



Background

- Soil moisture has a close relationship with soil carbon:
 - the carbon content (S) of soil affects the response of the moisture content to meteorological inputs (M);
 - the moisture content of soil (θ), along with its temperature (T), affects the amount and type of respiration that can occur.
- The COSMOS-UK sensor network, Flux Net eddy covariance towers and earth observation products mean there is more data than ever.
- Here we leverage these new sources of data to disentangle the relationship between soil moisture and carbon through machine learning approaches.
- We aim to relax the assumptions used in land surface models and remove their reliance on poorly resolved soil textural estimates.

Soil carbon: $S \sim \theta_{VWC} + M$

- Pattern recognition at seasonal scale and precipitation event scale: can we discern soil organic carbon from soil moisture dynamics?
- Machine learning can help us combine multiscale temporal dynamics with static information such as historical climate and topography.
- If we know θ and M : an alternative to expensive large-scale soil core lab analyses.

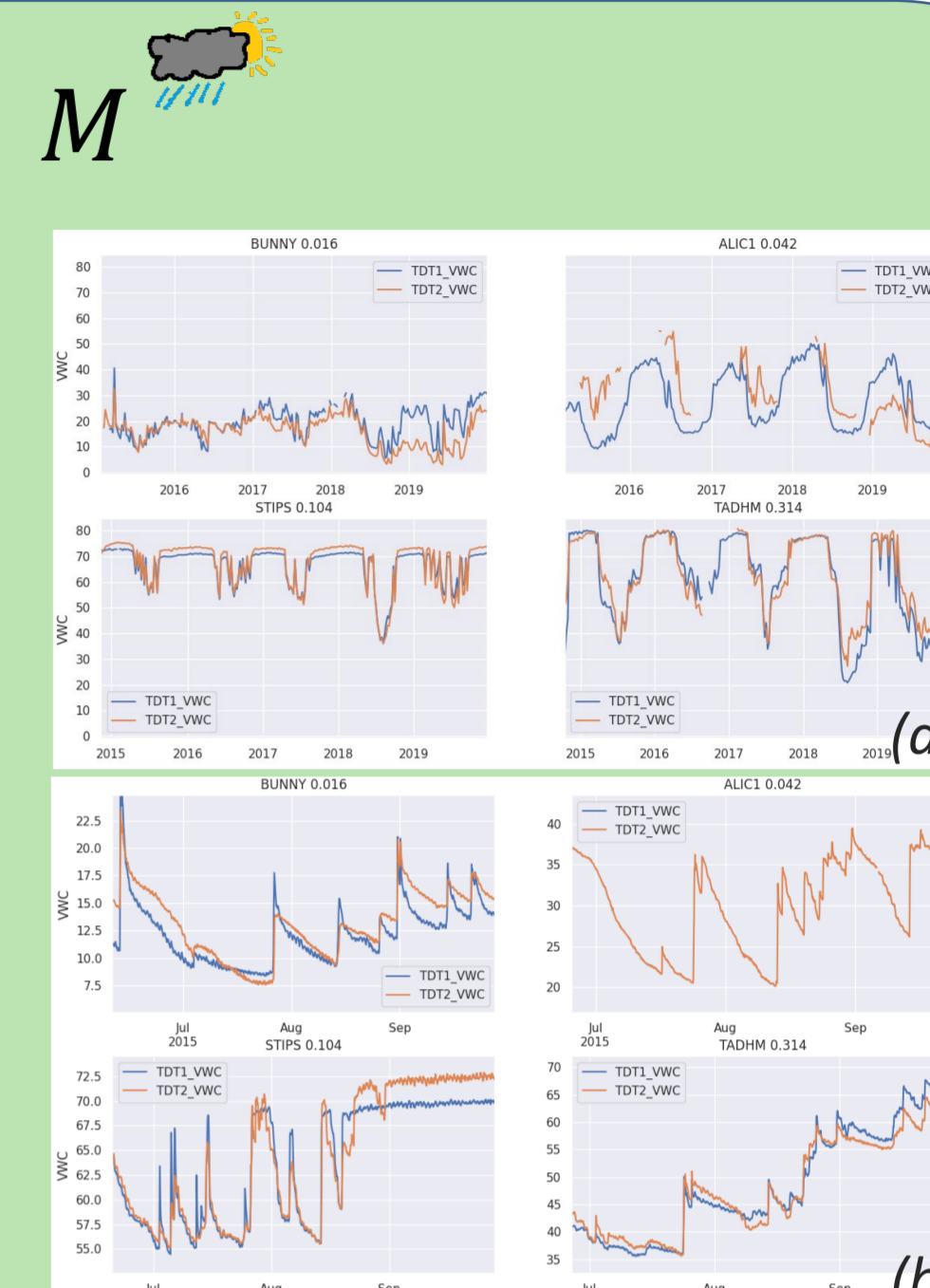


Fig 2. (a) Seasonal and (b) rainfall event scale dynamics at four COSMOS sites.

