Deriving winter wheat phenology from Sentinel-1, Sentinel-2, and Landsat 8 time series with Deep Learning

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Motivation

- **Studies on phenology estimation commonly use SOS and EOS approaches**
  - Explicit phenological stages are not directly targeted (Pipia et al., 2022)
- **Combination of different input data has not been studied much**
  - Availability of optical data is a problem (Gao & Zhang, 2021)
  - SAR data provide complementary information
  - Deep learning is a suitable tool for data fusion (Lobert et al., 2021)

Aim of the work

- **Development of a Deep Learning model that**
  1. exploits the combination of different remote sensing and meteorological data
  2. can predict the dates of different phenological stages for winter wheat on the plot level
  3. is trained on a large reference data set

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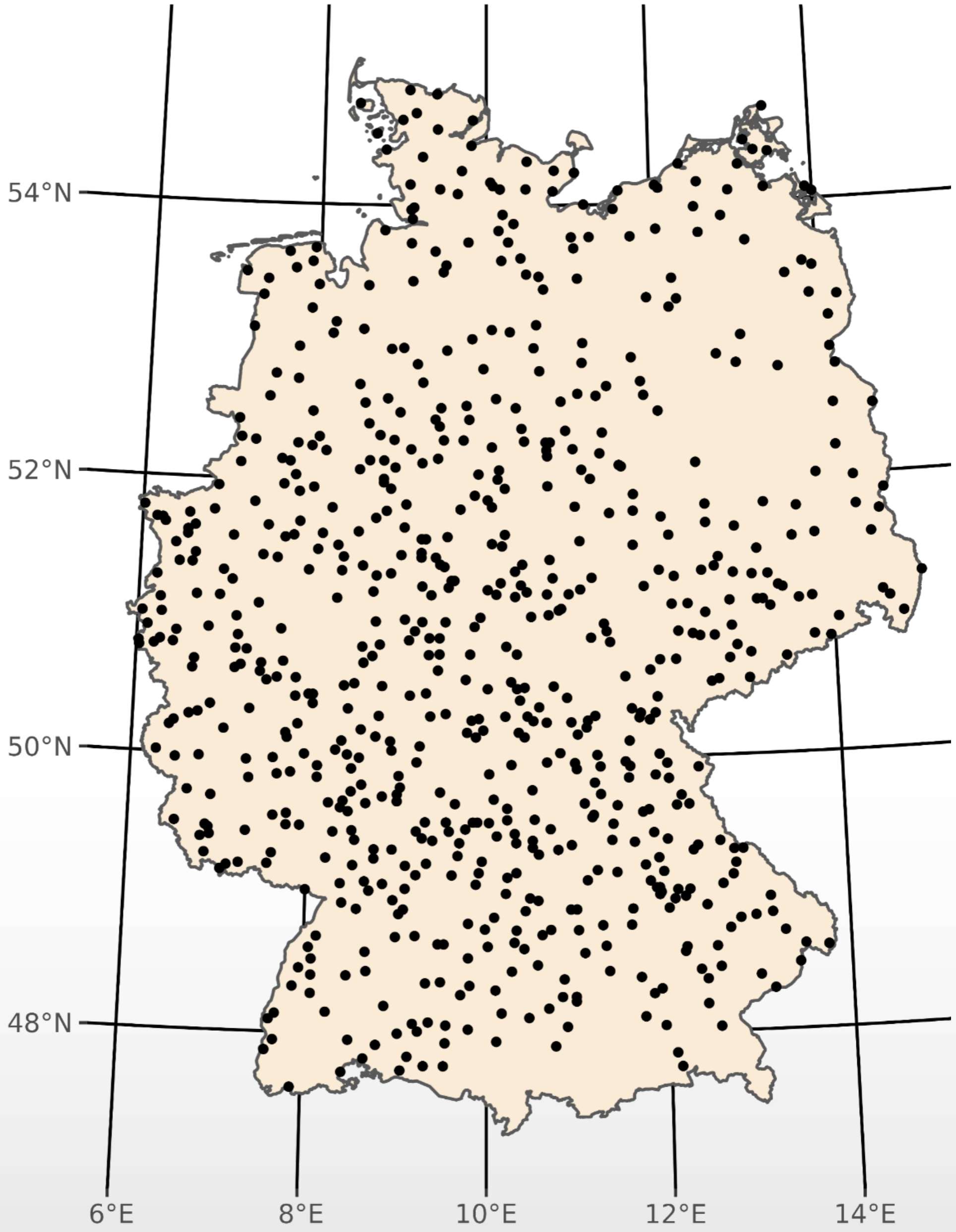
Phenological observations

