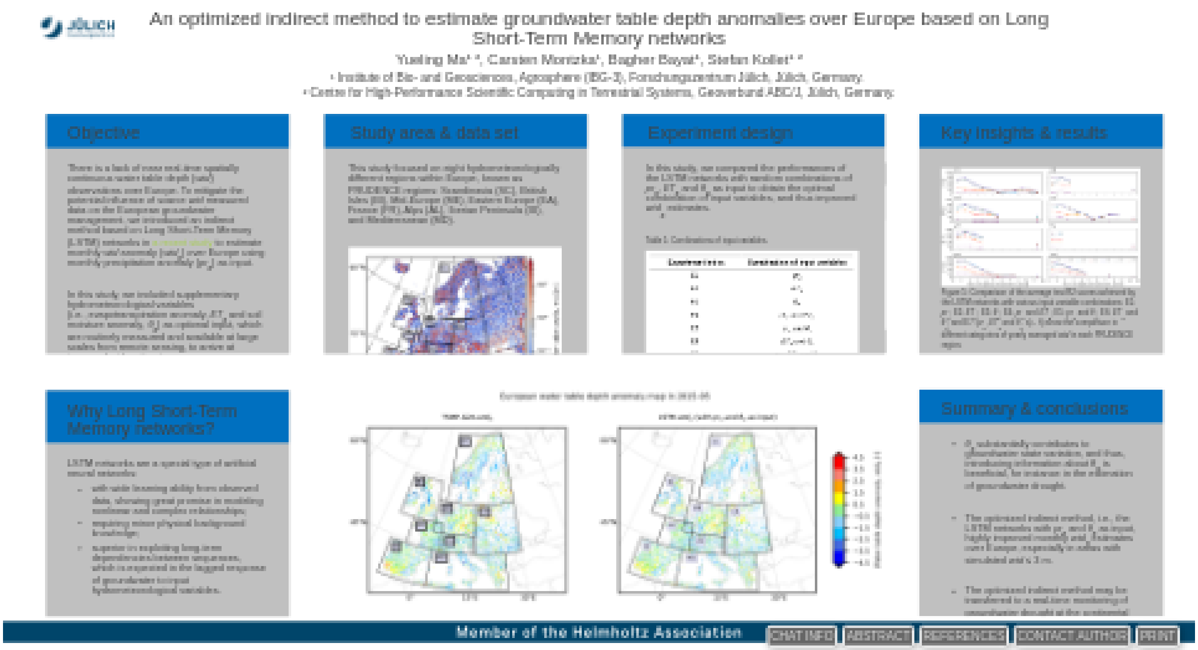
An optimized indirect method to estimate groundwater table depth anomalies over Europe based on Long Short-Term Memory networks



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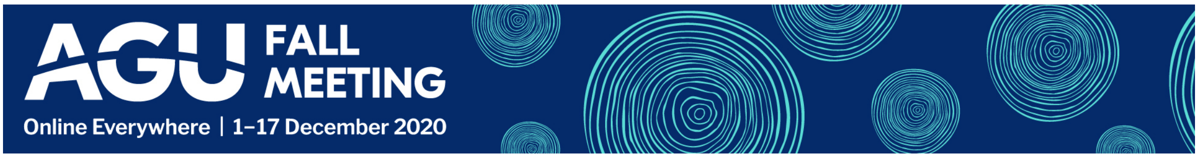
PRESENTED AT:



OBJECTIVE

There is a lack of near real-time spatially continuous water table depth (*wtd*) observations over Europe. To mitigate the potential influence of scarce *wtd* measured data on the European groundwater management, we introduced an indirect method based on Long Short-Term Memory (LSTM) networks in a recent study (https://hess.copernicus.org/preprints/hess-2020-382/)to estimate monthly *wtd* anomaly (wtd_a) over Europe using monthly precipitation anomaly (pr_a) as input.

In this study, we included supplementary hydrometeorological variables (i.e., evapotranspiration anomaly, ET_a and soil moisture anomaly, θ_a) as optional input, which are routinely measured and available at large scales from remote sensing, to arrive at improved wtd_a estimates.

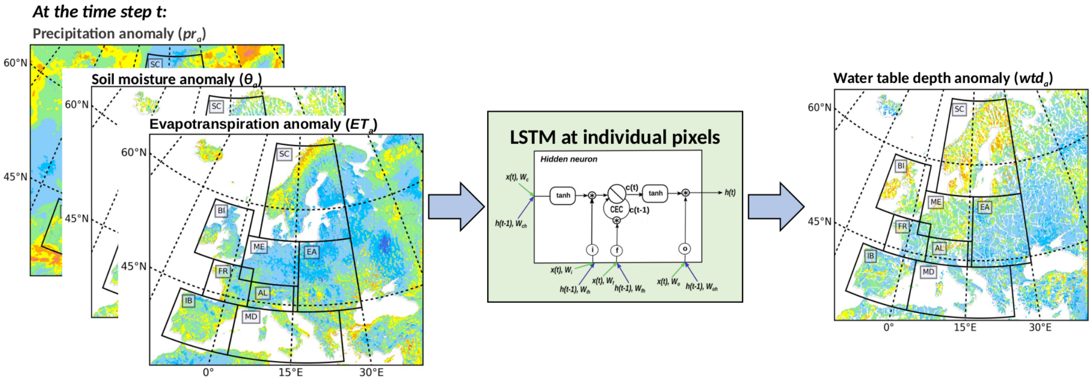


Figure 1: An optimized indirect method based on Long Short-Term Memory networks to estimate wtda over Europe from other hydrometeorological variables that have spatio-temporally continuous observations.

