Incorporating high-resolution climate, remote sensing and topographic data to map annual forest growth in central and eastern Europe

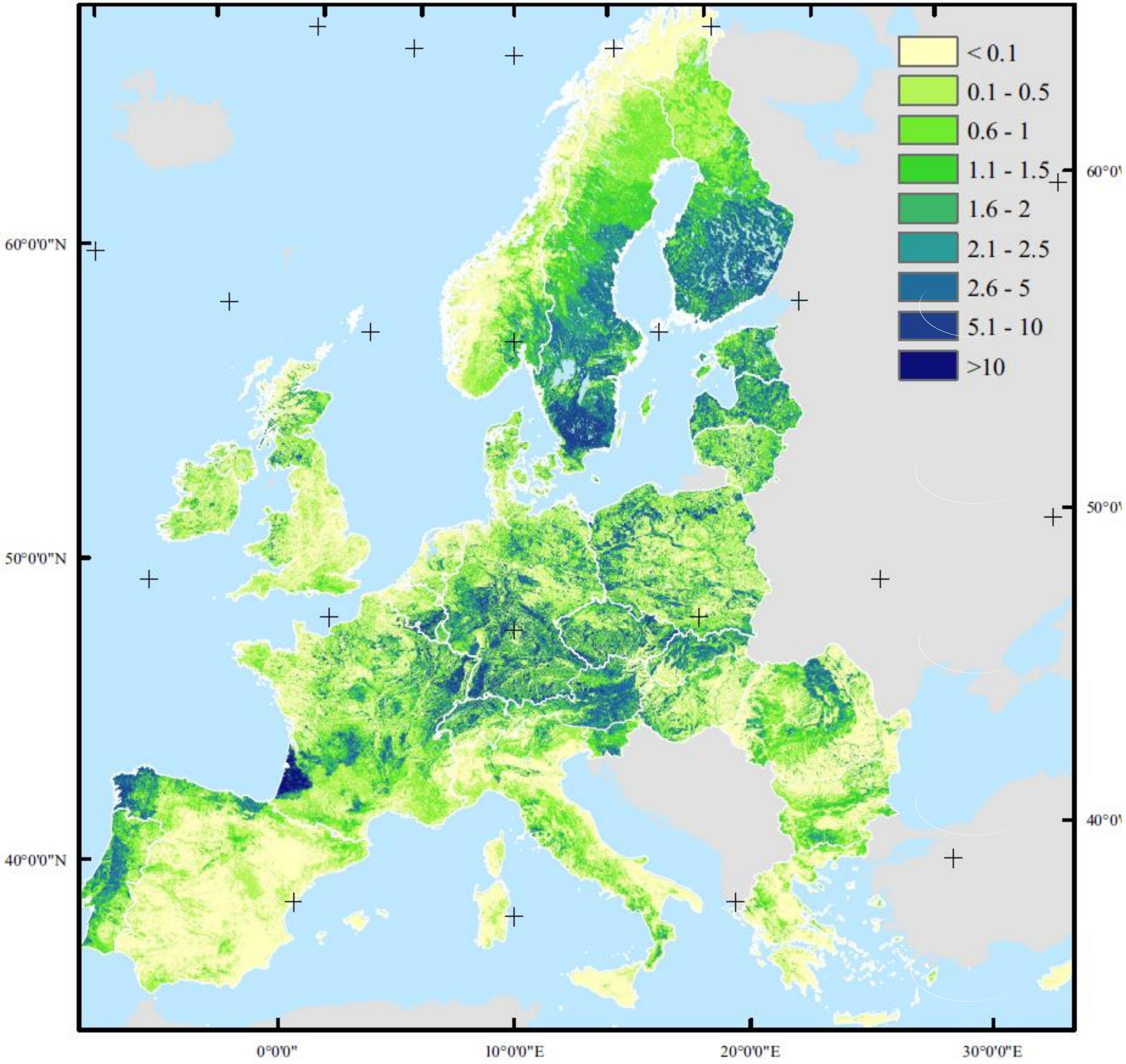
Jernej Jevšenak, Marcin Klisz, Jiří Mašek, Vojtěch Čada, Pavel Janda, Miroslav Svoboda, Ondřej Vostarek, Vaclav Treml, Ernst van der Maaten, Andrei Popa, Ionel Popa, Marieke van der Maaten-Theunissen, Tzvetan Zlatanov, Tobias Scharnweber, Svenja Ahlgrimm, Juliane Stolz, Irena Sochová, Catalin Roibu, Hans Pretzsch, Gerhard Schmied, Enno Uhl, Ryszard Kaczka, Piotr Wrzesiński, Martin Šenfeldr, Marcin Jakubowski, Jan Tumajer, Martin Wilmking, Nikolaus Obojes, Michal Rybníček, Mathieu Lévesque, Aleksei Potapov, Soham Basu, Marko Stojanović, Stefan Stjepanović, Adomas Vitas, Domen Arnič, Sandra Metslaid, Anna Neycken, Peter Prislan, Claudia Hartl, Daniel Ziche, Petr Horáček, Jan Krejza, Sergei Mikhailov, Jan Světlík, Aleksandra Kalisty, Tomáš Kolář, Vasyl Lavnyy, Maris Hordo, Walter Oberhuber, Tom Levanič, Ilona Mészáros, Lea Schneider, Jiří Lehejček, Rohan Shetti, Michal Bošeľa, Paul Copini, Marcin Koprowski, Ute Sass-Klaassen, Şule Ceyda Izmir, Remigijus Bakys, Hannes Entner, Jan Esper, Karolina Janecka, Edurne Martinez del Castillo, Rita Verbylaite, Mátyás Árvai, Justine Charlet de Sauvage, Katarina Čufar, Markus Finner, Torben Hilmers, Zoltán Kern, Klemen Novak, Radenko Ponjarac, Radosław Puchałka, Bernhard Schuldt, Nina Škrk, Vladimir Tanovski, Christian Zang, Anja Žmegač, Cornell Kuithan, Marek Metslaid, Eric Thurm, Polona Hafner, Luka Krajnc, Mauro Bernabei, Stefan Bojić, Robert Brus, Andreas Burger, Ettore D'Andrea, Todor Đorem, Mariusz Gławęda, Jožica Gričar, Marko Gutalj, Emil Horváth, Saša Kostić, Bratislav Matović, Maks Merela, Boban Miletić, András Morgós, Rafał Paluch, Kamil Pilch, Negar Rezaie, Julia Rieder, Niels Schwab, Piotr Sewerniak, Dejan Stojanović, Tobias Ullmann, Nella Waszak, Ewa Zin, Mitja Skudnik, Krištof Oštir, Anja Rammig & **Allan Buras**

EnviLink Conference

15th – 17th May 2024, Sękocin Stary, Poland

Unterstützt von / Supported by

Alexander von Humboldt Stiftung / Foundation



Verkerk et al., 2013, For. Ecol. Manag.