- Network from German Weather Service (DWD)
- Reported by trained volunteers for nearby plots (max. 5 km)
- Ca. 700 points for winter wheat

2017 - 2019

Images from: Harfenmeister et al. (2021) & Deutscher Wetterdienst (2019)



Seeding

Leaf development

Stem elongation

Heading

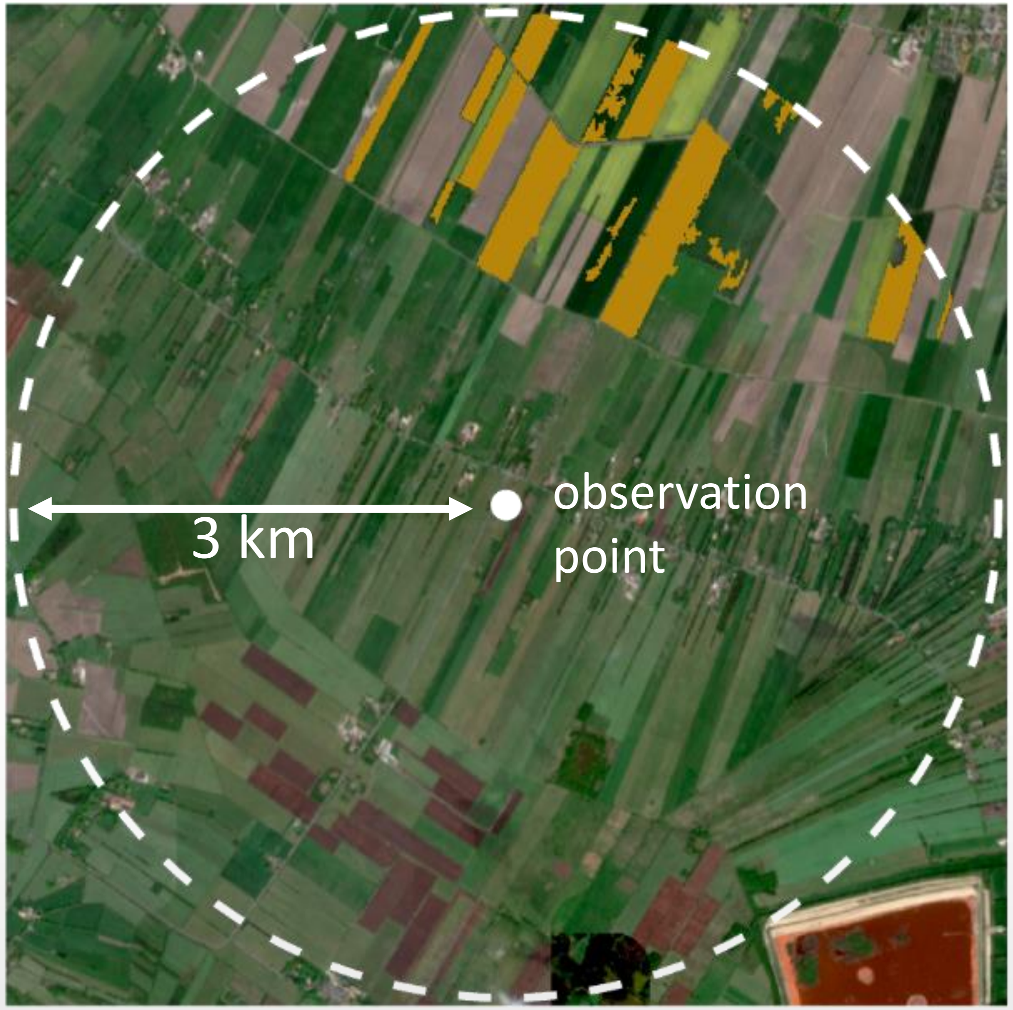
Milk ripeness

Yellow ripeness

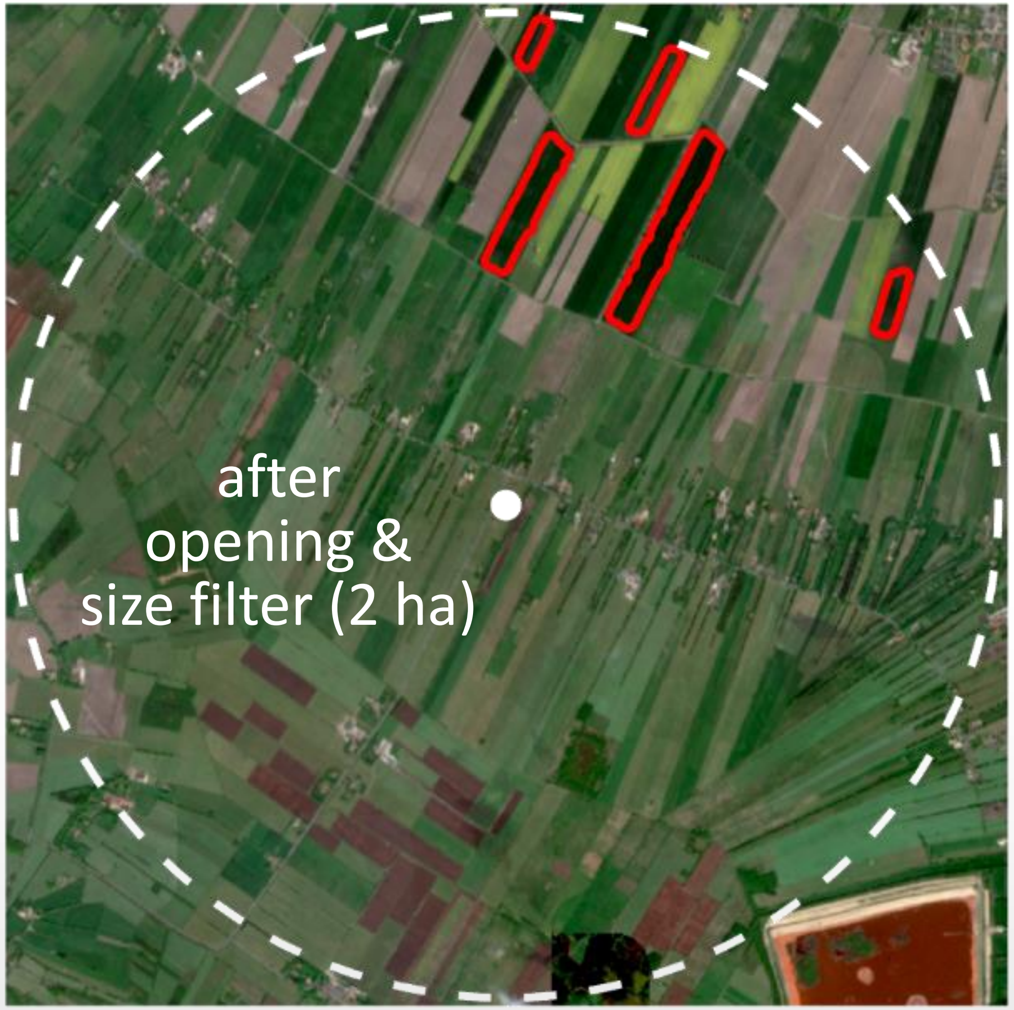
Harvest

Parcel boundaries

Winter wheat from crop type map (Blickensdörfer et al., 2022)