STUDY AREA & DATA SET

This study focused on eight hydrometeorologically different regions within Europe, known as PRUDENCE regions: Scandinavia (SC), British Isles (BI), Mid-Europe (ME), Eastern Europe (EA), France (FR), Alps (AL), Iberian Peninsula (IB), and Mediterranean (MD).

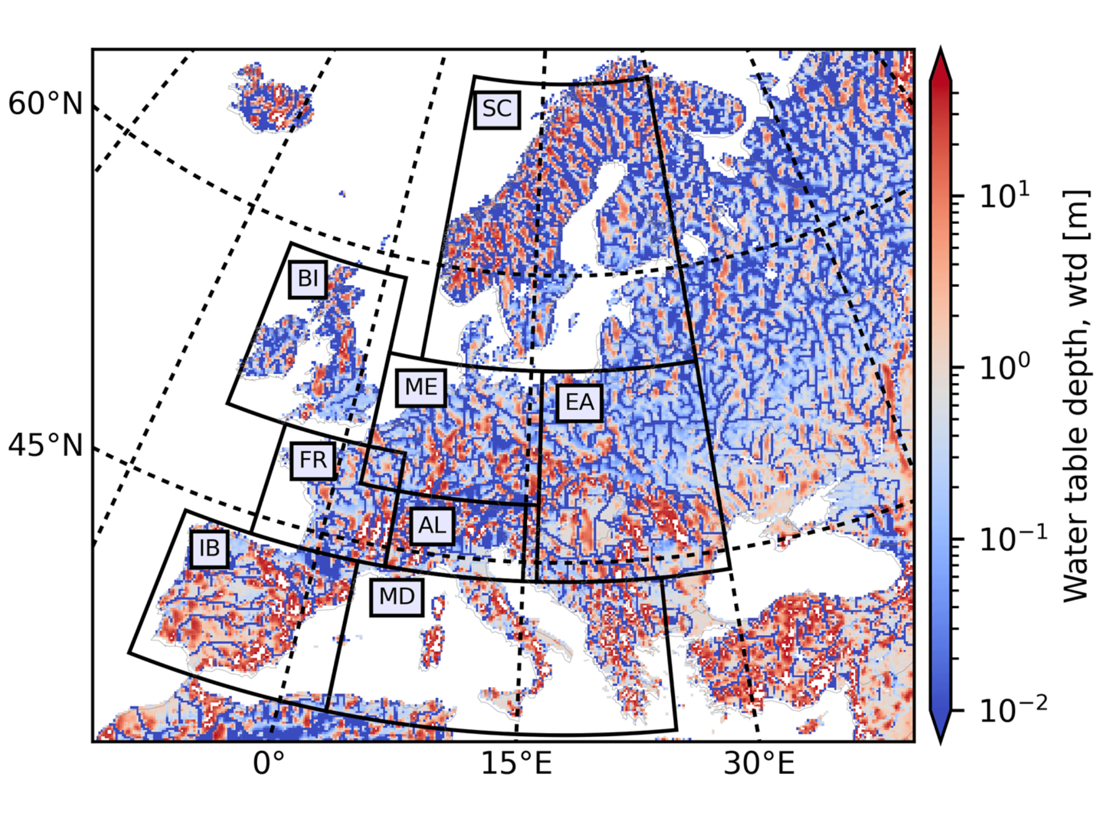


Figure 3: *Wtd* [m] climatology over the European continent between 01/1996 and 12/2016 extracted from the TSMP-G2A data set. Areas bounded by the thick black lines show PRUDENCE regions (i.e., SC: Scandinavia; BI: British Isles; ME: Mid-Europe; EA: Eastern Europe; FR: France; AL: Alps; IB: Iberian Peninsula; MD: Mediterranean).

Using the equation below, monthly anomaly data were obtained from daily integrated hydraulic simulation results over Europe (named the TSMP-G2A data set (https://www.nature.com/articles/s41597-019-0328-7)) from 01/1996 to 12/2016, with a spatial resolution of 0.11° (~ 12.5 km, EUR-11). Note that to avoid future information from leaking into the training process, we only used the data from 01/1996 to 12/2012 (i.e., the training period) to calculate the climatological average and standard deviation values.

Monthly anomaly, v_a,

$$v_a = (v_m - v_{av})/v_{sd},$$

where, v is the investigated variable, such as *wtd*; v_m is monthly data of calculated from the TSMP-G2A data set; v_{av} is the climatological average of v_m (i.e., averages of v_m in January, February, …, December); v_{sd} is the climatological standard deviation of v_m.

EXPERIMENT DESIGN

In this study, we compared the performances of the LSTM networks with random combinations of pr_a, ET_a and θ_a as input to obtain the optimal combination of input variables, and thus improved wtd_a estimates.

Table 1: Combinations of input variables.

