Estimating annual water storage variations in medium-scale (2000–10 000 km²) basins using microwave-based soil moisture retrievals

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Abstract. Due to their shallow vertical support, remotely sensed surface soil moisture retrievals are commonly regarded as being of limited value for water budget applications requiring the characterization of temporal variations in total terrestrial water storage (dS/dt). However, advances in our ability to estimate evapotranspiration remotely now allow for the direct evaluation of approaches for quantifying dS/dt via water budget closure considerations. By applying an annual water budget analysis within a series of medium-scale (2000–10 000 km²) basins within the United States, we demonstrate that, despite their clear theoretical limitations, surface soil moisture retrievals derived from passive microwave remote sensing contain statistically significant information concerning dS/dt. This suggests the possibility of using (relatively) higher-resolution microwave remote sensing products to enhance the spatial resolution of dS/dt estimates acquired from gravity remote sensing.

1 Introduction

Within the past decade, the analysis of data products from the Gravity Recovery and Climate Experiment (GRACE) satellite mission (Tarpley et al., 2004a, b) has led to an enhanced appreciation of the role played by interannual variations of total terrestrial water storage (dS/dt) within the terrestrial water budget (Chen et al., 2009; Rodell et al., 2007; Syed et al., 2008). However, the application of GRACE storage retrievals is potentially limited by their extremely coarse spatial resolution (~200 000 km²). This has spurred interest in the development of spatial downscaling techniques for GRACE-based dS/dt. These approaches have generally been based on the use of (relatively) higher-resolution water storage predictions obtained from distributed land surface model predictions (Reager et al., 2015; Wan et al., 2015) or a combination of land surface model output and independent evapotranspiration (ET) and precipitation (P) flux estimates (Ning et al., 2014). In contrast, microwave-based surface soil moisture (θ) retrievals provide a direct assessment of soil water storage that can be obtained at relatively finer resolutions (typically ~1000 km²). However, such retrievals are hampered by both shallow vertical support (reflecting soil moisture conditions only in the top several centimeters of the soil column) and substantially reduced accuracy for dense vegetative cover. As a result, they are generally assumed to be of limited value for the examination of dS/dt and are commonly neglected in water budget studies. However, recent empirical work demonstrates that microwave-based θ retrievals are generally well-correlated with GRACE-based storage estimates (Abelen and Seitz, 2013; Abelen et al., 2015). This suggests that θ retrievals retain some value for water-budget studies – particularly at spatial scales finer than the resolution of GRACE products.

Confirming such potential will require the availability of accurate terrestrial water flux variables. Recent progress in the remote sensing of dS/dt and θ has been mirrored by the increased consideration of satellite-derived ET retrievals.
in a water balance context (Senay et al., 2011; Hain et al., 2015; Hendrickx et al., 2016; Wang-Erlandsson et al., 2016). In particular, when combined with \( P \) and basin-outlet stream flow \( (Q) \) measurements, satellite-derived \( E_T \) estimates can be used to verify estimates of \( dS/\,dt \) obtained from independent sources (Han et al., 2015). This opens up the possibility for the objective “top-down” evaluation of \( dS/\,dt \) estimates obtained from various remote sensing sources and the opportunity to empirically confront “bottom-up” expectations for these products based solely on theoretical considerations.

Here, we combine \( E_T \) estimates acquired from thermal infrared (TIR) remote sensing with ground-based \( Q \) and \( P \) measurements to evaluate the water balance performance of passive microwave (PM) estimates of annual \( dS/\,dt \) for a set of medium-scale (2000–10 000 km\(^2\)) river basins within the United States. The analysis will focus on two primary tasks: (1) evaluating the suitability of existing \( E_T, Q, \) and \( P \) datasets to accurately estimate \( dS/\,dt \) and (2) empirically investigating the ability of interannual \( dS/\,dt \) estimates acquired from microwave remote sensing of soil moisture to close the interannual terrestrial water balance. As discussed above, this particular application of \( \theta \) is arguably inconsistent with their known theoretical limitations. Therefore, our focus will be on empirically evaluating their ability to provide \( dS/\,dt \) closure within an annual water budget analysis and examining how these results fit with a priori theoretical expectations.