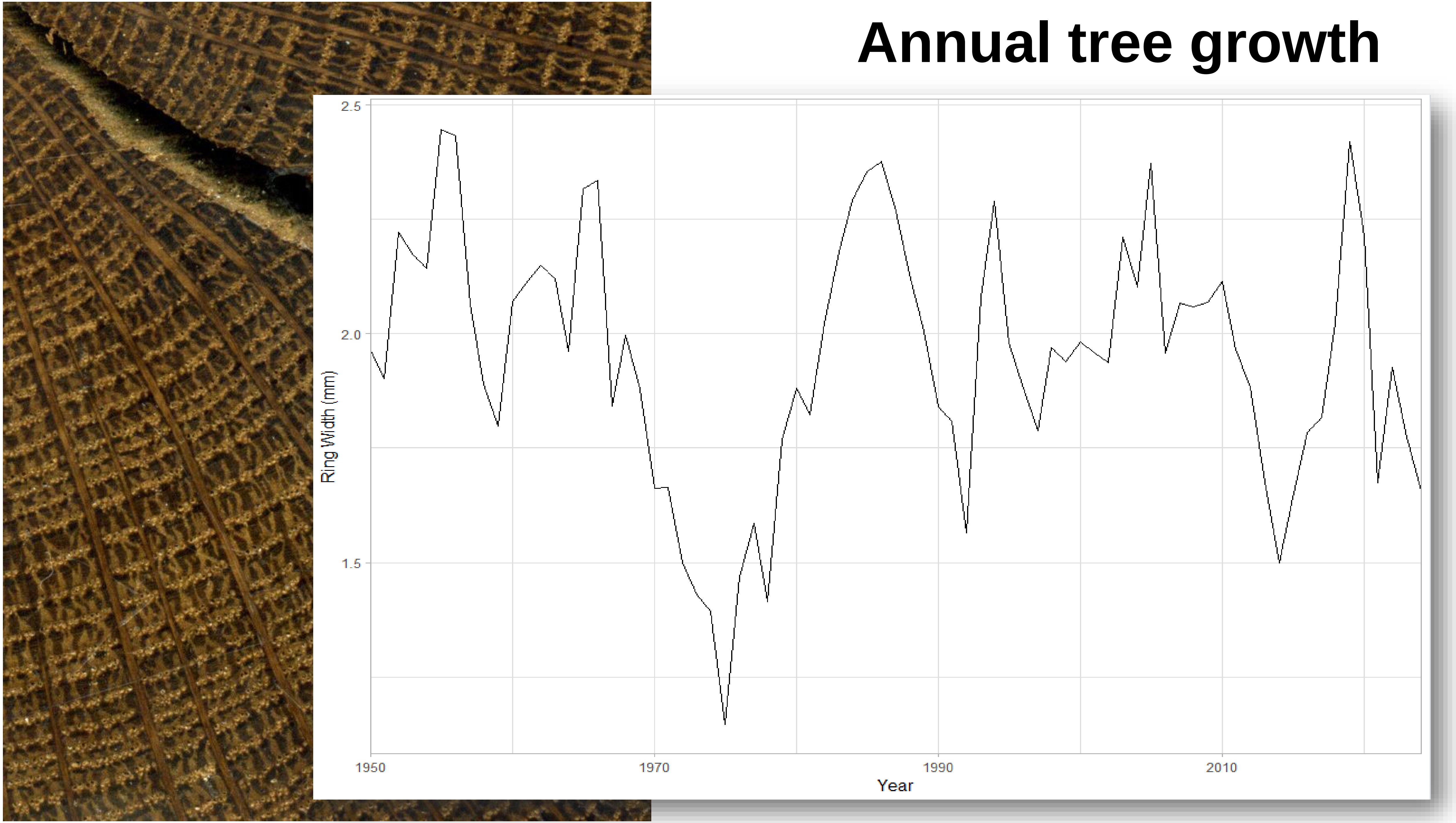
Maps of forest growth

- Spatial and temporal variation in tree-growth
- Approximate net primary production
- Study variation in carbon sequestration
- Estimate the effects of large-scale extreme events on tree growth
- Assess the future performance of tree growth under changing climate

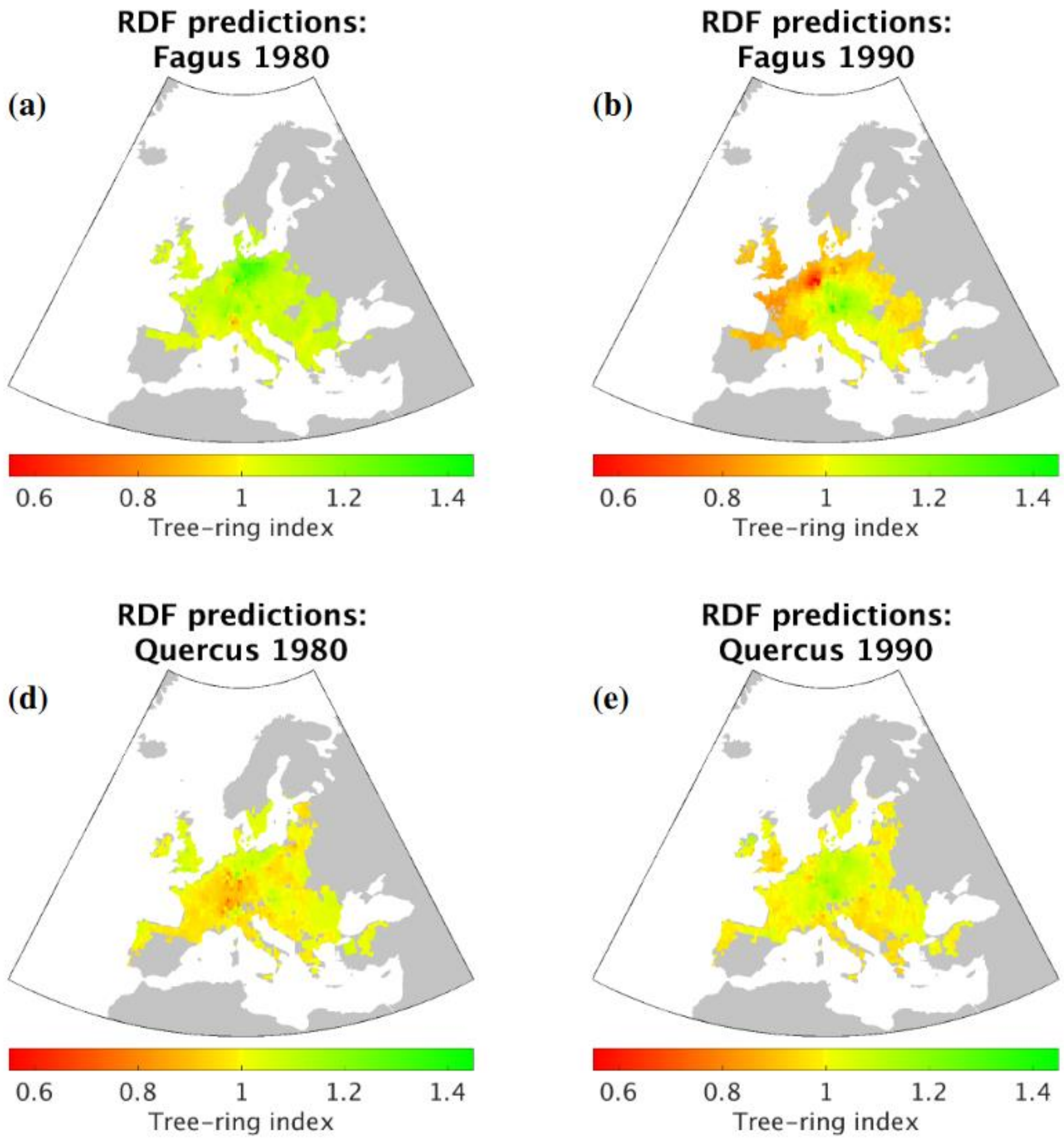
Annual tree growth

Annual tree growth

Annual tree growth



Maps of forest growth



Bodesheim et al., 2022, Environ. Data Science

- **Spatial and temporal variation in tree-growth**
- **Approximate net primary production**
- **Study variation in carbon sequestration**
- **Estimate the effects of large-scale extreme events on tree growth**
- **Assess the future performance of tree growth under changing climate**

Earth Observations from satellites (EOS) and tree growth

Correlation between maximum latewood density of annual tree rings and NDVI based estimates of forest productivity

R. D. D'ARRIGO[1], C. M. MALMSTROM[2], G. C. JACOBY[1], S. O. LOS[3] and D. E. BUNKER[1]

[1]Tree Ring Laboratory, Lamont-Doherty Earth Observatory, Palisades, NY 10964, USA; e-mail: druidrd@ldeo.columbia.edu
[2]Department of Botany and Plant Pathology, Michigan State University, East Lansing, MI 48824, USA; e-mail: carolyn@bsrsi.msu.edu
[3]Science Systems and Applications Inc. code 923, NASA/Goddard Space Flight Center, Greenbelt, MD 20771, USA; e-mail: sietse@scirocco.gsfc.nasa.gov

Spatio-temporal assessment of beech growth in relation to climate extremes in Slovenia – An integrated approach using remote sensing and tree-ring data

Mathieu Decuyper[a,d,m,*], Roberto O. Chávez[b], Katarina Čufar[e], Sergio A. Estay[c,i], Jan G.P.W. Clevers[a], Peter Prislan[f], Jožica Gričar[f], Zalika Črepinšek[g], Maks Merela[e], Martin de Luis[h], Roberto Serrano Notivoli[j], Edurne Martinez del Castillo[h], Danaë M.A. Rozendaal[a,d,k,l], Frans Bongers[d], Martin Herold[a], Ute Sass-Klaassen[d]

Article

Exploring Relationships among Tree-Ring Growth, Climate Variability, and Seasonal Leaf Activity on Varying Timescales and Spatial Resolutions

Upasana Bhuyan [1,*], Christian Zang [2], Sergio M. Vicente-Serrano [3] and Annette Menzel [1,4]

Original Articles

Inconsistent relationships between annual tree ring-widths and satellite-measured NDVI in a mountainous subarctic environment

Lucas Brehaut[a], Ryan K. Danby[a,b,*]

The effect of growing season and summer greenness on northern forests

R. K. Kaufmann,[1,2] R. D. D'Arrigo,[3] C. Laskowski,[4] R. B. Myneni,[1] L. Zhou,[5] and N. K. Davi[3]

Received 29 January 2004; revised 9 March 2004; accepted 1 April 2004; published 7 May 2004.

