Supporting Information for

GLOBGM v1.0: a parallel implementation of a 30 arcsec PCR-GLOBWB-MODFLOW global-scale groundwater model

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S1 Development of transient evaluation dataset

The transient model evaluation of the GLOBGM for the CONUS (See Section 3.3.2 of the paper) required a selection of useful NWIS wells, extraction of model results (time-series), matching with model layers, and the computation of statistics (correlation, interquartile error, trend). Here, these steps are described in more detail, closely following the work of de Graaf et al. (2017). First, two steps were performed for downloading the NWIS data:

1. Download well locations (.csv) from https://nwis.waterdata.usgs.gov/nwis/gwlevel for attributes:
    - *Agency*
    - *Site identification number*
    - *Decimal latitude*
    - *Decimal longitude*
    - *Altitude of Gage/land surface*
    - *Well depth*
    - *Field water-level measurements begin date*
    - *Field water-level measurements end date*
    - *Field water-level measurements begin count*
    - *Number of observations*: 60
2. Download the corresponding time-series (.txt), e.g. with a Python script. Result (31,858 sites): https://github.com/UU-Hydro/GLOBGM/tree/v1.0-gamma/model_evaluation/analyze_gw_head_input/nwis.zip

Then, the transient GLOBGM model results for 1958-2015 were extracted for sedimentary basins only:

3. For all well locations of 1, extract time-series from MODFLOW binary output for sedimentary basins only (see for result https://doi.org/10.24416/UU01-44L775, folder /original/output/version_1.0/transient_1958-2015_timeseries/):
    a. For the most upper layer (model_results_folder_top.zip)
    b. For the lower layer (model_results_folder_bot.zip)

    (Note that time-series for 3a and 3b are identical in case there is no confining layer present.)

For each NWIS well, the following steps were performed, see the R-script (https://github.com/UU-Hydro/GLOBGM/blob/v1.0-gamma/model_tools_src/r/analyze_gw_head/analyze_gw_head.R):

4. Does the well have a valid date attribute?
    - If no: exclude the well; done. If yes: conditionally accept (pending for criteria 5)
5. Does the well have groundwater heads (*sl_lev_va*) or water table depths (*lev_va*)?
    - If no: exclude the well; done. If yes: if only water table depths are present, continue to step 6, else continue to step 7.
6. Compute head time-series by multiplying the water table depth time-series with minus one.
7. Compute monthly averaged and quarterly averaged head for the observation well.
8. Does the well time-series have heads defined for each quarter for 5 consecutive years?
    - If no: exclude the well; done. If yes: continue to step 9.

- Note that we here assume that 5 years are sufficient to capture seasonal variation, similar to the work of de Graaf et al., (2017). However, compared to that work, we believe that our quarterly-based selection procedure is an improvement for selecting time-series.

For computing the monthly-averaged statistics (timing and amplitude errors, trend), the measured heads should be matched with computed heads from the correct model layer. For the GLOBGM, a model layer selection procedure is required in case two model layers are present at the well location (confining layer and aquifer). When a well depth measurement is present, we simply compare the well depth to the confining (upper) model layer thickness to select the upper or lower model layer. However, when the well location does not have a well depth, we do not directly exclude this well from our statistics, but we estimate the model layer by using soil moisture data from the European Space Agency Climate Change Initiative Soil Moisture dataset, derived from the combined active and passive satellite sensors (v05.2; Gruber et al., 2019, 2017; Dorigo et al., 2017). First, we check if a soil moisture time-series is present at the well location (monthly averaged). If this is the case a correlation is computed with the NWIS time-series. If a correlation is found, we then assume that the well time-series represents the upper model layer and otherwise represents the lower model layer. The following steps were performed (see R-script):

9. Is there only one model layer defined at the well location (hence only the aquifer)?
    - If yes: select the time-series with computed heads for the lower model layer; done. If no: pending for criteria 10.
10. Does the well have a well depth (attribute *well_depth_va*)?
    - If yes: pending for criteria 11. If no: pending for criteria 12.
11. Is the well depth smaller than the thickness of the upper confining model layer?
    - If yes: select the time-series with computed heads for the upper model layer; done. If no: select the time-series with computed heads for the lower model layer.
12. Is there a soil-moisture time-series available at the well location?
    - If yes: extract the time-series for the soil moisture NetCDF and pend for criteria 13. If no: exclude well; done.
13. Is there a (monthly averaged) correlation between the well time-series and the soil moisture time-series (true if value > 0.5 including lag of -3:3)?
    - If yes: select the time-series with computed heads for the upper layer. If no: select the time-series with computed heads for the lower layer.

All monthly-averaged statistics are computed using the R-script for (pair-wise) data values only, resulting in the summary file: https://github.com/UU-Hydro/GLOBGM/blob/v1.0-gamma/model_evaluation/analyze_gw_head_output/summary_1km.txt

The fields used for aggregation (average) over HUC4 catchment boundaries, are:

- *RHO_p_month*: correlation representing timing error.
- *QRE7525_evalua*: interquartile range error representing amplitude error. In the paper absolute values are taken.
- *ms_slope* and *mo_slope*: slope [m/year] of the simple linear regression representing trend, for measurement and model respectively.

S4 References for Supplementary Information

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