Section 2 describes the water balance datasets and study basins. Section 3 examines the ability of existing flux and storage products to close the terrestrial water balance within a set of larger-scale (150 000–1 000 000 km\(^2\)) hydrologic basins where GRACE-based \( dS/\,dt \) can be directly utilized (see task #1 defined above). Based on verification results in Sect. 3, Sect. 4 derives a technique for estimating \( dS/\,dt \) from microwave remote sensing and evaluates the ability of microwave-based \( dS/\,dt \) to close the terrestrial water balance within a second set of medium-scale (2000–10 000 km\(^2\)) basins (see task #2 defined above). Results are discussed in Sect. 5 and conclusions summarized in Sect. 6.

2 Study basins and datasets

Within a closed hydrologic basin, the annual water budget equation can be summarized as follows:

\[
P - Q - E_T = dS/\,dt, \tag{1}
\]

where \( P, Q, \) and \( E_T \) (mm yr\(^{-1}\)) represent annual sums of fluxes, and \( dS/\,dt \) (mm yr\(^{-1}\)) is the annual change in terrestrial water storage. Besides \( Q, \) all other lateral water fluxes (into or out of the basin) are assumed to be negligible. See Sect. 2.2 below for a description of data products used to describe flux terms on the left-hand side of (1). Here, the storage change term \( dS/\,dt \) is independently obtained using both gravity-based (GR) retrievals of total terrestrial water storage and PM-based retrievals of surface soil moisture content. In both cases, annual change estimates are based on the differencing of temporally averaged storage retrievals acquired at (or near) the end of each calendar year. Based on constraints associated with the availability of various remote sensing products, the analysis is conducted within a time period from 1 January 2003 to 31 December 2010. Additional methodological details are given below.

2.1 Study basins

For the analysis, hydrologic basins are sought with the following: excellent ground-based rain gauge coverage, the availability of good remotely sensed \( E_T \) products, and the relative absence of complex topography and/or dense vegetation conditions known to reduce the accuracy of existing long-term, satellite-based soil moisture products. In addition, arid areas are avoided due to their known lack of interannual \( dS/\,dt \) variability. The North American Mississippi River system is one of only a handful of continental-scale river basins that generally meets all of these criteria. Therefore, water budget closure will be examined in two separate sets of basins within the Mississippi River system. To start, a large-scale analysis will be conducted on five major Mississippi River sub-basins: the Missouri, the Arkansas, the Red, the Ohio and the Upper Mississippi – see Fig. 1 and Table 1. The primary focus in these large-scale basins will be evaluating the ability of existing \( P, Q, E_T, \) and GRACE-based \( dS/\,dt \) product to close the annual water budget. The results of this water balance analysis will then be used to refine the geographic focus and water flux processing approach applied in the medium-scale analysis described below.

Following this large-scale water balance analysis, the performance of a microwave-based \( dS/\,dt \) proxy is examined within 16 (smaller) medium-scale (2000–10 000 km\(^2\)) unregulated basins positioned along an east–west transect across the United States Southern Great Plains (SGP) region (see Fig. 1 and Table 2). A complete justification of this geographic emphasis is given in Sect. 3. However, in general, medium-scale basins were selected following a screening analysis applied by the Model Parameter Estimation Experiment project (Duan et al., 2006), which removed basins with either inadequate rain gauge coverage or excessive human regulation of stream flow. Moving from west to east, these basins exhibit progressively higher mean \( P \) and annual runoff ratios \( (Q/P) \) (Fig. 1 and Table 2). Associated with this climatic gradient is a gradual west–east increase in vegetation biomass. Western basins are characterized by large fractions of rangeland, grassland, and winter wheat land cover with relatively low biomass. In contrast, basins located along the eastern edge of the transect contain significant upland forest cover and intensive summer agricultural cultivation in low-lying areas.
Figure 1. Map of the 5 large-scale basins (color shading – see Table 1) and 16 unregulated medium-scale basins (red outlines – see Table 2) considered in the analysis.

Table 1. Attributes of large-scale basins in Fig. 1.

