

Unraveling the temporal variation in a 16-year net ecosystem exchange time series of a Belgian mixed forest

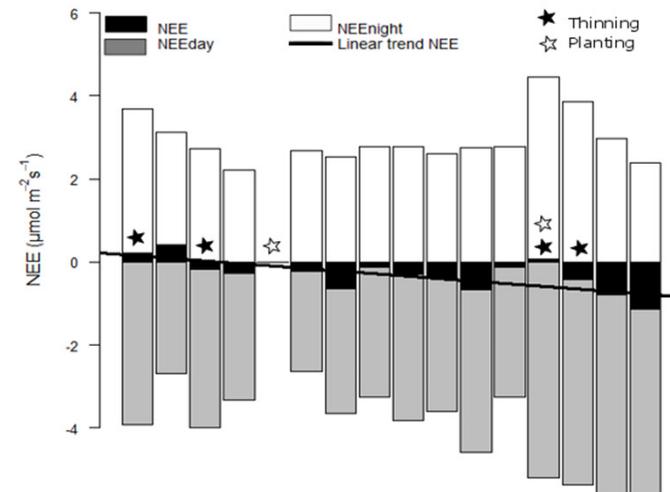
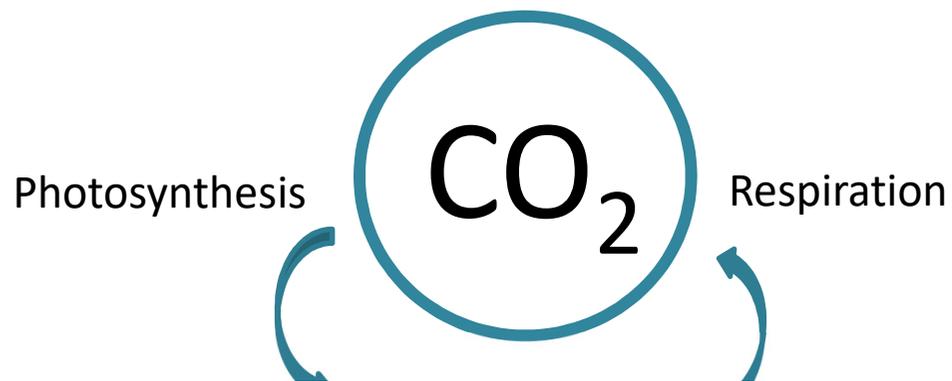
Joanna A. Horemans¹, Ivan A. Janssens¹, Bert Gielen¹, Marilyn Roland¹, Arne Verstraeten², Johan Neiryck², Reinhart Ceulemans¹

¹Centre of Excellence PLECO, Department of Biology, University of Antwerp, Universiteitsplein 1, B-2610 Wilrijk, Belgium

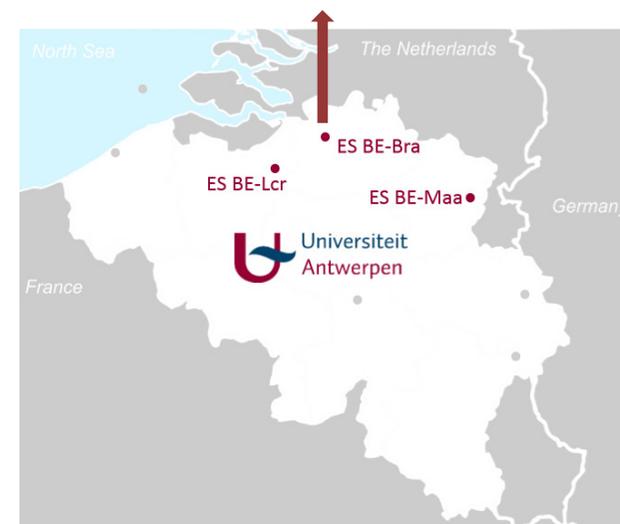
²INBO, Research Institute for Nature and Forest, Kliniekstraat 25, 1070 Brussels, Belgium