ca. 37.000 plots extracted for analysis



Stade
Lüneburg
NIEDERSACHSEN

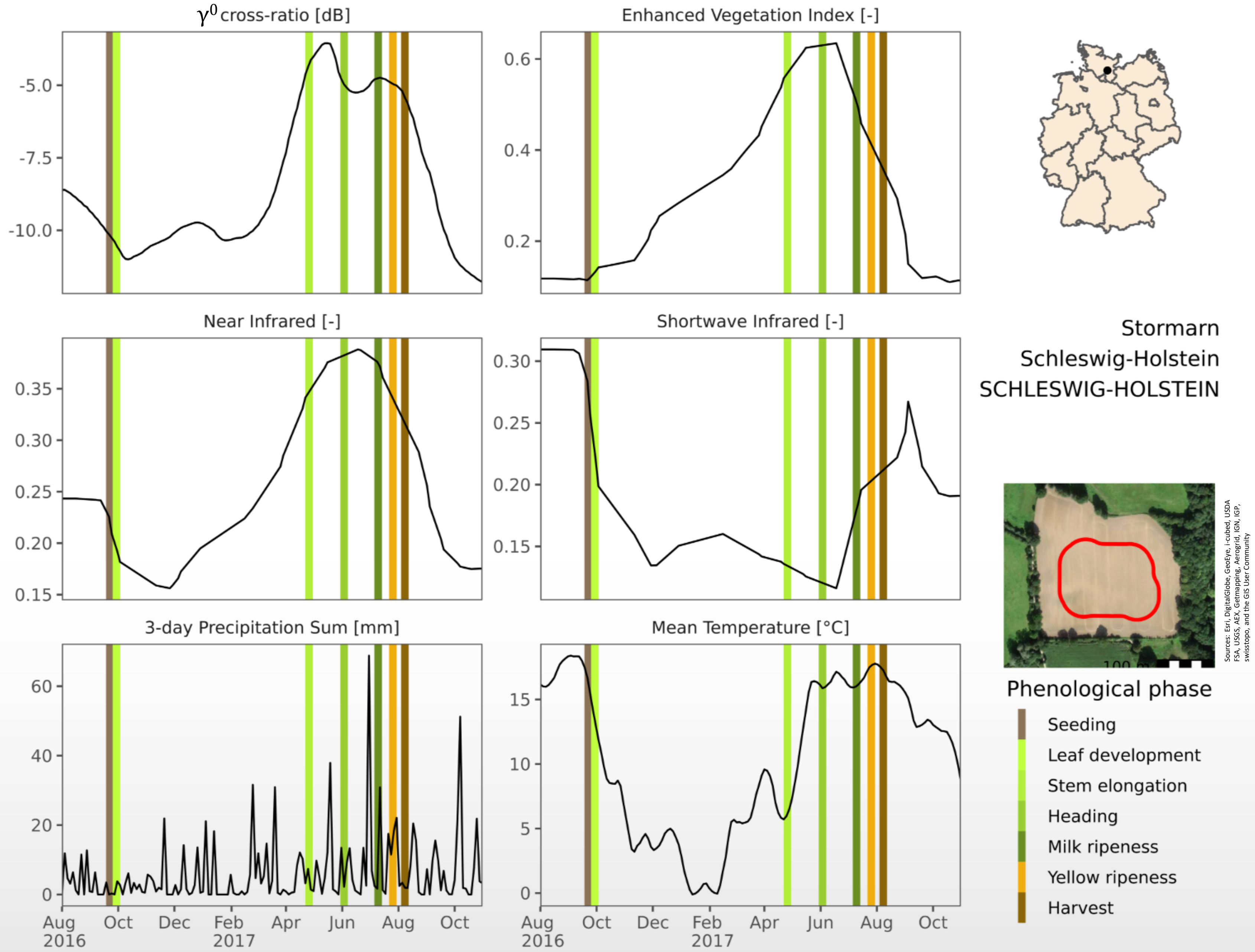
Winter wheat pixels from CTM 2019

Plots used for analysis

Multisensor Input

- Sentinel-2 & Landsat 8
  - all corresponding bands + EVI
- Sentinel-1
  - all orbits/directions
  - γ^0 backscatter coefficient
- Meteorological data
  - precipitation
  - air temperature
  - solar radiation