Experiment index	Combination of input variables
E1	pr_a
E2	ET_a
E3	θ_a
E4	pr_a and ET_a
E5	pr_a and θ_a
E6	ET_a and θ_a
E7	pr_a, ET_a and θ_a

We categorized pixels in each PRUDENCE region into groups based on yearly averaged *wtd* calculated from the TSMP-G2A *wtd* data from 1996 to 2016, and the categories are [unit: m]: 1) 0.0-1.0; 2) 1.0-2.0; 3) 2.0-3.0; 4) 3.0-4.0; 5) 4.0-5.0; 6) 5.0-6.0; 7) 6.0-7.0; 8) 7.0-8.0; 9) 8.0-9.0; 10) 9.0-10.0; 11)10.0-50.0. To save the computing time, we randomly selected ≤ 200 pixels in each group to apply the LSTM-network-based method.

At individual pixels, the data were separated into:

- a training set (01/1996 - 12/2012, totally 204 time steps) for network training;
- a validation set (01/2013 - 12/2014, totally 24 time steps) for network validation;
- a test set (01/2015 – 12/2016, totally 24 time steps) for network testing.

Figure 4 gives the workflow for the LSTM-network-based method to handle data at the individual pixel level. Here we used the coefficient of determination (R^2) as the evaluation metric.

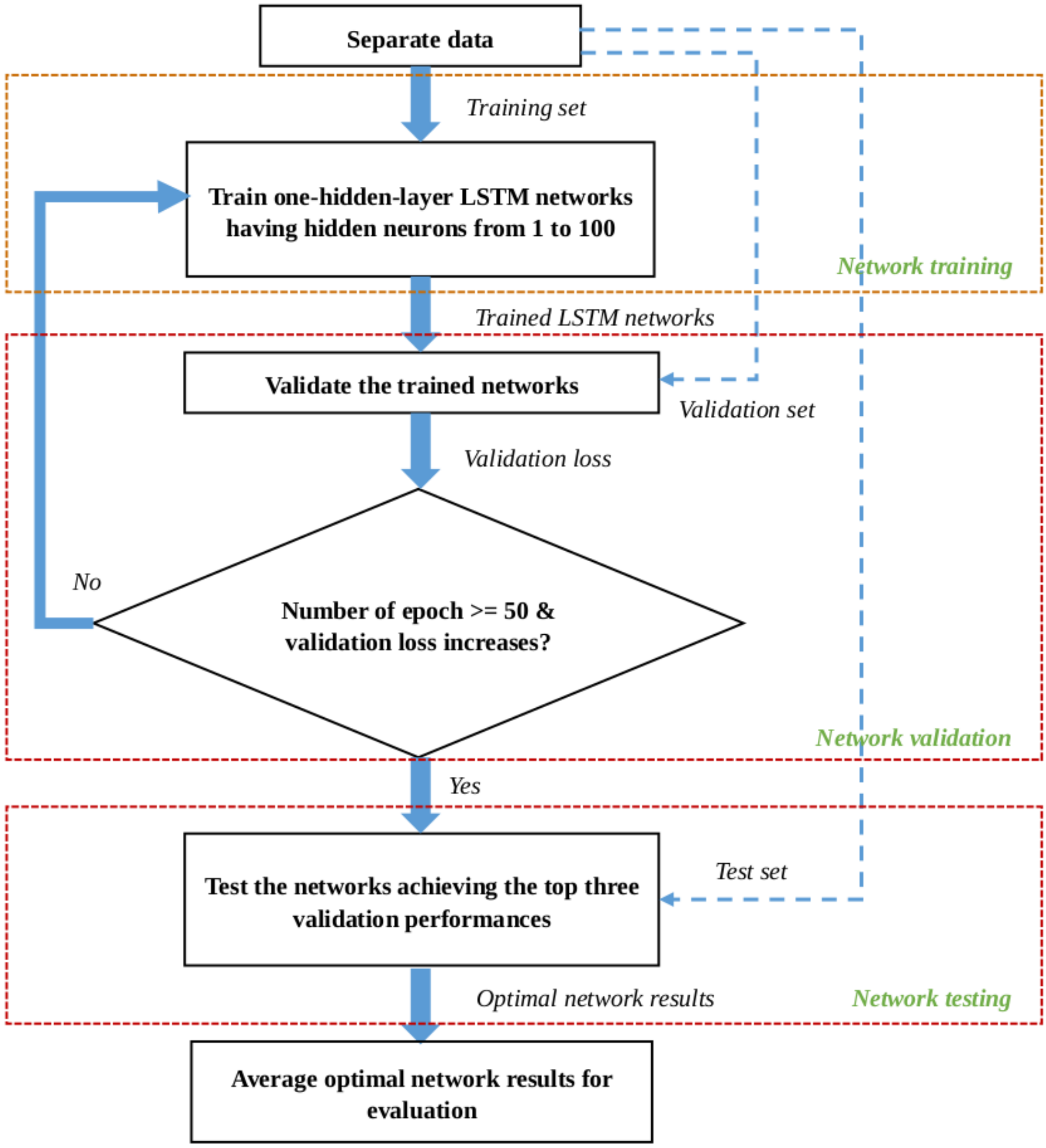


Figure 4: Workflow for the LSTM-network-based method to handle data at the individual pixel level.