NRC Research Press

ARTICLE

Climate impacts on radial growth and vegetation activity of two co-existing Mediterranean pine species

Edmond Pasho and Arben Q. Alla

Diverse relationships between forest growth and the Normalized Difference Vegetation Index at a global scale

Sergio M. Vicente-Serrano [a,*], J. Julio Camarero [a], José M. Olano [b,c], Natalia Martín-Hernández [a], Marina Peña-Gallardo [a], Miquel Tomás-Burguera [d], Antonio Gazol [a], Cesar Azorin-Molina [e], Upasana Bhuyan [f], Ahmed El Kenawy [g]

Check for updates

Temporal connections between long-term Landsat time-series and tree-rings in an urban–rural temperate forest

Mitchell T. Bonney [*], Yuhong He

Department of Geography, Geomatics and Environment, University of Toronto Mississauga, 3359 Mississauga Rd, Mississauga, Ontario L5L 1C6, Canada

Main Research Idea

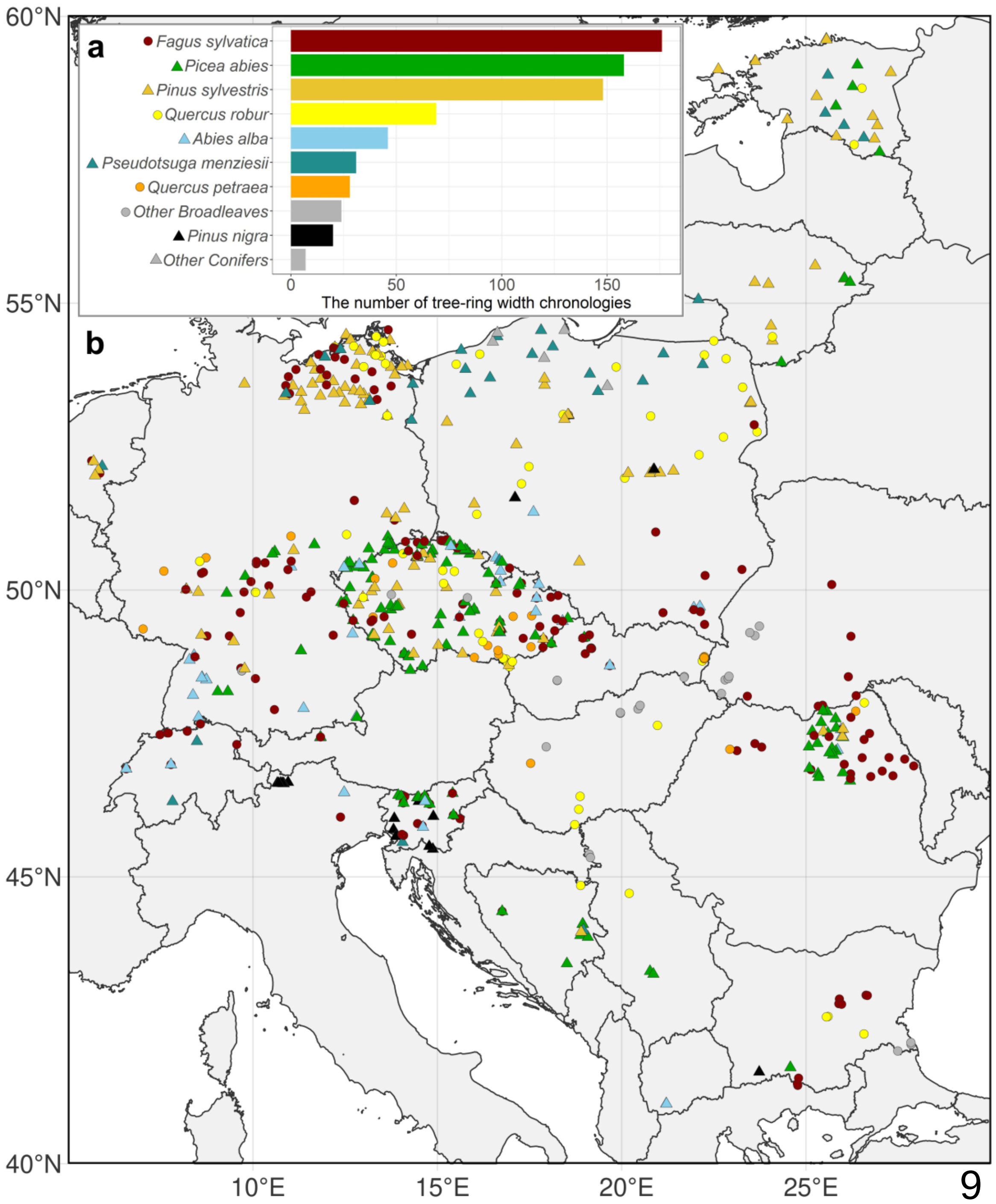
Combining high-resolution climate, remote sensing and topographic data to model radial tree-growth

Main Research Idea

Combining high-resolution climate, remote sensing and topographic data to model radial tree-growth

TREOS

- **A sub-continental Tree-Ring and EOS network with more than 700 sites**
- **sampled after the end of growing season in 2018**
- **8 main and 5 minor tree species**



Briefly about the methods

Extraction of E-OBS climate data (seasonal and long-term averages)

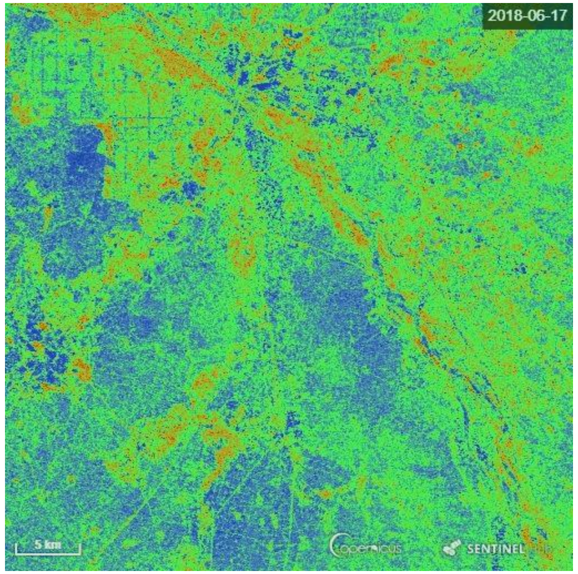
- **temperatures**
- **precipitation**
- **climatic water balance**

Briefly about the methods

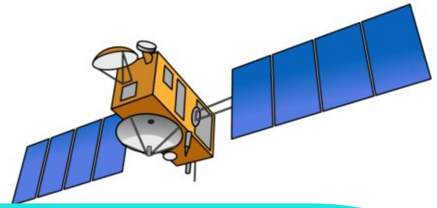
Extraction of E-OBS climate data (seasonal and long-term averages)
- **temperatures**
- **precipitation**
- **climatic water balance**

Extraction of EOS data

Sentinel 1
- Synthetic-aperture radar (SAR), 5 m resolution
- VV and VH backscatter give information on surface roughness, water content, geometrical properties of vegetation, leaf area index (LAI)
- Radar vegetation index (RVI) increases with forest biomass



Briefly about the methods



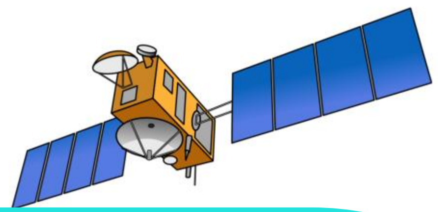
Extraction of E-OBS climate data (seasonal and long-term averages)
- temperatures
- precipitation
- climatic water balance

Extraction of EOS data

Sentinel 1
- Synthetic-aperture radar (SAR), 5 m resolution
- VV and VH backscatter give information on surface roughness, water content, geometrical properties of vegetation, leaf area index (LAI)
- Radar vegetation index (RVI) increases with forest biomass

Sentinel 2, surface reflectance, 10-20 m resolution
- NDVI, EVI (measure photosynthetic activity)
- NDRE (red edge – vegetation health)
- NDMI (proxy for moisture)

Briefly about the methods



Extraction of E-OBS climate data (seasonal and long-term averages)
- **temperatures**
- **precipitation**
- **climatic water balance**

Extraction of EOS data

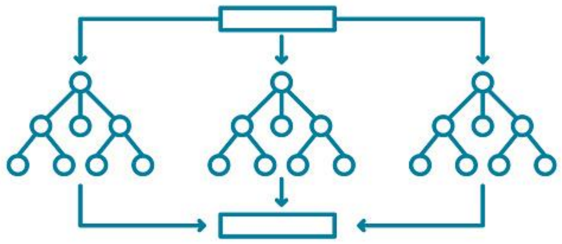
Elevation data - EU-DEM raster with 25m resolution