→ Smoothed and harmonized to 3-day interval



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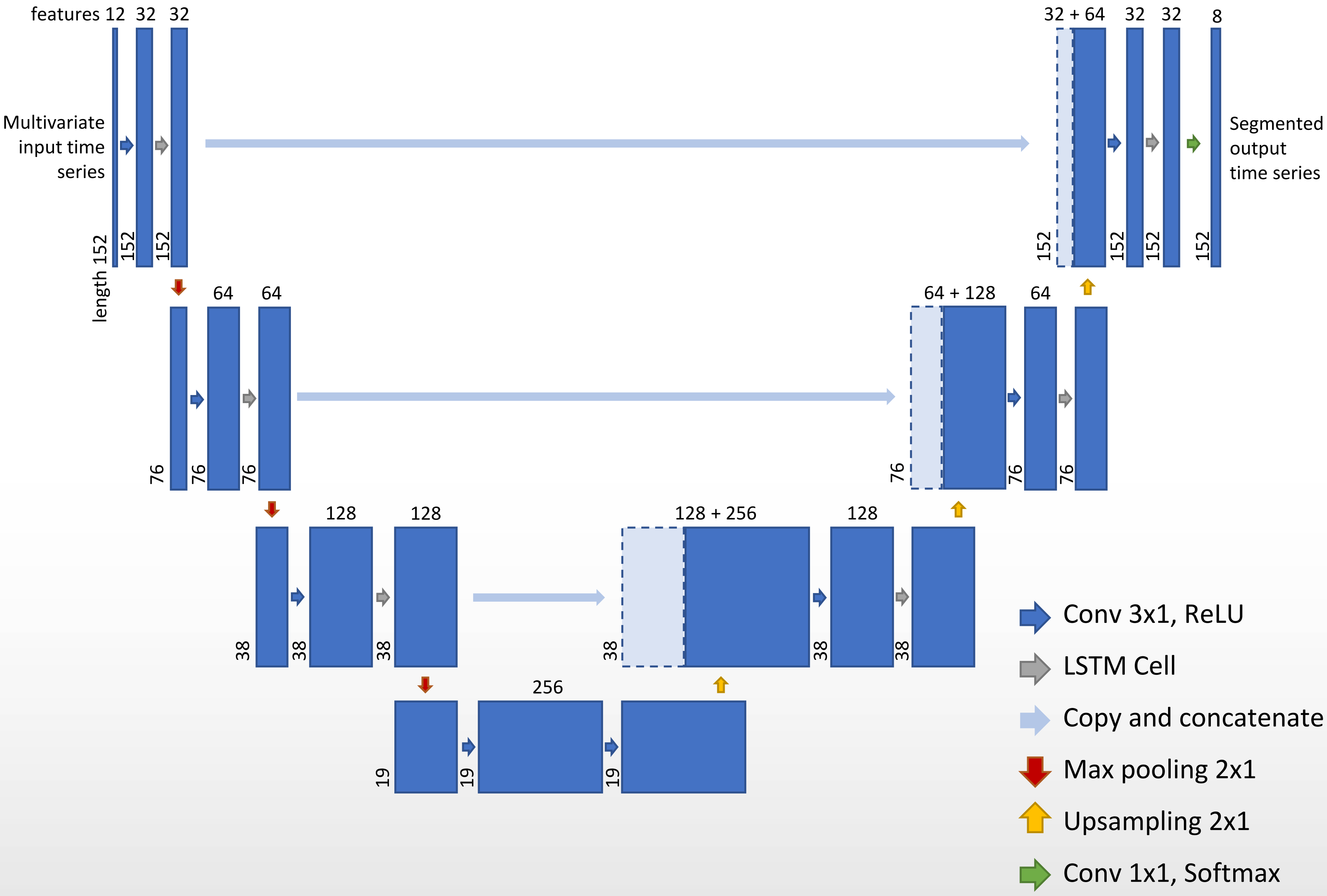
1D temporal U-Net