KEY INSIGHTS & RESULTS

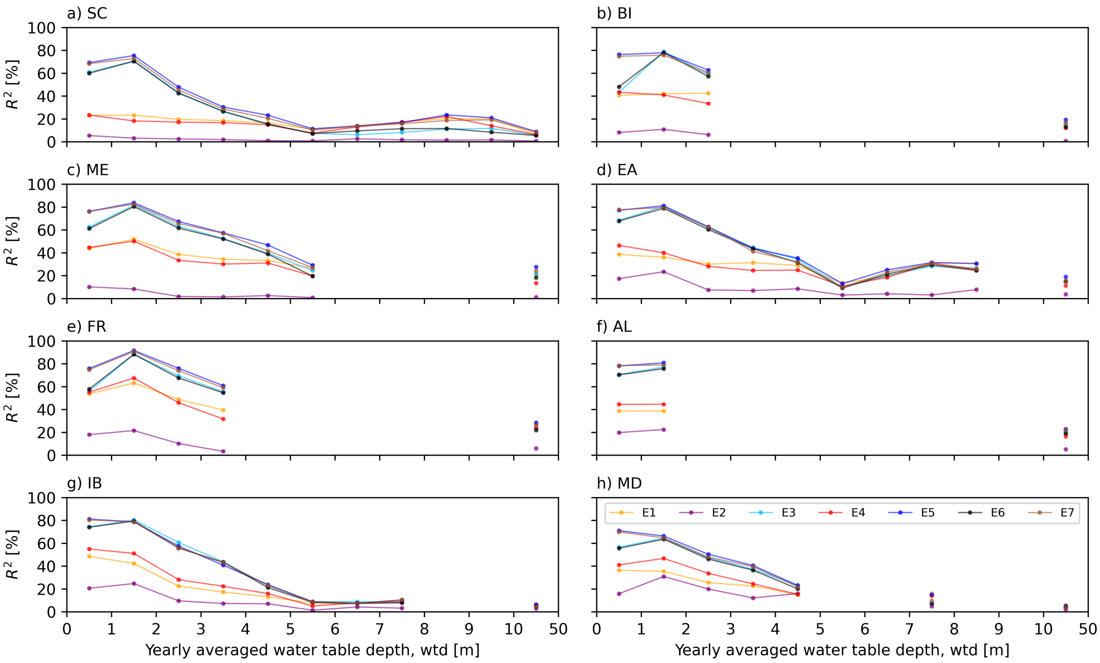


Figure 5: Comparison of the average test R2 scores achieved by the LSTM networks with various input variable combinations: E1: pr_a; E2: ET_a; E3: θ_a; E4: pr_a and ET_a; E5: pr_a and θ_a; E6: ET_a and θ_a; and E7: pr_a, ET_a and θ_a. a) - h) show the comparison in different categories of yearly averaged *wtd* in each PRUDENCE region.

Findings:

- For increasing yearly averaged *wtd*, the average test R^2 scores generally decreased for all the LSTM networks, indicating a decrease in the network test performances;
- There was a small contribution of ET_a to the estimation of wtd_a over Europe;
- The networks with θ_a as one of their input variables (i.e., E3, E5, E6 and E7) outperformed the other variable combinations in terms of test performances;
- The optimal combination of input variables was pr_a and θ_a (i.e., E5, deep blue lines in Figure 5), and the networks with this combination achieved average test R^2 between 47.88% and 91.62% in areas with simulated *wtd* ≤ 3 m.

WHY LONG SHORT-TERM MEMORY NETWORKS?

LSTM networks are a special type of artificial neural networks:

- with wide learning ability from observed data, showing great promise in modeling nonlinear and complex relationships;
- requiring minor physical background knowledge;
- superior in exploiting long-term dependencies between sequences, which is expected in the lagged response of groundwater to input hydrometeorological variables.

Due to limited data available at each pixel (i.e., a total of 252 time steps), we built small LSTM networks at the local scale, having one input layer, one hidden layer, and one output layer.