Sentinel 1
- **Synthetic-aperture radar (SAR), 5 m resolution**
- **VV and VH backscatter give information on surface roughness, water content, geometrical properties of vegetation, leaf area index (LAI)**
- **Radar vegetation index (RVI) increases with forest biomass**

Sentinel 2, surface reflectance, 10-20 m resolution
- **NDVI, EVI (measure photosynthetic activity)**
- **NDRE (red edge – vegetation health)**
- **NDMI (proxy for moisture)**

Modelling approach

- Machine learning – Random Forest of Regression Tress (RF)



Modelling approach

- Machine learning – Random Forest of Regression Tress (RF)

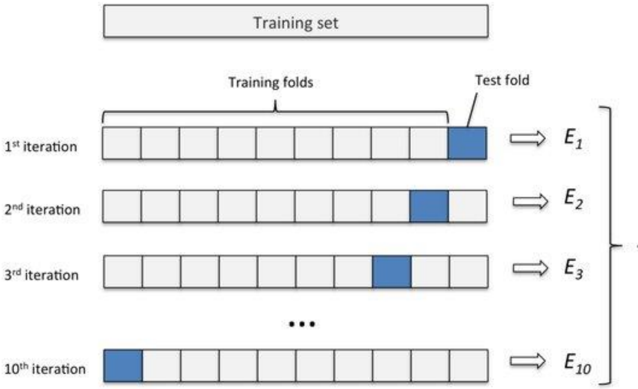
- RF were calibrated at different levels of complexity
  - General model using all data
  - 3 forest type models
  - 8 species-specific models

Modelling approach

- Machine learning – Random Forest of Regression Tress (RF)

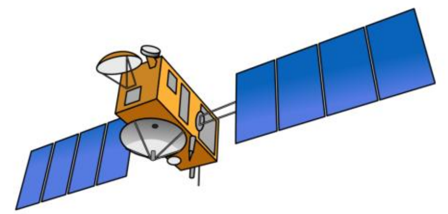
- RF were calibrated at different levels of complexity
  - General model using all data
  - 3 forest type models
  - 8 species-specific models

- Model evaluation exclusively on independent data (*k* –fold spatially blocked cross-validation)

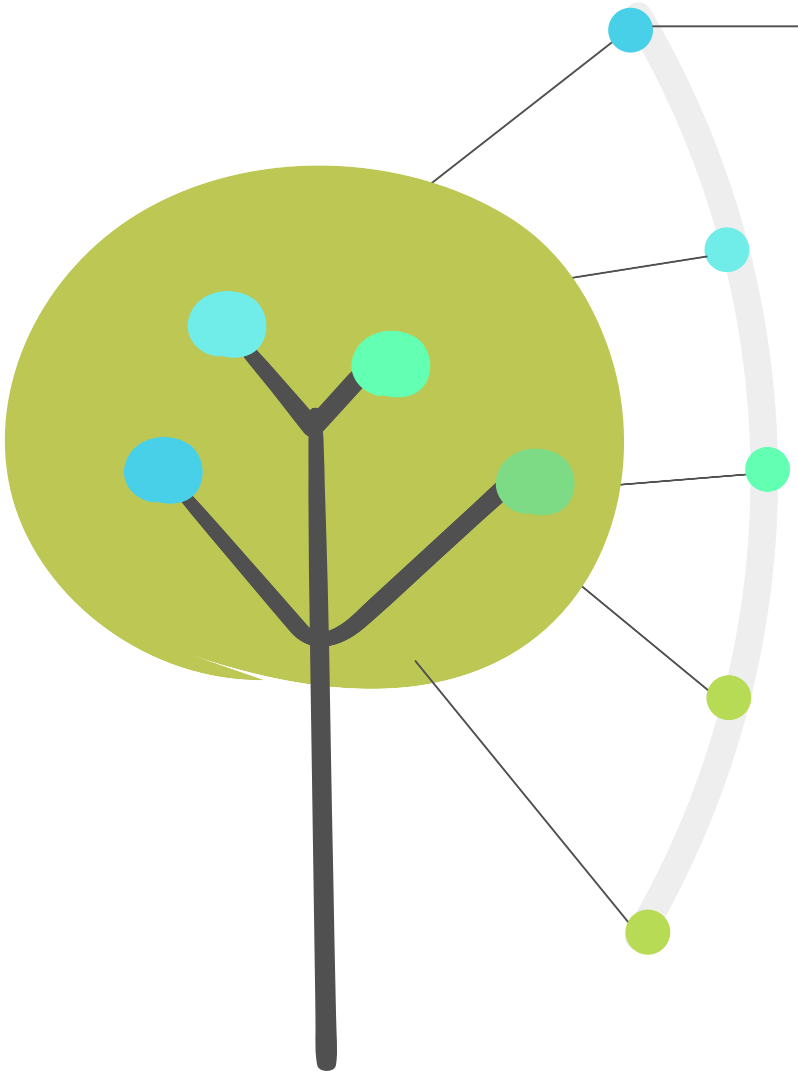


Modelling approach

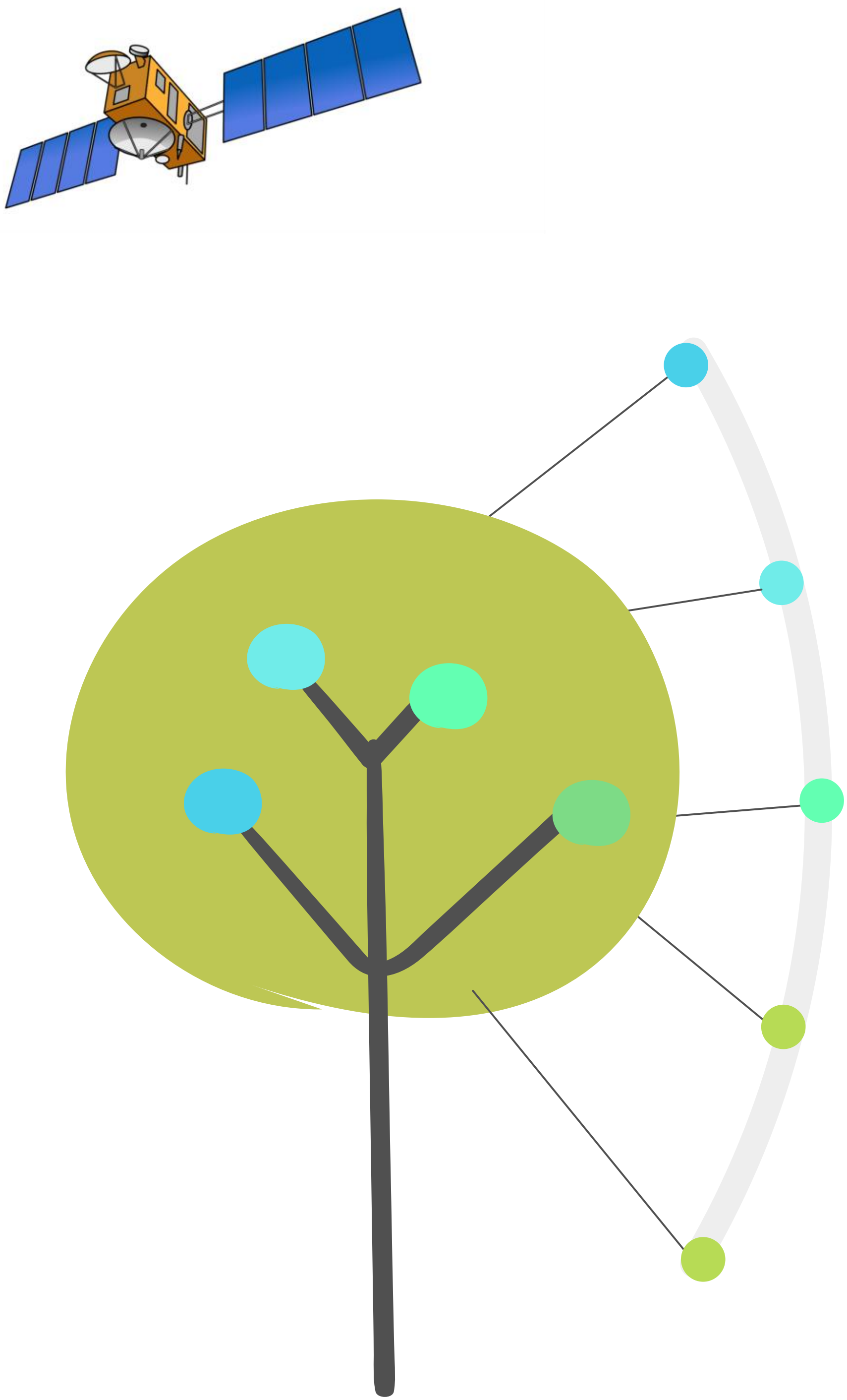
- Machine learning – Random Forest of Regression Tress (RF)
- RF were calibrated at different levels of complexity
  - General model using all data
  - 3 forest type models
  - 8 species-specific models
- Model evaluation exclusively on independent data (*k* –fold spatially blocked cross-validation)
- The estimation of area of applicability (AOA) for the established models