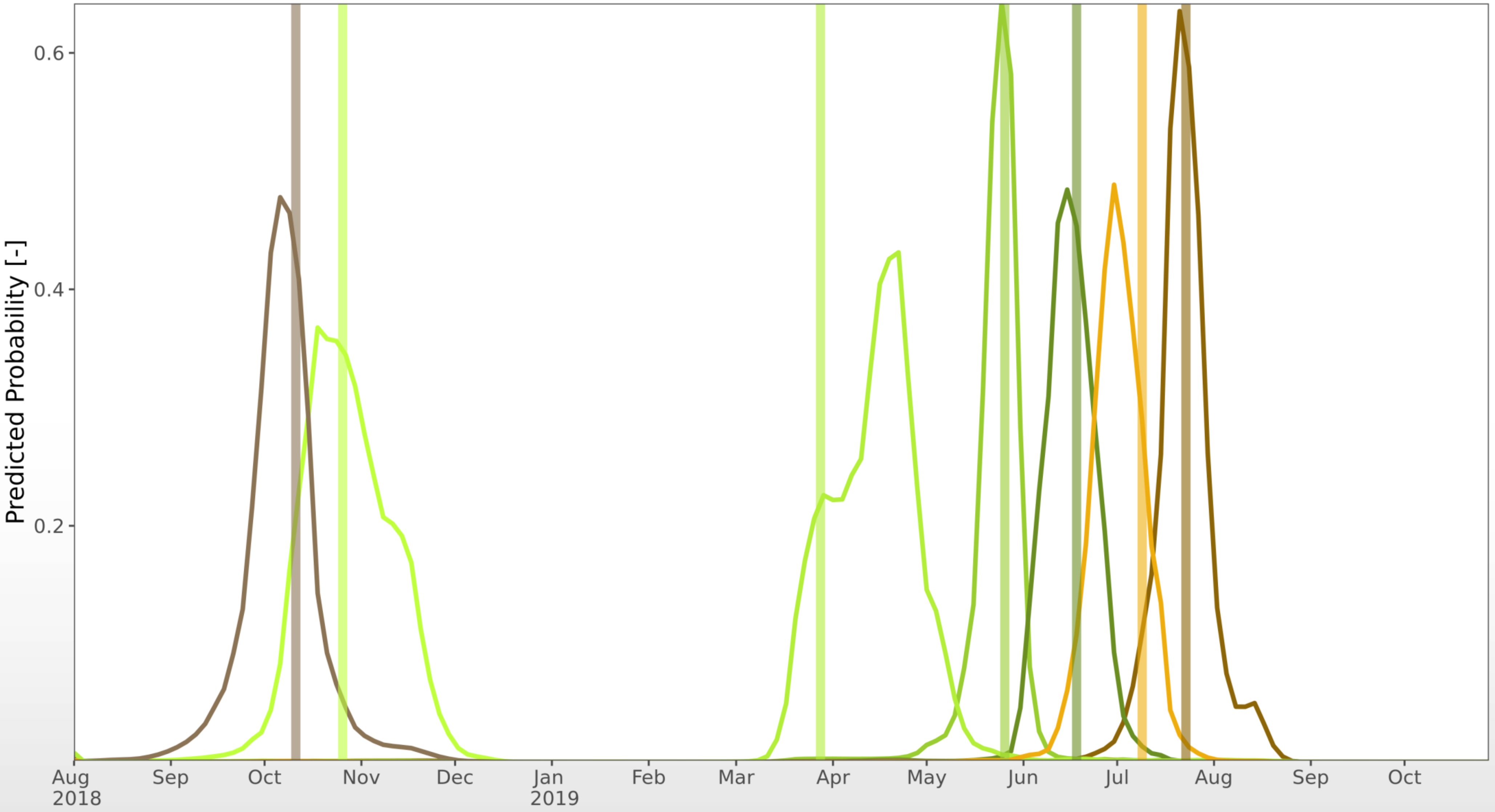
- Segment time series instead of imagery
- inspired from medical applications
- Multi-hierarchy approach



Ronneberger et al. (2015)

Perslev et al. (2019)

