Interpretable Machine Learning to Understand Multi-Scale Meteorological Impacts on Ecosystem Carbon Uptake

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Motivation

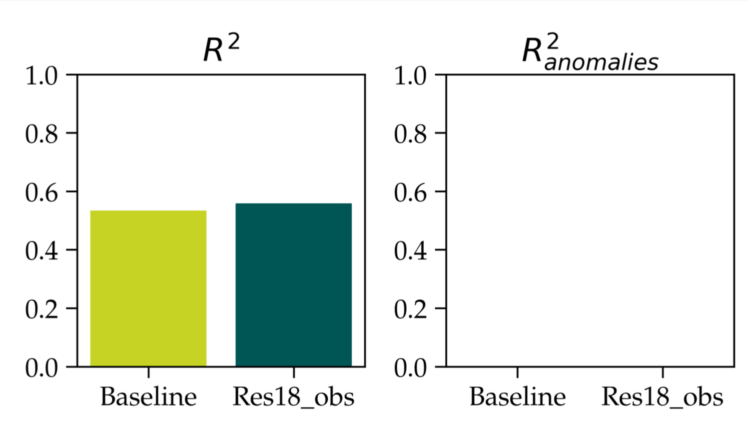
- **Meteorological factors**, such as variations in weather patterns and extreme climate events, are one of the **main drivers** of **interannual variations** in **carbon uptake** in **terrestrial ecosystems**.
- However, **quantifying** the **impact** of **multi-scale meteorological events**, their **timing** and **duration** on the carbon balance is challenging.
- Here, we make use of **observational and land model carbon flux data** and adapt **interpretable machine learning** to **quantify** the effect of **multi-scale meteorological events** on forest carbon uptake.

Take Home Message

Our method of **interpretable machine learning** can quantify the effects of **multi-scale** and **multi-variate** meteorological events on the carbon balance of forest ecosystems.

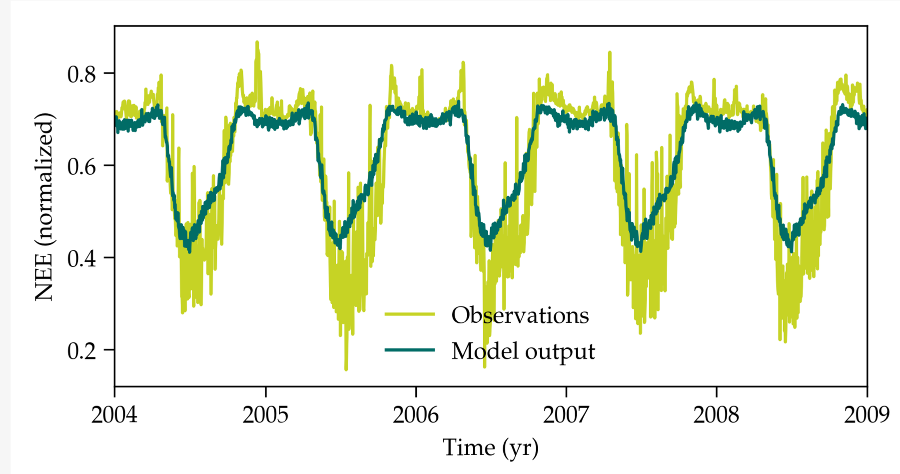
- The interpretable machine learning method **links model predictions to past meteorological events** with respect to their **position in time** and **time-scale**.
- The method also determines the **importance of the various meteorological predictors** in modelling carbon anomalies.
- The machine learning model trained on observations fails to describe anomalies in the NEE data. This could be due to the **limited amount of training data**.