<table>
<thead>
<tr>
<th>River basin</th>
<th>USGS station no.</th>
<th>USGS station name</th>
<th>Basin size (km²)</th>
<th>Annual P (mm)</th>
<th>Runoff ratio Q/P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Missouri</td>
<td>06934500</td>
<td>Missouri River at Hermann, MO</td>
<td>1 347 556</td>
<td>563</td>
<td>0.10</td>
</tr>
<tr>
<td>Arkansas</td>
<td>07263450</td>
<td>Arkansas River at Little Rock, AR</td>
<td>409 201</td>
<td>747</td>
<td>0.14</td>
</tr>
<tr>
<td>Red</td>
<td>07344370</td>
<td>Red River at Spring Bank, AR</td>
<td>153 906</td>
<td>850</td>
<td>0.13</td>
</tr>
<tr>
<td>Upper Miss.</td>
<td>07022000</td>
<td>Mississippi River at Thebes, IL</td>
<td>496 016</td>
<td>898</td>
<td>0.31</td>
</tr>
<tr>
<td>Ohio</td>
<td>03611500</td>
<td>Ohio River at Metropolis, IL</td>
<td>527 557</td>
<td>1187</td>
<td>0.45</td>
</tr>
</tbody>
</table>

2.2 Data products and processing

A range of ground and remotely sensed datasets were acquired to characterize components of the terrestrial water balance summarized in Eq. (1). The acquisition and processing of these datasets is described below.

2.2.1 Thermal remote sensing of $E_T$

Daily evapotranspiration estimates were obtained from the Atmosphere–Land Exchange Inverse (ALEXI) algorithm. In particular, ALEXI exploits the moisture signal conveyed by the mid-morning rise in satellite-observed land surface temperature (LST) in order to capture water limitations on surface energy fluxes (Anderson et al., 2007a, b; Hain et al., 2009, 2011). Based on this principle, ALEXI produces estimates of daily evapotranspiration without direct knowledge of antecedent precipitation or soil water balance considerations (Anderson et al., 2011). This ensures that ALEXI evapotranspiration estimates are independent of those derived via water balance calculations.

ALEXI evapotranspiration has been evaluated using a spatial disaggregation technique (DisALEXI) which uses high-resolution LST retrievals from Landsat to downscale ALEXI fluxes to a 30 m pixel level (Anderson et al., 2004). Typical accuracies obtained in comparison with eddy-covariance tower observations are on the order of 5 to 15% for daily to seasonal evapotranspiration estimates during snow-free periods (Anderson et al., 2012; Cammalleri et al., 2013, 2014a; Semmens et al., 2016).

Here, the ALEXI model was processed over CONUS at a spatial resolution of 4 km for the period 2003–2010 and forced with meteorological inputs from the Climate Forecast System Reanalysis (CFSR; Saha et al., 2010), thermal infrared land surface temperature from the Geostationary Operational Environmental Satellites (GOES East and West), and leaf area index estimates obtained from the 4-day 1 km Combined Aqua-Terra MODIS product (MCD15A3).

Daily, instantaneous, clear-sky latent heat fluxes retrieved from ALEXI were upscaled to daytime-integrated evapotranspiration estimates assuming a self-preservation of the ratio of latent heat flux and incoming shortwave radiation ($f_{SUN}$) during daytime hours (Cammalleri et al., 2014b). Hourly CFSR incoming shortwave radiation inputs were integrated to produce daily estimates (24 h) of insolation used in this temporal upscaling. Currently, ALEXI is not executed over snow-covered surfaces. These periods were instead gap-filled with a linear interpolation of $f_{SUN}$ and a snow albedo correction to account for differences in surface net radia-
tion over snow-covered versus snow-free surfaces. Resulting 4 km ALEXI daily evapotranspiration estimates were temporally summed within calendar years to produce annual $E_T$ (mm yr$^{-1}$) and spatially averaged within each of the basins listed in Tables 1 and 2. Annual ALEXI $E_T$ estimates acquired in this way have been successfully applied to verify interannual evapotranspiration estimates acquired from land surface modeling (Han et al., 2015).