Context and research question

CO₂ net flux = Net Ecosystem Exchange NEE
Negative value = carbon uptake

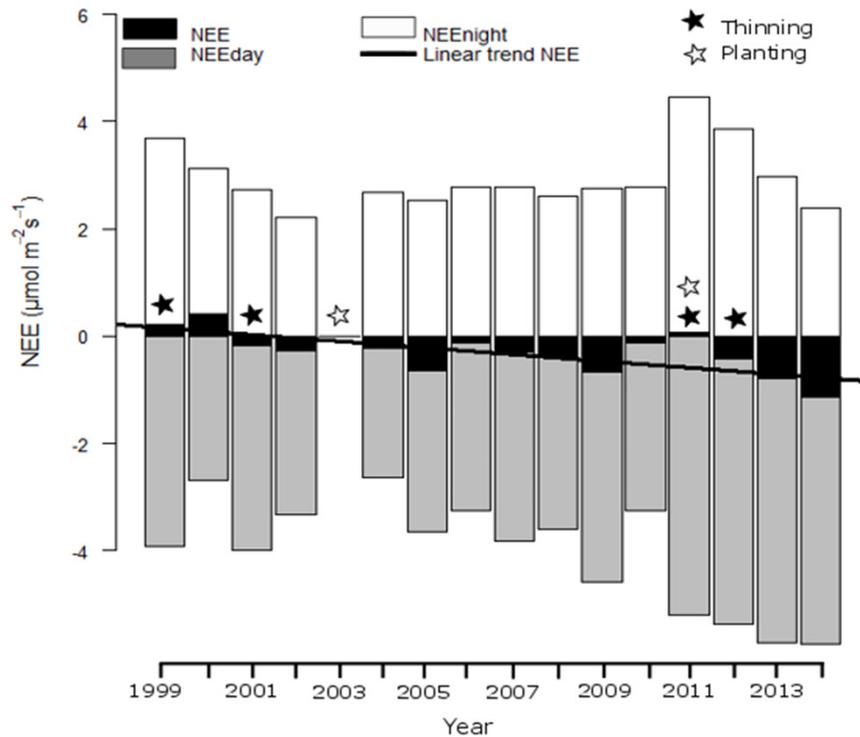


How do we explain the variation in NEE on different temporal scales?

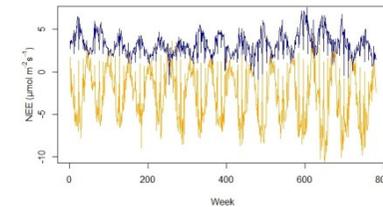


Course of the study

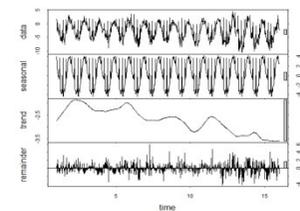
How can we explain the variation in NEE on different temporal scales?



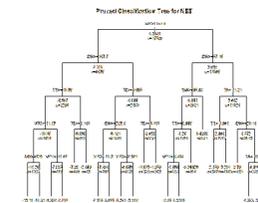
1: data assimilation



2: time series decomposition



3: random forest analysis



Data assimilation

Water availability

Precipitation **PR**

Ground water table depth **GWT**

Atmosphere and soil

Ozone **O3**

Nitric oxide **NO**

Nitrogen dioxide **NO2**

Sulphur dioxide **SO2**

Carbon dioxide **CO2**

pH soil

ANC soil



Photosynthesis and respiration

Enhanced Vegetation index **EVI**

respiration **INT_{lc}** at 0 Wm^{-2}

Quantum yield **QY**

optimum **GPP_{opt}** at an R_g value of 1000 Wm^{-2} .