Model Peformance on unseen data

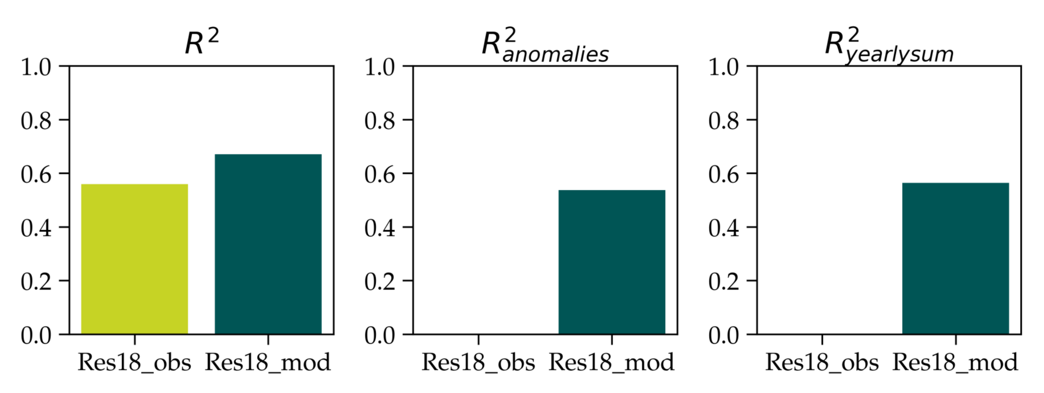


The machine learning model trained on observations (**Res18_obs**) captures the seasonal cycle quite well, but fails to describe anomalies in the NEE data.

- Comparison between Baseline (mean seasonal cycle) and Res18_obs.
- NEE observations and Res18_obs prediction for multiple years at the DE-Hai test site.



