



Using GRACE satellite data to analyse spatiotemporal variations of groundwater storage in the Bug River Basin (Polish–Ukrainian–Belarusian borderland)

Justyna Śliwińska-Bronowicz

Centrum Badań Kosmicznych Polskiej Akademii Nauk (CBK PAN), Warsaw, Poland

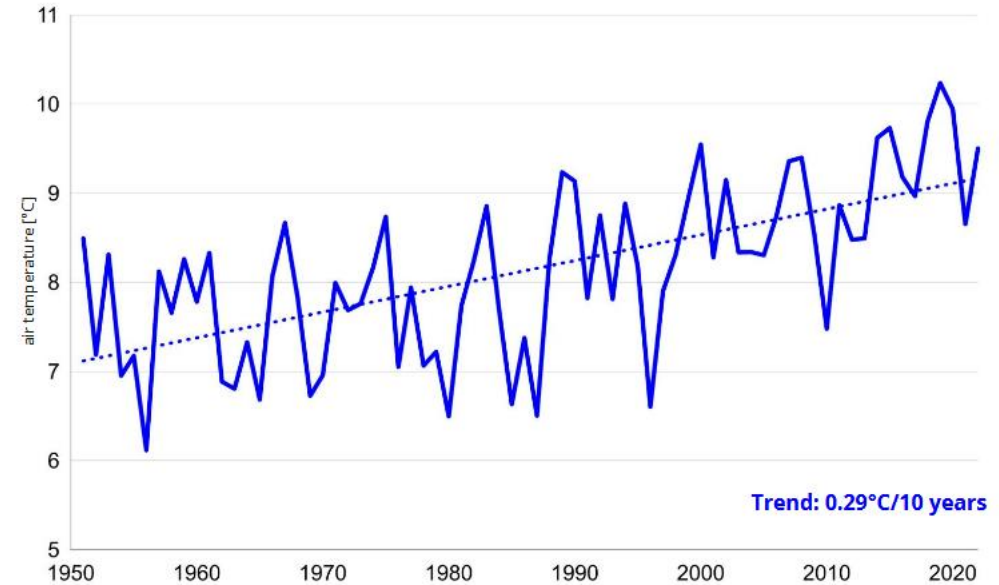
Tatiana Solovey, Rafał Janica, Agnieszka Brzezińska, Anna Stradczuk

Polish Geological Institute – National Research Institute (PGI-NRI), Warsaw, Poland

Motivation

In recent years, Europe's water resources have been exposed to a number of negative phenomena that can be linked to climate change:

- rising average temperatures,
- increased evapotranspiration intensity,
- changes in rainfall patterns (fewer rainy days and more frequent short and intense downpours),
- reduced winter snowfall, and the resulting decrease in water recharge from spring snowmelt



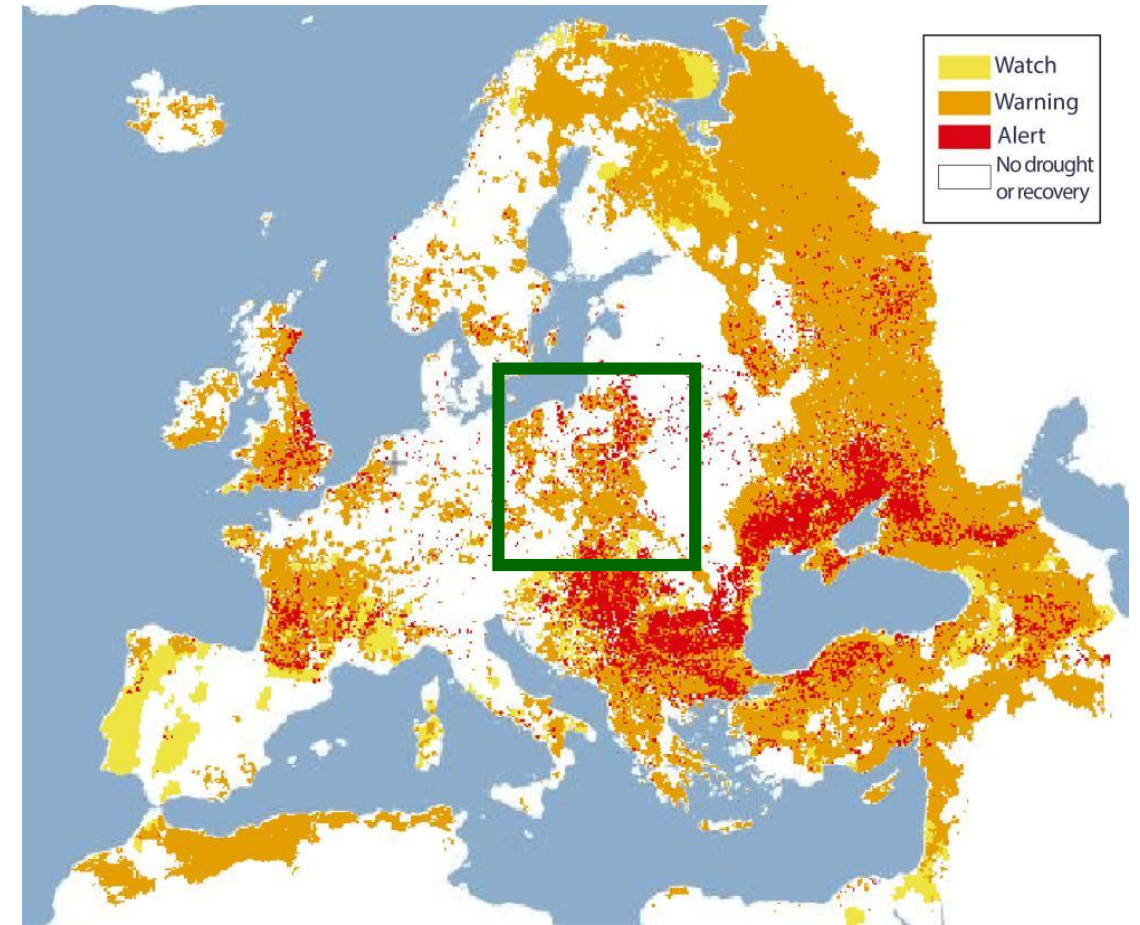
Average annual temperature in Poland during the period 1951-2020.

Source: CLIMATE OF POLAND 2024. Report of Institute of Meteorology and Water Management (IMGW).

<https://imgw.pl/wp-content/uploads/2025/07/CLIMATE-OF-POLAND-2024.pdf>

Motivation

- Drought indicators: alarming/warning conditions across much of Europe, especially the southeast
- **Poland:** recent drought warnings for most regions
- In the EU, **groundwater** provides about 65% of drinking water and 25% of agricultural irrigation. In Poland, 70% of drinking water comes from **groundwater**
- Intensive abstraction (domestic, agriculture, industry) negatively affects water resources, including **groundwater**