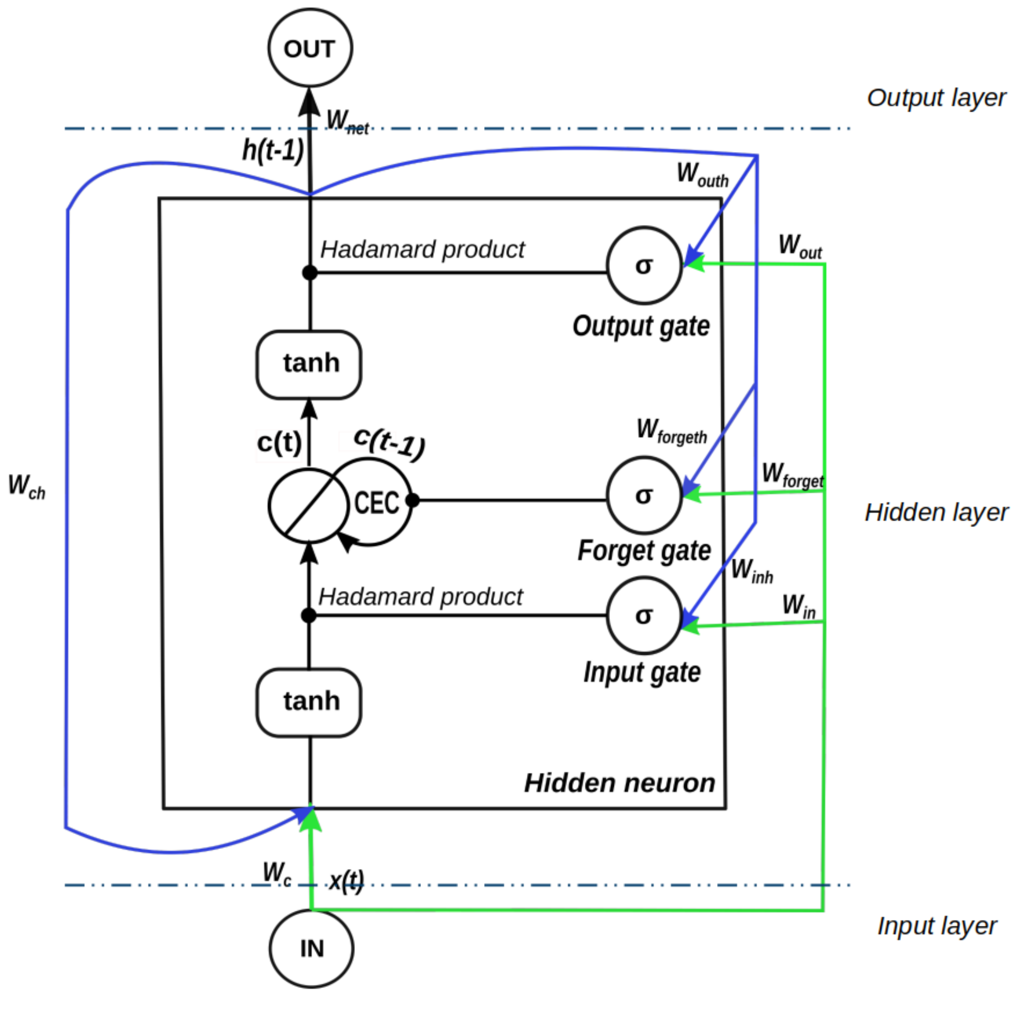
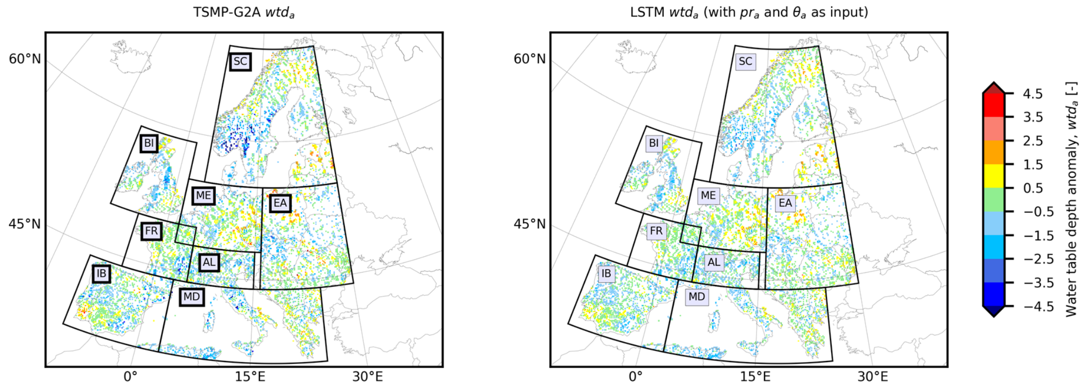
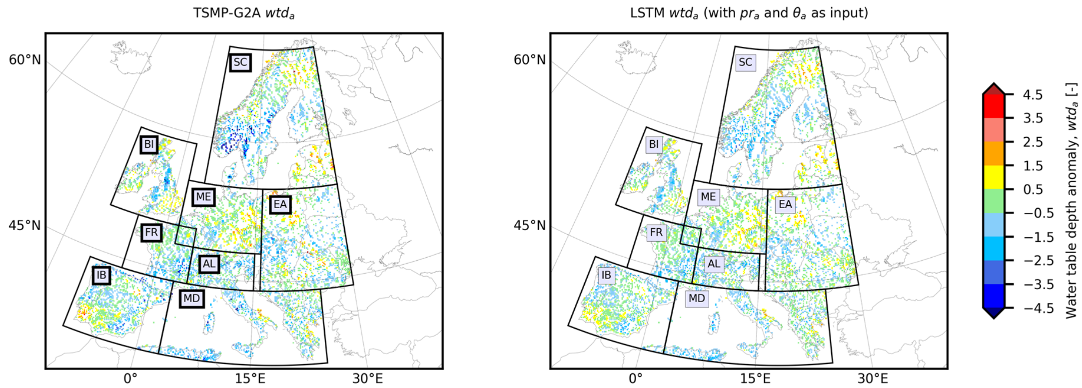


Figure 2: One-hidden-layer LSTM network with one hidden neuron. The green lines indicate the entry points of new inputs into the hidden neuron. The blue lines show the entry points of previous outputs into the hidden neuron, where w* is the weight on a linkage; h(∗) is the output of the hidden neuron; x(t) is the input at the time step t; and c(∗) is the cell state. σ represents a sigmoid function, and tanh is a hyperbolic tangent function.