### 2.2.2 Land surface model predictions of $E_T$

For the purposes of cross-comparison with ALEXI $E_T$ results, annual $E_T$ was also acquired from 0.125° resolution Noah v3.2 simulations (Chen et al., 2001; Chen and Dudhia, 2001; Ek et al., 2003) generated as part of North American Land Data Assimilation Phase 2 (NLDAS-2) activities (Xia et al., 2012). Hourly Noah predictions of (1) direct evaporation from the surface soil, (2) direct evaporation of canopy-intercepted precipitation, and (3) transpiration via plant root uptake of soil water were aggregated to produce an hourly evapotranspiration estimate. Annual $E_T$ averages were then obtained by summing these estimates for the calendar years 2003 to 2010 and spatially averaging these summations within the basins indicated in Fig. 1.

### 2.2.3 Ground-based observations of $P$ and $Q$

Daily stream-flow magnitudes were obtained from United States Geological Survey (USGS) stream gauging stations located at the outlet of basins listed in Tables 1 and 2. These values were aggregated into (calendar year) sums and normalized by basin drainage area to obtain units of water depth per year (mm yr$^{-1}$). Annual total (liquid plus solid phase) precipitation ($P$) (mm yr$^{-1}$) was based on the temporal aggregation of rain gauge observations acquired by the National Centers for Environmental Prediction (NCEP)'s Climate Prediction Center (CPC) and re-sampled onto a 0.125° grid by the NLDSE-2 project (Xia et al., 2012). These annual averages were then spatially averaged within each of the basins listed in Tables 1 and 2.

### 2.2.4 Gravity remote sensing of $dS / dt$

Monthly GRACE terrestrial water storage deviation ($S_{GR}$) data were obtained by separately applying the rescaling coefficients of Landerer and Swenson (2012) to gridded 1° GRACE Level-3 terrestrial water storage products provided by the GeoForschungsZentrum (GFZ; version RL05.DSTvSCS1409), University of Texas Center for Space Research (CSR; version RL05.DSTvSCS1409), and the NASA/CalTech Jet Propulsion Laboratory (JPL; version RL05.DSTvSCS1411). GRACE-based annual estimates of terrestrial water storage variations ($dS_{GR} / dt$) were then derived via simple linear averaging of the GFZ, CSR and JPL terrestrial storage product to estimate $S_{GR,Dec,i}$ and $S_{GR,Jan,i+1}$ (where $i$ is an annual index) and the subsequent application of year-over-year differencing:

$$(dS_{GR}/dt)_i = (S_{GR,Dec,i} + S_{GR,Jan,i+1}) / 2 - (S_{GR,Dec,i-1} + S_{GR,Jan,i}) / 2. \quad (2)$$

Finally, gridded 1° $dS_{GR} / dt$ (mm yr$^{-1}$) products were spatially averaged within all of the coarse-scale basins listed in Table 1. Note that GRACE Level-3 values capture monthly deviations from a long-term average datum (based on average 2004–2009 conditions) and not absolute storage levels. However, the distinction is immaterial since our focus lies

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**Table 2. Attributes of medium-scale basins in Fig. 1.**

