Supplementary material to: Evidence of daily hydrological loading in GPS time series over Europe

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Content

This file contains the following supporting information:

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5. Set up of the Community Land Model (CLM-3.5)
6. Assimilation of GRACE data into CLM3.5

1 Removing outliers and offsets from GPS time series

Outliers were eliminated from the daily GPS position time series based on the following criteria: 1) a data point with a formal uncertainty larger than 3 times the root mean square (RMS) scatter of the time series and 2) a data point that differs from the least squares model fit to time the series (defined below) by more than 3 times the RMS scatter.

We use a least squares model fit to the GPS daily height time series, with parameters that include a constant initial offset \( a \), a constant velocity \( v \), annual and semi-annual variations, and in the case of equipment changes and/or coseismic offset, one or more offset parameters \( n_c \). The daily height of each
site $u(t_i)$ can hence be written as:

$$u(t_i) = a + vt_i + c \sin(2\pi t_i) + d \cos(2\pi t_i) + e \sin(4\pi t_i) + f \cos(4\pi t_i) + \sum_{j=1}^{n_{ct}} g_i H(t_i - T_j) + \epsilon(t_i),$$

(1)

where $t_i$ is the epoch of observation $i$ in decimal year, $c$ and $d$ are the coefficients of annual periodic motion, $e$ and $f$ are the coefficients of semi-annual periodic motion, $g$ and $T$ are magnitude and epoch of the offset, $H$ is the Heaviside step function, and $\epsilon$ is the observational error. The epoch of offsets due to equipment changes and coseismic events are provided in the EPN website [ftp://epncb.oma.be/pub/station/coord/EPN/EPN_discontinuities.snx](ftp://epncb.oma.be/pub/station/coord/EPN/EPN_discontinuities.snx)

### 2 Removing non-tidal atmospheric and oceanic loading deformation from GPS time series

Earth’s atmosphere experiences dynamic mass changes on a wide variety of temporal and spatial scales. Over land, they cause elastic deformation of Earth’s surface through tidal and non-tidal variations. The elastic deformations in response to atmospheric load redistribution are estimated through convolution of a Green’s function with global atmospheric pressure fields assuming a spherical nonrotating elastic layered Earth Model (e.g., Petrov and Boy 2004, Dill and Dobslaw 2013). However, for a precise estimation of atmospheric loading deformations, we require a model of the oceanic response to atmospheric load changes over the ocean as well.

For time periods longer than 2-3 weeks, the water column tends to fully compensate isostatically for the effects of the atmospheric pressure changes over the ocean surface, thus the net atmospheric pressure acting on the ocean floor is equal to zero. However, at each time step, the average of atmospheric pressure over the ocean cannot result in ocean bottom pressure changes due to conservation of global ocean mass. It is thus typically assumed that ocean bottom pressure only changes corresponding to a uniform value equal to the mean surface pressure over the ocean (Dickman 1988). This effect is described by an inverted barometer or static response of ocean to the atmospheric pressure changes (Wunsch and Stammer 1997), and oceanographic effects are usually ignored.

For shorter time spans, typically less than a week, changes in atmospheric pressure occur due to winds and sea-level variability occurs due to oceanographic components including changes in the circulation, heat and freshwater content, and storm surge. For these time spans, a (dynamic) oceanic model is required to estimate elastic deformation at the ocean bottom and in land (the effect is often called non-tidal ocean loading).

One should note that effects of non-tidal atmospheric and oceanic mass changes
have already been removed up to spherical harmonics degree and order 100 from GRACE-derived TWS changes using AOD1B RL05 products (Dobslaw et al., 2013). This spectral bound corresponds to the native resolution of GRACE measurements (∼ 200 - 300 km). However, our GRACE-assimilated TWS changes resolve large- and small-scale hydrological mass redistribution including changes that occur beyond degree and order 100. We therefore require to accurately remove effects of atmospheric and oceanic mass changes including changes that occur beyond degree and order 100 from GPS height time series. We thus make use of different atmospheric and oceanic loading displacement fields estimated using several different global atmospheric pressure data sets and ocean models. Since the optimal signal to noise ratio of each model is unknown, we test the performance of different models by comparing with GPS height time series. Note that the aim of this study is not to fully assess performance of different atmospheric and oceanic loading displacement models. Rather, comparing results from several different models provides information on the reliability and accurate evaluation of our assimilated water storage product through an optimal model by removing the non-tidal atmospheric and oceanic effects from the GPS height time series.