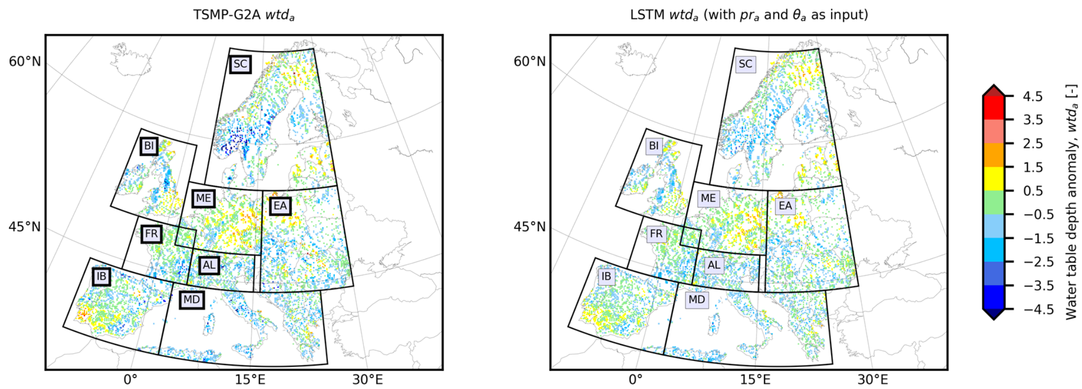
European water table depth anomaly map in 2015-01



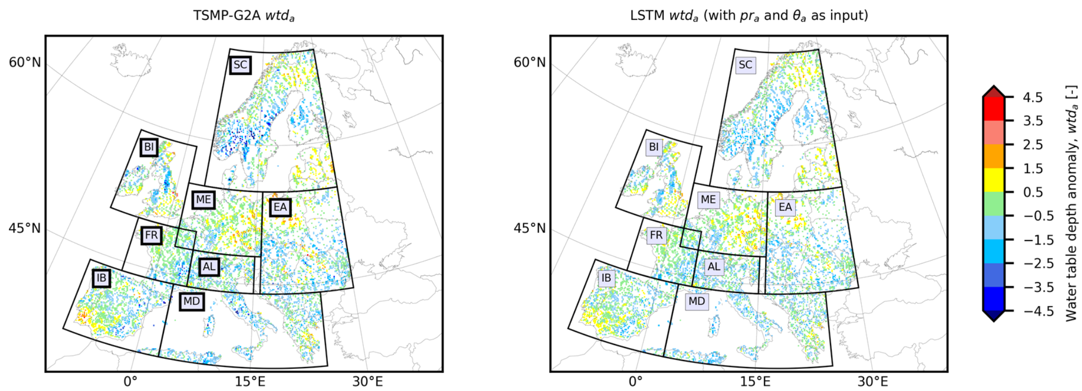
European water table depth anomaly map in 2015-02



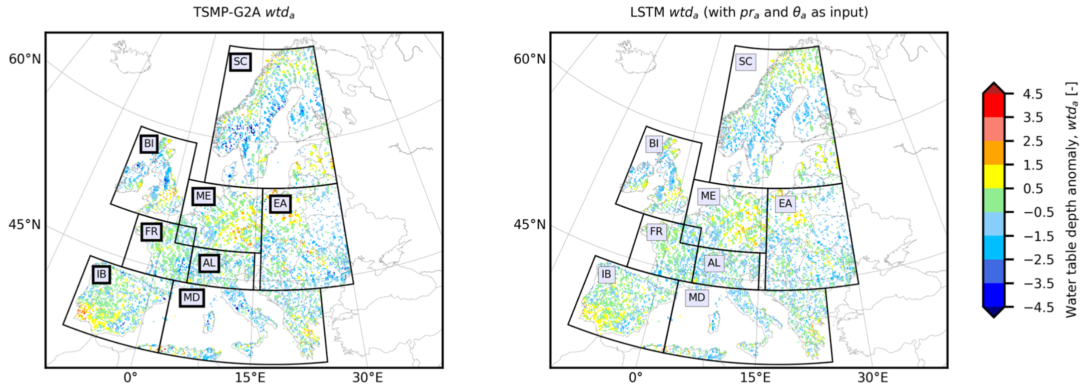
European water table depth anomaly map in 2015-03



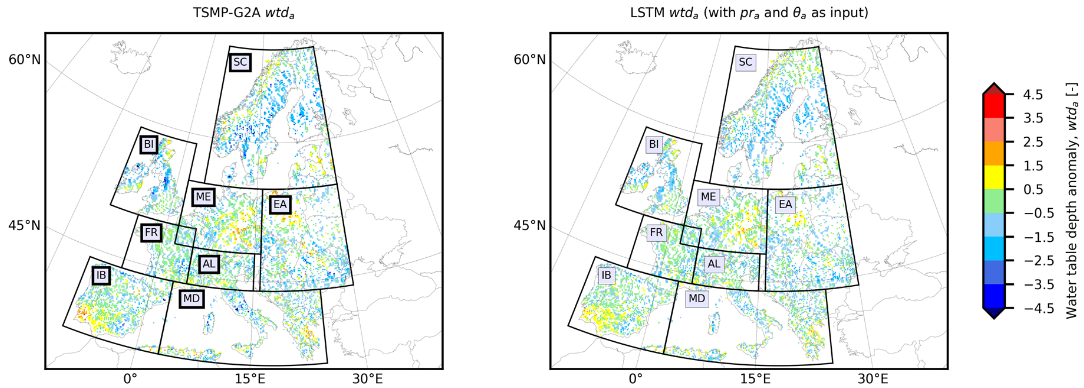
European water table depth anomaly map in 2015-04