Soil moisture: $\theta_{VWC} \sim M + S$

- Neural network model based on:
 - (i) Causal convolutions to capture short timescale dynamics;
 - (ii) Attention layers for longer timescale contextual patterns.
- Replace dependence on soil texture with satellite products:
 - (i) Land Surface Temperature (MODIS, Copernicus);
 - (ii) Soil Water Index (Copernicus).

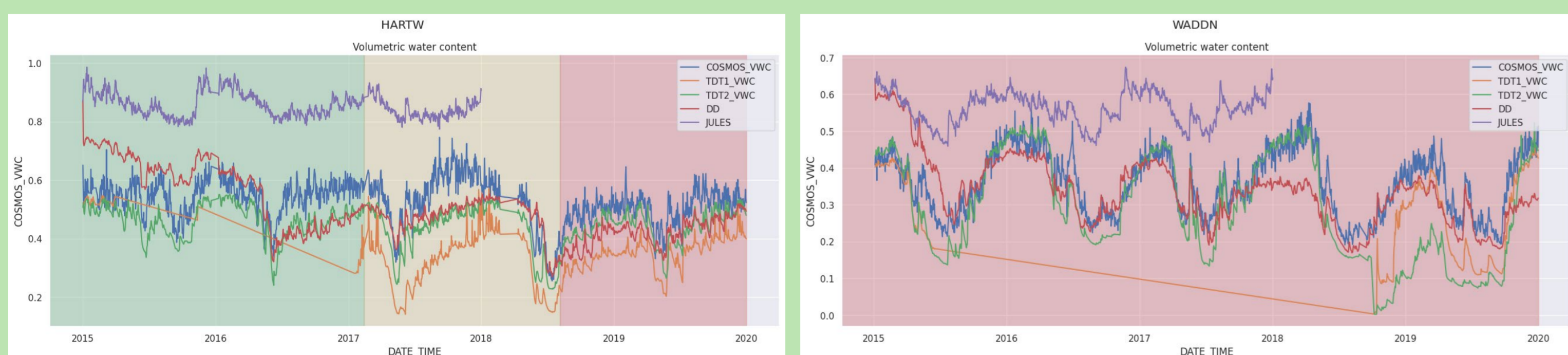


Fig 1. Comparing model results (DD) to data at COSMOS sites using the JULES model as initial condition. TDT are point probes, COSMOS is the neutron count-derived site-scale data. Green, yellow and red backgrounds denote training, validation and test periods.

Soil respiration: $\Delta S \sim \theta_{VWC} \cdot T$

- Net ecosystem exchange of CO₂ (NEE) modelled using data from GHG flux towers.
- Observing NEE at night allows separation of soil respiration from photosynthesis.
- Replacing functions of T and θ from theory with neural networks allows nonlinear functional forms to be learned directly from flux tower data.

