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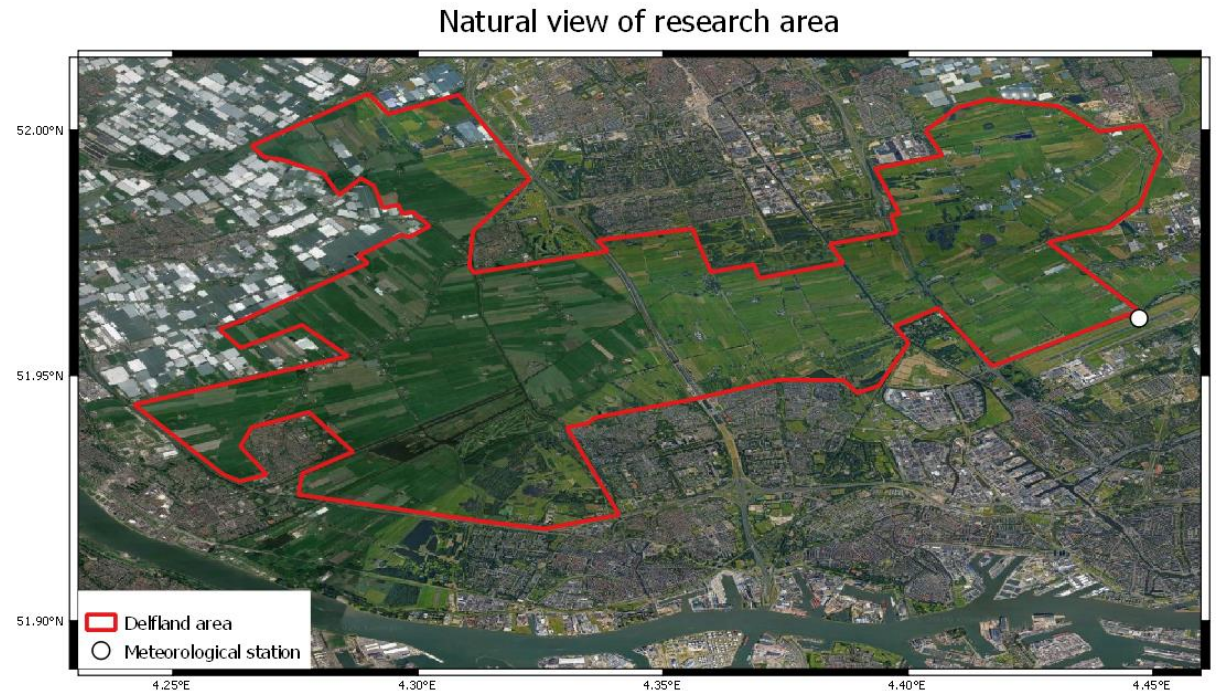
Dynamics of peat polders in the Netherlands

Comparing SAR backscatter and derived
parameters with meteorological variables to
improve InSAR deformation estimates.



The peat polder problem

- Peat is composed of organic materials that oxidize and emit greenhouse gases when exposed to air. Oxidation of peat soils results in volume reduction and consequent **subsidence of a few cm per year**. The sinking land causes increasingly severe socio-economic impact.
- Subsidence has high **spatial variability** due to local soil morphology, and possibly high intra-annual **temporal variability** which is caused by precipitation and evapotranspiration.
- To study the deformation dynamics over large areas, with high precision and frequent revisit times, InSAR is the proposed solution but ambiguity must be corrected.



The InSAR observation problem

- Sentinel-1 InSAR observations suffer from lack of coherence and **ambiguity** in late summer. During this period, peat soils reverse the subsidence process partially. This can happen fast after strong precipitation. [Camporese et al. 2006]
- We investigate possible corrections to S-1 InSAR, that contain information about the water content of the soil to correct the ambiguity in estimated subsidence at a 200m resolution.
- Cumulative Rainfall Surplus with Saturation limit
Is used as the baseline from ancillary data for comparison