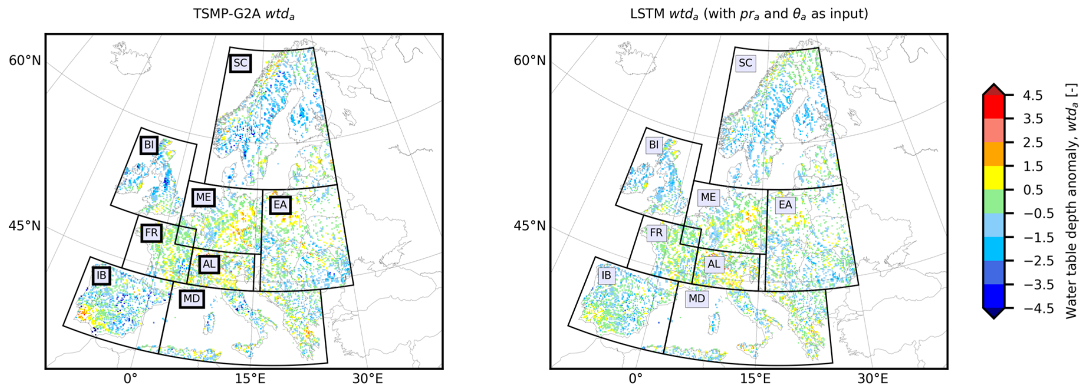
European water table depth anomaly map in 2015-05



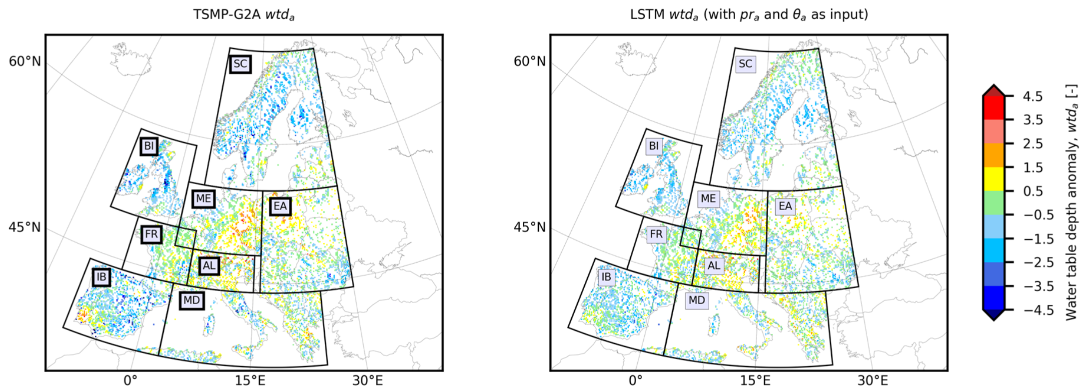
European water table depth anomaly map in 2015-06



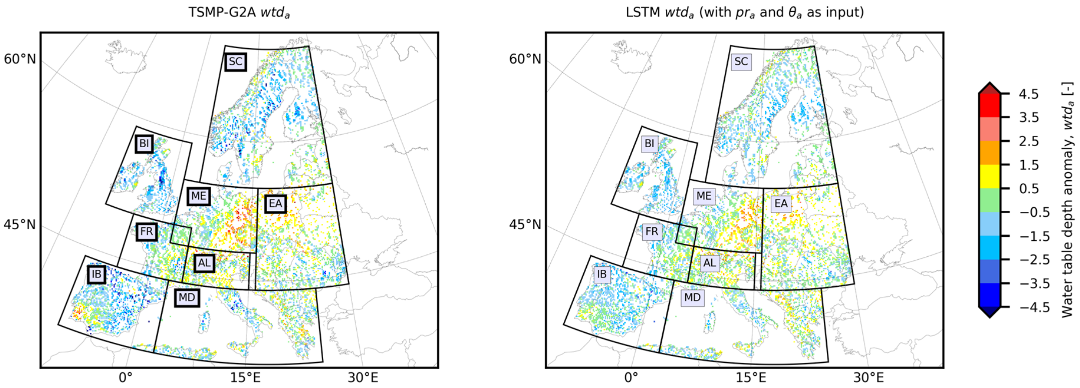
European water table depth anomaly map in 2015-07



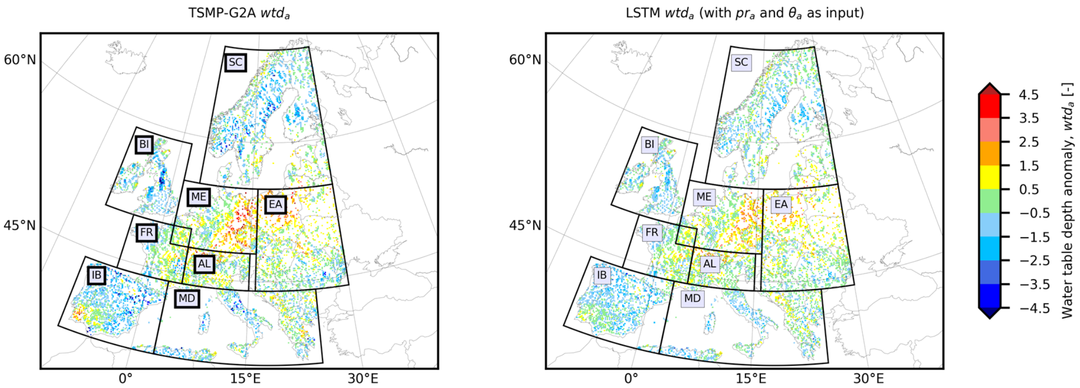
European water table depth anomaly map in 2015-08