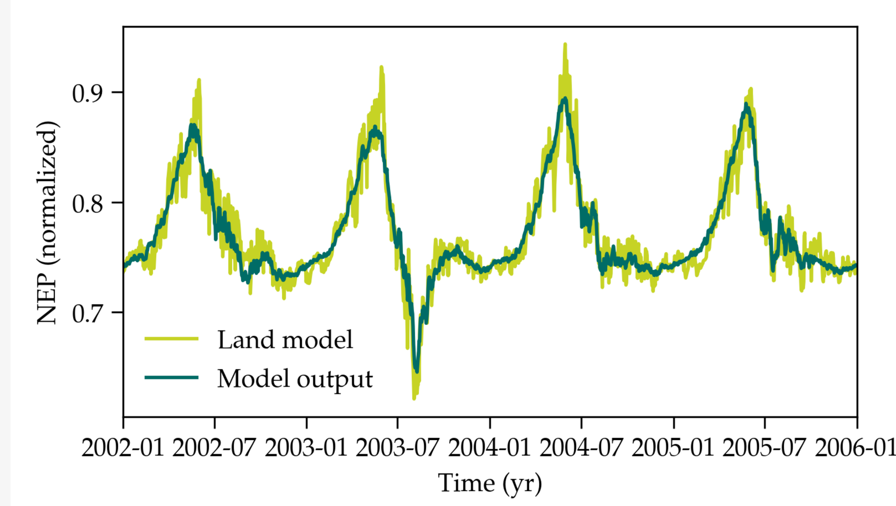
Model trained on land model data



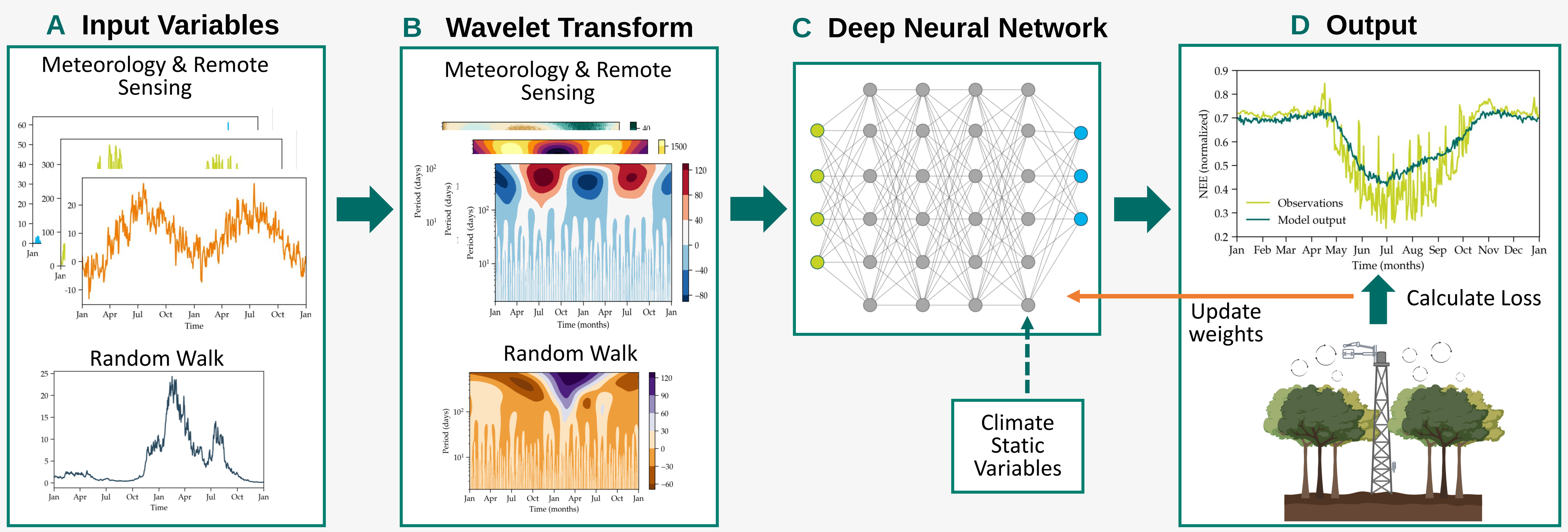
- Comparison between Res18_obs and Res18_mod

We train the same model architecture with significantly more training data from a land model run with climate forcing (**Res18_mod**). The performance increases significantly.

- NEP land model output and Res18_mod prediction for multiple years at a forest pixel in Germany



Model Architecture



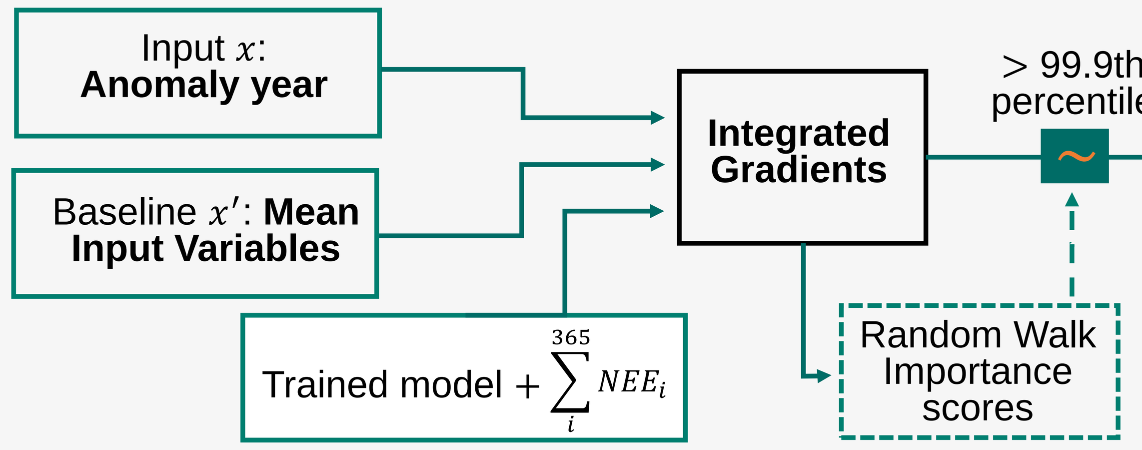
A Input variables: 10 variables + validation variable (random walk) as input
B Wavelet-Transform: Time-series transformed into 2D image reflecting frequencies and their location in time
C ResNet-18: Pre-trained Convolutional Neural Network architecture adapted from the field of computer vision
D Model output: Net Ecosystem Exchange (NEE) from Fluxnet

(Parts of this figure were created with BioRender.com)