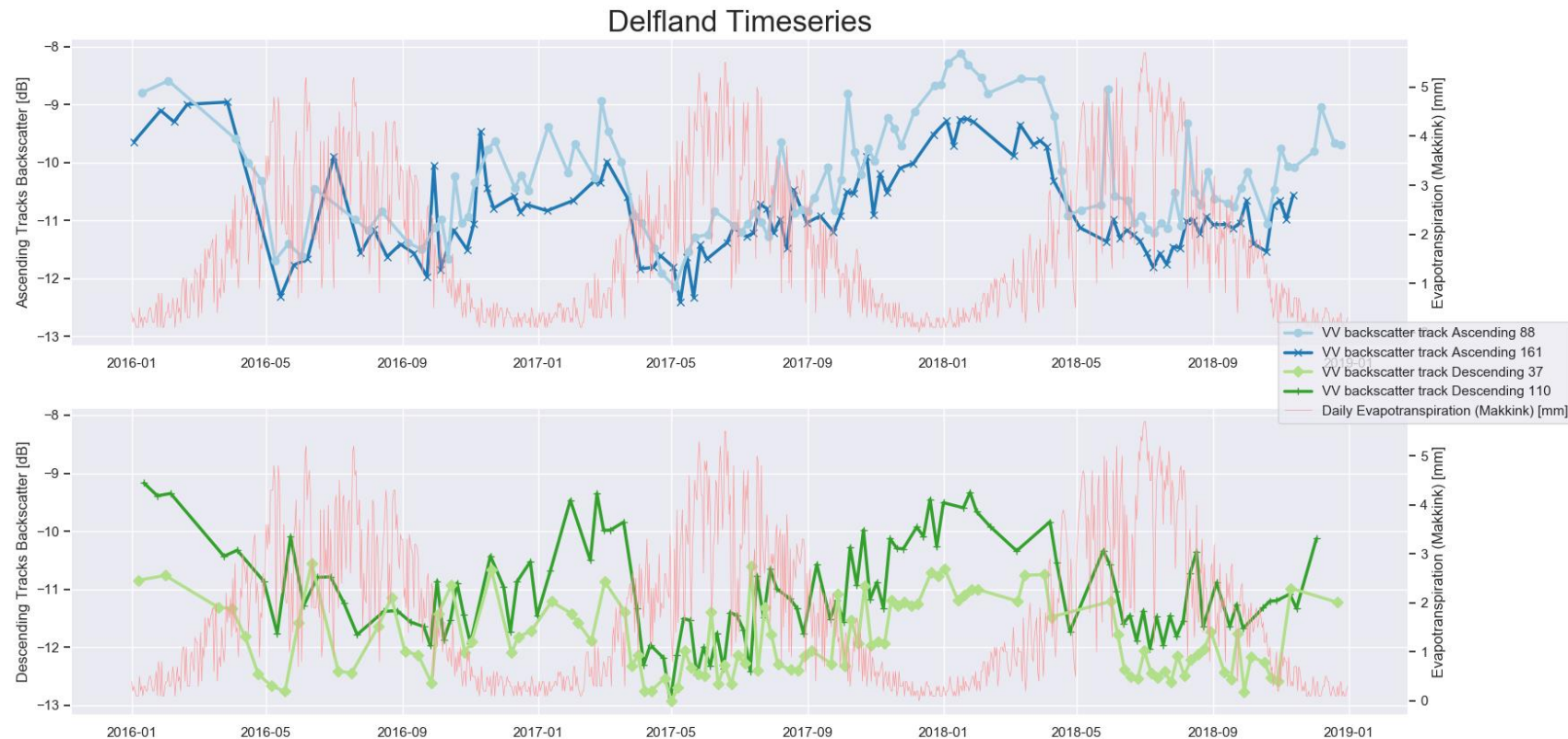
$$CRFS_{sat} = \sum precipitation - \sum evapotranspiration$$

- VV backscatter per viewing geometry (σ_{θ}^0)
- VV normalized backscatter (σ_{norm}^0)
- Surface Soil Moisture (SSM)
- Soil Water Index (SWI)