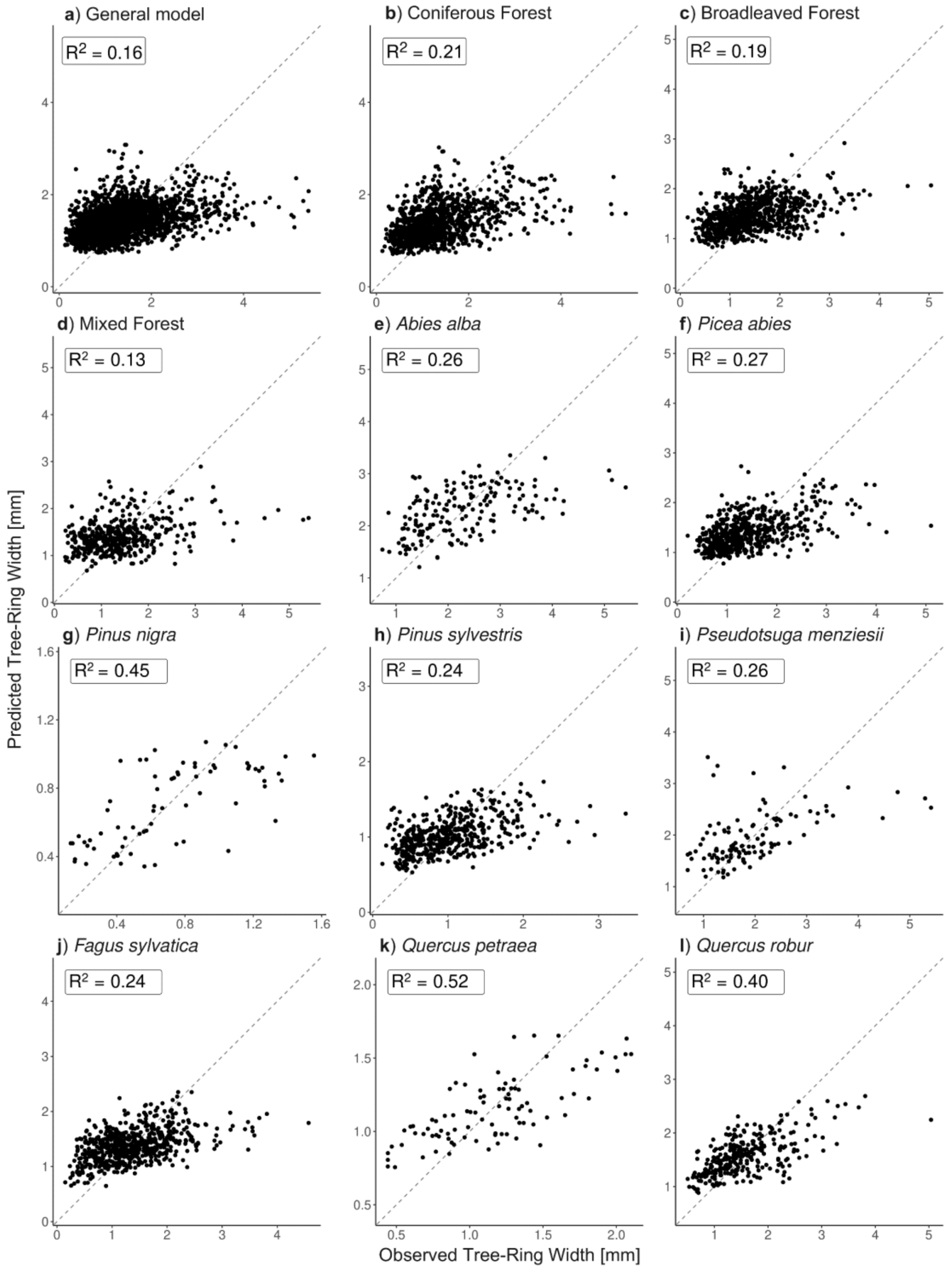


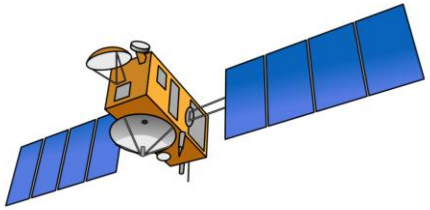
Results



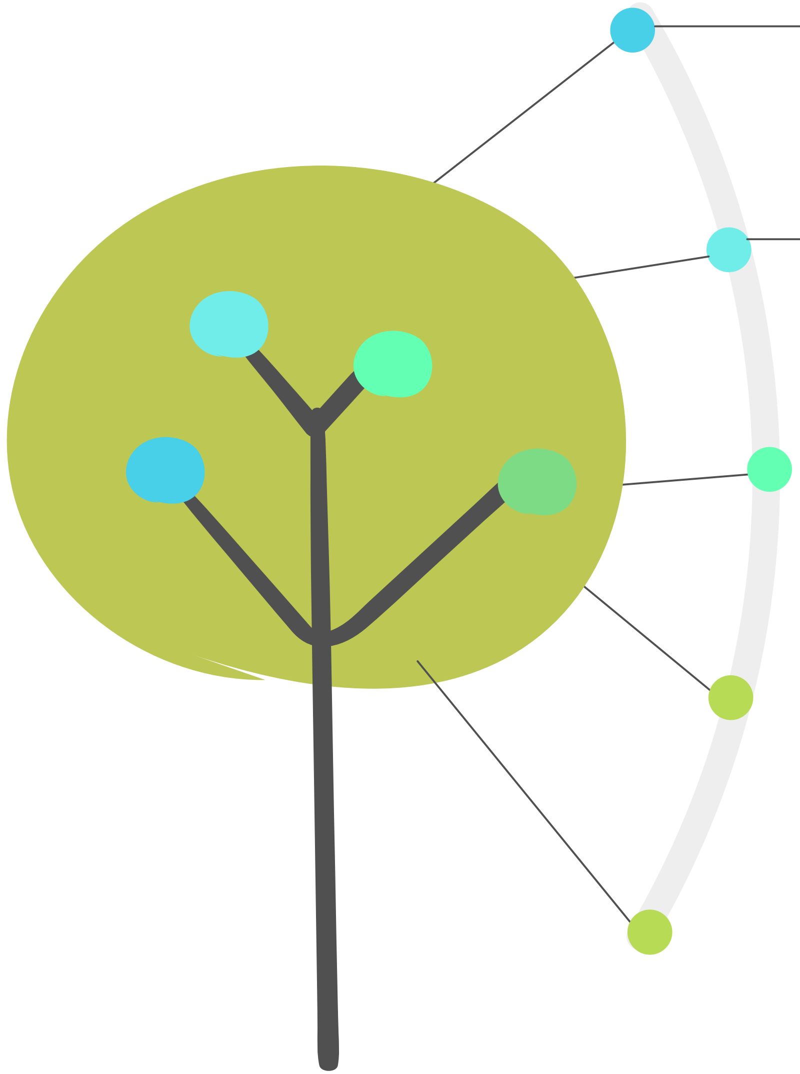
The explained variance ranged from 13% to 52% and was generally higher for species-specific models




a) General model
R² = 0.16
b) Coniferous Forest
R² = 0.21
c) Broadleaved Forest
R² = 0.19
d) Mixed Forest
R² = 0.13
e) Abies alba
R² = 0.26
f) Picea abies
R² = 0.27
g) Pinus nigra
R² = 0.45
h) Pinus sylvestris
R² = 0.24
i) Pseudotsuga menziesii
R² = 0.26
j) Fagus sylvatica
R² = 0.24
k) Quercus petraea
R² = 0.52
l) Quercus robur
R² = 0.40
Predicted Tree-Ring Width [mm]
Observed Tree-Ring Width [mm]