<table>
<thead>
<tr>
<th>Basin number</th>
<th>USGS station no.</th>
<th>USGS station Name</th>
<th>Basin size (km$^2$)</th>
<th>Annual $P$ (mm)</th>
<th>Runoff ratio $Q / P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>07144780</td>
<td>Ninemach River AB Cheney Re, KS</td>
<td>2049</td>
<td>768</td>
<td>0.08</td>
</tr>
<tr>
<td>2</td>
<td>07144200</td>
<td>Arkansas River at Valley Center, KS</td>
<td>3402</td>
<td>842</td>
<td>0.11</td>
</tr>
<tr>
<td>3</td>
<td>07152000</td>
<td>Chikasakia River near Blackwell, OK</td>
<td>4891</td>
<td>896</td>
<td>0.19</td>
</tr>
<tr>
<td>4</td>
<td>07243500</td>
<td>Deep Fork near Beggs, OK</td>
<td>5210</td>
<td>945</td>
<td>0.15</td>
</tr>
<tr>
<td>5</td>
<td>07147800</td>
<td>Walnut River at Winfield, KS</td>
<td>4855</td>
<td>980</td>
<td>0.31</td>
</tr>
<tr>
<td>6</td>
<td>07177500</td>
<td>Bird Creek Near Sperry, OK</td>
<td>2360</td>
<td>1025</td>
<td>0.23</td>
</tr>
<tr>
<td>7</td>
<td>06908000</td>
<td>Blackwater River at Blue Lick, MS</td>
<td>2924</td>
<td>1140</td>
<td>0.29</td>
</tr>
<tr>
<td>8</td>
<td>07196500</td>
<td>Illinois River near Tablequah, OK</td>
<td>2492</td>
<td>1175</td>
<td>0.29</td>
</tr>
<tr>
<td>9</td>
<td>07019000</td>
<td>Meramec River near Eureka, MO</td>
<td>9766</td>
<td>1187</td>
<td>0.28</td>
</tr>
<tr>
<td>10</td>
<td>07052500</td>
<td>James River at Galena, MO</td>
<td>2568</td>
<td>1255</td>
<td>0.31</td>
</tr>
<tr>
<td>11</td>
<td>07186000</td>
<td>Spring River near Wace, MO</td>
<td>2980</td>
<td>1258</td>
<td>0.27</td>
</tr>
<tr>
<td>12</td>
<td>07056000</td>
<td>Buffalo River near St. Joe, AR</td>
<td>2148</td>
<td>1238</td>
<td>0.37</td>
</tr>
<tr>
<td>13</td>
<td>06933500</td>
<td>Gasconade River at Jerome, MO</td>
<td>7356</td>
<td>1293</td>
<td>0.24</td>
</tr>
<tr>
<td>14</td>
<td>07067000</td>
<td>Current River at Van Buren, MO</td>
<td>4351</td>
<td>1309</td>
<td>0.31</td>
</tr>
<tr>
<td>15</td>
<td>07068000</td>
<td>Current River at Doniphan, MO</td>
<td>5323</td>
<td>1314</td>
<td>0.36</td>
</tr>
<tr>
<td>16</td>
<td>07290000</td>
<td>Big Black River NR Bovina, MS</td>
<td>7227</td>
<td>1368</td>
<td>0.37</td>
</tr>
</tbody>
</table>
The primary application of d$S_{GR} / dt$ retrievals will be to verify annual water balance closure within the coarse-scale basins listed in Table 1. However, we will also apply d$S_{GR} / dt$ within the medium-scale basins to calibrate microwave-based $dS / dt$ estimates (see Sect. 4.1) and as a baseline for evaluating microwave-based $dS / dt$ as a source of downscaling information (see Sect. 4.2). These applications will be approached with caution since the spatial resolution of the d$S_{GR} / dt$ retrievals ($\sim 200,000 \text{ km}^2$) is much coarser than the size of the medium-scale basins considered here (2000–10,000 km$^2$). The impacts of this significant scale mismatch will be discussed below.

### 2.2.5 Passive microwave remote sensing of soil moisture

PM-based surface soil moisture retrievals were based on the application of the Land Parameter Retrieval Model (LPRM; Owe et al., 2001) to Advanced Microwave Scanning Radiometer – EOS (AMSR-E) C- and X-band brightness temperature observations obtained from both ascending (13:30 LT) and descending (01:30 LT) orbits of the NASA Aqua satellite (Owe et al., 2008). AMSR-E LPRM Level 3 soil moisture data products were downloaded from the NASA Global Change Master Directory (http://gcmd.nasa.gov). The Aqua satellite was launched in June 2002 and remained operational until October 2011. Soil moisture datasets acquired from AMSR-E represent the longest surface soil moisture data record currently available from a single satellite sensor. The processing of these datasets into $dS / dt$ estimates is discussed in Sect. 4.

### 2.3 Statistical approach

The temporal length of required remotely sensed datasets imposes a serious challenge for this analysis. The primary limiting factor for this length is the availability of a consistent microwave-based $\theta$ dataset. As noted above, the data period utilized here (2003–2010) represents the longest current period of (temporally consistent) microwave-based $\theta$ retrievals available from any single sensor (AMSR-E). Nevertheless, it still provides only eight annual values upon which to evaluate the annual closure expressed in Eq. (1). Longer $\theta$ datasets based on the merger of multi-sensor $\theta$ retrievals exist (Liu et al., 2011). However, concerns about their temporal consistency currently limit their value for analyses conducted at interannual timescales (Loew et al., 2013).

