Terrestrial water storage on the South American continent: Data from numerical simulations, observations, and deep learning
(https://doi.org/10.5880/GFZ.1.3.2020.002)

Christopher Irrgang[1], Jan Saynisch-Wagner[1], Robert Dill[1], Eva Boergens[1], Maik Thomas[1,2]

1. *GFZ German Research Centre for Geosciences, Potsdam, Germany*
2. *Freie Universität Berlin, Institute of Meteorology, Berlin, Germany*

1. Licence

2. Citation

When using the data please cite:

Irrgang, C.; Saynisch-Wagner, J.; Dill, R.; Boergens, E.; Thomas, M. (2020): Terrestrial water storage on the South American continent: Data from numerical simulations, observations, and deep learning. GFZ Data Services. https://doi.org/10.5880/GFZ.1.3.2020.002

The data are supplementary material to:

Irrgang, C., Saynisch-Wagner, J., Dill, R., Boergens, E., & Thomas, M. (2020). Self-validating deep learning for recovering terrestrial water storage from gravity and altimetry measurements. Geophysical Research Letters, 47, e2020GL089258. https://doi.org/10.1029/2020GL089258

3. Data Description

In Irrgang et al. (2020), we have trained a convolutional neural network to perform a so-called downscaling task. This downscaling aims to recover the fine-structure continental water storage distribution on the South American continent from coarse-resolution space-borne gravimetry observations. Here, we share data sets that were used for training the neural network, namely (1) monthly averaged pairs of gridded terrestrial water storage anomalies (TWSA) of the South American continent, and (2) monthly averaged surface water storage anomalies (SWSA) in the Amazonas region. All data extend over the time period 2003-2019. TWSAs were used as target (output) values of the neural network and were derived from the Land Surface Discharge Model (LSDM, Dill, 2008). The corresponding input values were calculated by spatially smoothing the TWSA fields with a 600 km Gaussian filter. The SWSAs were derived by utilizing satellite altimetry data provided by the Database for Hydrological Time Series of Inland Waters (DAHITI, Schwatke et al., 2015) and water surface change data provided by the Global Inundation Extent from Multi-Satellites (GIEMS, Prigent et al., 2007). After training the neural network over the time period of 2003 to 2018, its performance was tested and compared to LSDM for the subsequent year 2019.

4. File description

The data set comprises four NetCDF files. All files contain water storage values in the units of meters [m] as equivalent water height. The domain of interest is the South American continent with the spatial extent -56.25°N to 13.25°N and -83.25°E to -33.25°E on a 0.5°x0.5° longtitude-latitude grid. The temporal resolution is one month and the maps contain monthly averaged values for the respective month. All meta data are also stored in the NetCDF files.

1.1. File inventory

- **altimetry_sws_anomalies_amazonas_2003_2019.nc**
  This file contains the Altimetry-based surface water storage anomalies in the Amazons region of the South American continent. These data were used to constrain the neural network trained and to validate the neural network performance.

- **cnn_tws_anomalies_southamerica_2019.nc**
  This file contains the neural network downscaling prediction of the terrestrial water storage on the South American continent for the year 2019.

- **lsdm_tws_anomalies_southamerica_2003_2019.nc**
  This file contains numerically simulated fields of the terrestrial water storage on the South American continent. These data were used as target output fields in the neural network training.

- **lsdm_tws_anomalies_southamerica_2003_2019_gauss600.nc**
  This file is based on the data in lsdm_tws_anomalies_southamerica_2003_2019.nc, but with an additional spatial gauss filter step. These data were used as input fields in the neural network training.

1.2. File naming convention

The file naming convention is as follows:

[SOURCE]_[VARIABLE]_[REGION]_[TIME]_[FILTER].nc

SOURCE: The data is based on Altimetry observations (altimetry), on the numerical hydrology model LSDM (lsdm), or on the artificial neural network (cnn)-

VARIABLE: The files contain surface water storage anomalies (sws) or terrestrial water storage anomalies (tws) with the unit meters [m] as equivalent water height.

REGION: Spatial domain of the data is the South American continent or the Amazonas region.

TIME: Data are either provided for a single year (e.g., 2019) or for a time span (e.g. 2003-2019). All data have the same monthly temporal resolution.

FILTER: The suffix "gauss600" indicates that the data have been spatial smoothed with a 600 km Gaussian filter.

5. References

Dill, R. (2008). Hydrological model LSDM for operational Earth rotation and gravity field variations (Tech. Rep.). Helmholtz-Zentrum Potsdam Deutsches GeoForschungsZentrum. https://doi.org/11.2312/GFZ.b103-08095

Irrgang, C., Saynisch-Wagner, J., Dill, R., Boergens, E., & Thomas, M. (2020). Self-validating deep learning for recovering terrestrial water storage from gravity and altimetry measurements. Geophysical Research Letters, 47, e2020GL089258. https://doi.org/10.1029/2020GL089258

Prigent, C., Papa, F., Aires, F., Rossow, W. B., & Matthews, E. (2007). Global inundation dynamics inferred frommultiple satellite observations, 1993–2000. Journal of Geophysical Research, 112, D12107. https://doi.org/10.1029/2006JD007847

Schwatke, C., Dettmering, D., Bosch, W., & Seitz, F. (2015). Dahiti—An innovative approach for estimating water level time series over inland waters using multi-mission satellite altimetry. Hydrology and Earth System Sciences, 19(10), 4345–4364. https://doi.org/10.5194/hess-19-4345-2015