The GPS displacements are in the IGB08 reference frame (Rebischung et al., 2012) which is defined by the center of surface figure of the Earth (CF). We use the vertical displacement time series (in the CF frame) from five models:

(1) ESMGFZ: three-hourly 0.5° × 0.5° grid of non-tidal atmospheric and oceanic loading displacement models provided by GeoForschungsZentrum Potsdam (GFZ). The non-tidal atmospheric loading deformations are calculated using atmospheric surface pressure data from the European Centre for Medium-Range Weather Forecasts (ECMWF) re-analysis ERA-Interim for 1979-2006 (Dee et al., 2011) and the operational ECMWF analyses for all subsequent years (Dobslaw et al., 2017). An inverted barometric ocean response is considered over the ocean for estimating atmospheric loading deformation. The oceanic induced displacement fields are estimated using ocean-bottom pressure data obtained from Max-Planck-Institute for Meteorology Ocean Model (MPIOM). The MPIOM is a global ocean general circulation model (Jungclaus et al., 2013) that is forced with ECMWF atmospheric data and wind stress and provides ocean bottom pressure changes deviated from inverted barometric effects.

One should recognize that ESMGFZ displacements field are calculated on the basis of load Love numbers given for the elastic Earth model ak135 (Kennett et al., 1995). We used the PREM Earth model for estimating hydrological loading deformation. Also the subsequent atmospheric and oceanic loading models are calculated based on PREM model. Thus, there is an inconsistency in the Earth models used in the calculation of deformation from TWS changes. However, given the 0.5° resolution of ESMGFZ model, the differences due to inconsistency is negligible (Wang and Dickinson, 2012).

(2) ATMIB: three-hourly 0.5° × 0.5° grid of non-tidal atmospheric loading
(3) ERAin: six-hourly 0.5°×0.5° non-tidal atmospheric loading displacement model provided by the EOST loading service. This displacement field is estimated using ECMWF’s ERA Interim atmospheric reanalysis pressure data, assuming an inverted barometric response over the ocean.

(4) ATMMO: six-hourly 0.5°×0.5° tailored non-tidal atmospheric and oceanic displacement model provided by the EOST loading service. This model uses operational ECMWF atmospheric pressure data over land and Toulouse Unstructured Grid Ocean model (TUGO-m) over the ocean. TUGO-m is a barotropic dynamic ocean model that is forced by ECMWF atmospheric pressure and winds (an update of the previous model MOG2D, Carrère and Lyard (2003)). TUGO-m provides sea-level height changes due to full response of the ocean to the surface pressure changes (both dynamic and inverted barometric changes).

The Barotropic ocean models assume a uniform density for the water column from the ocean surface to the ocean floor. Therefore, the pressure acting on the ocean bottom in TUGO-m includes the sum of atmospheric surface pressure over the ocean as implicitly expressed with the inverted barometric sea-level change, and the ocean pressure change due to oceanographic sea-level change. For computations of the ATMMO displacement field, the ECMWF atmospheric pressure changes over the ocean are added to the ocean bottom pressure changes taken from TUGO-m to ensure an inverted barometric ocean response at periods longer than 2-3 weeks. The displacement field from the ATMMO model includes combined effect of non-tidal atmospheric and oceanic loading.