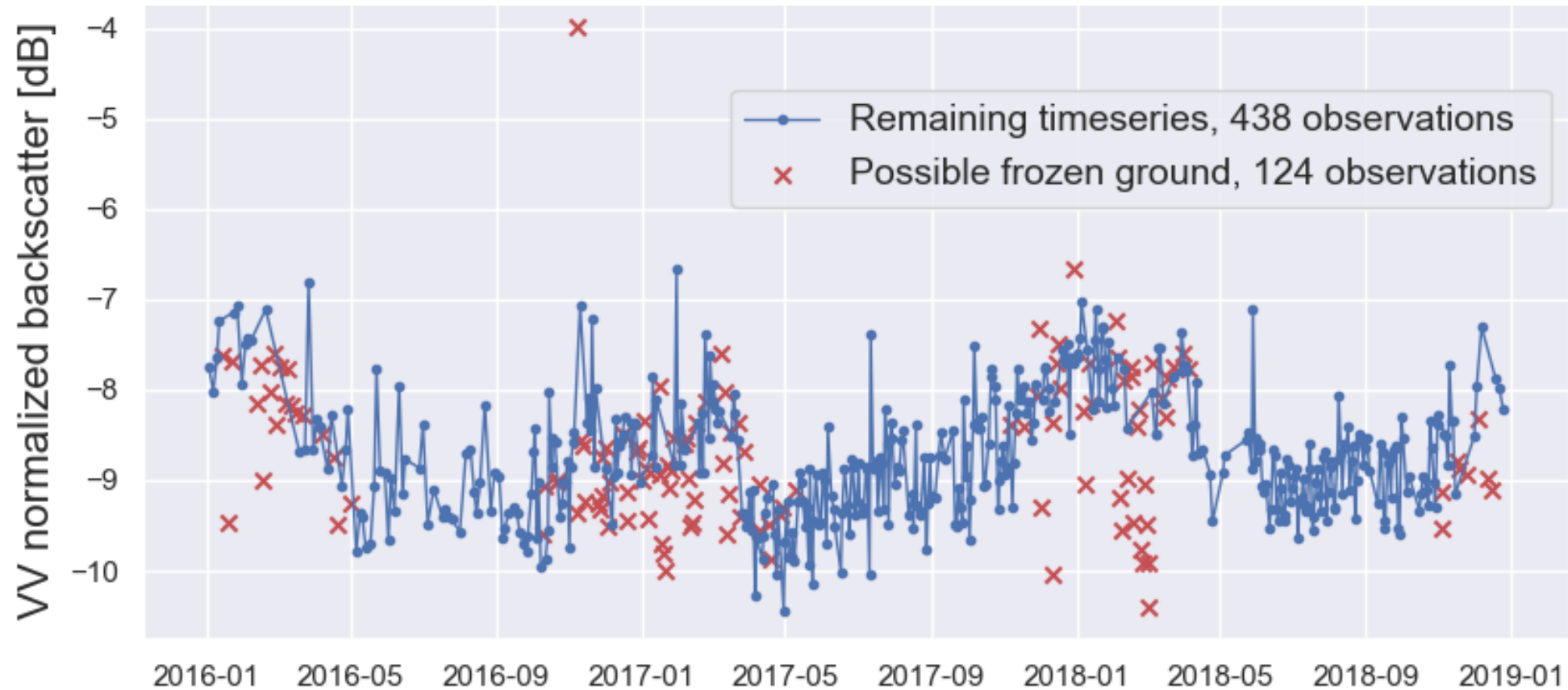
Combine geometries to increase temporal resolution

The viewing geometries can be combined by normalizing the backscatter timeseries ($\sigma_{\theta}^0 \rightarrow \sigma_{norm}^0$). This is done with a histogram matching procedure for each 200m pixel [Mladenova et al. 2013]

The temporal resolution increase must be done to capture more dynamics than seasonal effects. The seasonal component can be seen here in the comparison of separate viewing geometries and the daily Makkink Evapotranspiration.



Masking of frozen soils



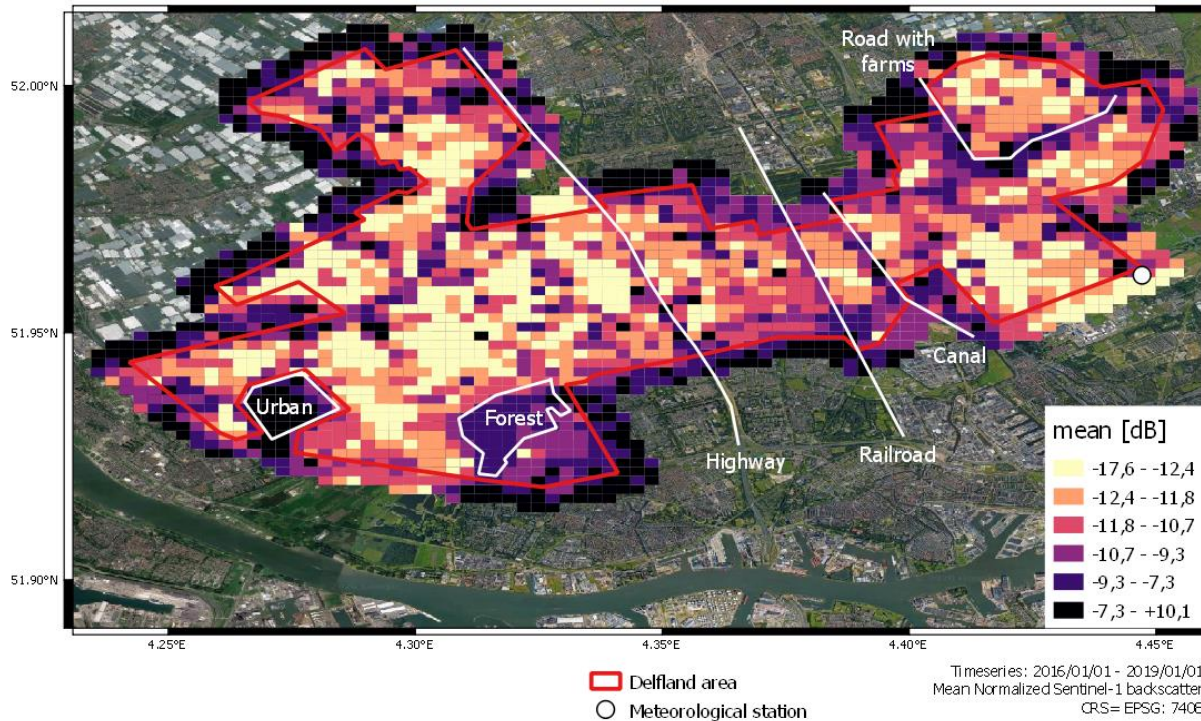
SSM increases backscatter when it is free to move. When the soil freezes, the free water becomes solid and therefore the information about the water content is lost.

