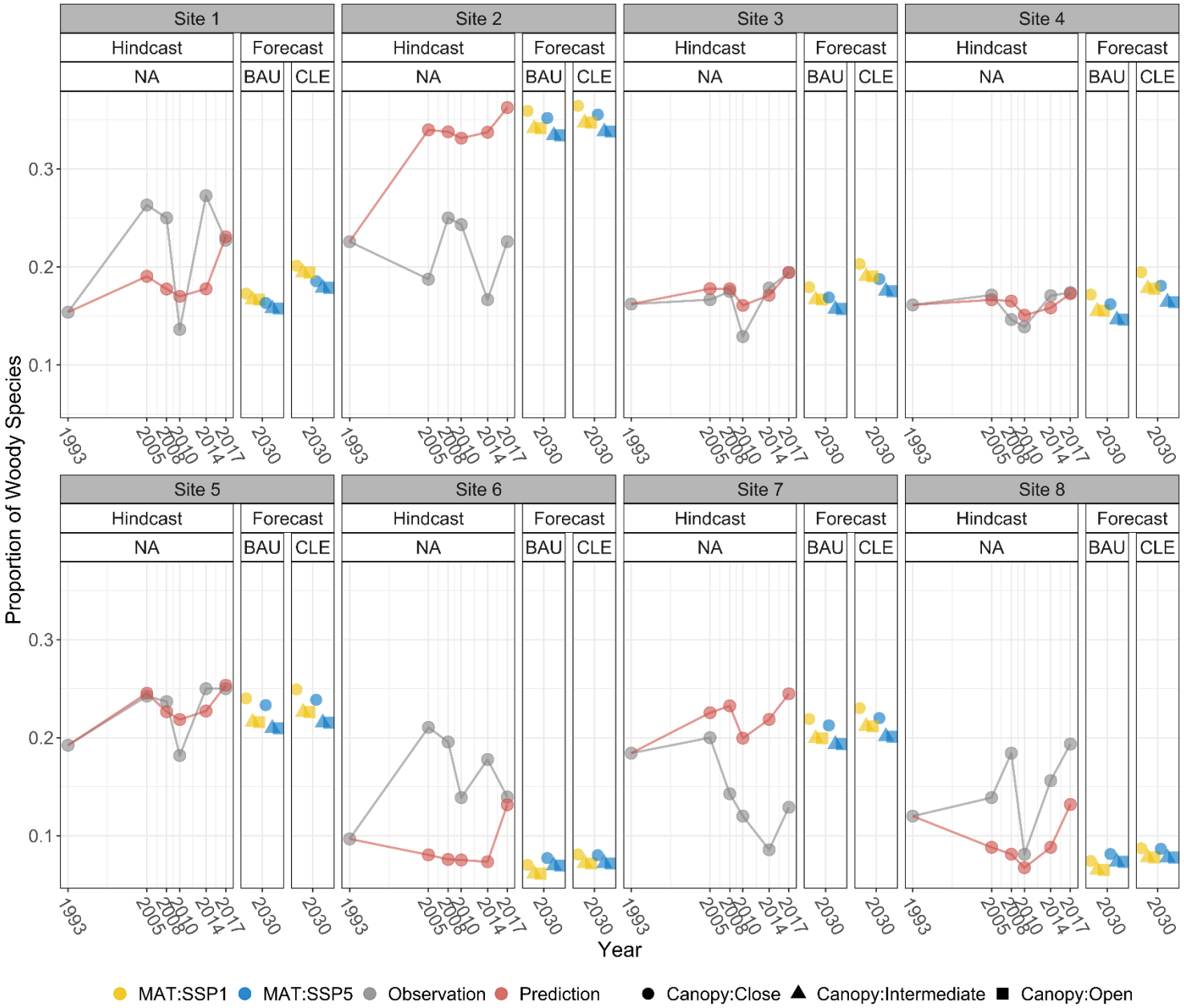
- **Species richness** in the Austrian sites was predicted to increase from 1993 to 2030 following the observed trend in the data up to 2017.
- While decreasing N deposition and canopy opening led to further increases in species richness towards 2030.
- Climate warming was projected to lead to a decrease in species richness

3 RESULTS-PREDICTING (CASE STUDY IN AUSTIRA)

- **Total vegetation cover** in the Austrian sites was predicted to decrease from 1993 to 2030, following the observed trend in the data up to 2017.
- Decreasing N deposition and climate warming led to further decrease in total vegetation cover towards 2030.
- While canopy opening was projected to lead to an increase in total vegetation cover.