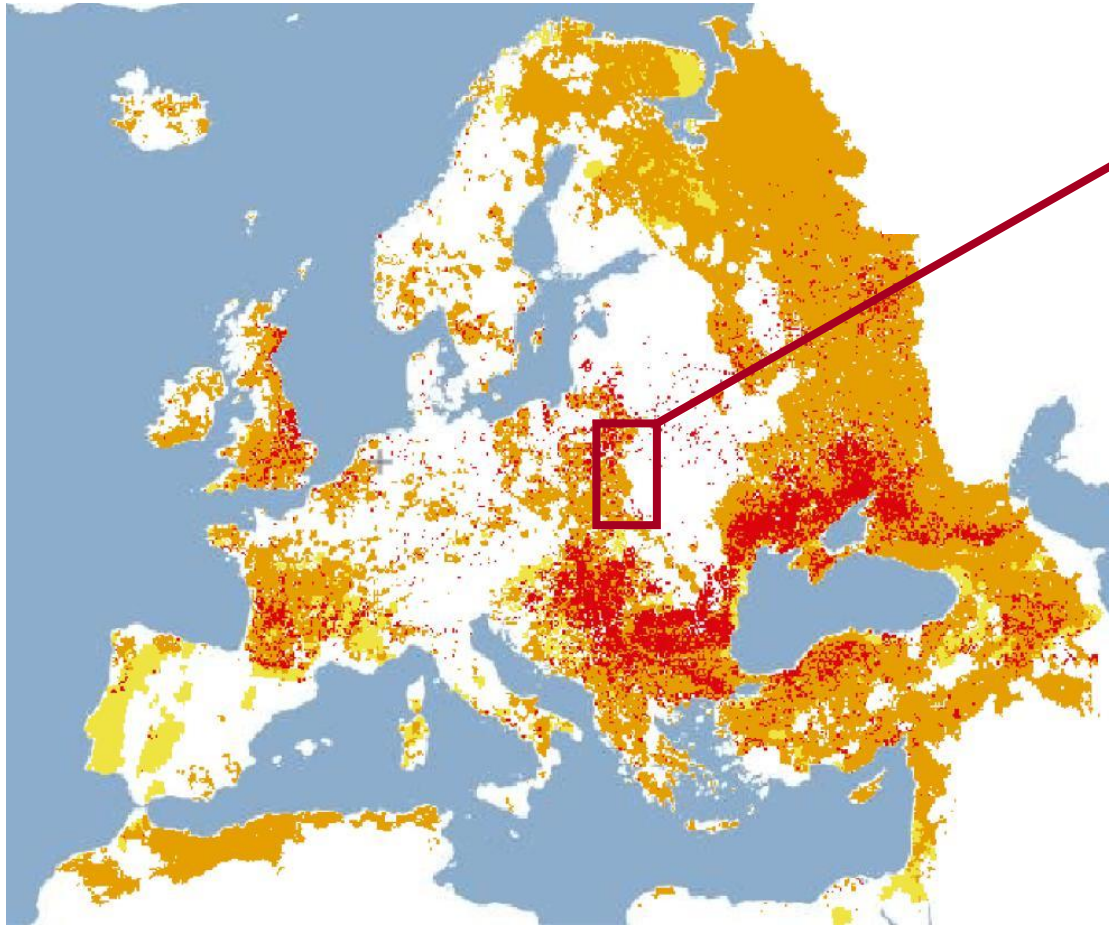


Drought situation in Europe in August 2025

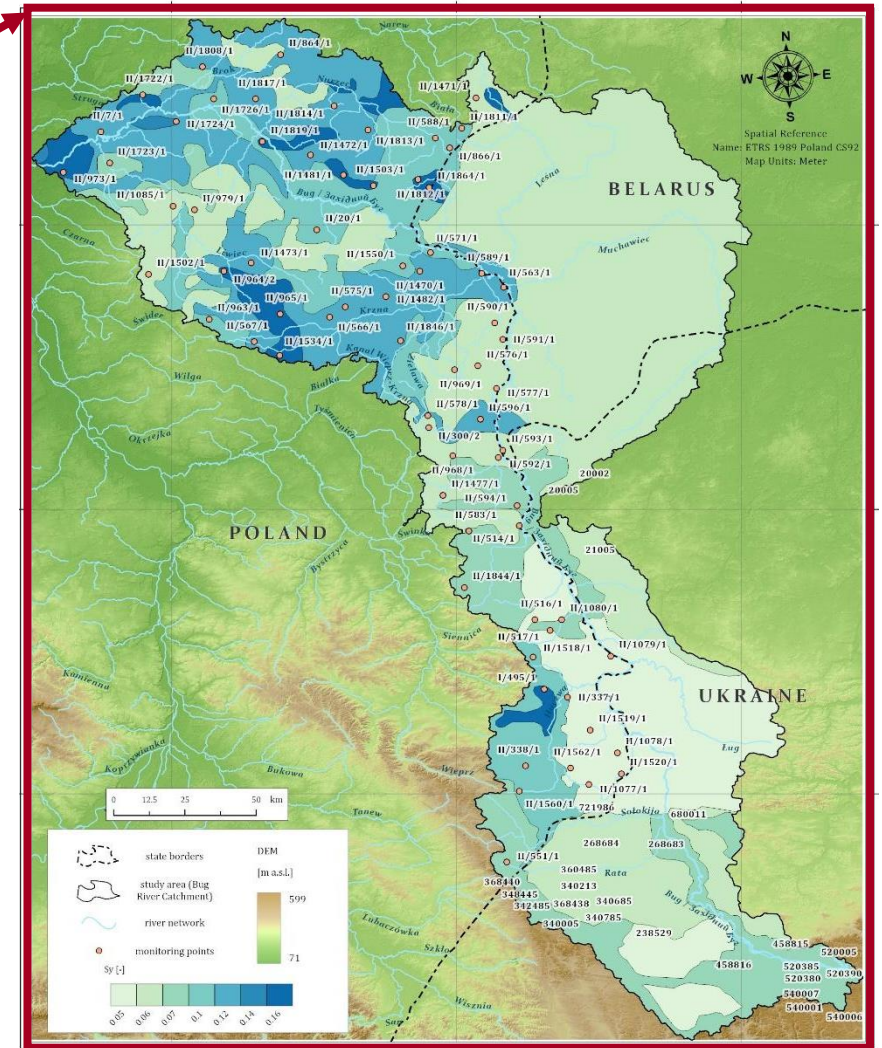
Source: https://joint-research-centre.ec.europa.eu/european-and-global-drought-observatories/current-drought-situation-europe_en

- Analysis of **spatial and temporal variations in terrestrial water storage (TWS) and groundwater storage (GWS) in the Bug River Basin (BRB)** – transboundary aquifer spanning Poland, Ukraine, and Belarus
- Introducing a novel method for estimating GWS using GRACE/GRACE-FO data and hydrological modelling, featuring three key innovations:
 1. **Downscaling of GRACE-derived TWS to $0.1^\circ \times 0.1^\circ$** using Random Forests, with precipitation, evapotranspiration, river runoff, and soil moisture as predictors
 2. **Modified GWS calculation** that incorporates the influence of groundwater table depth on satellite-based estimates.
 3. **Calibration of satellite-derived GWS with in-situ measurements** through a combination of Random Forests and kriging to improve accuracy
- Validation of GRACE/GRACE-FO-derived GWS using in-situ groundwater level measurements

Study area



- Catchment area of ~40,000 km² spanning Poland, Ukraine, and Belarus
- About 75% lies in lowland regions (north), while the remaining 25% consists of uplands (south)



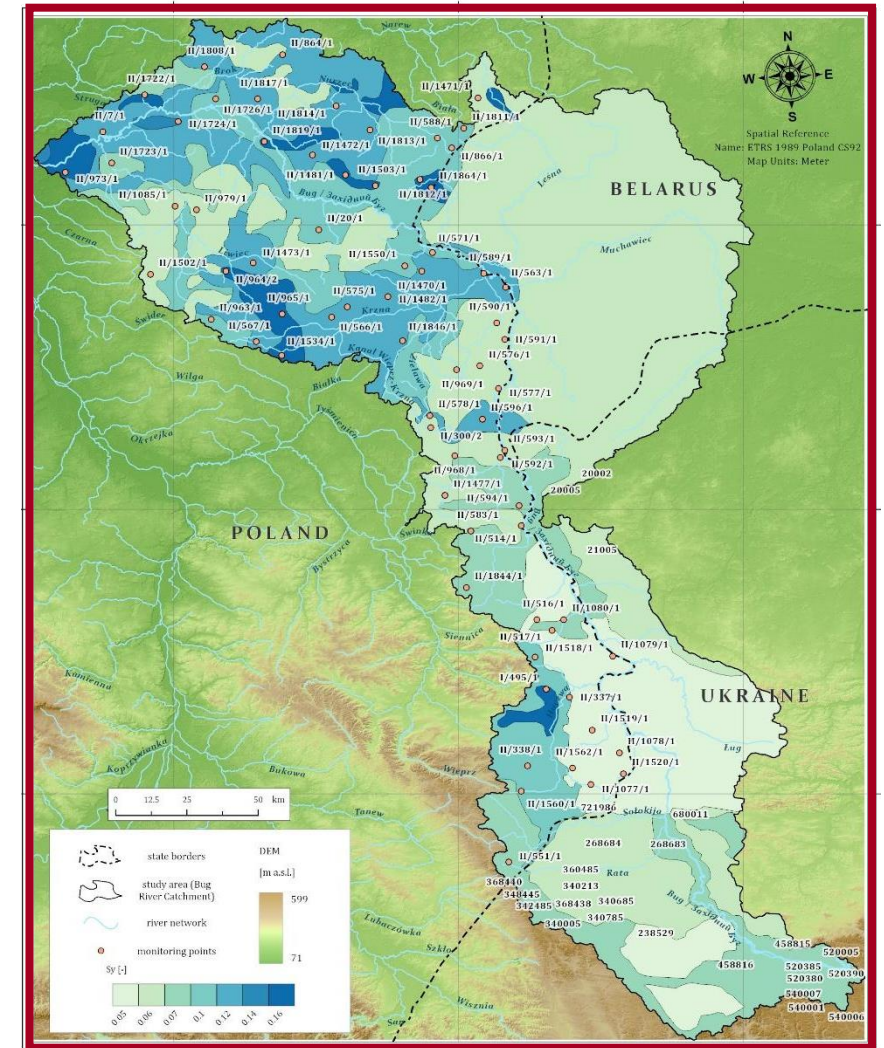
Bug River Basin with location of wells and Sy values