The restriction of the annual analysis to only 8 years limits our ability to robustly assess closure using temporal sampling alone. Therefore, whenever possible, we will sample closure evaluation statistics across both space and time to maximize the total degrees of freedom available for a statistical analysis. However, due to significant amounts of both spatial and temporal auto-correlation in $P - Q - E_T$ fields, considerations must be made for oversampling (in both space and time) when calculating effective sample sizes. To address this we applied the approach of Bretherton et al. (1999) who recommended (for the case of sampling quadratic statistics) an effective sampling size $N^*$ of

$$N^* = N(1 - \rho^2)/(1 + \rho^2),$$

where $N$ is the original sample size and $\rho$ the auto-correlation at individual sampling points. In particular, we applied Eq. (3) separately in both space and time, utilizing both temporal (separated in time, sampled over time, and then averaged across various basins) and spatial (separated in space, sampled over space, and then averaged over various years) samples of $\rho$ to obtain both spatial and temporal sample size reduction factors. Next, the total sample size (i.e., total time samples $\times$ total space samples) was multiplied by both reduction factors to estimate effective sample sizes in both time and space. For example, in the large-scale basin analysis, we have a total sample size of 40 annual values (5 basins over 8 years); however, after accounting for oversampling in both space and time, the effective sample size was reduced to 9.7. Likewise, for the medium-scale basins analysis, the total sample size of 128 annual values (16 basins over 8 years) was reduced to an actual effective size of 48.4. These effective sample sizes were then used to calculate effective degrees of freedom for all statistical hypothesis tests.

### 3 Water balance closure within large-scale basins

All water storage and flux products described above contain significant errors and biases. In addition, it is possible that non-resolved flux terms in Eq. (1) may hinder closure versus observed storage changes. Therefore, before deriving and evaluating an approach to estimate $dS / dt$ for medium-scale basins using microwave-based remote sensing, we will first verify the ability of water balance datasets introduced in Section 2 to close the terrestrial water balance via Eq. (1). Due to the coarse spatial resolution of GRACE, a direct closure analysis is possible only for the large-scale basins listed in Table 1. Based on $E_T$ values derived from ALEXI, Fig. 2 plots annual variations of $P - Q - E_T$ and (GRACE-based) d$S_{GR} / dt$ for all five large-scale basins. In all basins except the Missouri, annual values of $P - Q - E_T$ depart significantly from zero – illustrating the general importance of annual $dS / dt$ on the terrestrial water budget. Within the Missouri, $P - Q$ is roughly balanced by $E_T$, and therefore, alone among other basins examined here, the annual estimation of d$S_{GR} / dt$ does not appear to be a requirement for closing the annual water budget. This may be linked to the very large reservoir capacity of the Missouri River Basin system and the active management of $Q$ to minimize interannual reservoir and channel level variability. This aggressive level of management ensures that the Missouri River Basin exhibits the smallest standard deviation of interannual $P - Q - E_T$.
variability (~30 mm yr⁻¹ - see Fig. 2) of any large basin considered in this analysis.

The best closure results in Fig. 2 are obtained in the Arkansas River and Red River basins. In these two basins, GRACE-based \( \frac{dS}{dt} \) closely matches interannual variations in \( P - Q - E_T \). This suggests that in the United States SGP region, both the assumptions underlying Eq. (1) and the water flux datasets considered are sufficiently accurate to characterize interannual variations in \( \frac{dS}{dt} \). In contrast, there is clear evidence of a low bias in annual \( P - Q - E_T \) relative to \( \frac{dS}{dt} \) within both the Upper Mississippi and Ohio River Basins. Given the frequency and extent of wintertime snow cover in these basins, it seems reasonable to ascribe this bias to known under-catch issues associated with the gauge-based measurement of snowfall (Goodison et al., 1998). In addition, there exists a potential for systematic errors in cold-season ALEXI \( E_T \) estimates (which are based on a simple extrapolation approach).

Figure 3a shows annual \( P - Q - E_T \) versus \( \frac{dS}{dt} \) for all five large-scale basins. The sampled correlation in Fig. 3a is marginal (0.37 [-]) but improves considerably (0.52 [-]) when the 8-year mean of annual \( P - Q - E_T \) is subtracted from yearly \( P - Q - E_T \) results for each basin (Fig. 3b). This is equivalent to imposing closure of \( P - Q - E_T \) within each basin over the entire 8-year period. In addition, replacing ALEXI \( E_T \) with Noah-based \( E_T \) reduces the sampled correlations in both Fig. 3a and b (from 0.37 to 0.33 [-] and from 0.52 to 0.33 [-], respectively). This implies that preference should be given to the remote-sensing-based ALEXI \( E_T \) product.

