

Crop Monitoring in Ireland with SAR to Quantify Agricultural Stability and Climate Resilience

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Motivation

Given Ireland's rapidly changing climate¹, it is difficult to monitor crops using traditional optical-based remote sensing methods due to the extensive number of overcast days. Increasing trends in the frequency and quantity of rainfall indicate that cloud-cover will continue impact the utility of optical agricultural monitoring in Ireland. Sentinel-1 can provide information on crop production status at a higher temporal resolution than traditional optical instruments like Sentinel-2, providing up to 61 acquisitions annually.

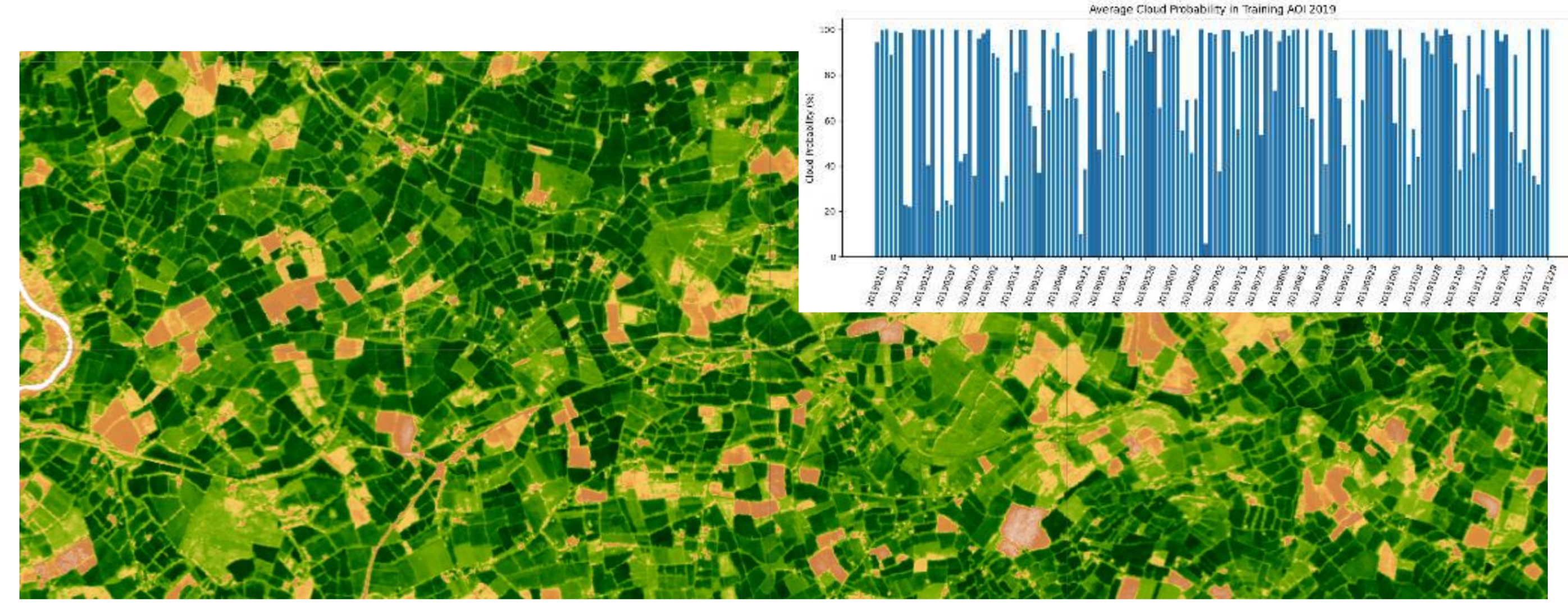


Fig 1A. Median Composite of EVI over the Area of Interest, 2019

Fig 1B. Plot of Sentinel-2 Cloud Probability, 2019

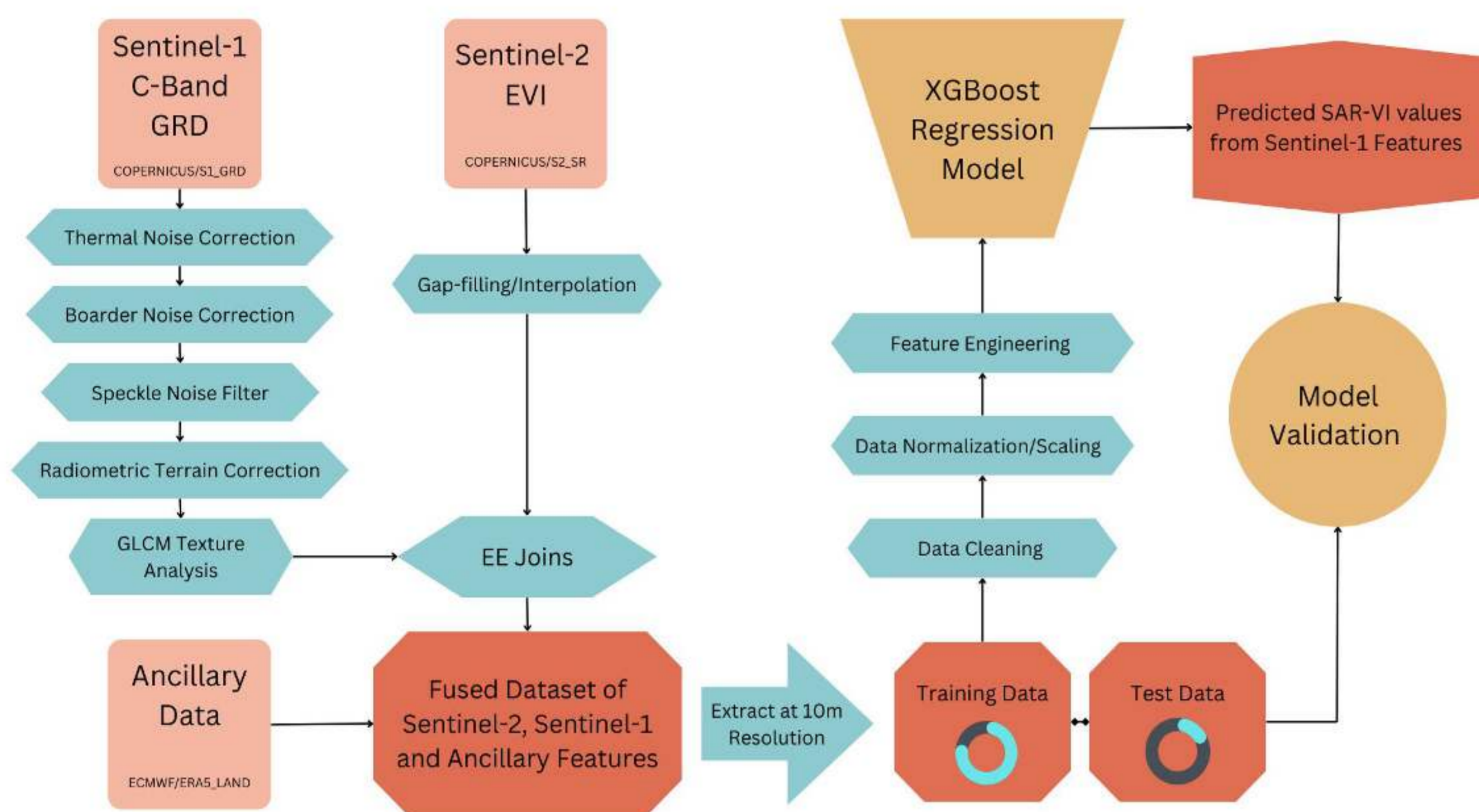


Fig 2. Flowchart of methodology implementation, including preprocessing of Sentinel-1

Methods

Dual-Pol Sentinel-1 GRD scenes were preprocessed² in GEE for 2019 in VV/VH polarization over our AOI in Co. Wexford. GLCM Texture Analysis was applied to the processed Sentinel-1 data to provide neighbouring pixel statistics for the model. Ancillary data, namely precipitation was also included due to the impact of heavy rainfall on backscatter measurements.

Clouds were masked out and interpolation was used to increase the temporal resolution of Sentinel-2 EVI to match S1 acquisitions for training. The ESA/WorldCover LULC map was used as a crop mask and the dates were filtered to the most prominent growing season in the training data.

Finally, An XGBoost Regression Model was trained and validated using 10-fold cross validation in Python.

Results

The XGBoost Regressor Model achieved fairly satisfactory results with an R^2 score of 0.61 after tuning.

This demonstrates potential for combining existing SAR Vegetation Indices to create a more correlated measure of crop growth.