In-situ groundwater level (GWL) measurements

Groundwater Level (GWL) monitoring in the BRB

- **Network:** 71 stations monitoring three aquifer systems:
(1) shallow groundwater, (2) deeper confined groundwater,
(3) deep, nearly static reserves
- **Point selection:**
 - 27 stations monitoring the shallowest aquifer system
 - Seasonal GWL variability strongly linked to meteorological conditions
 - Observations from 2009–2022 (post-modernization, automated measurements)
 - Excluded stations with confined aquifers, strong local effects, or low-quality data
- **Specific yield (Sy):** Calculated based on soil type and aquifer properties
- **Computation of $GWS_{in-situ}$** at each monitoring point:

$$GWS_{in-situ} = -GWL \cdot Sy$$



*Bug River Basin with location of wells
and Sy values*

Improved methodology for GWS_{sat} – 3 steps



1. Downscaling of TWS_{GRACE} data into $0.1^\circ \times 0.1^\circ$ grids

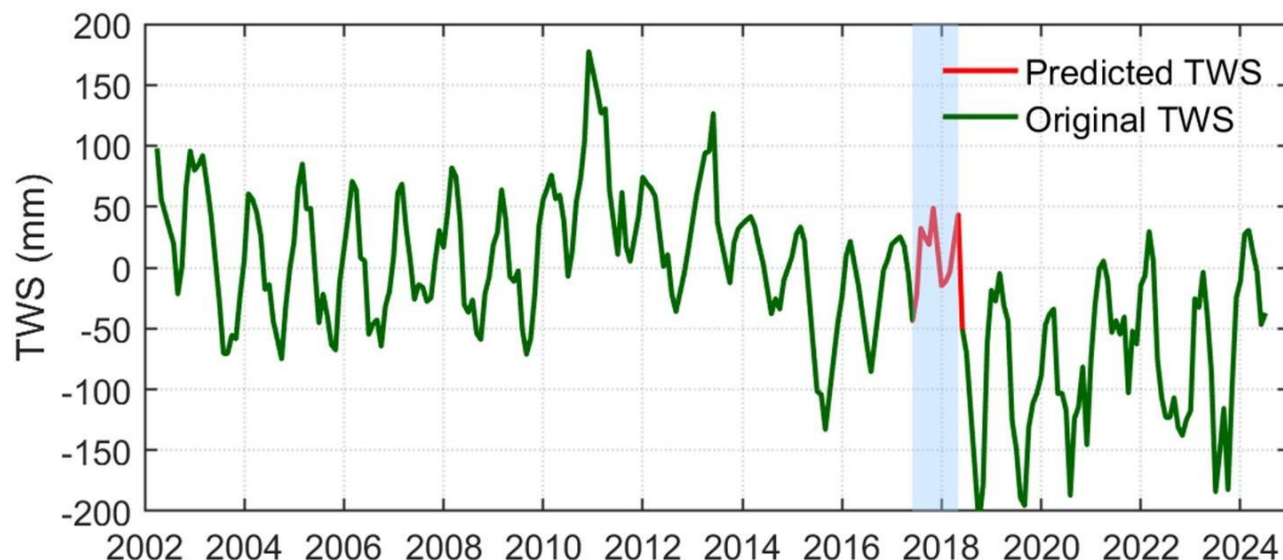
2. Differentiation between ΔTWS_{GRACE} and ΔTWS_{GLDAS} depending on aquifer depth

3. Calibration of satellite-based GWS (GWS_{sat}) using in-situ data

1. Downscaling of TWS_{GRACE} data into 0.1°× 0.1° grids

Pre-processing:

Filling a gap between GRACE and GRACE-FO using Autoregressive Integrated Moving Average (ARIMA)



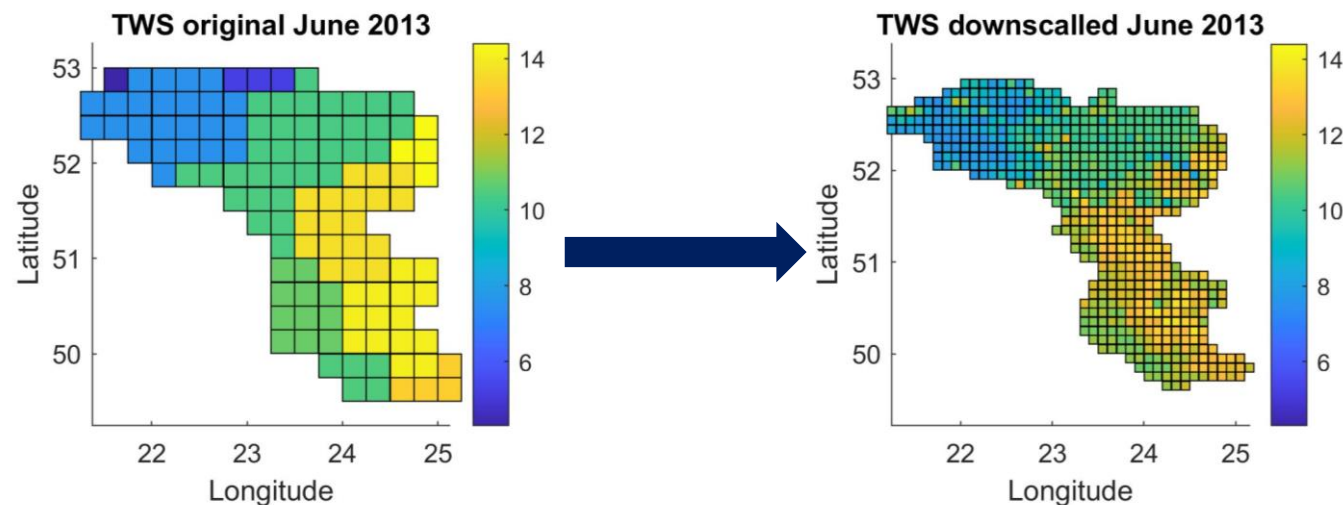
GRACE/GRACE-FO-based TWS time series with the data gap filled for a sample grid cell centred at 51.5°N, 25.5°E

1. Using ordinary least squares regression to model the linear trend in TWS series
2. Subtracting the fitted linear trend from the original time series
3. Defining ARIMA model ($D = 0$, $SP = 12$, $ARLags = 1:3$, $MALags = 1:3$, $SARLags = [6, 12, 24, 36, 48]$, $SMALags = 12$)
4. Forecasting the missing values for 11 months) using the estimated ARIMA model and all available data prior to the gap
5. Re-adding the linear trend to the ARIMA forecast to reconstruct the full TWS series
6. Interpolating the reconstructed series to mid-month timestamps

D: differencing, SP: seasonality period, ARLags: autoregressive lags, MALags: moving average lags, SARLags: seasonal autoregressive lags, SMALags: seasonal moving average lags

1. Downscaling of TWS_{GRACE} data into $0.1^\circ \times 0.1^\circ$ grids

Downscaling inputs



Data sources:

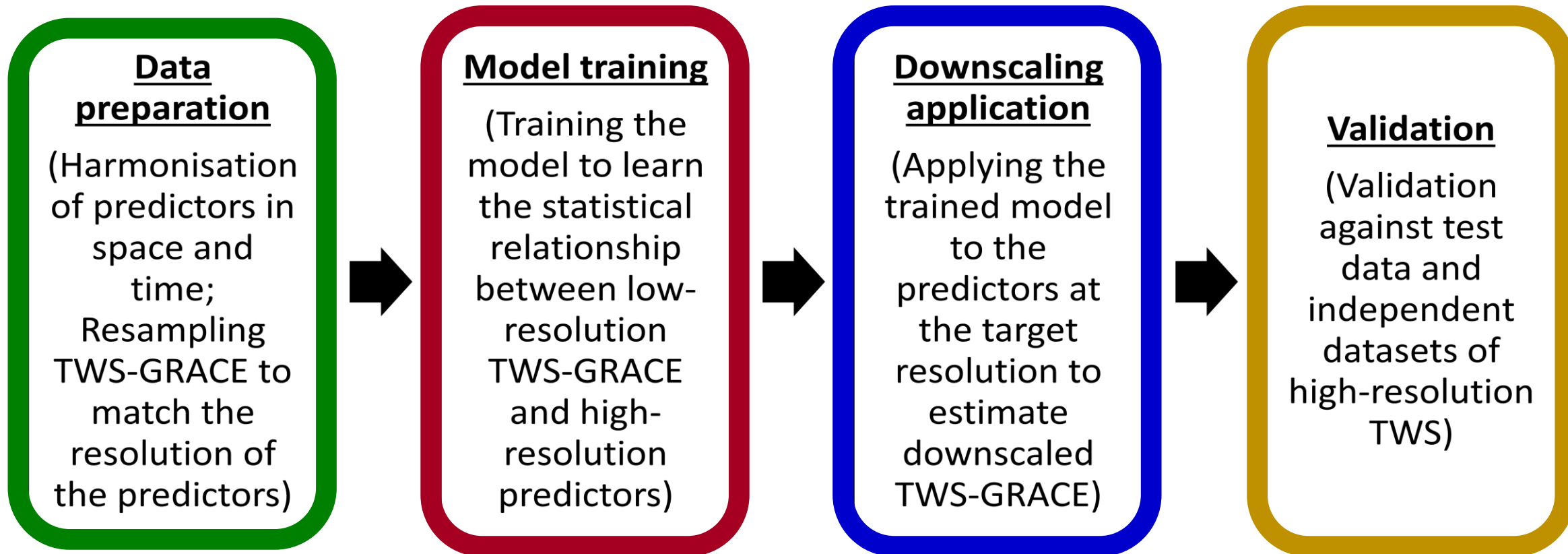
- GRACE CSR RL06.3 mascon solution (https://www2.csr.utexas.edu/grace/RL06_mascons.html)
- E-OBS (https://surfobs.climate.copernicus.eu/dataaccess/access_eobs.php#datafiles)
- SSEBop (<https://earlywarning.usgs.gov/fews/product/460>)
- GLDAS (<https://disc.gsfc.nasa.gov/datasets>)
- Streamflow data (<https://danepubliczne.imgw.pl/datastore>)