Therefore a conservative masking approach is used to remove all days with a minimum temperature below 0° Celsius.

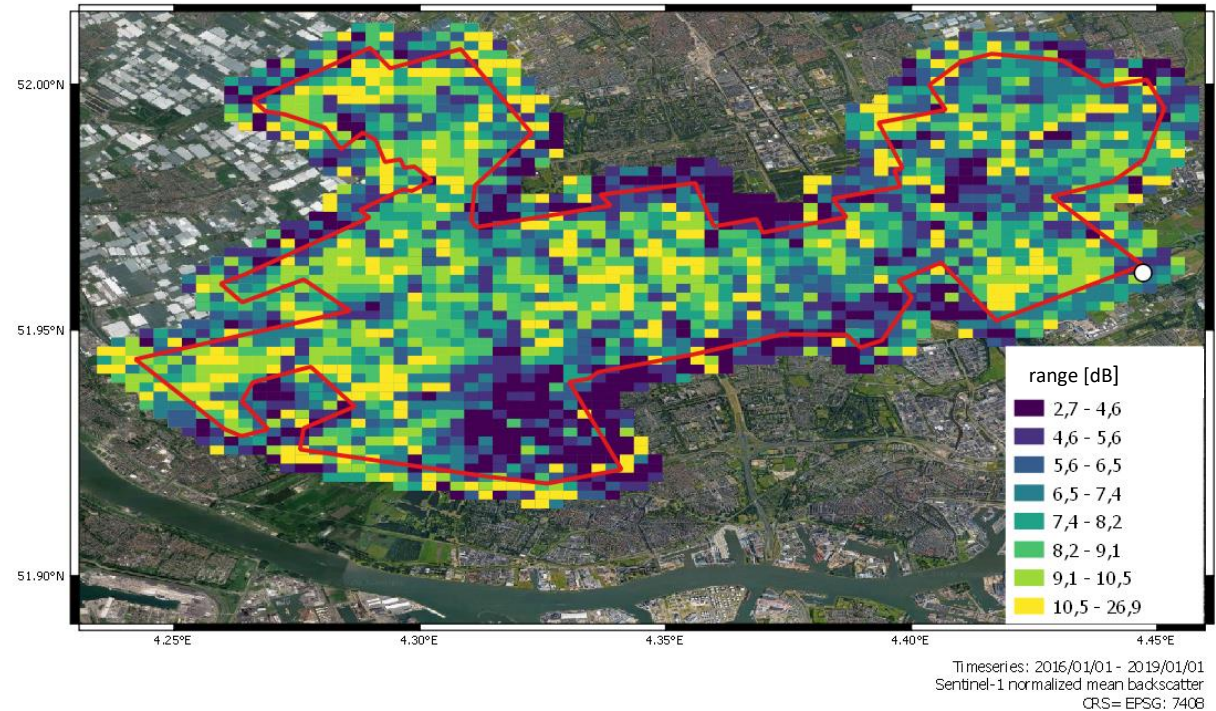
What's happening spatially?