$$NEE = \frac{-QY * R_g}{1 - (R_g/1000) + (QY * R_g/GPP_{opt})} + INT_{lc}$$

Meteorology

Air temperature **TA**

Soil temperature **TS**

Maximal wind speed **WS**

Vapor pressure deficit **VPD**

Day

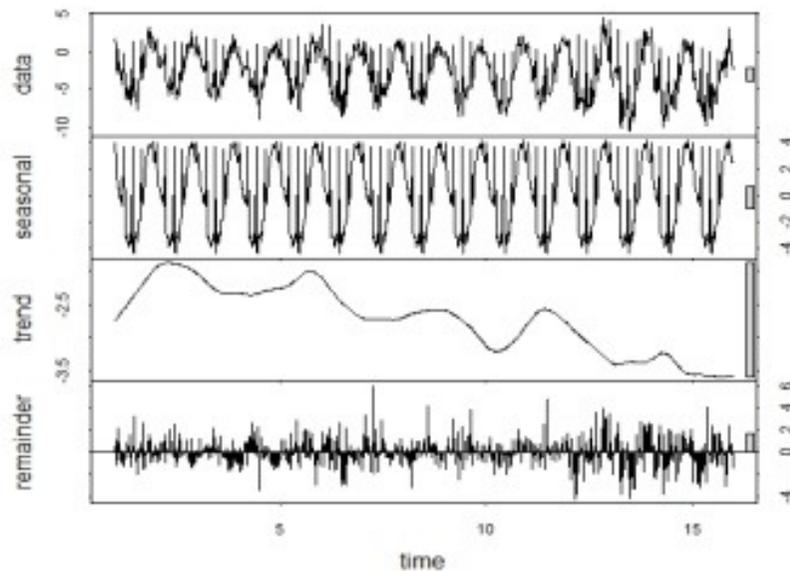
Shortwave incoming radiation

SW

Cloudiness **CLO**

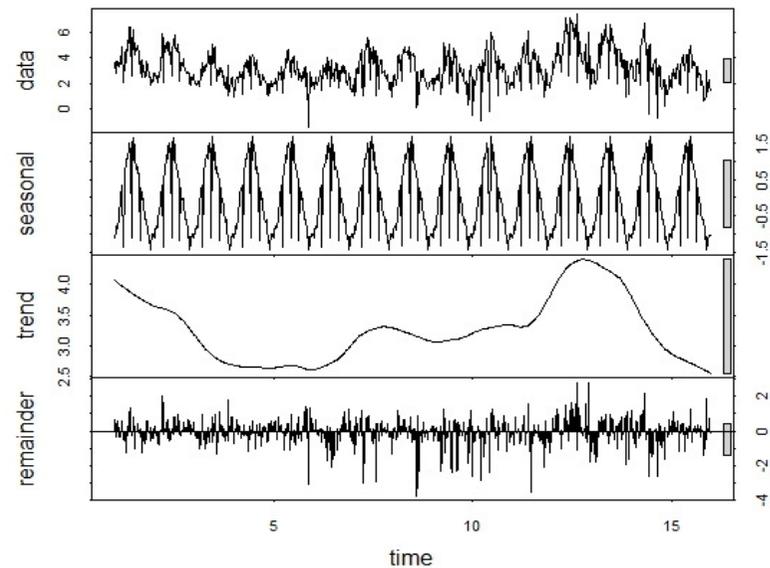
Time series decomposition

Weekly time series of NEE_{day} + 19 drivers



60 weekly time series

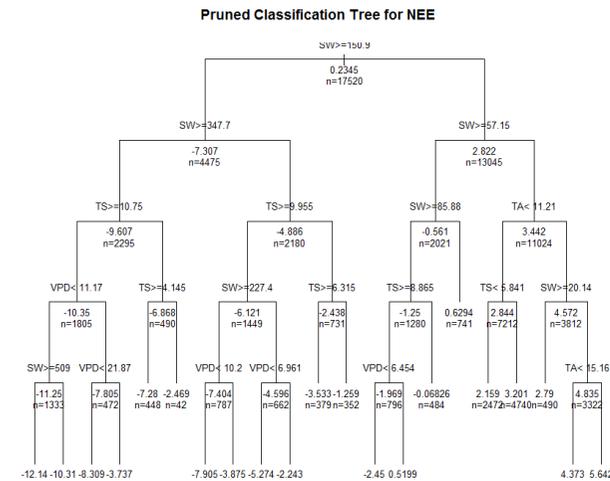
Weekly time series of NEE_{night} + 17 drivers