Downscaling using **Random Forests**

Higher-resolution data used as **predictors**:

- **Precipitation from E-OBS** (originally in $0.1^\circ \times 0.1^\circ$ grids)
- **Evapotranspiration from SSEBop** (Simplified Surface Energy Balance operational) (originally at 1km resolution, $\sim 0.01^\circ \times 0.01^\circ$ grids)
- **Runoff from in-situ data** – point data
- **Soil moisture storage (SMS) from GLDAS_NOAH025_M_2.1** (originally in $0.25^\circ \times 0.25^\circ$ grids)

1. Downscaling of TWS_{GRACE} data into $0.1^\circ \times 0.1^\circ$ grids



We tested:
 $0.1^\circ \times 0.1^\circ$,
 $0.25^\circ \times 0.25^\circ$,
 $0.5^\circ \times 0.5^\circ$,
and $1^\circ \times 1^\circ$

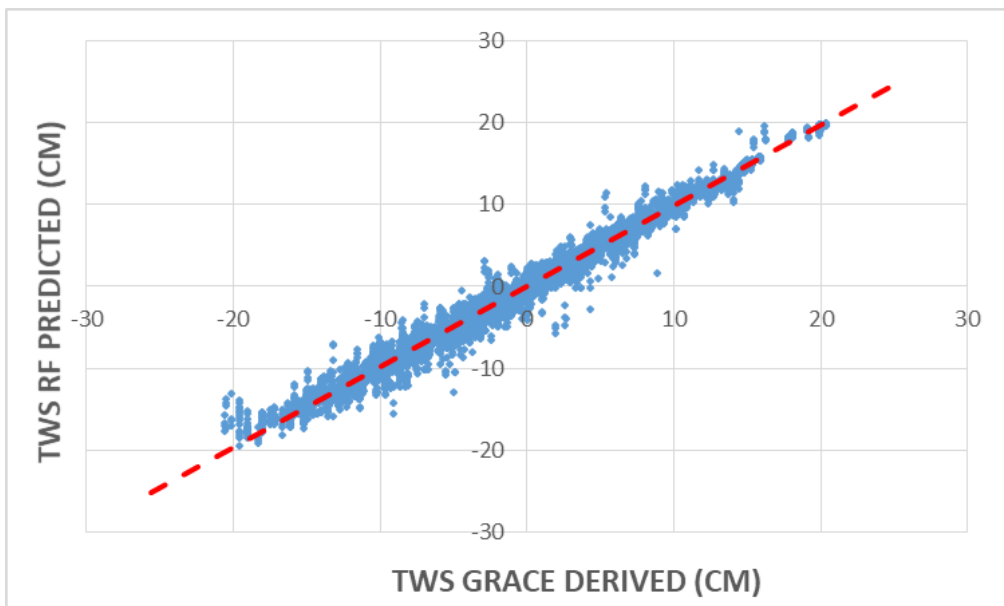
- Training performed for each epoch separately
- 80% of the data used for training, 20% of data used for validation
- 100 regression trees
- Minimum leaf size of 5

Prediction at the target $0.1^\circ \times 0.1^\circ$ grid points was performed using the trained model

- Validation:
1. Based on test data
 2. Based on comparison of TWS data before and after downscaling

1. Downscaling of TWS_{GRACE} data into 0.1°× 0.1° grids

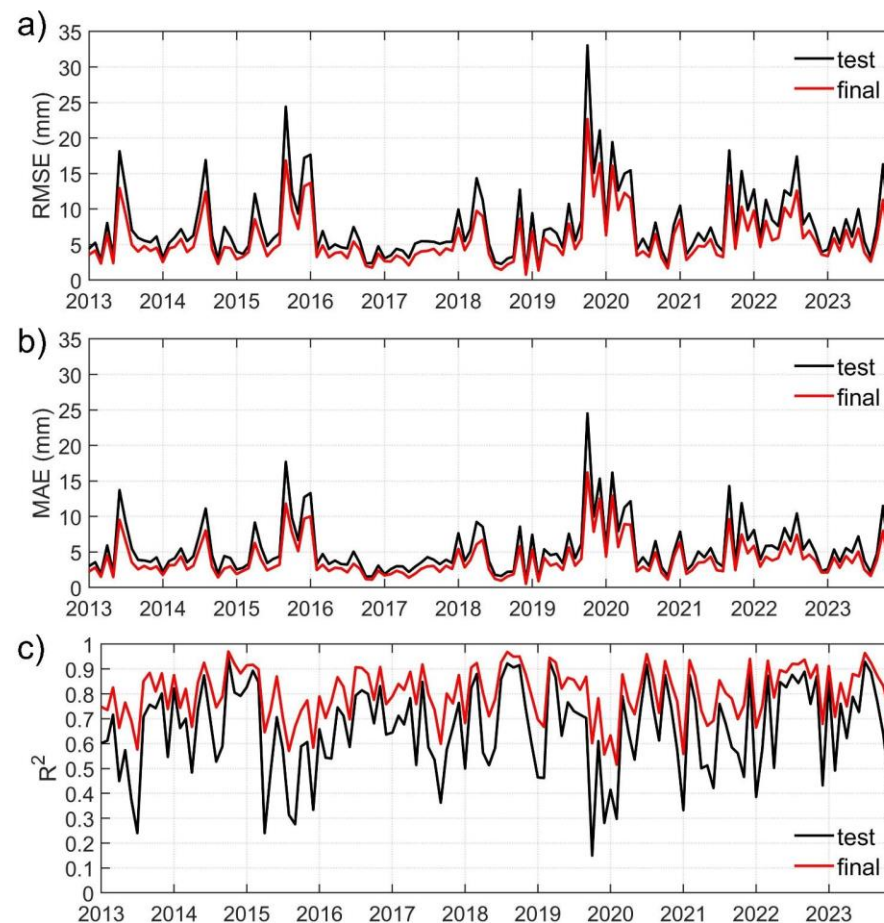
Downscaling performance



Scatter plot of GRACE-based TWS before and after downscaling

Median value of root mean square error (RMSE), mean absolute error (MAE), and R^2 across all epochs

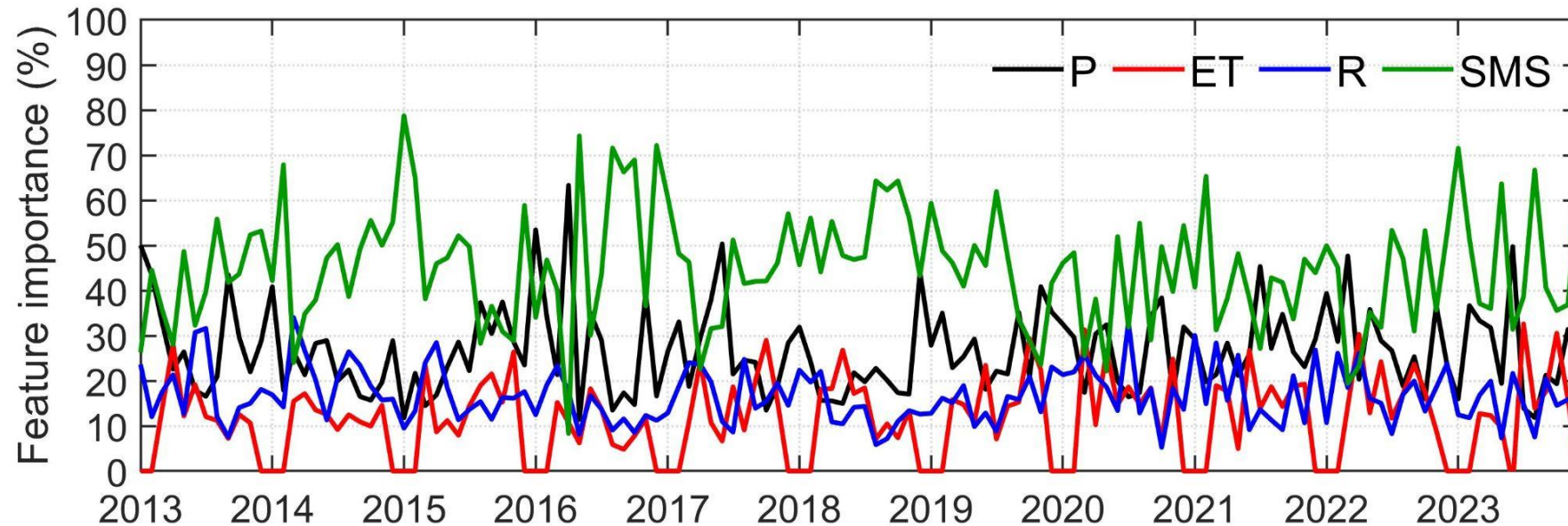
| | Median |
|-------|--------|
| RMSE | 4.6 mm |
| MAE | 3.1 mm |
| R^2 | 0.91 |



Temporal variability of root mean square error (RMSE), mean absolute error (MAE), and R^2 calculated based on test data as well as from comparison with the original TWS prior to downscaling (final)

1. Downscaling of TWS_{GRACE} data into 0.1°× 0.1° grids

Contribution of each predictor to the model training and downscaling



P – precipitation

ET – evapotranspiration

R – runoff

SMS – soil moisture storage

Relative contribution of each predictor to the model training and downscaling process across individual epochs

2. Differentiation between ΔTWS_{GRACE} and ΔTWS_{GLDAS}

Differentiation between ΔTWS_{GRACE} and ΔTWS_{GLDAS} – **classical approach**

$$\Delta GWS_{sat} = \Delta TWS_{GRACE} - \Delta TWS_{GLDAS}$$

$$\Delta TWS_{GLDAS} = \Delta SMS + \Delta SnWS + \Delta CWS$$

where:

Δ – month-to-month change, i.e., the difference between the value in a given month and the value in the previous month, SMS – soil moisture storage, SnWS – snow water storage, CWS – canopy water storage.