(5) ECCO2: daily 0.5°×0.5° non-tidal oceanic loading displacement model provided by the EOST loading service. ECCO2 displacement field is estimated using ocean bottom pressure data derived from the Estimating the Circulation and Climate of the Ocean Phase 2 (ECCO2) Menemenlis et al. (2008). The ECCO2 ocean model is a baroclinic general circulation model that assimilates several data sets including satellite altimetry sea-level anomaly, sea surface temperature and many in situ observations. The ECCO2 ocean model is forced by winds, heat and freshwater fluxes from the national Center for Environmental Prediction (NCEP) operational analyses products. The Baroclinic ocean models assume density distribution due to different temperature and salinity within the water column from the ocean surface to the bottom. Therefore, the pressure acting on the ocean bottom does not correspond to sea-level anomaly from the model. Unlike the TUGO-m ocean model, the ECCO2 models provides ocean bottom pressure changes as deviations from the inverted barometric changes.

We add the non-tidal ocean loading displacement from the ECCO2 model to
the non-tidal atmospheric loading displacements from ATMIB and ERAin. We produce five sets of models for the combined effects of non-tidal atmospheric and oceanic loading displacements: (1) ESMGFZ (2) ATMIB+ECCO2 (3) ERAin+ECCO2 (4) ATMMO; and (5) a composite model constructed from models (1)-(4). The composite model consists of non-tidal atmospheric loading displacements from several ECMWF surface pressure products, and non-tidal ocean loading displacements from MPIOM, TUGO-m and ECCO2 models. Vertical displacements from the models and GPS are detrended and are used to calculate the fraction of RMS scatter of observed deformations explained by the models.

The use of either ERAin+ECCO2 and ATMIB+ECCO2 models leads to very similar fits to GPS-measured vertical displacements (Figure S1a), as these models differ only between ECMWF operational and ERA Interim atmospheric pressure data. These models produce the greatest RMS reductions in GPS height time series. ATMMO model performs better fits to GPS height time series only at 45 stations (range RMS reduction 5%-10%), underlining the differences between TUG-m and ECCO2 non-tidal ocean loading models. The ESMGFZ model, for which the AOD1B data product is derived and which is used in the level 1-2 processing of GRACE gravity field, suggesting that over Europe there are large differences between this model with other models at daily periods. The composite model indicates very similar fits to the GPS time series to ERAin+ECCO2, ATMIB+ECCO2 and ATMMO models. However, the discrepancies between these models remain difficult to explain given the noise level in the daily GPS height time series. We therefore chose to use the composite model for further analysis.

The RMS scatters of 96% of the GPS stations are reduced after removing the combined effects of atmospheric and oceanic loading displacement using the composite model (Figure S1b). Seventy percent of these stations have a scatter decrease greater than 10%. Stations with the greatest response to atmospheric and oceanic loading (e.g., larger than 20%) are primarily located around the semi-enclosed seas including the Baltic Sea and the North Sea. Tides in these regions are very small and the mass redistribution of the sea is mostly caused by atmospheric pressure changes and winds at periods from 1-3 days to monthly (see Figure 2 in [Poropat et al., 2018]. This analysis suggests that non-tidal atmospheric and oceanic deformation have significant contributions to the vertical deformation in Europe. Thus, reducing GPS time series for these effects are vital for understanding underlying hydrological deformations in GPS time series and integration of terrestrial water mass changes inferred from the GPS and hydrological models (e.g., [Argus et al., 2017]).
3 Complementary results

3.1 Solution comparing modeled deformation from the original 0.11° grid and from a 3° grid

Figure S2 shows the effect from averaging modeled TWS changes from the original 0.11° grid to a 3° grid.

3.2 Coastal stations versus continental interior

Typically, in Eastern Europe GPS-derived vertical deformation after removing signals from atmosphere and ocean is dominated by the annual amplitude induced from hydrology (Figure S3 KHar). In Central Europe the annual amplitude related to hydrology is smaller and sub-monthly variability also has a significant contribution (Figure S3 Pous). Along the coast, GPS time series are more noisy and the signal related to hydrology is rather small (Figure S3 Gaia).
Fig. S2 Difference in the RMS reduction computed from daily CLM-DA on the original 0.11\(^\circ\) grid and daily CLM-DA averaged to a 3\(^\circ\) grid. Black triangles indicate an increase in RMS reduction.