Model output



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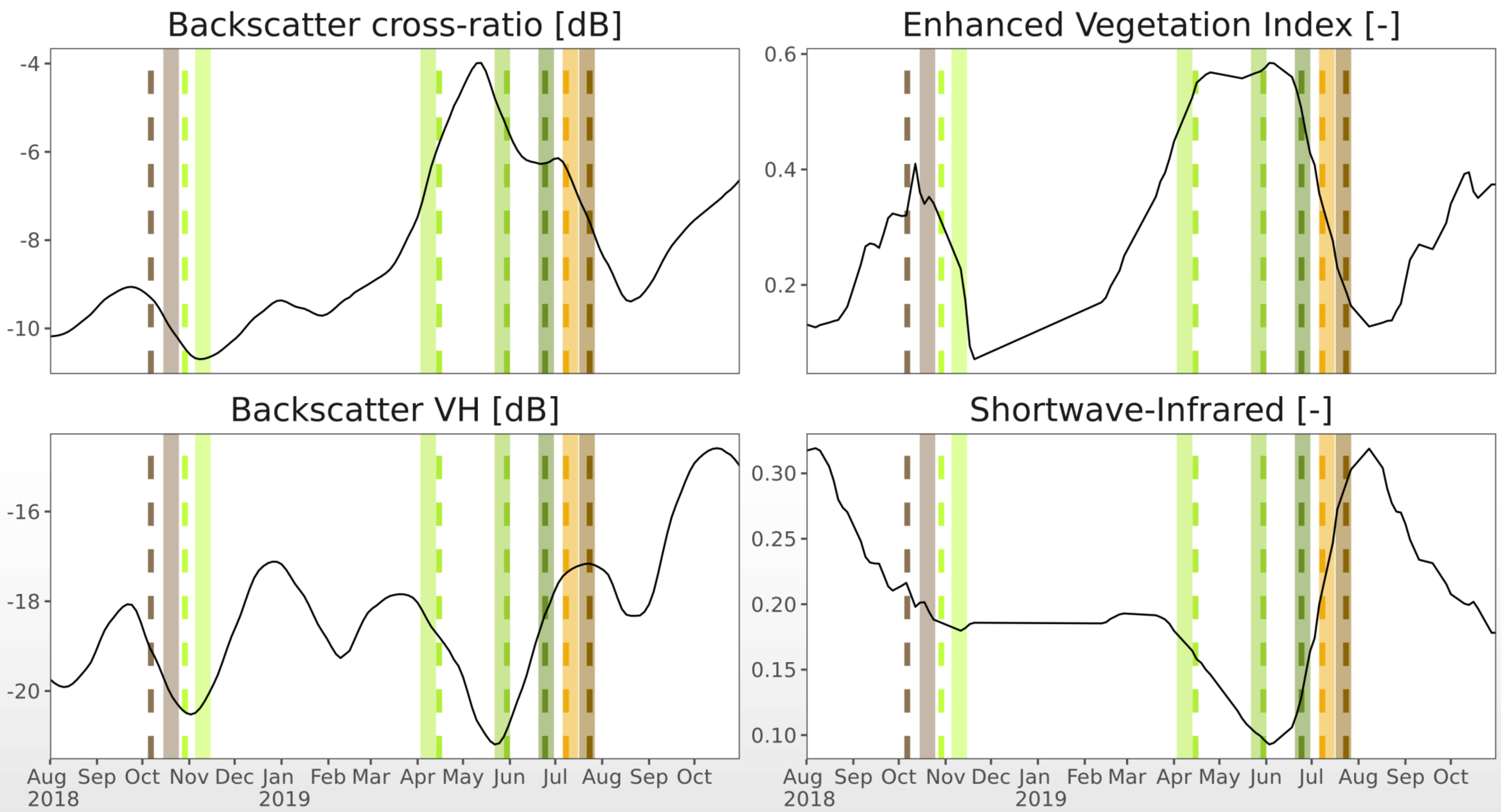
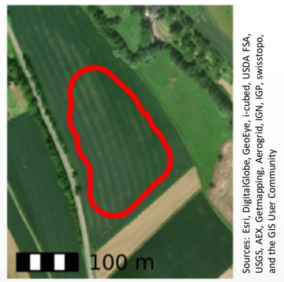
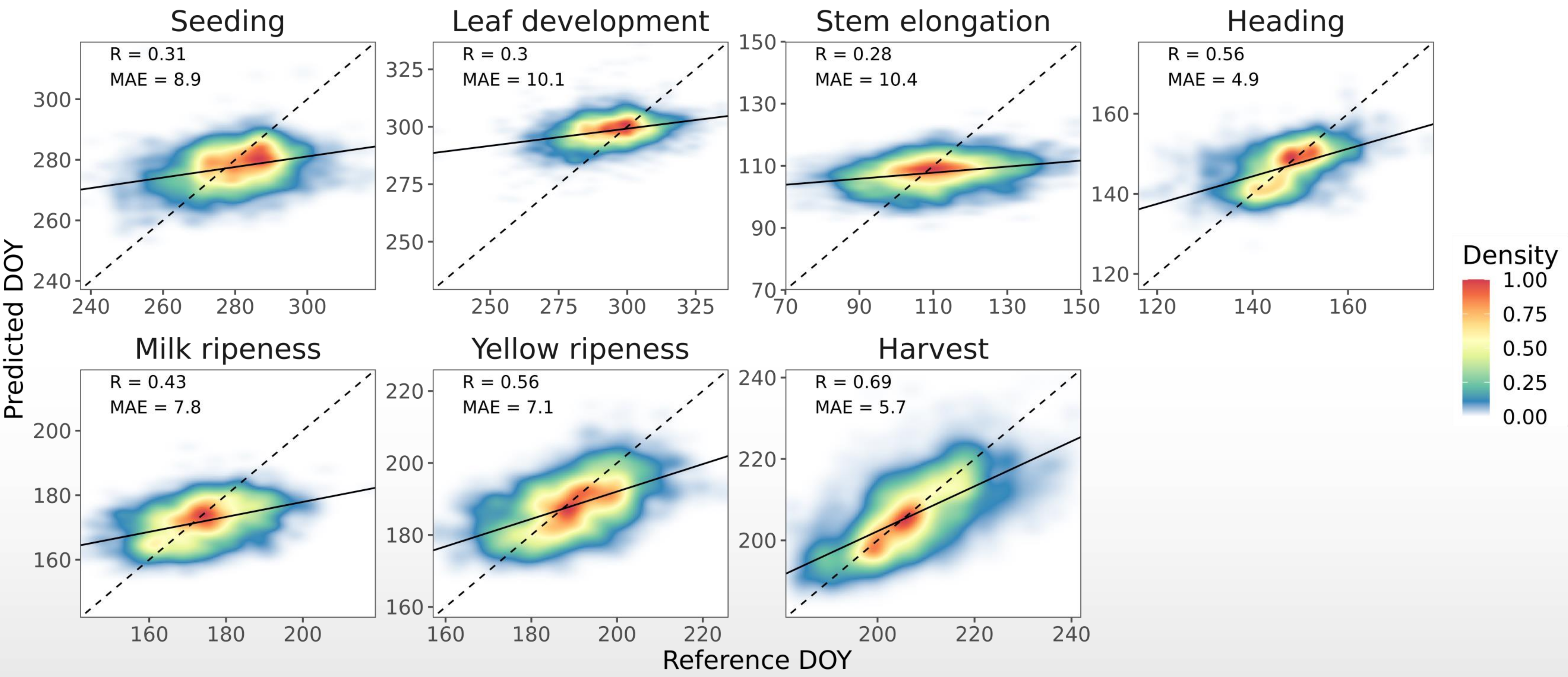
Example predictions



Karlsruhe, Landkreis Karlsruhe
BADEN-WÜRTTEMBERG



Validation



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Discussion & Findings

- **Late growth stages are detected well**
  - Major changes in structure and color
    - Also seen in the clear time series patterns
  - Less influence by management (except for harvest)

- **Early growth stages show problems**
  - Differences in soil management, previous crops, cultivation of catch crops
  - First leaves are small → dominant soil signal

Discussion & Findings

- **Combined data sources will improve parcel boundaries**
  - Crop type map (Blickensdörfer et al., 2022) & Segmented parcel boundaries (Tetteh et al., 2021)
- **Evaluation of the different feature combinations to be done**
  - Feature importance
  - Add red-edge bands (Scheffler et al., 2020) & 6-day coherence

Conclusion

- **Promising “all in – all out” approach**
  - No manual thresholding and feature combination
- **Generation of nation-wide phenology maps possible**
  - More details than EOS/SOS approaches
  - Accuracy depending on the stage
- **Support agricultural monitoring tasks**
  - Yield estimation, erosion modelling, etc.

Any further questions?

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