SWS (surface water storage) is not taken into account, as it is minor compared to variations in SMS and GWS in the study area.

This is a simplified approach. To obtain the most reliable estimate of GWS, the methodology should be adapted to local hydrogeological conditions

2. Differentiation between ΔTWS_{GRACE} and ΔTWS_{GLDAS}

Differentiation between ΔTWS_{GRACE} and ΔTWS_{GLDAS} – **new approach**

$$\Delta GWS_{sat} = \Delta TWS_{GRACE} - \sum \Delta TWS_{GLDAS}$$

where the number of months included in the summation of ΔTWS_{GLDAS} values depends on the depth to the groundwater level (GWL)

This approach takes into account the fact that the dynamics of ΔGWS is shaped by accumulation of effects from precipitation and evapotranspiration in the vadose (unsaturated) zone. This accumulation depends on the depth to GWL: with increasing GWL the accumulation period for ΔTWS_{GLDAS} also lengthens.

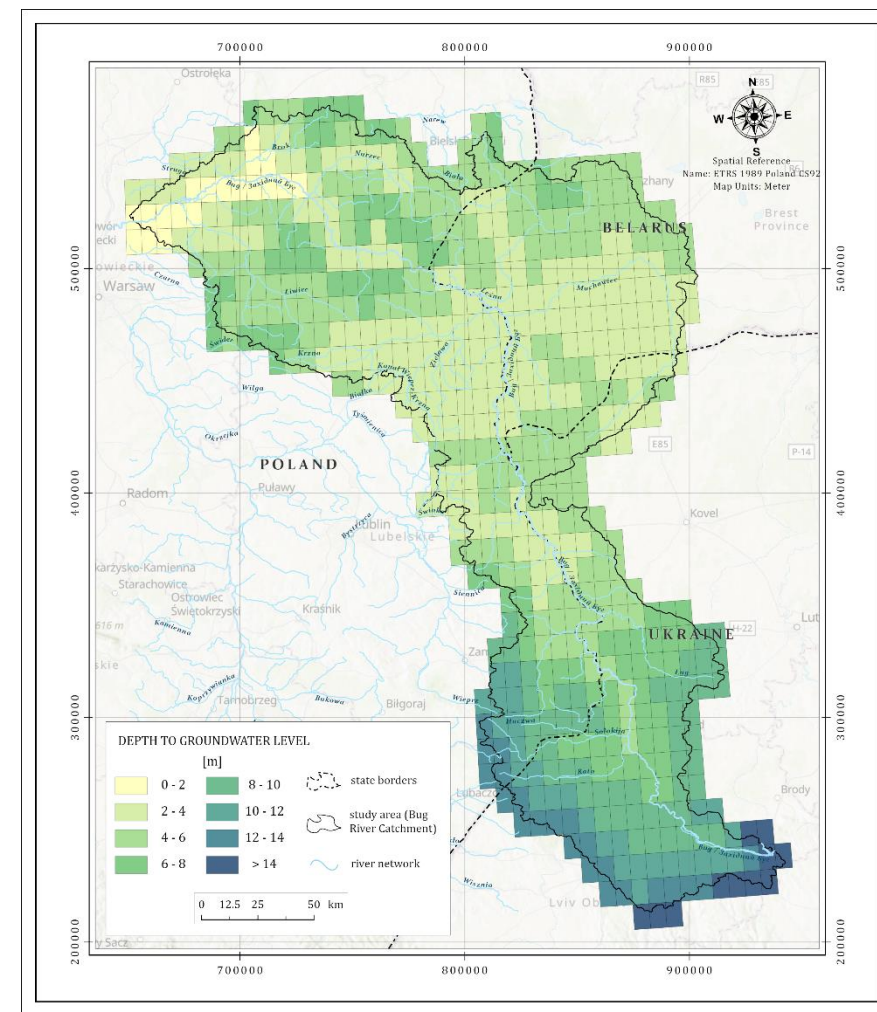
2. Differentiation between ΔTWS_{GRACE} and ΔTWS_{GLDAS}

Differentiation between ΔTWS_{GRACE} and ΔTWS_{GLDAS} depending on aquifer depth:

$$\Delta GWS_{sat} = \Delta TWS_{GRACE} - \sum \Delta TWS_{GLDAS}$$

| Depth to GWL (m below ground level) | Number of months of accumulation for ΔTWS_{GLDAS} |
|-------------------------------------|---|
| 0–2 | 2 (current month and 1 previous month) |
| 2–4 | 3 (current month and 2 previous months) |
| 4–6 | 4 (current month and 3 previous months) |
| 6–8 | 5 (current month and 4 previous months) |
| 8–10 | 6 (current month and 5 previous months) |
| 10–12 | 7 (current month and 6 previous months) |
| 12–14 | 8 (current month and 7 previous months) |
| 14–16 | 9 (current month and 8 previous months) |

- In the BRB catchment, the depth to the uppermost groundwater table ranges from 0 to 16 m.
- For every 2 m increase in GWL, the accumulation period for ΔTWS_{GLDAS} extends by one additional month.



Depth to GWL table within BRB catchment

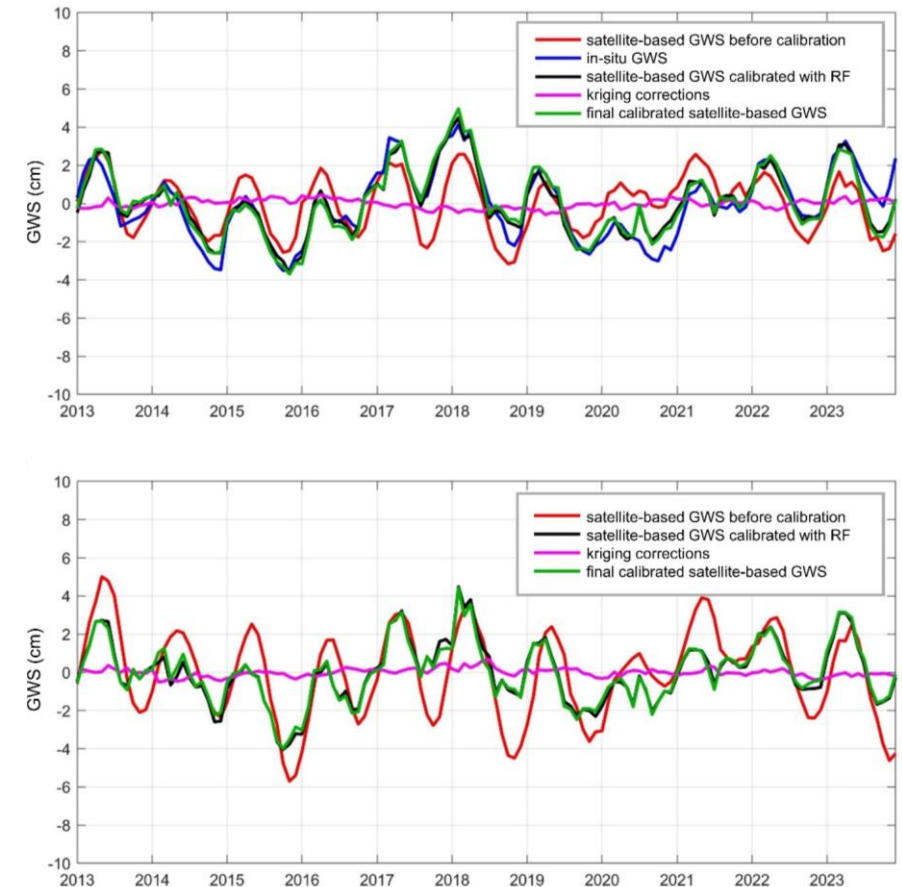
3. Calibration of satellite-based GWS (GWS_{sat}) using in-situ data

To ensure that GWS_{sat} variations accurately reflect observed changes over the study area, a **two-step calibration approach** was applied using in-situ GWS data from 15 monitoring points:

Step 1: RF model was trained to capture temporal relationships between GWS_{sat} and $GWS_{in-situ}$ in grid cells where in-situ observations were available.