Input variables for the observation-based model:

- Air Temperature (**TA**), vapor pressure deficit (**VPD**)
- Precipitation (**Prcp**), relative humidity (**RH**)
- Atmospheric Pressure (**PA**), wind speed (**WS**)
- Shortwave radiation (**SW**), potential SW (**SW_P**) Derivative of SW_P (**DV_SW_P**), Net radiation (**NETRAD**)
- Enhanced Vegetation Index (**EVI**)

Interpretation Setup

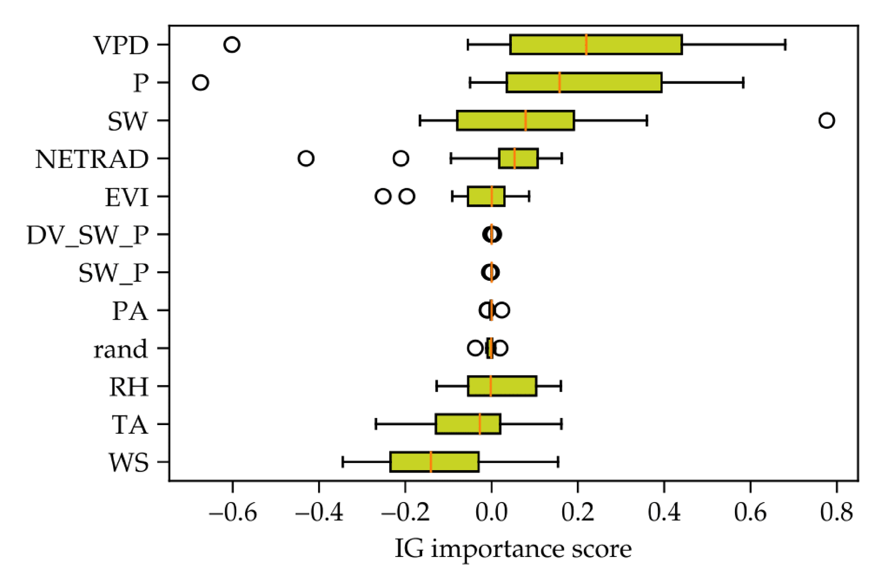


We use **Integrated Gradients (IG)** to interpret the machine learning model:

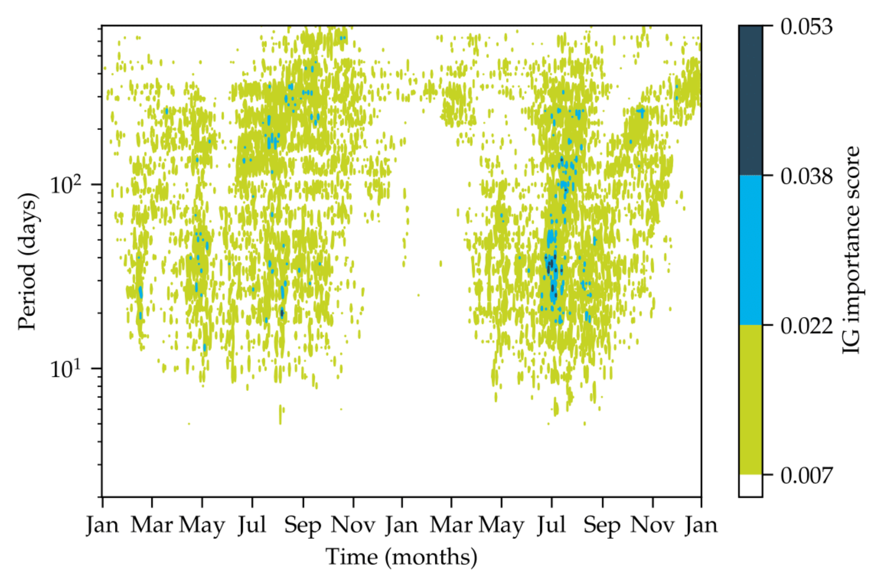
- IG is an Explainable Artificial Intelligence (XAI) method that returns for each input value, i.e. meteorological predictor in time and time-scale, an **importance score** for the predicted output, i.e. carbon balance, regarding a specific baseline.