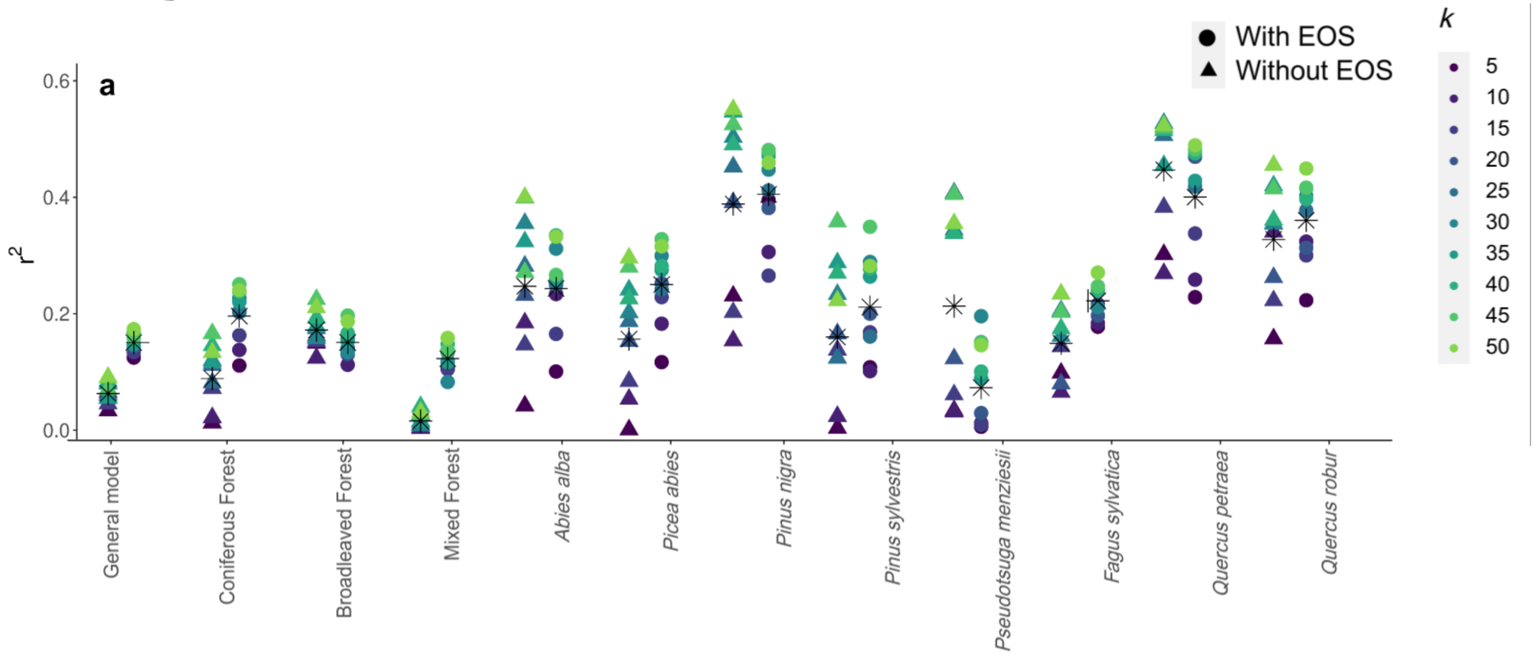


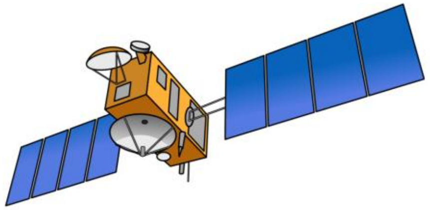
Results



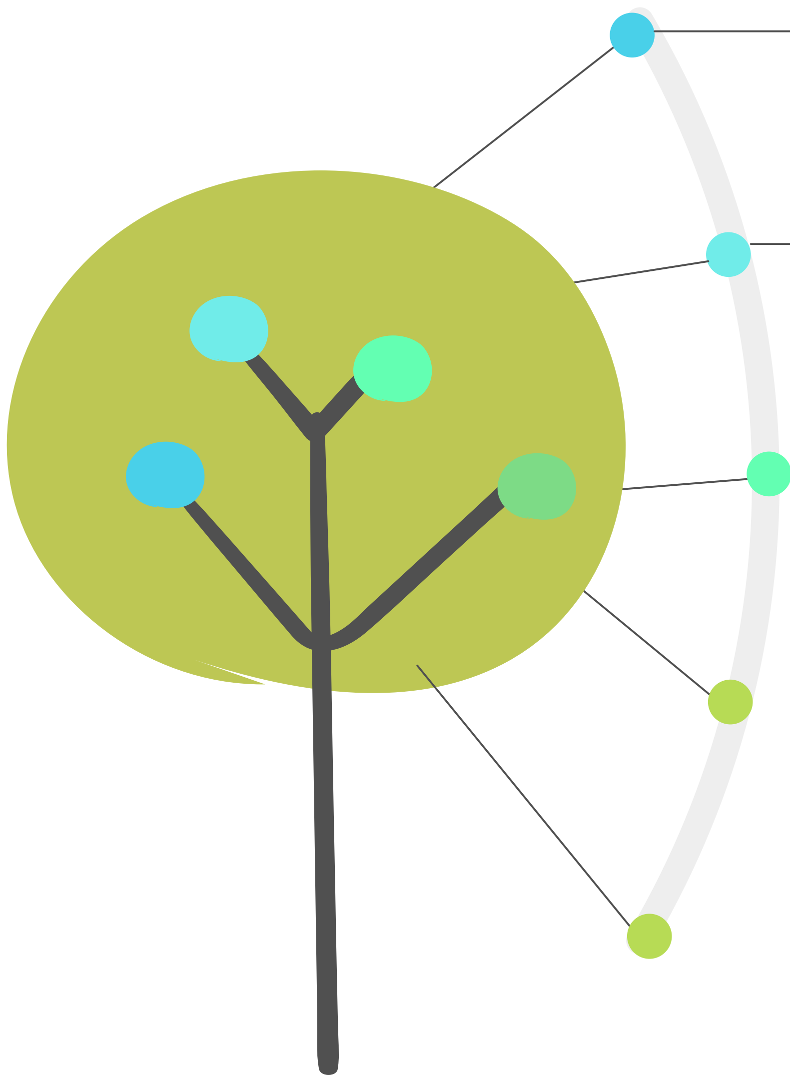
The explained variance ranged from 13% to 52% and was generally higher for species-specific models

Including EOS into the models improved the prediction accuracy of secondary tree growth in terms of Δr^2 by5 % on average, and up to 11%





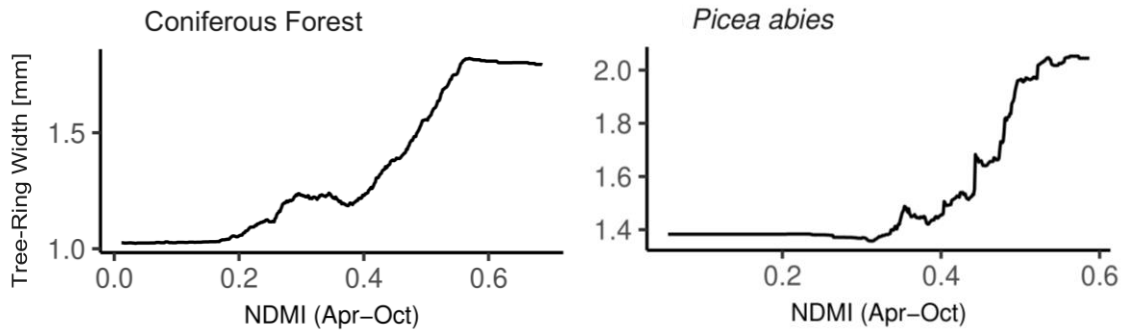
Results

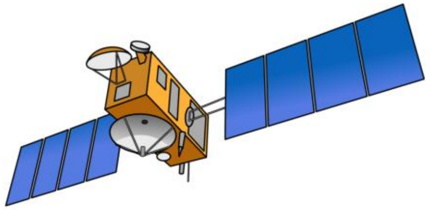


The explained variance ranged from 13% to 52% and was generally higher for species-specific models