Fig. S3 Three examples of GPS height time series for stations located in the continental interior of Eastern Europe (KHAR), in Central Europe (POUS) and at the Western coast (GAIA). The locations of these sites are shown in Figure S2. The gray dots are the original daily GPS height time series, the black line is GPS time series filtered with a 3rd-order butterworth applying a cutoff frequency of 0.1. The blue and red lines show modeled deformations from GRACE and CLM-DA, respectively.
We used the ITSG-2016n90 (Mayer-Gürr et al., 2016) monthly gravity field estimates, which are represented as spherical harmonic (SH) coefficients solved up to degree and order 90. As effects from ocean and atmosphere were already removed during gravity field processing (Flechtner et al., 2015), the (SH) coefficients primarily reflect gravity field variations due to hydrology.

We computed total water storage (TWS) anomalies on a 0.5°×0.5° grid according to Wahr et al. (1998). Within this scope, gravity effects resulting from the elastic response of the Earth’s crust and mantle to the deglaciation with respect to past ice ages were reduced from the spherical harmonic coefficients using the model of Simon et al. (2018). Since GRACE cannot measure degree 1 coefficients, they were substituted from a time series of geocenter motion derived by Rietbroek et al. (2012) to implicitly transform predicted time series into the CF system. Furthermore, the coefficient $c_{20}$ that is related to the Earth’s dynamic oblateness is corrupted by aliasing effects. Therefore, $c_{20}$ coefficients were replaced by a time series from satellite laser ranging (Cheng et al., 2013).

As GRACE derive TWS anomalies are contaminated by correlated noise leading to North-South striping patterns, the monthly gravity fields were filtered using the anisotropic DDK3 filter (Kusche, 2007). Both, the truncation of the spherical harmonic coefficients and filtering distort the gravity signal and produce leakage effects (Seo et al., 2006; Khaki et al., 2018). Here, the scaling factor approach of Landerer and Swenson (2012) was applied to restore signal loss. In line with Long et al. (2015) and Zhang et al. (2016), one scaling factor for each grid cell was computed by averaging scaling factors derived from five global hydrological models, i.e. (1) the Global Land Data Assimilation System (GLDAS) Community Land Model Version 4.0 (CLM4.0), (2) the GLDAS MOSAIC land surface model, (3) the GLDAS Variable Infiltration Capacity (VIC) Macroscale Hydrological Model, (4) the GLDAS NOAH land surface model, and (5) the WaterGAP Global Hydrology Model (WGHM).

For assimilating GRACE data into model, realistic errors on a geographical grid including spatial correlations are required (Schumacher et al., 2016). Here, starting from the full error covariance matrices of the spherical harmonic coefficients errors were propagated to fully occupied covariance matrices of monthly gridded, filtered, and rescaled TWS estimates. Then, leakage and rescaling errors were added following Landerer and Swenson (2012) and Zhang et al. (2016).

5 Set up of the Community Land Model (CLM-3.5)

CLM3.5 was set up for the European CORDEX domain on a 0.11° artificial non-rotated regular grid resulting into 99395 model grid cells over land. Atmo-
spheric forcing data was obtained from the Weather Research and Forecasting (WRF; Skamarock et al. (2008)) version V3.3.1 model output at 3-hourly resolution. Static surface data sets are identical to those of Keune et al. (2016) and include topography, soil properties plant functional types PFTs, and physiological vegetation parameters.

In the context of data assimilation, the uncertainty of model states is represented by an ensemble of model runs. Here, an ensemble of 64 ensemble members was generated by perturbing initial conditions, soil texture, and atmospheric forcing data. The ensemble of initial conditions was obtained by running the model once and extracting different states in Januaries 2002 to 2010. In line with Han et al. (2014), spatially uniform noise in the range of ±10% was added to the soil map. Furthermore, spatially, temporally, and cross-correlated random fields were applied to surface precipitation, temperature, and incident solar and long-wave radiation (Han et al. (2014)). First, normally distributed random noise was generated for each of the four variables with the standard deviation indicated in Table 1. Then, spatial correlation $r_{i,j}$ between two grid points $i$ and $j$ was subsequently generated by assuming an isotropic correlation structure depending on the distance $d_{i,j}$ between two grid points and the spatial correlation length $L$ given in Column 5 of Table 1 according to

$$r_{i,j} = \exp \left( -\frac{d_{i,j}}{L} \right).$$

After that, temporal correlation was introduced using a first-order autoregressive model with a decorrelation time of 24 hours following Evensen (2009). Finally, error cross correlations between the four forcing variables were imposed according to Column 6 of Table 1. In a last step, the generated noise was truncated to minimum and maximum values shown in Column 4. The resulting perturbation fields were either added or multiplied to the atmospheric field (Column 2).