- Grasslands, which make up the majority of the peat polders have low backscatter and higher variability.
- Roads, urban areas, more densely vegetated areas and farms have higher backscatter and less variability

Mean normalized backscatter with some spatial features annotated



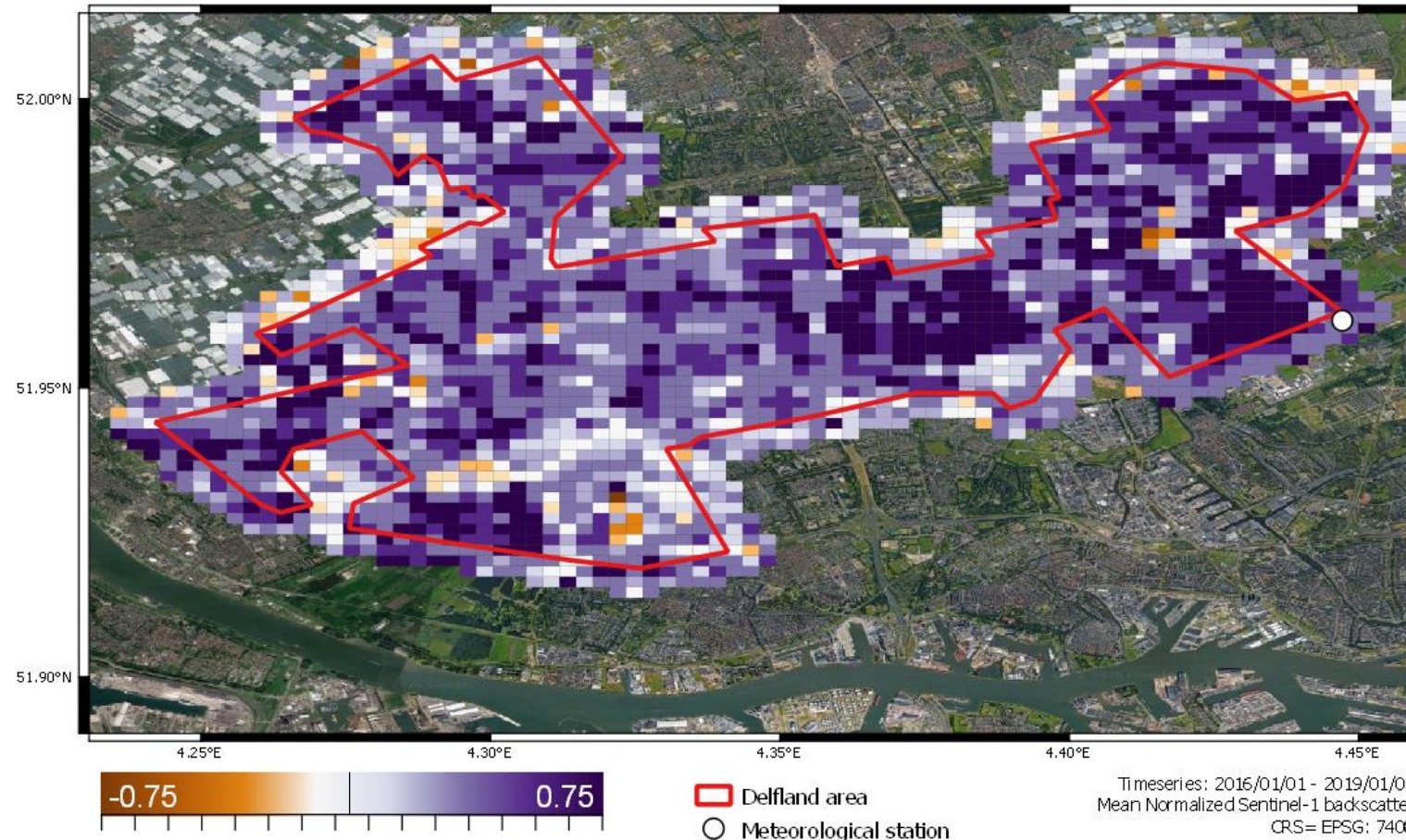
Backscatter range over the timeseries



Spatial result of normalized backscatter