Many indices have been developed to monitor crops using Sentinel-1 backscatter such as Radar Vegetation Index (RVI), Modified Dual Polarimetric SAR Vegetation Index (DPSVIm) and Cross Ratio (CR).³

After studying the correlation of these indices with EVI as a well defined proxy for crop health, the maximum Pearson correlation was only 0.31 and the time series was often difficult to interpret.

The ongoing work of this research aims to correct the high baseline in the predicted values as the current version of the model is limited in its ability to predict values <0.25 .

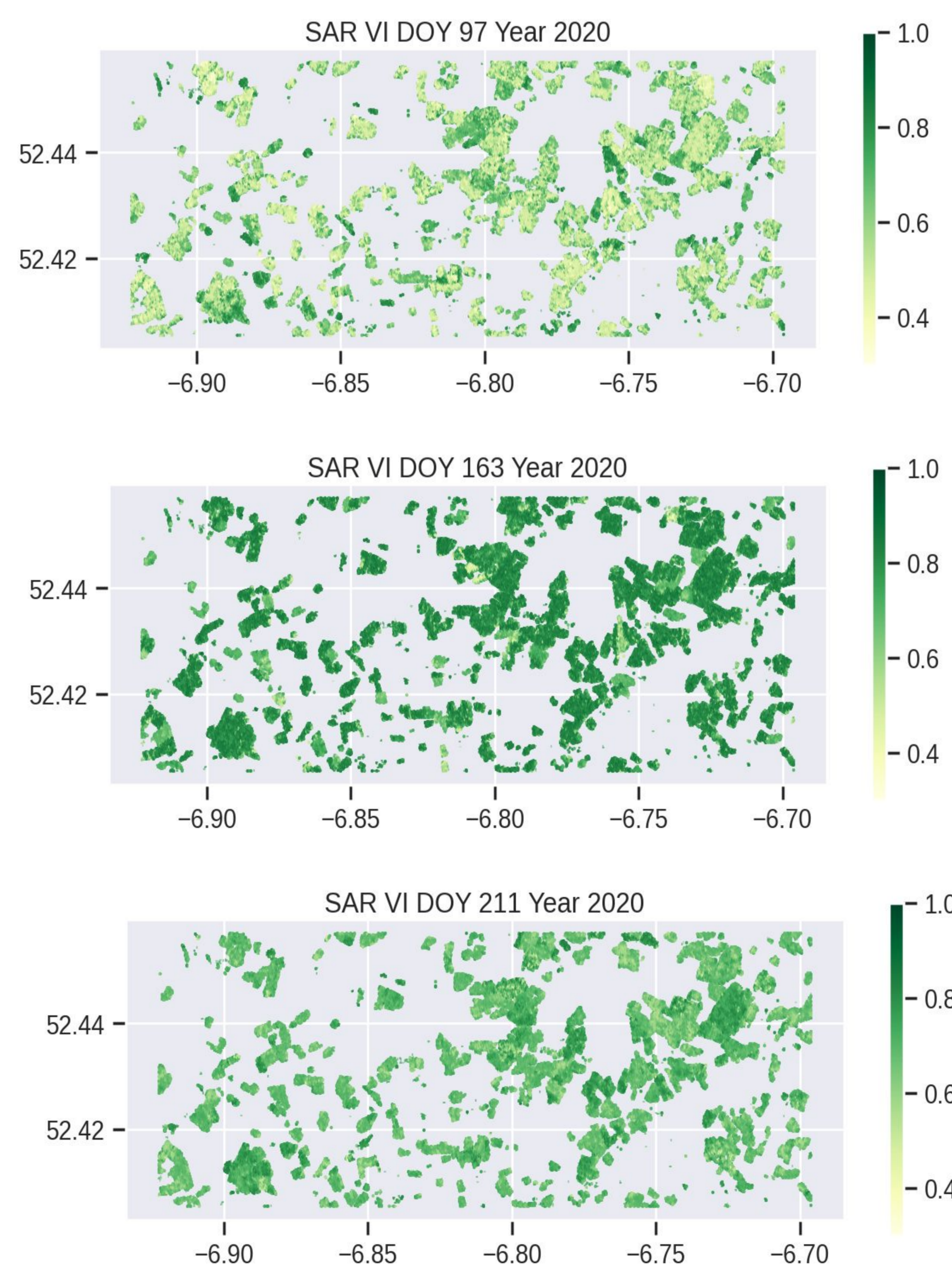


Fig 3. Selection of images from SAR-VI model predicting on unseen 2020 data, where 0-1 represents predicted EVI as a proxy for crop growth. Images represent the start of season, peak and end of season for the most common crop in the region, Spring Barley.