Quantitative analysis (Res18_obs)

- Box and whisker plot of actual total IG importance for each input variable.



- IG importance image for VPD. Absolute IG importance scores are summed over all anomaly examples.

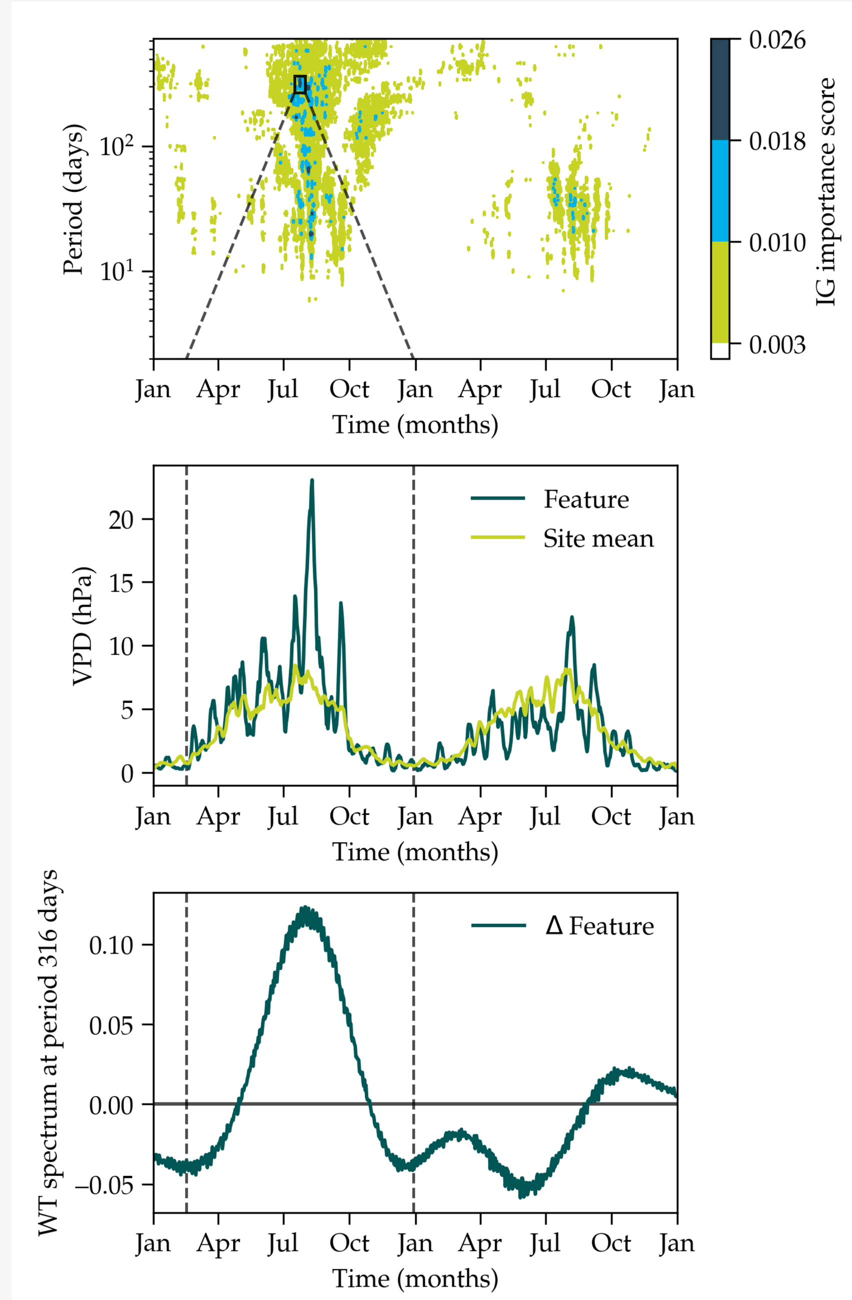


Case study: Heatwave 2003

Preliminary results