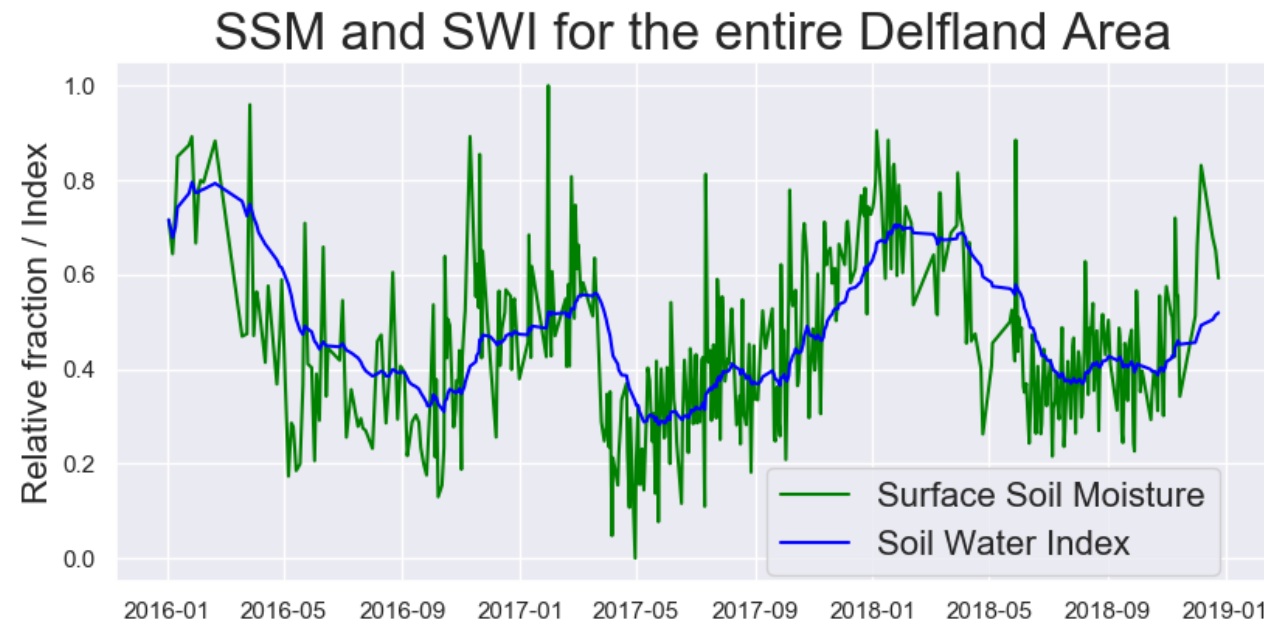
- Grasslands have expected positive correlation, negatively correlated pixels often show buildings, roads or significant water bodies.
- Masking these “non-grasslands” might improve the correlation results when using lower resolution.

Spearman Correlation of backscatter to saturated Cumulative Rainfall Surplus



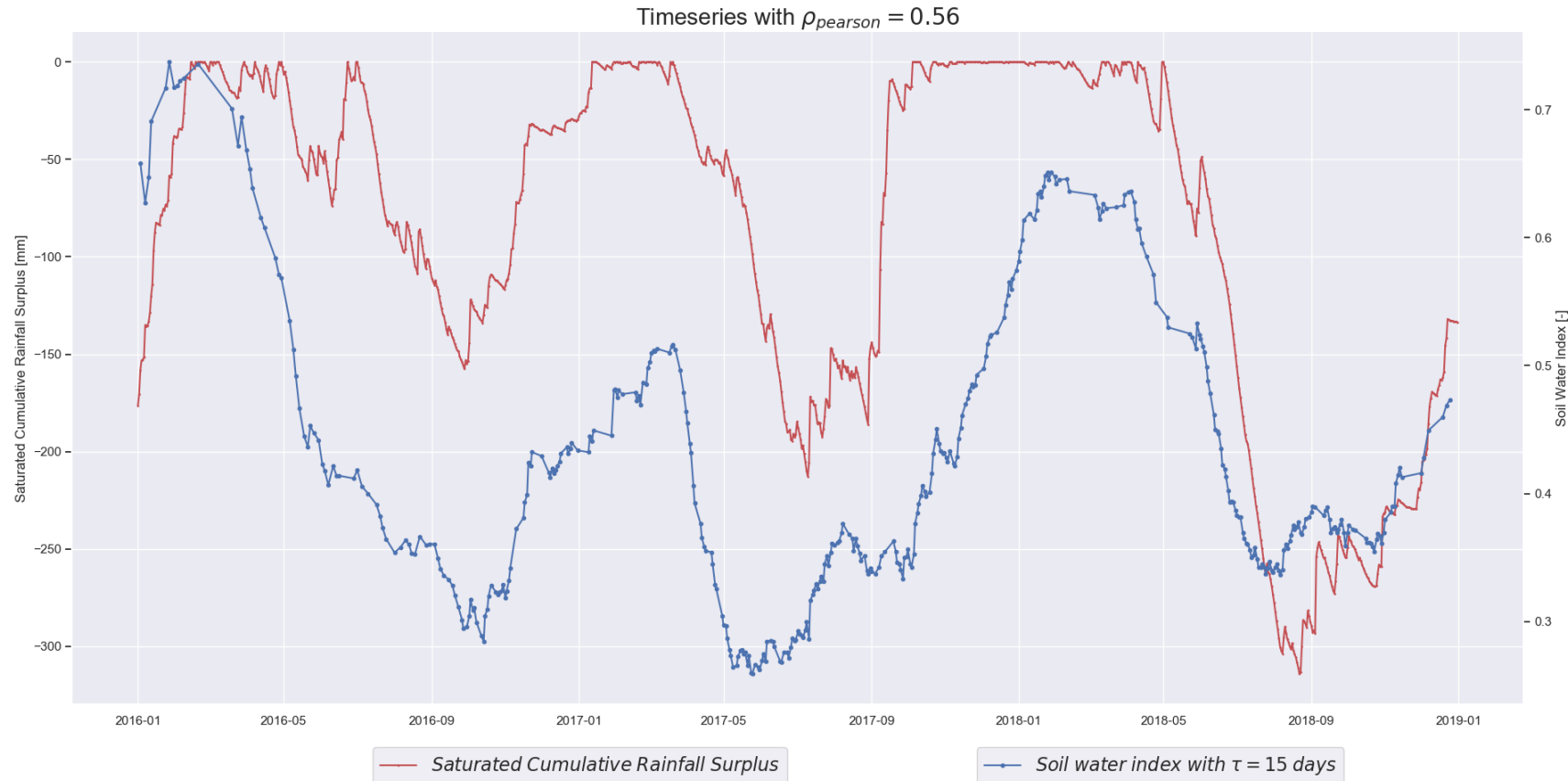
Can Soil Water Index tell more?