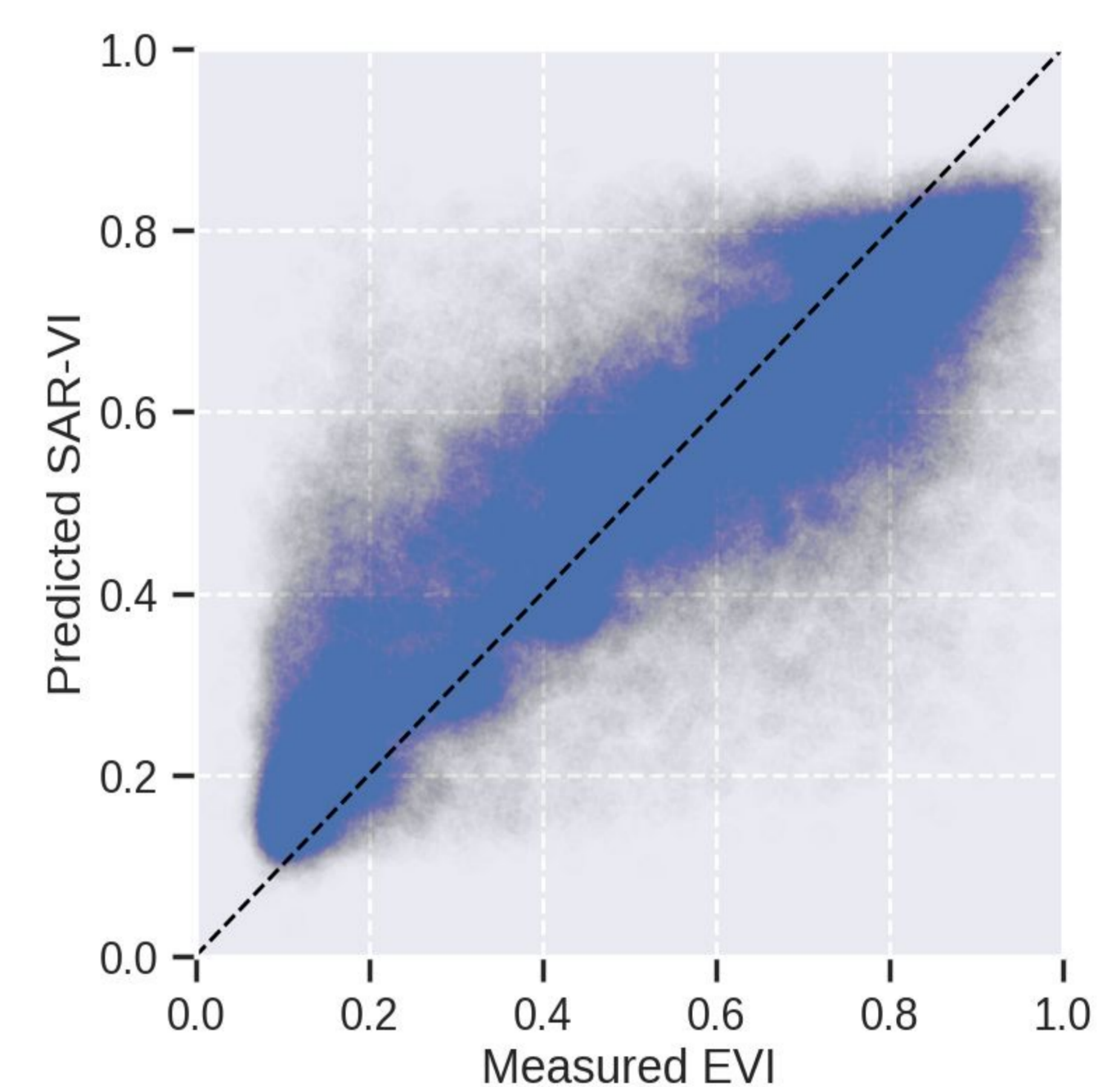


Fig 4. Predicted SAR-VI vs. Measured EVI from model testing

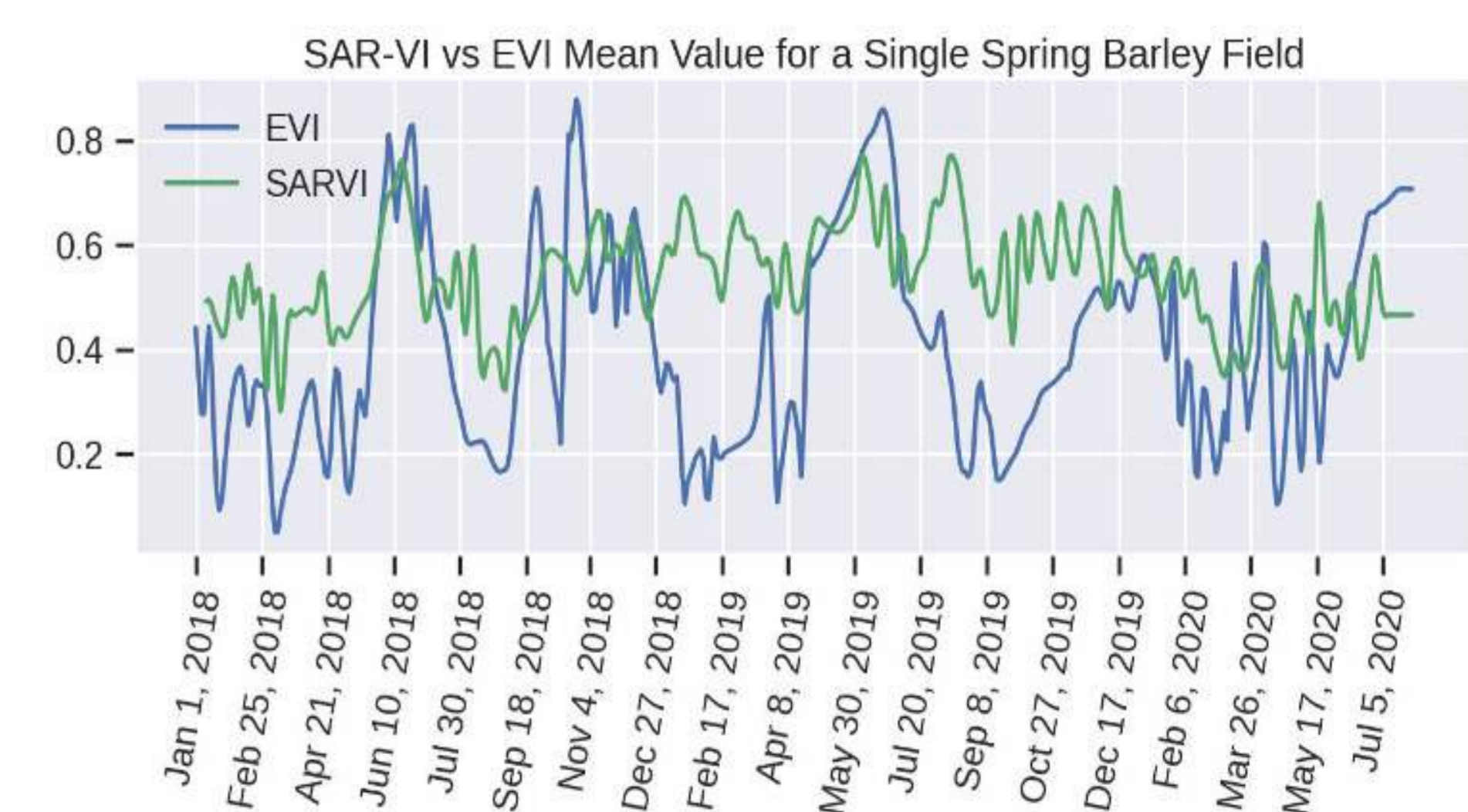


Fig 5. Time-series of SAR-VI vs. EVI averaged over one Field

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References

- [1] Walther C.A. Cámaro García and N. Dwyer (2023) EPA Research 2030 Reports, Epa.ie. Available at: <https://www.epa.ie/publications/research/epa-research-2030-reports/research-386.php> (Accessed: 29 August 2023).
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- [3] dos Santos, E. P., da Silva, D. D., do Amaral, C. H., Fernandes-Filho, E. I. and Dias, R. L. S. dos Santos, E. et al. (2022) "A Machine Learning approach to reconstruct cloudy affected vegetation indices imagery via data fusion from Sentinel-1 and Landsat 8", Computers and Electronics in Agriculture, 194, p. 106753. doi: 10.1016/j.compag.2022.106753.