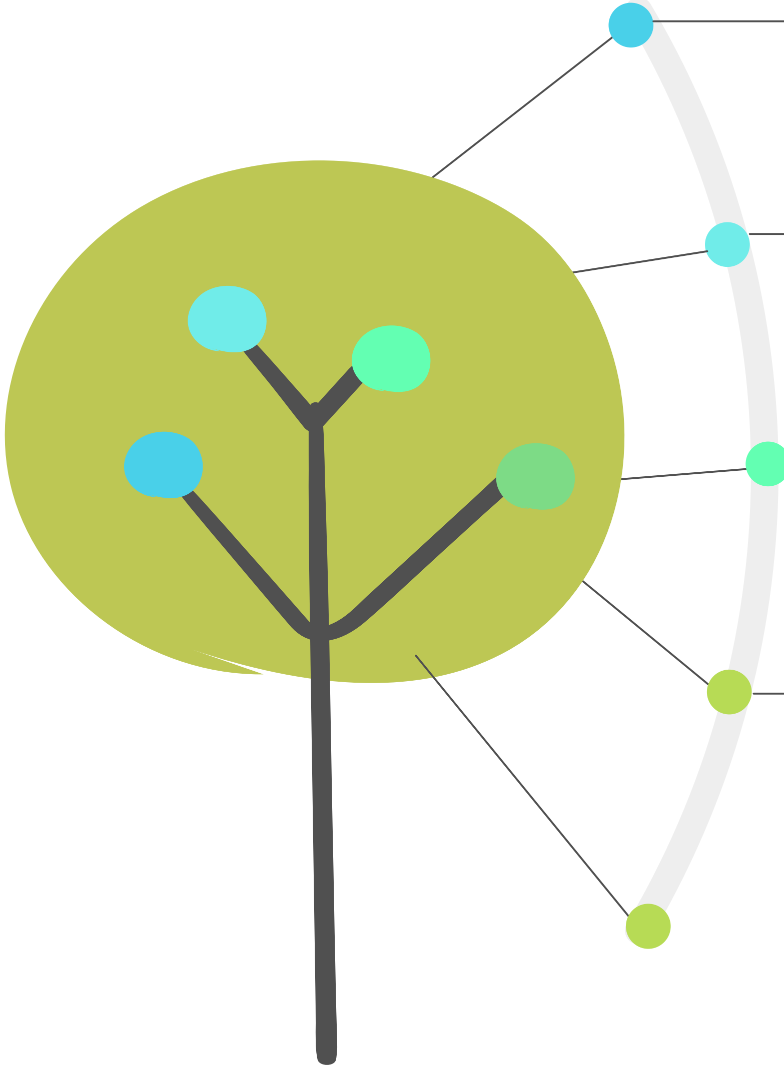
Including EOS into the models improved the prediction accuracy of secondary tree growth in terms of Δr^2 by 6% on average, and up to 11%

NDMI (moisture index) was the most important predictor variable across species





Results

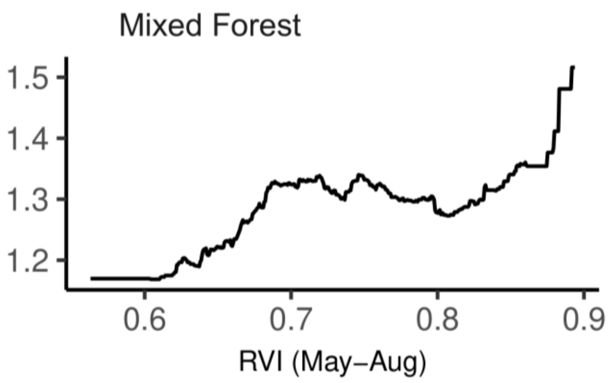


The explained variance ranged from 13% to 52% and was generally higher for species-specific models

Including EOS into the models improved the prediction accuracy of secondary tree growth in terms of Δr^2 by 6% on average, and up to 11%

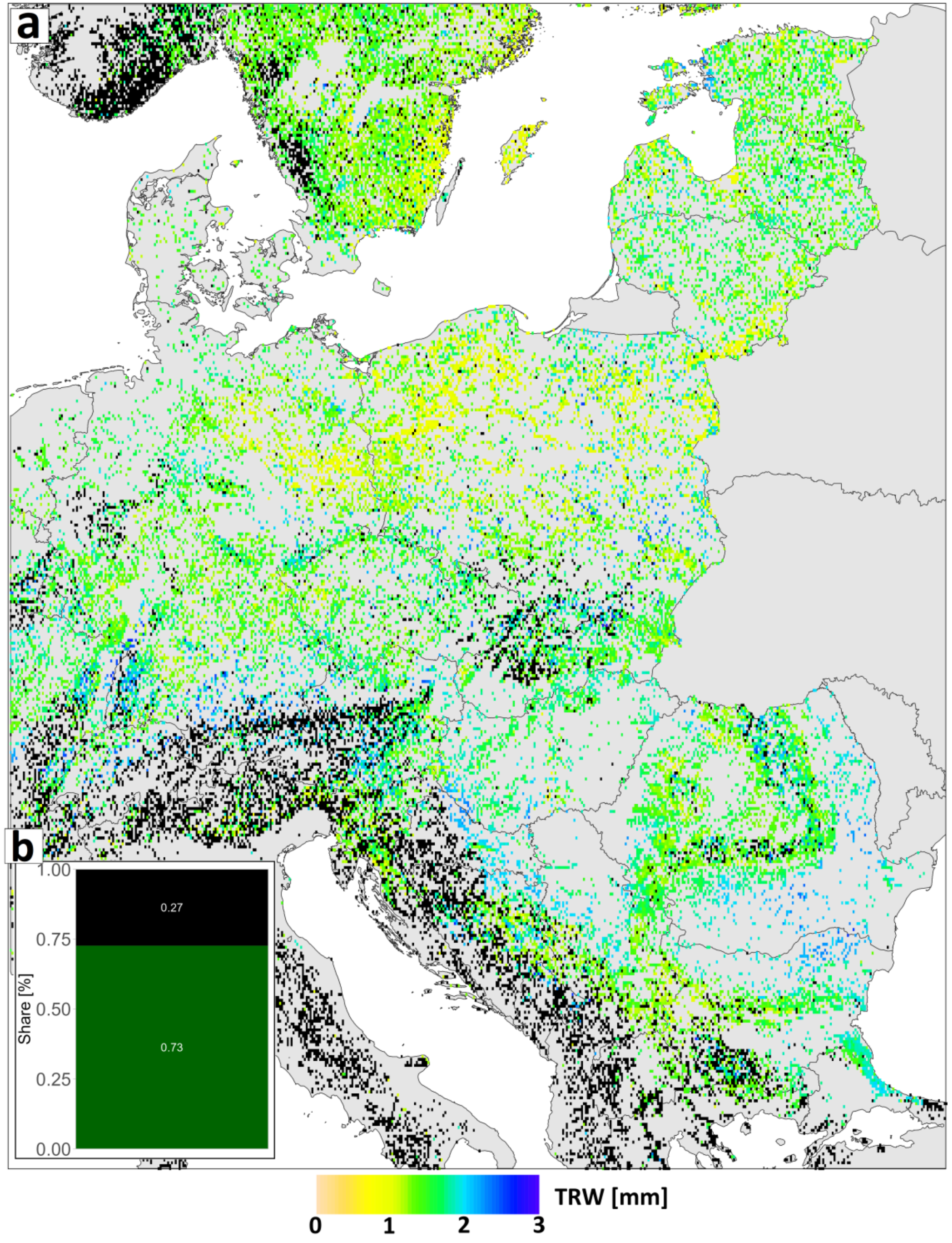
NDMI (moisture index) was the most important predictor variable across species

SAR (Sentinel - 1) was included in 8 out of 12 models



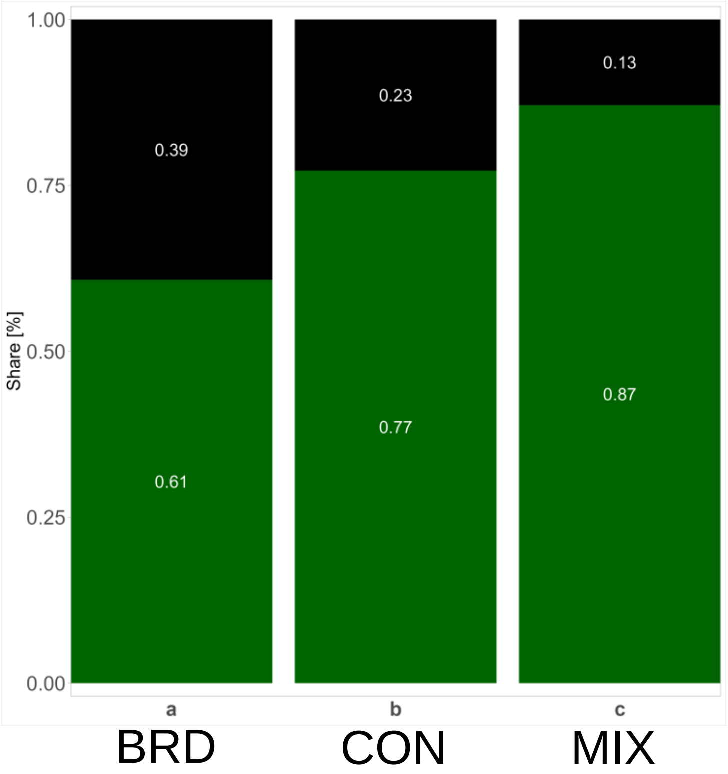
Annual radial tree growth for 2021 at 0.05 spatial resolution