- SWI contains relevant information because peat soil subsidence is a process happening in the entire peat layer and SWI can be related to the plant available water content. [Wagner et al. 2003]
- Lag between moisture deficit and subsidence is expected.



Soil Water Index compared to CRFS_{sat}

SWI is derived from Sentinel-1 backscatter timeseries through the use of Surface Soil Moisture as an intermediate product. ($\sigma_{norm}^0 \rightarrow SSM \rightarrow SWI$)

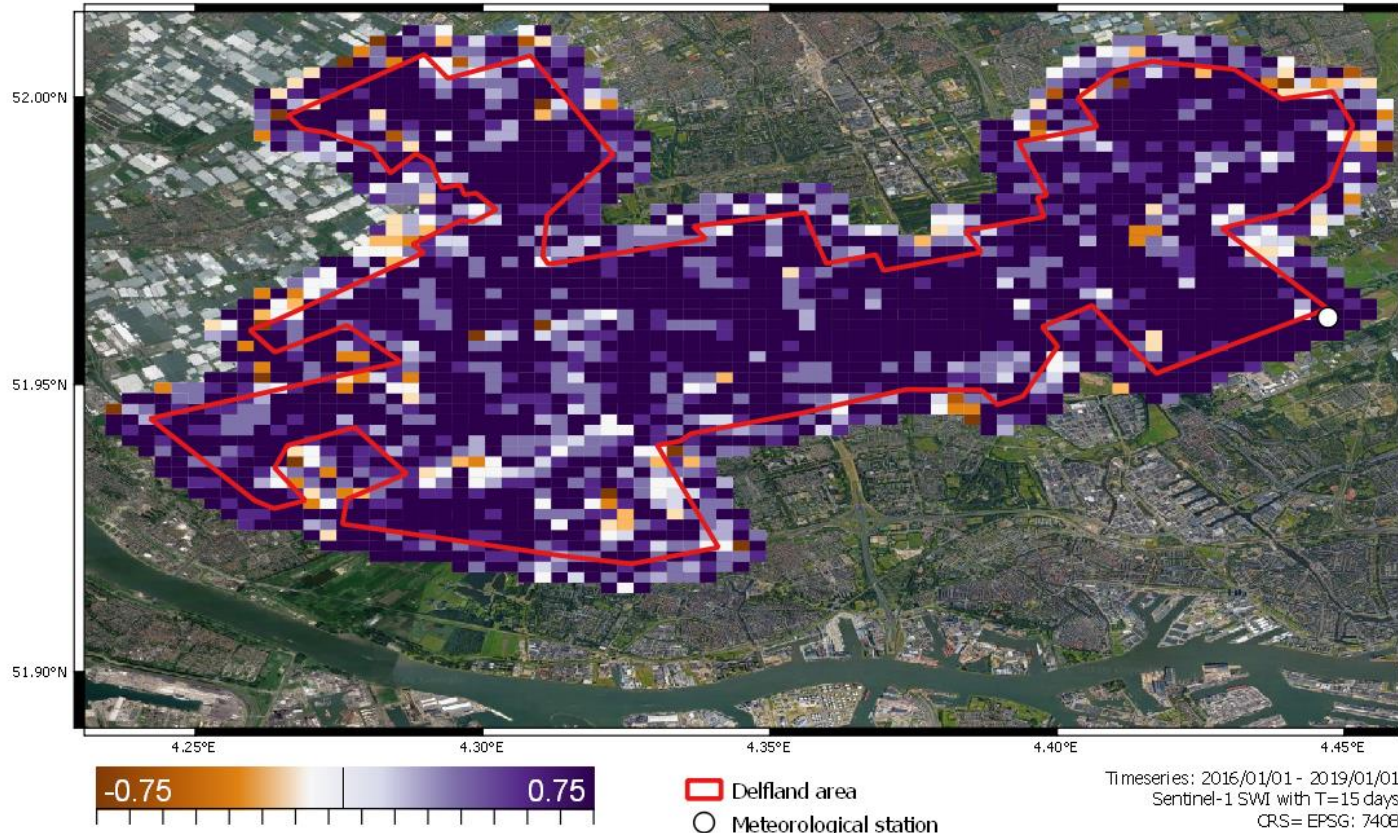


The timeseries show some similarity to the ancillary data derived CRFS_{sat}, hinting at further investigation of SWI as a satellite based InSAR ambiguity correction.

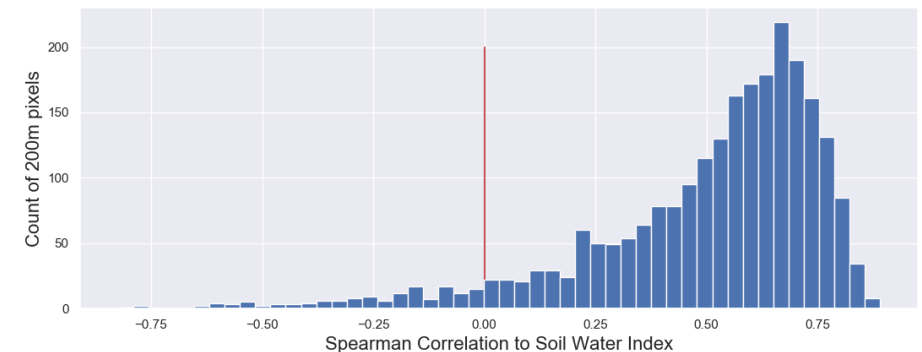
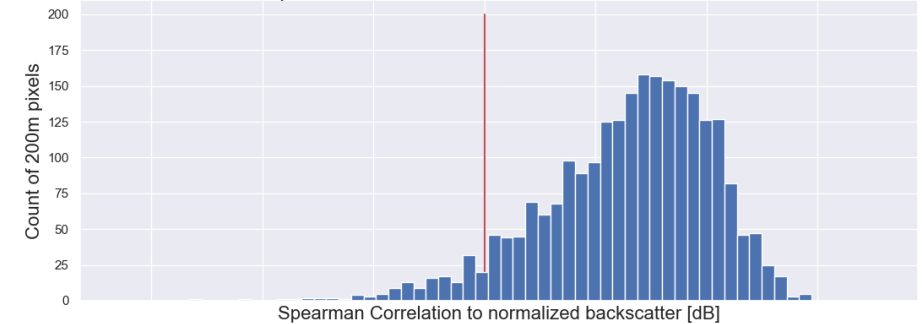
Comparison of Soil Water Index and Backscatter

- SWI shows higher correlations than backscatter and SSM with similar spatial patterns

Spearman correlation of SWI with T=15 to Saturated Cumulative Rainfall Surplus




Histogram of ρ_{spearman} with Saturated Cumulative Rainfall Surplus



Take home messages

- S-1 InSAR observations need additional information to correct the ambiguity in the estimated deformation in late summer.
- Grasslands have better correlations compared to urban areas, roads, waterbodies, farms and denser vegetation. Masking other land cover types will improve the overall correlations found.
- S-1 derived normalized VV backscatter (σ_{norm}^0) and Soil Water Index (SWI) are promising alternatives to saturated Cumulative Rainfall Surplus ($CRFS_{sat}$) for inSAR ambiguity correction at 200m resolution. SWI is the most correlated.



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