54 weekly time series

Random forest analysis

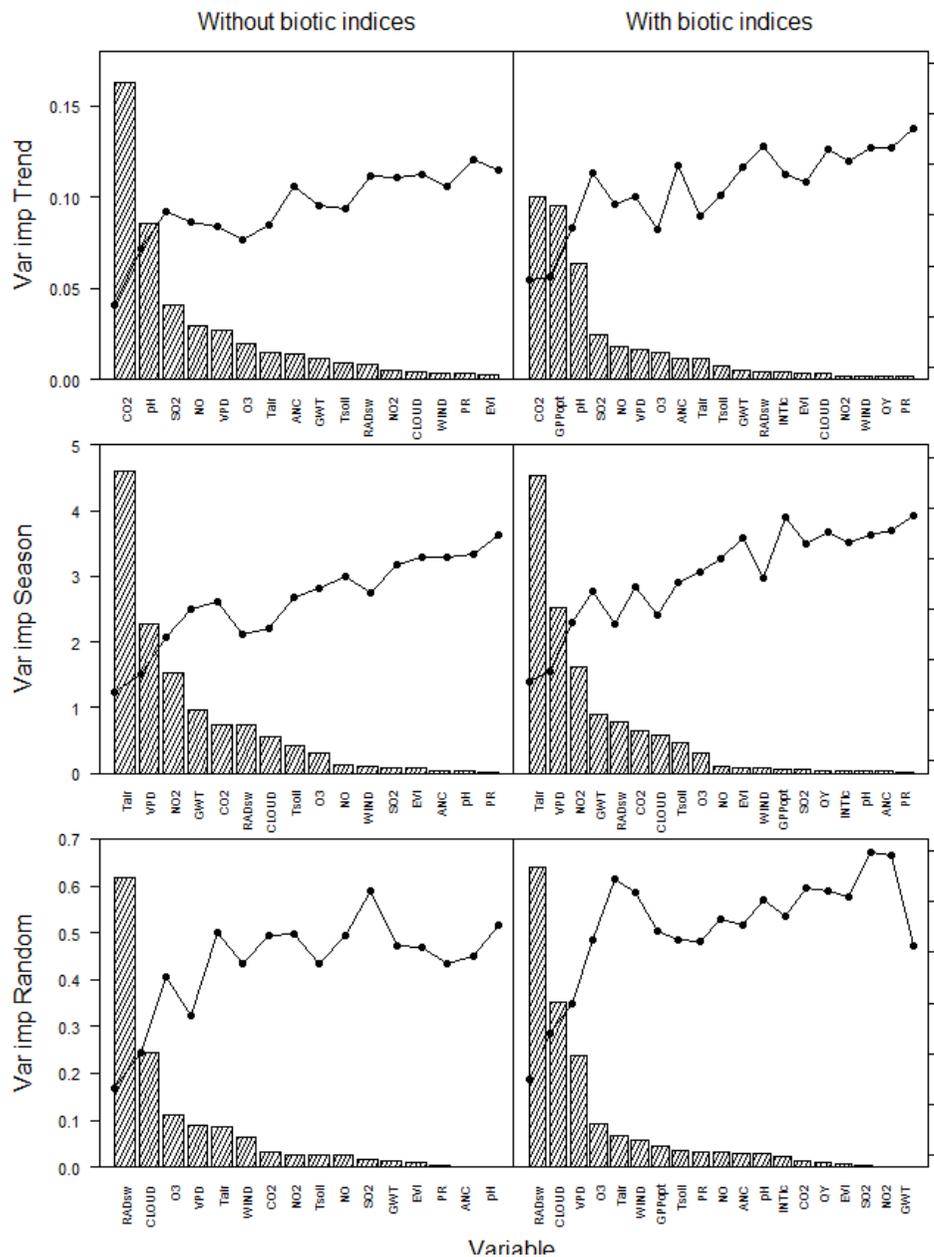
Non-parametric statistical technique aiming to optimize a model to explain the variance in the response variable by fitting an ensemble of regression trees (1000 trees)



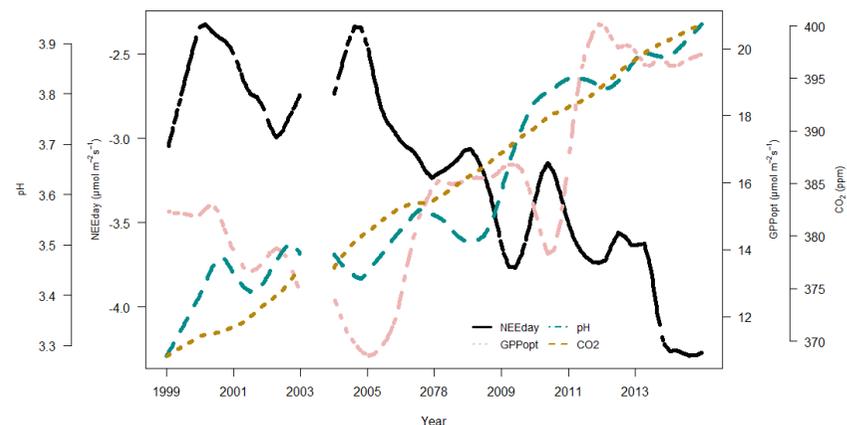
Variance importance (Vimp):
difference between prediction error when var x_i is noised up by randomly permuting its values, compared to prediction error under the observed values