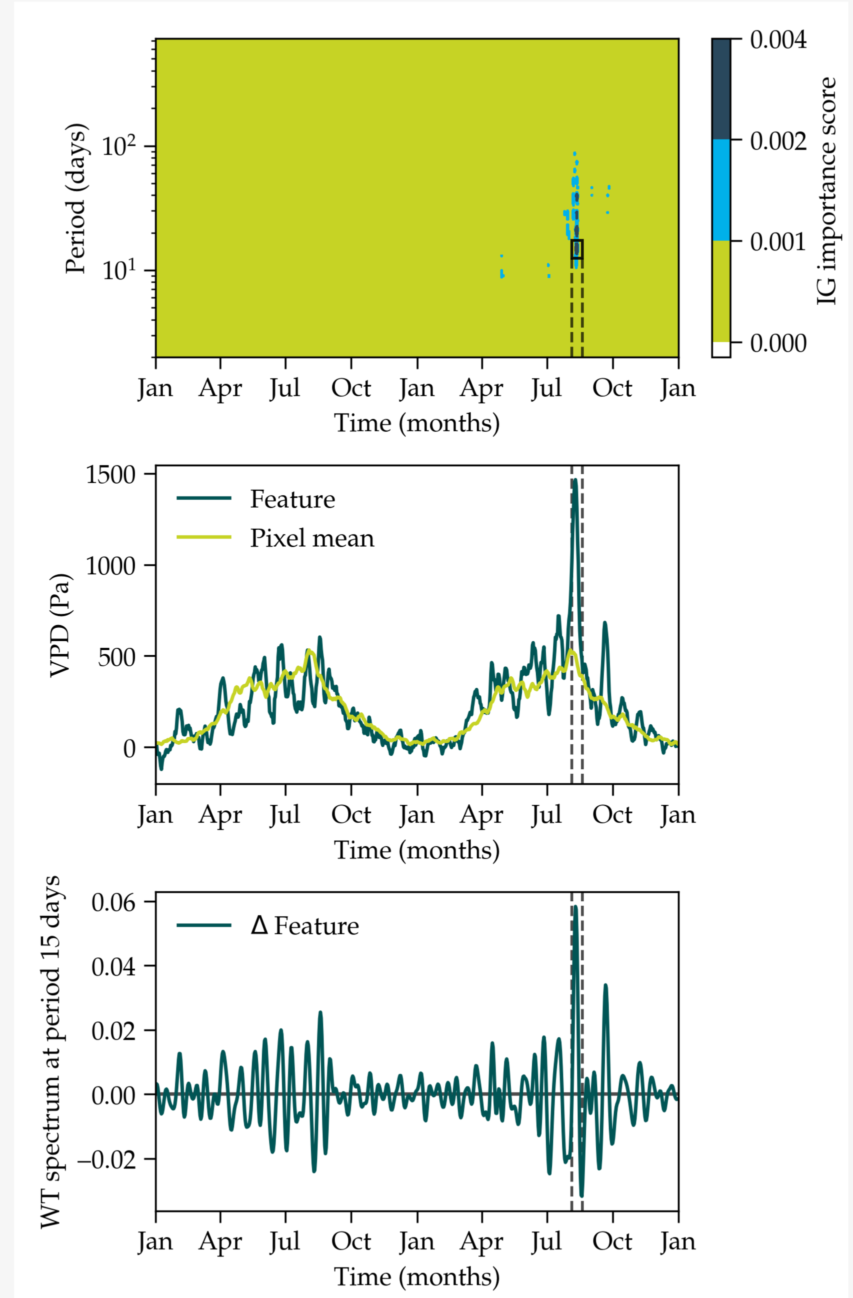
Res18_obs

- Interpretation scheme of VPD (most important variable) for 2004 of the Hainich forest site in Germany



Res18_mod

- Interpretation scheme of VPD (third most important variable) for 2003 of a forest pixel in Germany



More information

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