Step 2: Residuals were calculated at the calibration points as the differences between $GWS_{in-situ}$ and the calibrated GWS_{sat} . These residuals were spatially interpolated to the remaining grid cells using ordinary kriging.

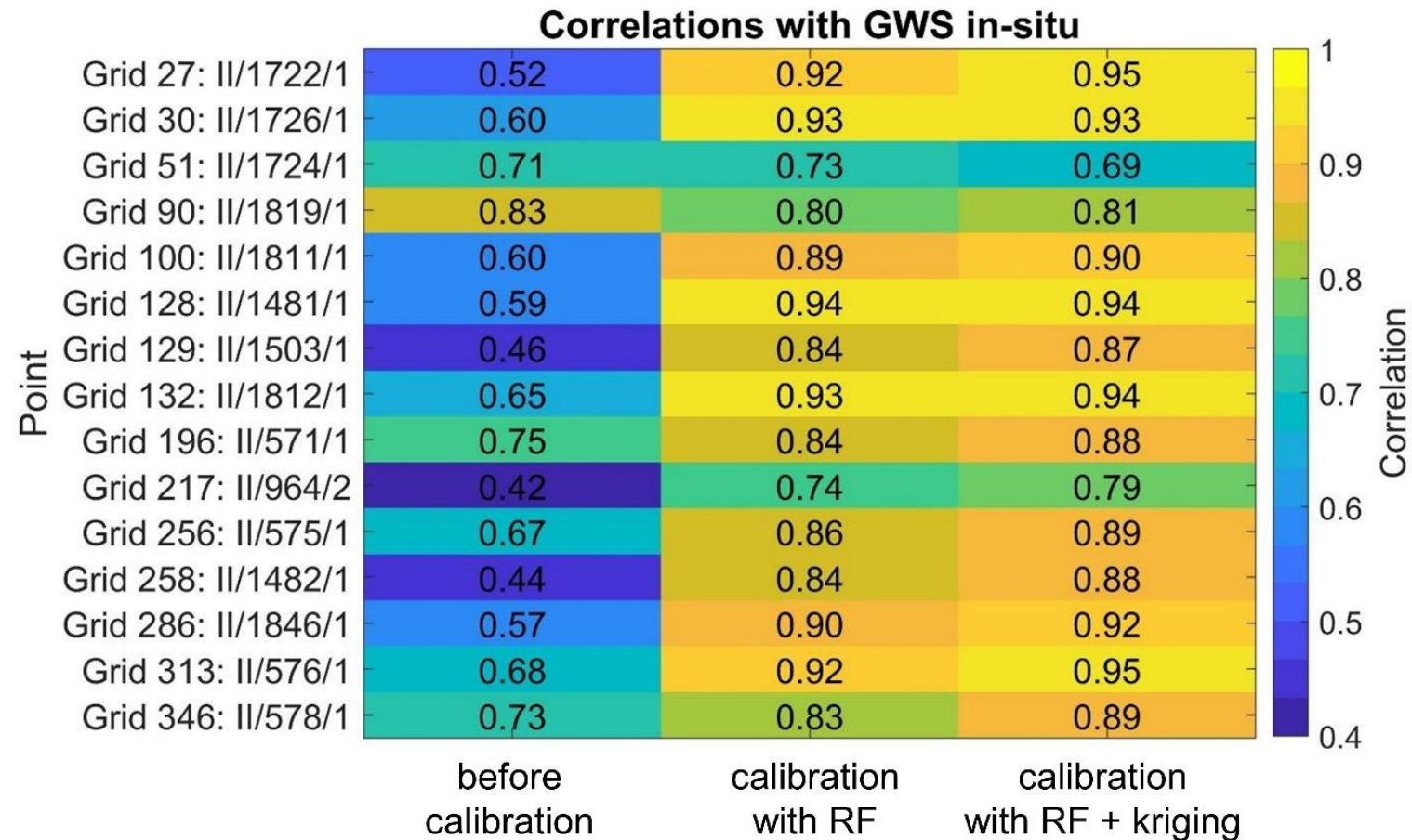
Finally, the calibrated GWS_{sat} at each of the grid points was obtained by summing the GWS values predicted from RF and the kriging interpolated residuals.



Comparison of satellite-based GWS before and after calibration for a grid cell with in-situ observations (top) and a grid cell without in-situ data, including kriging residuals (bottom)

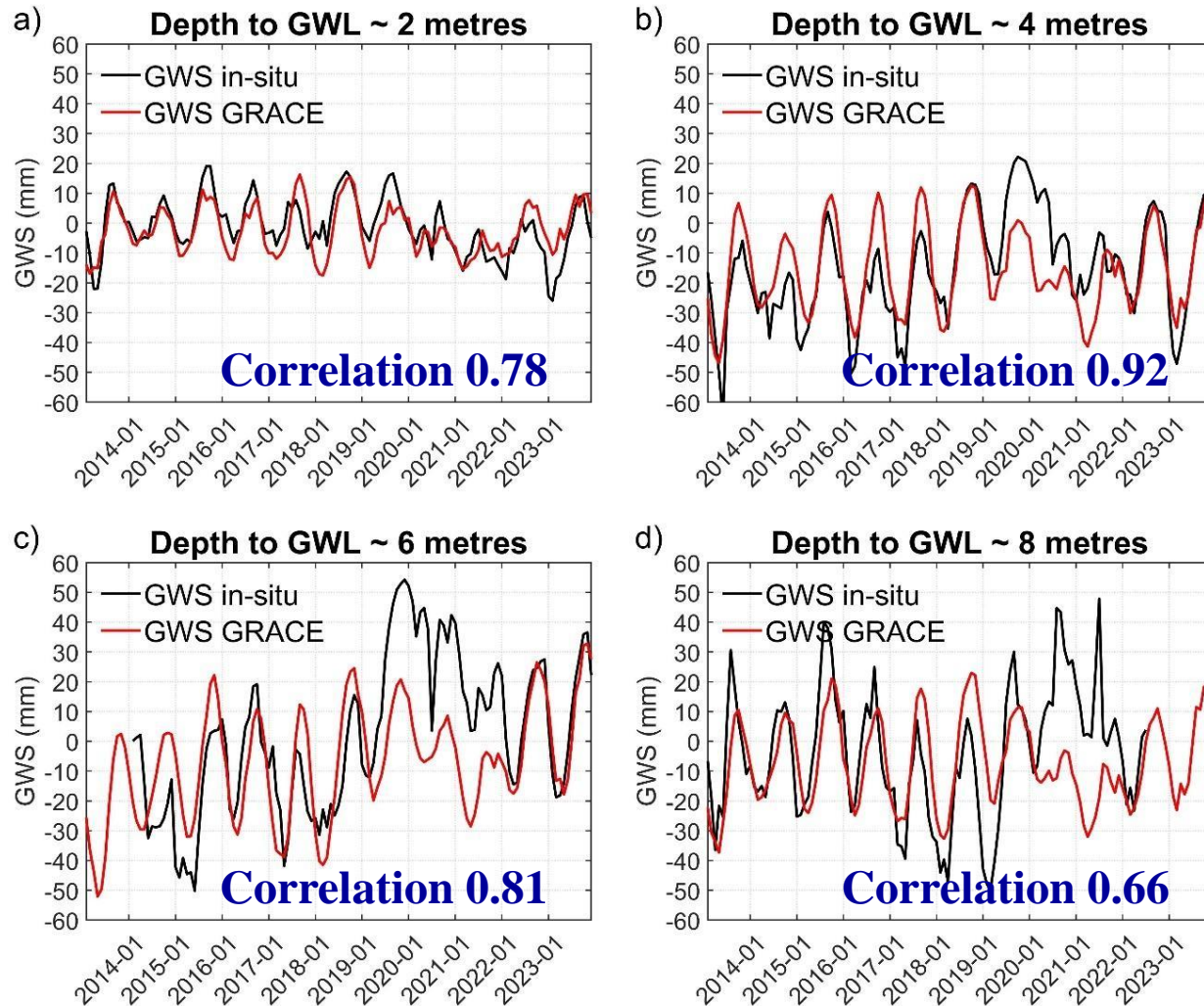
3. Calibration of satellite-based GWS (GWS_{sat}) using in-situ data

Impact of calibration on the correlation between GWS_{sat} and $GWS_{in-situ}$ at calibration points