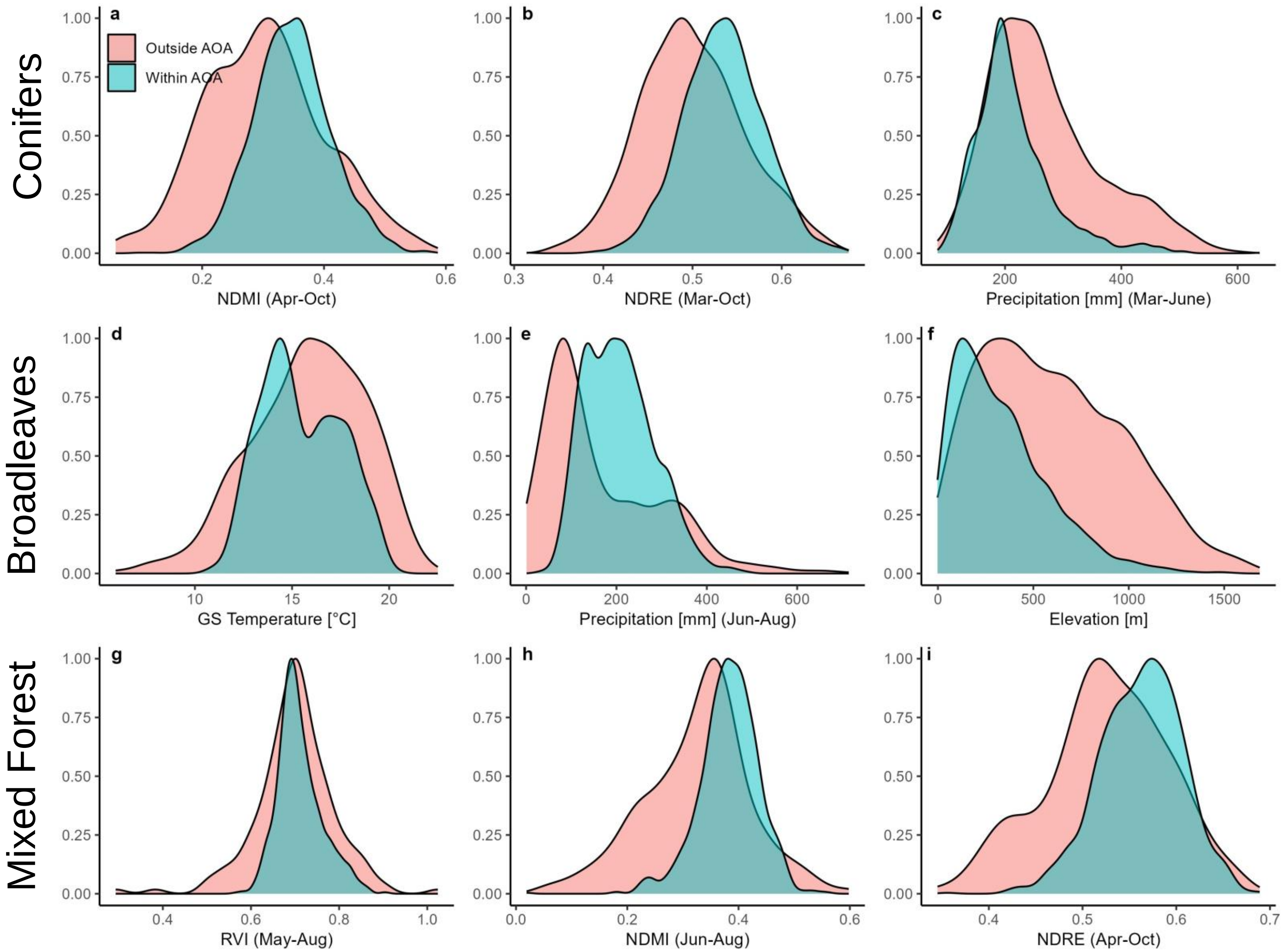
- Combination of the three forest type models
- Very realistic spatial distribution of tree-growth predictions



Annual radial tree growth for 2021 at 0.05 spatial resolution

The area of applicability (AOA) ranged from 61% - 87%





hank you for your listening

jernej.jevsenak@gozdis.si

Link to publication

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Check for updates

Incorporating high-resolution climate, remote sensing and topographic data to map annual forest growth in central and eastern Europe

Jernej Jevšenak [a,b,*], Marcin Klisz [c], Jiří Mašek [d], Vojtěch Čada [e], Pavel Janda [e], Miroslav Svoboda [e], Ondřej Vostarek [e], Vaclav Treml [d], Ernst van der Maaten [f], Andrei Popa [g,h], Ionel Popa [g], Marieke van der Maaten-Theunissen [f], Tzvetan Zlatanov [i], Tobias Scharnweber [j], Svenja Ahlgrimm [j], Juliane Stolz [f,k], Irena Sochová [l,m], Cătălin-Constantin Roibu [n], Hans Pretzsch [a], Gerhard Schmied [a], Enno Uhl [a,o], Ryszard Kaczka [d], Piotr Wrzesiński [c], Martin Šenfeldr [p], Marcin Jakubowski [q], Jan Tumajer [d], Martin Wilmking [j], Nikolaus Obojes [r], Michal Rybníček [l,m], Mathieu Lévesque [s], Aleksei Potapov [t], Soham Basu [u], Marko Stojanović [m], Stefan Stjepanović [v], Adomas Vitas [w], Domen Arnič [x], Sandra Metslaid [t], Anna Neycken [s], Peter Prislan [x], Claudia Hartl [y,z], Daniel Ziche [aa], Petr Horáček [l,m], Jan Krejza [u,m], Sergei Mikhailov [l,m], Jan Světlík [u,m], Aleksandra Kalisty [ab], Tomáš Kolář [l,m], Vasyl Lavnyy [ac], Maris Hordo [t], Walter Oberhuber [ad], Tom Levanič [ae,af], Ilona Mészáros [ag], Lea Schneider [ah], Jiří Lehejček [ai], Rohan Shetti [ai], Michal Bošeľa [aj], Paul Copini [ak,al], Marcin Koprowski [am,an], Ute Sass-Klaassen [ak,ao], Şule Ceyda Izmir [ap], Remigijus Bakys [aq], Hannes Entner [ad], Jan Esper [ar], Karolina Janecka [j,as], Edurne Martinez del Castillo [ar], Rita Verbylaite [at], Mátyás Árvai [au], Justine Charlet de Sauvage [s], Katarina Čufar [av], Markus Finner [ad], Torben Hilmers [a], Zoltán Kern [aw,ax], Klemen Novak [av], Radenko Ponjarac [ay], Radosław Puchałka [am,an], Bernhard Schuldt [az], Nina Škrk Dolar [av], Vladimir Tanovski [ba], Christian Zang [bb,a], Anja Žmegač [bb,a], Cornell Kuithan [f], Marek Metslaid [bc], Eric Thurm [k], Polona Hafner [ae], Luka Krajnc [ae], Mauro Bernabei [bd], Stefan Bojić [v], Robert Brus [be], Andreas Burger [j], Ettore D'Andrea [bf,bg], Todor Đorem [v], Mariusz Gławęda [bh], Jožica Gričar [bi], Marko Gutalj [v], Emil Horváth [bj], Saša Kostić [ay], Bratislav Matović [ay,v], Maks Merela [av], Boban Miletić [v], András Morgós [bk], Rafał Paluch [bl], Kamil Pilch [bl], Negar Rezaie [bf], Julia Rieder [az], Niels Schwab [bm], Piotr Sewerniak [bn], Dejan Stojanović [ay], Tobias Ullmann [bo], Nella Waszak [an], Ewa Zin [bl,bp], Mitja Skudnik [b,be], Krištof Oštir [bq], Anja Rammig [a], Allan Buras [a]

References

SCHMITT, Uwe, et al. The vascular cambium of trees and its involvement in defining xylem anatomy. In: Secondary xylem biology. Academic Press, 2016. p. 3-24.

Verkerk, P. J., Levers, C., Kuemmerle, T., Lindner, M., Valbuena, R., Verburg, P. H., & Zudin, S. (2015). Mapping wood production in European forests. Forest Ecology and Management, 357, 228-238.

Bodesheim, P., Babst, F., Frank, D. C., Hartl, C., Zang, C. S., Jung, M., ... & Mahecha, M. D. (2022). Predicting spatiotemporal variability in radial tree growth at the continental scale with machine learning. Environmental Data Science, 1, e9.