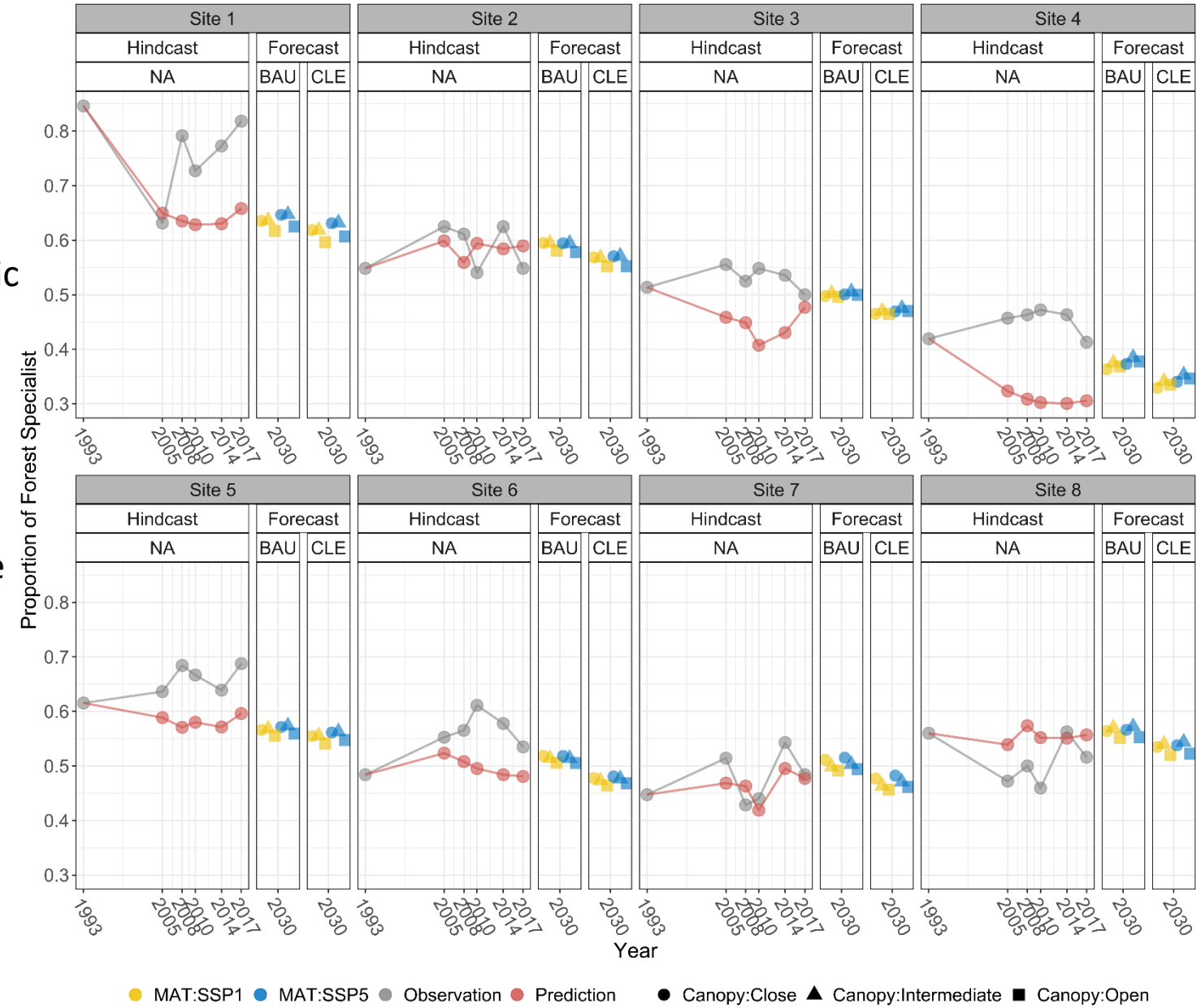
3 RESULTS-PREDICTING (CASE STUDY IN AUSTIRA)



- **The proportion of woody species** in the Austrian sites was predicted to increase from 1993 to 2030, following the observed trend in the data up to 2017.
- While decreasing N deposition led to a further increase in proportion of woody species towards 2030.
- Climate warming and canopy opening were both projected to lead to a decrease in proportion of woody species.