Correlations between GWS_{sat} and $GWS_{in-situ}$

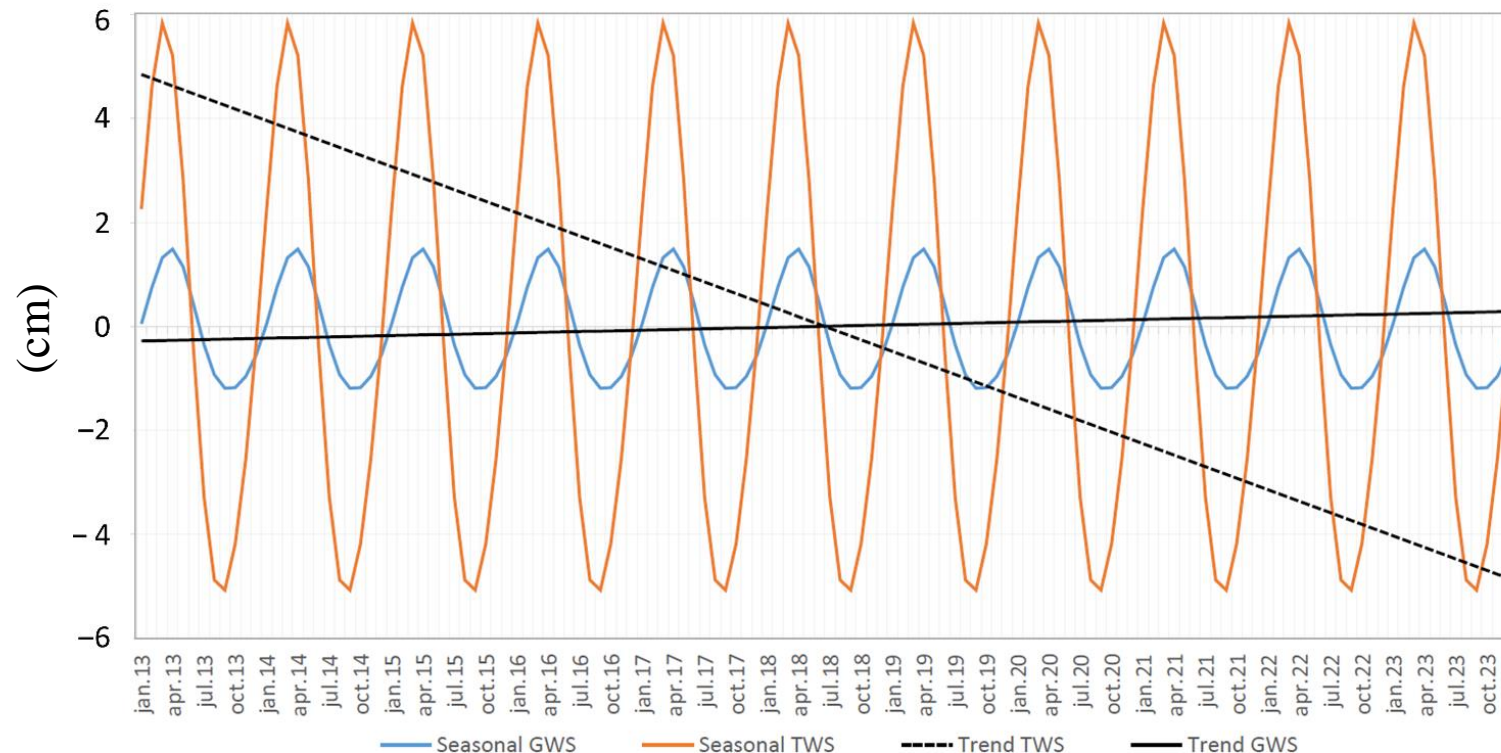
Correlation between GWS_{sat} and $GWS_{in-situ}$ in the study area averaged according to GWL depth



- The method improved correlations between $GWS_{in-situ}$ and GWS_{sat}
- The level of agreement between $GWS_{in-situ}$ and GWS_{sat} is dependent on the depth of groundwater table

Trends and annual signals in TWS_{GRACE} and GWS_{sat}

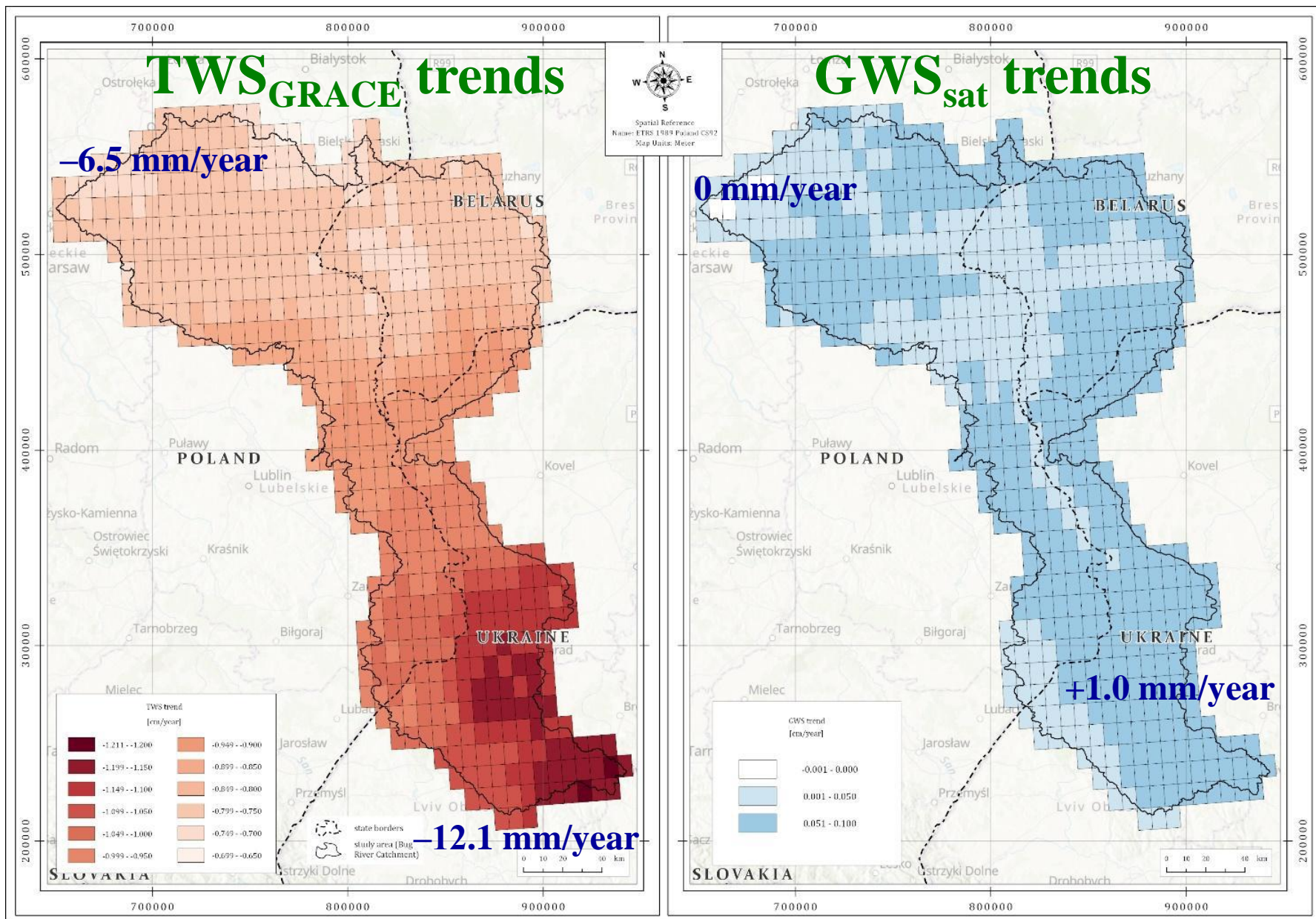
Trends and annual signals in TWS_{GRACE} and GWS_{sat} averaged over study area



- For both TWS_{GRACE} and GWS_{sat} , the long-term trend and seasonality are the dominant components.
- TWS exhibits a clear decreasing trend and high-amplitude seasonality.
- GWS shows trends close to zero, a low amplitude of seasonal signal, and a seasonal cycle shifted by ~ 1 month relative to TWS.
- The TWS extrema occur in March (maximum) and September (minimum).
- The GWS extrema occur in April (maximum) and in October (minimum).

| Water cycle component | Trend (cm/year) | Amplitude of annual oscillation (cm) |
|-----------------------|------------------|--------------------------------------|
| TWS | -0.89 ± 0.18 | 5.45 |
| GWS | $+0.05 \pm 0.04$ | 1.35 |