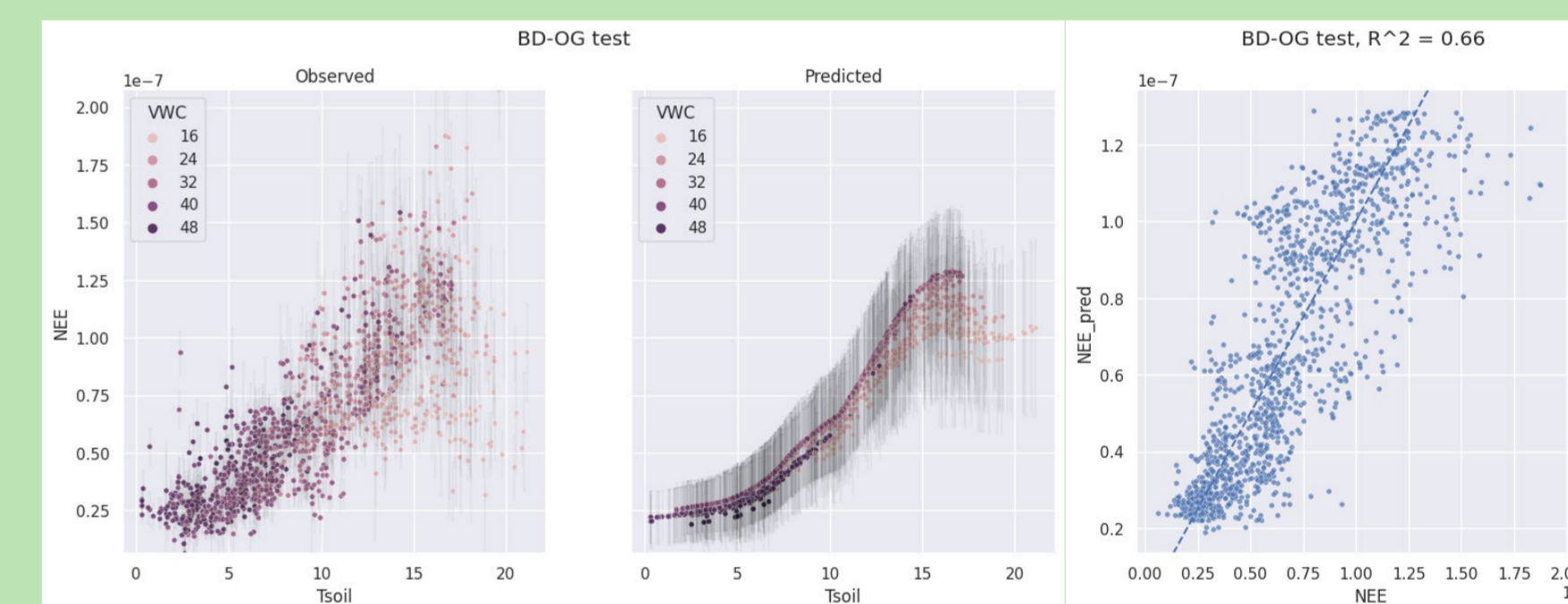


Fig 3. Comparing observed and predicted NEE.

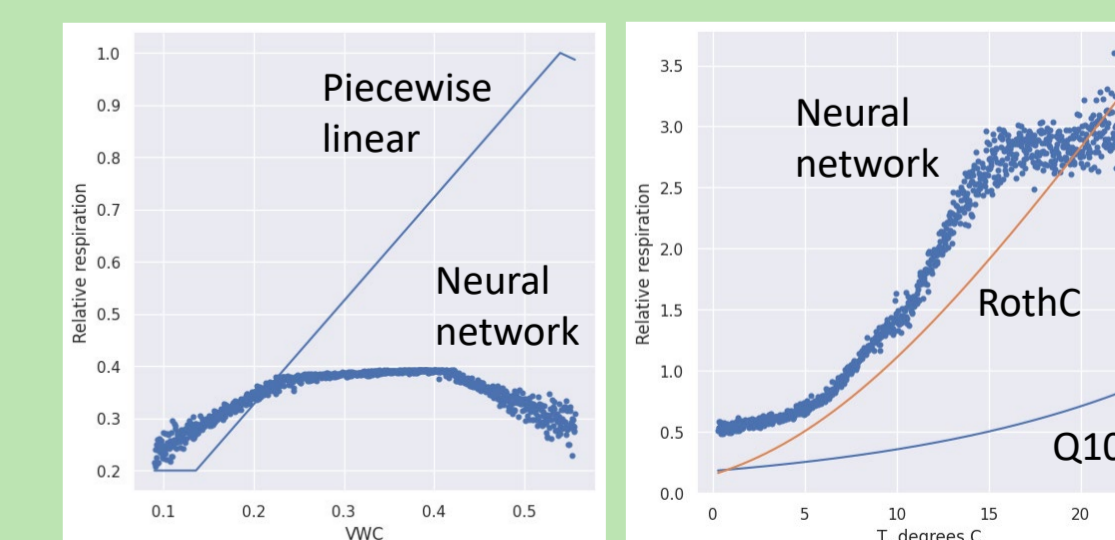


Fig 4. Comparing $f(\theta)$ and $g(T)$ from JULES with learned nonlinear functional forms.