3 RESULTS-PREDICTING (CASE STUDY IN AUSTIRA)

- **The proportion of forest specialists** in the Austrian sites was predicted to decrease from 1993 to 2030, while observations showed decreases or increases in this metric from 1993 to 2017, depending on site.
- Decreasing N deposition and canopy opening led to a decrease in the proportion of forest specialists towards 2030.
- Climate warming had limited effects on the proportion of forest specialists, but a slight increase with climate warming in the proportion of forest specialists towards 2030 at Site 1 and Site 4.



4 TAKE-HOME MESSAGE

- We presented machine learning models that included both regional global-change and site-specific drivers (i.e. soil and overstorey variables) to predict trajectories of temperate forest understorey responses to global change.
- The final machine learning models have relatively high R^2 values ranging from 0.642 to 0.707.
- Soil pH, CN ratio, overstorey SCA, and MAP are the most important drivers in explaining understorey change.
- The presented models are capable of making sensible predictions of the trajectories of forest understorey responses to global change and forest management interventions at specific sites.

AUTHORS

Bingbin Wen[1], *, Haben Blondeel[1], Lander Baeten[1], Michael P. Perring[1,2,3], Leen Depauw[1], Sybryn L. Maes[1,4], Luc De Keersmaeker[5], Hans Van Calster[5], Monika Wulf6, Tobias Naaf[6], Keith Kirby[7], Markus Bernhardt-Römermann[8,9], Thomas Dirnböck[10], František Máliš[11], Martin Kopecký[12,13], Ondřej Vild[12], Martin Macek[12], Radim Hédl[12,14], Markéta Chudomelová[12], Jonathan Lenoir[15], Jörg Brunet[16], Thomas A. Nagel[17], Kris Verheyen[1], Dries Landuyt[1]

Address:

1 Forest & Nature Lab, Department of Environment, Ghent University, Geraardsbergsesteenweg 267, 9090 Melle-Gontrode, Belgium
2 The UWA Institute of Agriculture, The University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia
3 UKCEH (UK Centre for Ecology & Hydrology), Environment Centre Wales, Bangor, Gwynedd, UK
4 Division of Forest, Nature & Landscape, KU Leuven, Leuven, Belgium
5 Research Institute for Nature and Forest, Brussels, Belgium
6 Leibniz-Centre for Agricultural Landscape Research (ZALF), Müncheberg, Germany
7 Department of Biology, University of Oxford, Oxford, OX1 3RBL, UK
8 Institute of Ecology and Evolution, Friedrich Schiller University Jena, Dornburger Str. 159, 07743, Jena, Germany
9 iDiv - German Centre for Integrative Biodiversity Research Halle-Jena-Leipzig, Puschstrasse 4, 04103 Leipzig, Germany
10 Environment Agency Austria, A-1090 Vienna, Austria.
11 Faculty of Forestry, Technical University in Zvolen, Zvolen, Slovakia
12 Institute of Botany of the Czech Academy of Sciences, Zámek 1, CZ-252 43, Průhonice, Czech Republic
13 Faculty of Forestry and Wood Sciences, University of Life Sciences Prague, Kamýcká 129, CZ-16521, Praha 6-Suchdol, Prague, Czech Republic
14 Department of Botany, Palacký University in Olomouc, Šlechtitelů 27, 78371 Olomouc, Czech Republic
15 UMR CNRS 7058 Ecologie et Dynamique des Systèmes Anthropisés (EDYSAN), Université de Picardie Jules Verne, 1 rue des Louvels, 80000 Amiens, France
16 Southern Swedish Forest Research Centre, Swedish University of Agricultural Sciences, Box 190, 23422 Lomma, Sweden
17 Department of Forestry and Renewable Forest Resources, Biotechnical Faculty, University of Ljubljana, Večna pot 83, 1000 Ljubljana, Slovenia
** bingbin.wen@ugent.be*

FACULTY OF BIOSCIENCE ENGINEERING

THANK YOU!

Scan the QR code and vote for me!

GHENT UNIVERSITY

ForNa Lab

FAST FORWARD

CHINA SCHOLARSHIP COUNCIL