Minimal depth (MinD):
average of the depth of the first split for var x_i over all trees in the forest

Results daytime NEE



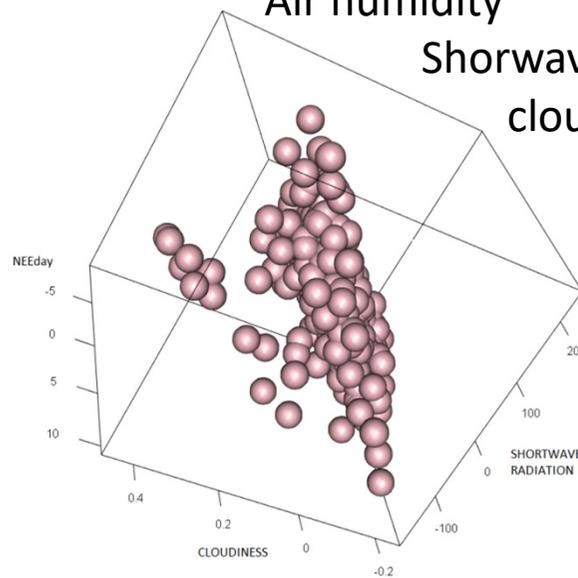
CO2 concentration, Soil solution acidity, Physiological state



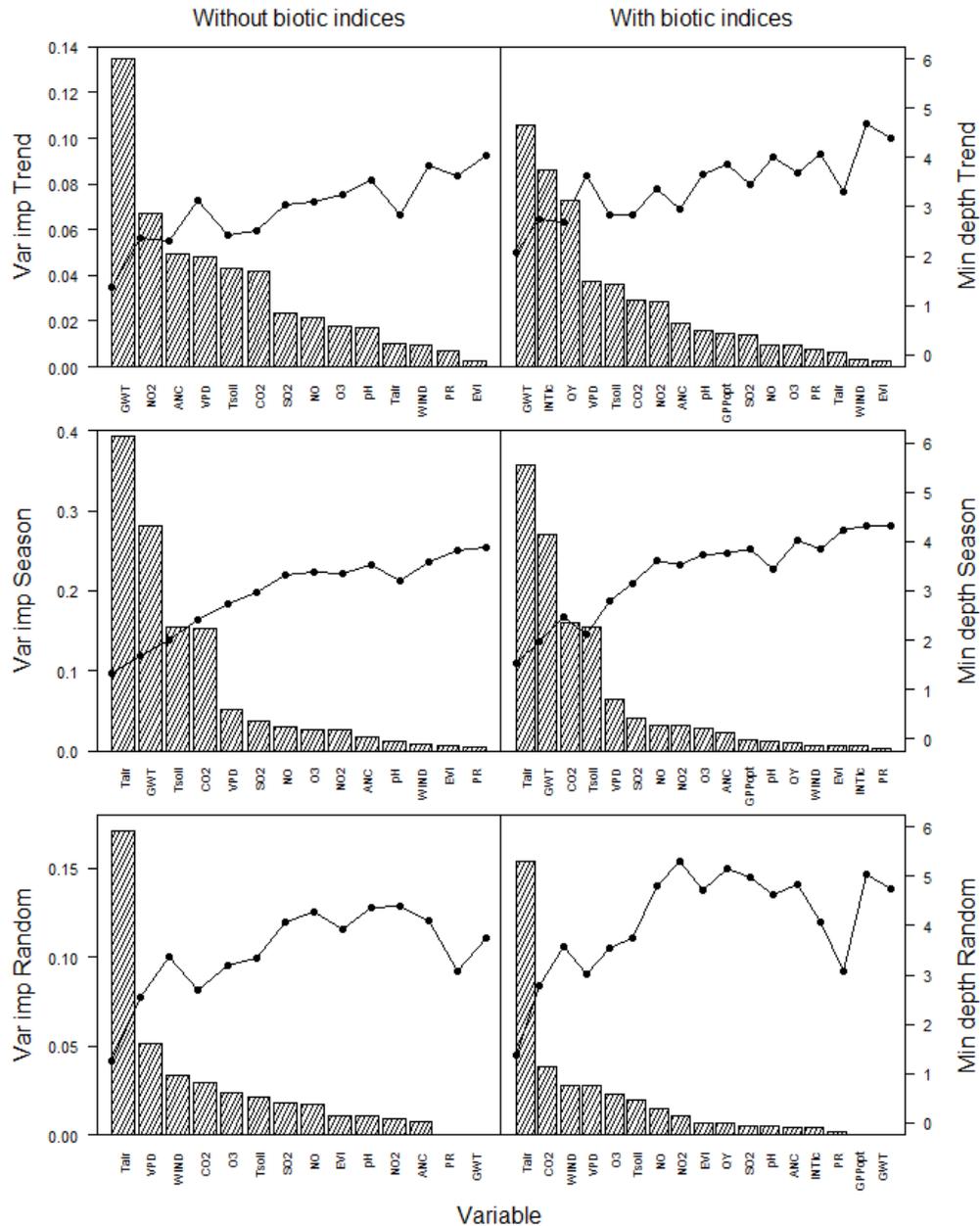
Min depth S

Air temperature
Air humidity
Shortwave radiation
cloudiness

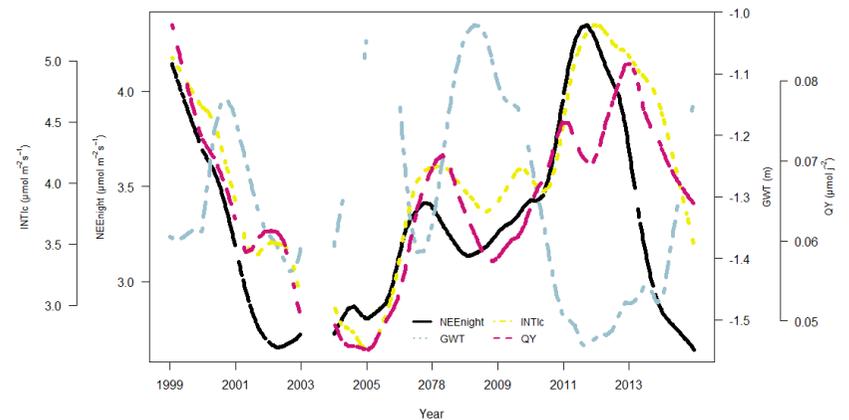
Min depth Random



Results nighttime NEE

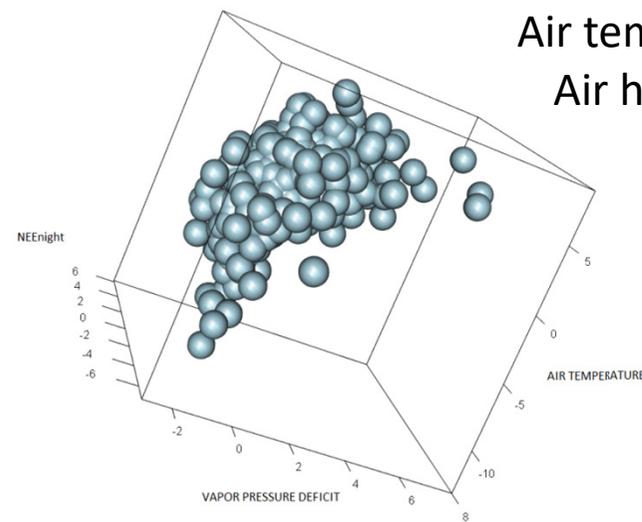


Groundwater table depth
Physiological state



Air temperature
Groundwater table depth

Air temperature
Air humidity



Conclusion and limitations



The new methodology, i.e. combining time series decomposition and random forest analysis is an excellent tool for studying NEE drivers of a forest.

Drivers of NEE change with temporal scales



Uncertainty NEE not taken into account



Causality drivers -> NEE not proved



Only true for this forest?



Perspectives



We expect the drivers to be spatially heterogeneous. The same work on many different locations would lead to more insight in the global carbon balance



This study gives valuable information for model development, needed to make projections of forest responses to climate change.



The results show that forest models should take into account the change in NEE drivers over different temporal scales and the changes in the forests physiological state over longer time scales.



A photograph of a forest path lined with tall, thin trees. The ground is covered in fallen brown leaves, and sunlight filters through the canopy, creating dappled shadows. The text "THANK YOU" is overlaid in the center in a white, sans-serif font.

THANK YOU