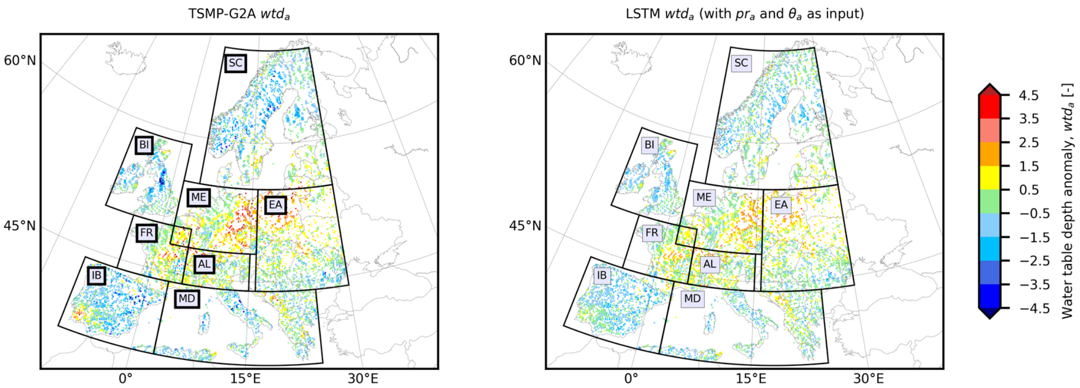
European water table depth anomaly map in 2015-09



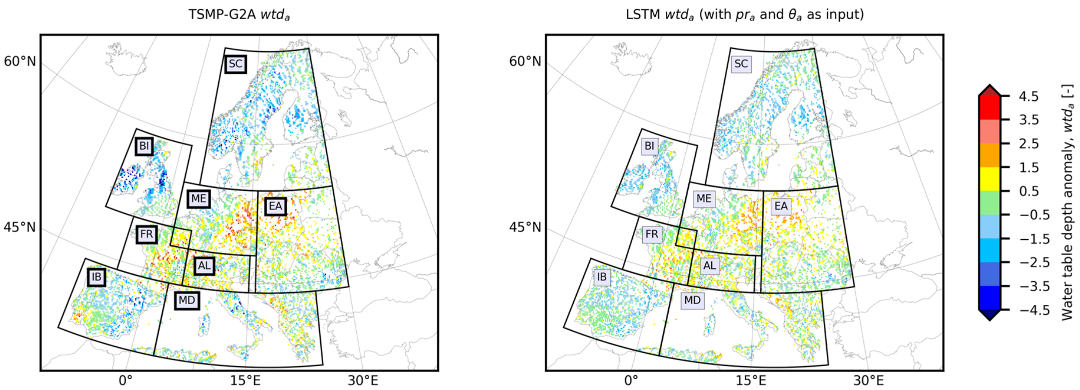
European water table depth anomaly map in 2015-10



European water table depth anomaly map in 2015-11



European water table depth anomaly map in 2015-12



SUMMARY & CONCLUSIONS

- θ_a substantially contributes to groundwater state variation, and thus, introducing information about θ_a is beneficial, for instance in the estimation of groundwater drought.

- The optimized indirect method, i.e., the LSTM networks with pr_a and θ_a as input, highly improved monthly wtd_a estimates over Europe, especially in areas with simulated $wtd \leq 3$ m.

- The optimized indirect method may be transferred to a real-time monitoring of groundwater drought at the continental scale using remotely sensed soil moisture observations.

ABSTRACT

Long Short-Term Memory (LSTM) networks are a deep learning technology to exploit long-term dependencies in the input-output relationship, which has been observed in the response of groundwater dynamics to atmospheric and land surface processes. We introduced an indirect method based on LSTM networks to estimate monthly water table depth anomalies (wtd_a) across Europe from monthly precipitation anomalies (pr_a). The network has further been optimized by including supplementary hydrometeorological variables, which are routinely measured and available at large scales. The data were obtained from daily integrated hydraulic simulation results over Europe from 1996 to 2016, with a spatial resolution of 0.11° (Furusho-Percot et al., 2019), and separated into a training set, a validation set and a test set at individual pixels. We compared test performances of the LSTM networks locally at selected pixels in eight PRUDENCE regions with random combinations of monthly pr_a, evapotranspiration anomaly, and soil moisture anomaly (θ_a) as input variables. The optimal combination of input variables was pr_a and θ_a, and the networks with this combination achieved average test R^2 between 47.88% and 91.62% in areas with simulated $wtd \leq 3$ m. Moreover, we found that introducing θ_a improved the ability of the trained networks to handle new data, indicating the substantial contribution of θ_a to explain groundwater state variation. Therefore, including information about θ_a is beneficial, for instance in the estimation of groundwater drought, and the proposed optimized method may be transferred to a real-time monitoring of groundwater drought at the continental scale using remotely sensed soil moisture observations.

Furusho-Percot, C., Goergen, K., Hartick, C., Kulkarni, K., Keune, J. and Kollet, S.: Pan-European groundwater to atmosphere terrestrial systems climatology from a physically consistent simulation, Sci. data, 6(1), 320, doi:10.1038/s41597-019-0328-7, 2019.

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