Spatial distribution of trends in TWS_{GRACE} and GWS_{sat}



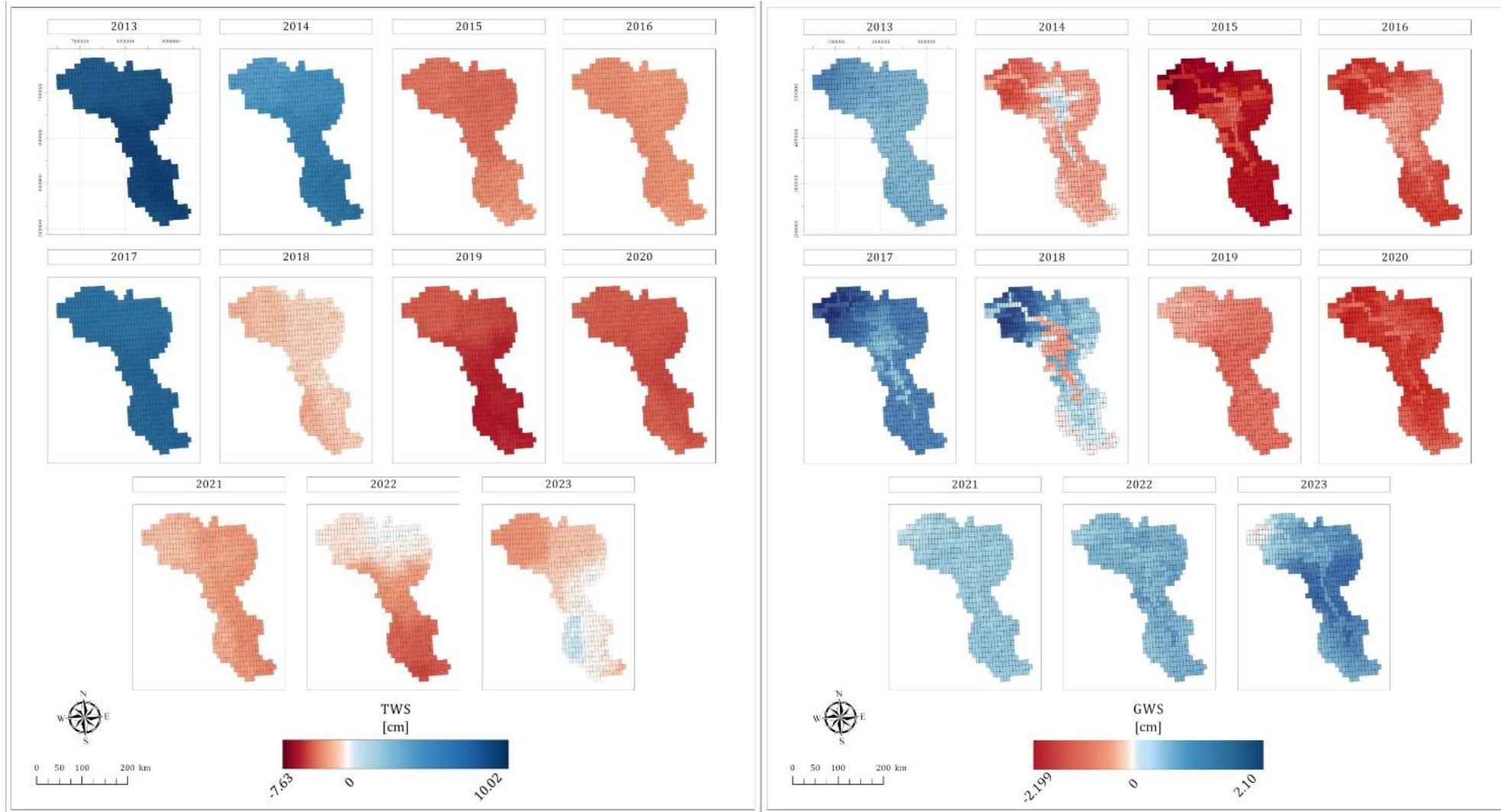
TWS:

- Maximum TWS decline (-12.1 mm/year) occurs in the south-eastern part of the basin, where recent droughts have been most severe.

GWS:

- Trends are not statistically significant.
- In contrast to other parts of the basin, areas with shallow groundwater levels (up to 4 m, north-western part) do not show a GWS increase.

Spatial distribution of annual average in TWS_{GRACE} and GWS_{sat}

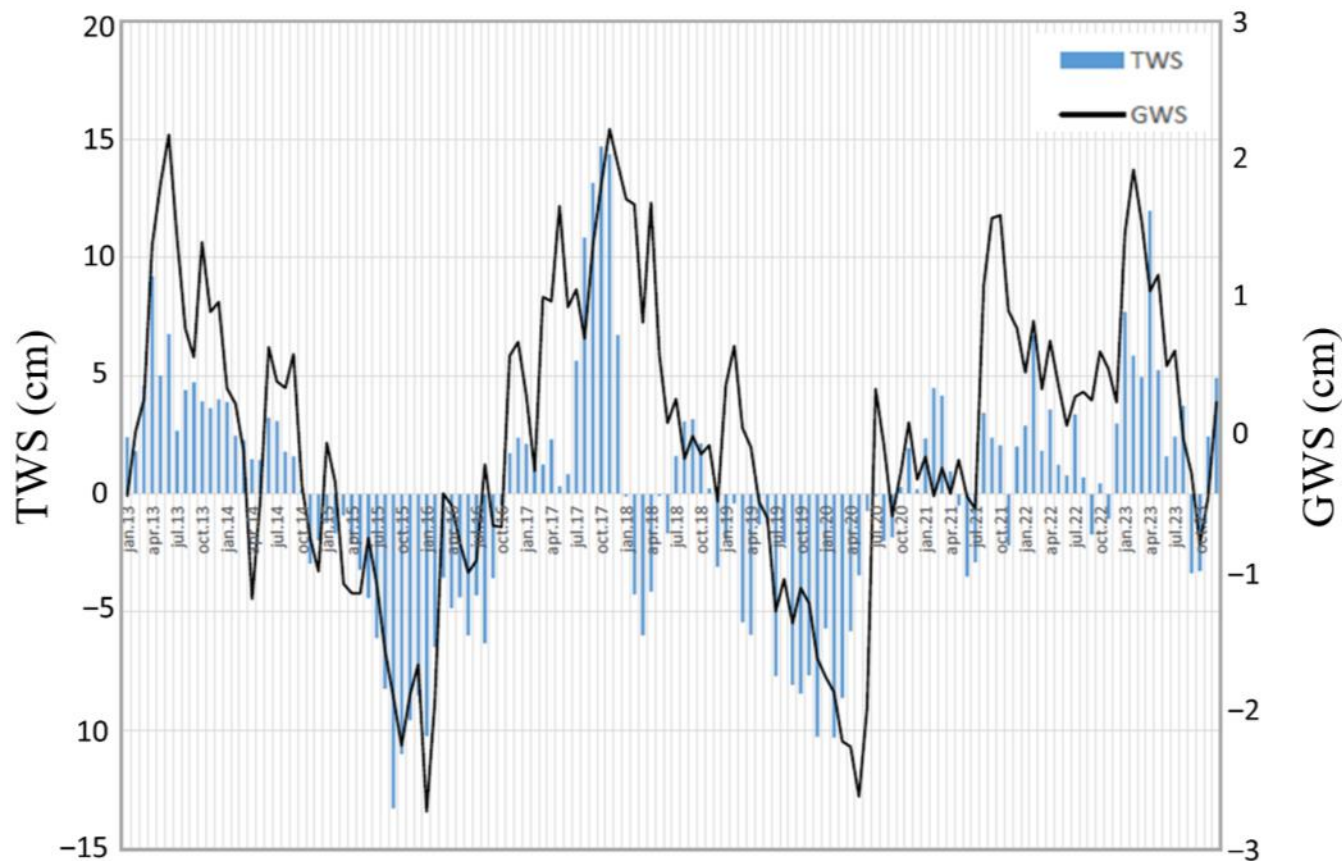


Red: water storage decline
Blue: water storage increase

Spatial distribution of annual average of TWS_{GRACE} and GWS_{sat}

- Annual TWS variations are dominated by years with negative values
- GWS showed negative values only during 2014–2016 and 2019–2020

Non-seasonal variability in TWS_{GRACE} and GWS_{sat}



Non-seasonal variations in TWS_{GRACE} and GWS_{sat} determined by removing trend and seasonal changes from the series

- Around four-year cycles are evident in both TWS and GWS. However, since 2020, the observed patterns have become less distinct.
- A two-month lag in GWS variability relative to TWS was also noted.
- The greatest discrepancies between TWS and GWS occur in 2017–2018 (GRACE/GRACE-FO data gap).

- The depth of the groundwater table determines the response time of GWS to atmospheric factors (precipitation, evapotranspiration). Incorporating this effect into GWS_{sat} estimation significantly improves agreement with in-situ measurements.
- Our approach, which derives GWS_{sat} from downscaled TWS_{GRACE} data and TWS_{GLDAS} while accounting for GWL depth, yielded correlations with $GWS_{in-situ}$ ranging from 0.66 to 0.95, with increasing consistency observed in the shallowest aquifers.
- Changes in GWS for the Bug River Basin do not show a clear declining trend (+0.5 mm/year), although TWS exhibits a negative trend of about −9 mm/year.
- These discrepancies in trend magnitudes between TWS and GWS result from the high resilience of groundwater reservoirs in the Bug River Basin to water losses caused by increased evapotranspiration or limited precipitation.

Thank you

The study was conducted as part of the project GRANDE-U “Groundwater Resilience Assessment through iNtegrated Data Exploration for Ukraine”
(NSF Awards No. 2409395 and 2409396, NCN Grant No. 2023/05/Y/ST10/00234)