**Table 1** Parameters of the additive and multiplicative perturbation fields including cross correlations. Perturbations are truncated to a certain interval provided in column 4.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Noise</th>
<th>Standard deviation</th>
<th>Minimum, Maximum</th>
<th>Spatial correlation scale</th>
<th>Cross Correlation of perturbations in</th>
<th>P</th>
<th>T</th>
<th>SR</th>
<th>LR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>Mult.</td>
<td>0.3</td>
<td>[0.3, 1.7]</td>
<td>80 km</td>
<td>1 0 -0.8 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>Add.</td>
<td>2 K</td>
<td>[-5, 5]</td>
<td>250 km</td>
<td>0 1 0.4 0.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar radiation</td>
<td>Mult.</td>
<td>0.3</td>
<td>[0.3, 1.7]</td>
<td>250 km</td>
<td>-0.8 0.4 1 -0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long wave rad.</td>
<td>Add.</td>
<td>30 W/m²</td>
<td>[-70, 70]</td>
<td>250 km</td>
<td>0.5 0.4 -0.5 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
6 Assimilation of GRACE data into CLM3.5

Assimilation of GRACE derived TWS anomalies (TWSA) into the Community Land Model Version 3.5 (CLM3.5) was realized within the modular high-performance data assimilation framework TerrSysMP-PDAF Version 1.0 [Kurtz et al. (2016)]. Here, the local Ensemble Transform Kalman Filter (LETKF) [Hunt et al. (2007)] was applied with a localization radius of 5° and a forgetting factor of 0.7. Data assimilation updates the model state vector, which is composed by the TWS components of 99395 model grid cells, i.e. the sum of soil liquid water and soil ice at each soil layer, snow water, canopy water, and water of the unconfined aquifer. All TWS components are updated individually. For consistent representation of modeled TWS and measured TWS, GRACE derived TWSA were adjusted to the long-term mean of modeled TWS before data assimilation.

The assimilation algorithm includes four major steps: i) the model is forwarded one month, ii) the model states are projected into observation space (observation operator), iii) the assimilation increments are computed during the analysis step (LETKF), and iv) the model is updated. Details on each of the processing steps are provided in Springer (2019). While forwarding the model for one month running means were computed for all model state components to match the characteristics of monthly averaged GRACE observations. Then, the model state vector was set up using the temporally averaged quantities and the observation operator was applied, i.e. the state vector was vertically aggregated and spatially averaged to the observation grid of 0.5° [Schumacher et al. 2016]. Different concepts exist for applying the assimilation increments to the model [Girotto et al. 2016]. Here, the entire increment was applied to the last time step of the month as e.g. in [Eicker et al. 2014]. Then, the model was continued for the next month.

GRACE observations are highly correlated in space. We considered the full error covariance matrices of GRACE derived TWSA during the update step. The impact of different error models for GRACE observations was assessed in detail by Springer (2019). Note that temporal correlations between monthly GRACE solutions were not considered here.

Constraints were applied to avoid unrealistically large assimilation increments and to keep the model state variables physically consistent. The assimilation increments of soil liquid water and soil ice were limited to half of their current value. This avoids negative model states and maintains the vertical distribution of water within the soil column. Furthermore, the volumetric soil water content was adjusted to match updated soil liquid water and soil ice. Updating snow water also requires to adapt snow depth, the number of snow layers and their thickness. As water of the unconfined aquifer can be assumed to change slowly with time, the corresponding increments were restricted to 5 mm.
References