Due to the coarse spatial resolution of GRACE-based \( \frac{dS}{dt} \), a comparable water balance analysis cannot be applied to the medium-scale basins listed in Fig. 1 and Table 2. Instead we will cross-apply general tendencies observed in the large-scale closure analysis (Figs. 2 and 3) to refine the medium-scale analysis presented below. In particular, the medium-scale basins listed in Table 2 are selected based on the principal of minimization of both human regulation (to avoid the lack of annual \( P - Q - E_T \) signal noted in the Missouri Basin) and cold season impacts (to avoid the low bias in annual \( P - Q - E_T \) observed in the Ohio and Upper Mississippi River basins). Overall, these two considerations motivate our decision to utilize only lightly regulated MOPEX basins within the SGP portion of the Mississippi River system (see Fig. 1 and earlier discussion in Sect. 2.1).

In addition, based on annual water balance closure results presented in Figs. 2–3, ALEXI-based (as opposed to Noah-based) \( E_T \) will be used and closure will be imposed on 8-year \( P - Q - E_T \) totals.

4 Microwave-based closure for medium-scale basins

As discussed above, the primary focus of this analysis is the utilization of new \( E_T \) remote sensing products to objectively evaluate the contribution of microwave surface soil moisture retrievals towards describing interannual \( P - Q - E_T \) variations within medium-scale basins. To this end, this section will describe the derivation of a new microwave-based proxy for \( \frac{dS}{dt} \) and its empirical evaluation within the specific set of medium-scale basins listed in Table 2.
4.1 Microwave-based $dS/dt$ estimation

Any transition between surface soil moisture and terrestrial water storage must account for relative variations in the temporal scale and phase of both quantities. In particular, the tendency for terrestrial water storage to be temporally smoothed and lagged in time with respect to corresponding surface soil moisture variations (Chagnon, 1987; Entekhabi et al., 1992; Swenson et al., 2008). Based on this reasoning, instantaneous 0.25° LPRM surface soil moisture retrievals (see Sect. 2.2) were averaged in time and space into a single monthly value for each of the basins in Tables 1 and 2. Next monthly (basin-scale) soil moisture averages for October, November, and December ($\theta_{PM, Oct}$, $\theta_{PM, Nov}$, and $\theta_{PM, Dec}$) were merged into a single, end-of-calendar-year estimate of PM-based $\theta_{PM}$:

$$\theta_{PM,i} = W_{Oct} \cdot \theta_{PM, Oct,i} + W_{Nov} \cdot \theta_{PM, Nov,i} + W_{Dec} \cdot \theta_{PM, Dec,i},$$  \hspace{1cm} (4)

where $i$ is an annual index (here corresponding to calendar years between 2003 and 2010), and $W$ are constant weighting factors (summing to unity) applied to each month. Annual changes in $\theta_{PM}(d\theta_{PM}/dt)$ were then derived from annual differencing of $\theta_{PM,i}$ with $\theta_{PM,i-1}$. This entire procedure was done separately for LPRM retrievals acquired during both ascending and descending AMSR-E orbits. Finalized values of $d\theta_{PM}/dt$ were then obtained by averaging results obtained from both orbits. Our decision to utilize a calendar year to accumulate annual flux or storage change totals in Eq. (1) is largely arbitrary, and the impact of utilizing other annual periods will be discussed below.

In addition to the specification of $W$, we also allowed for the application of a single calibration factor $K_{PM}$ (mm) when converting volumetric $d\theta_{PM}/dt$ ($m^3 m^{-3} yr^{-1}$) variations into annual $dS/dt$ depth changes (mm yr$^{-1}$):

$$dS_{PM}/dt = K_{PM} d\theta_{PM}/dt.$$

$$dS_{PM}/dt = K_{PM} d\theta_{PM}/dt.$$

$$K_{PM} = \sigma (dS_{GR}/dt) / \sigma (d\theta_{PM}/dt).$$  \hspace{1cm} (6)

where the $\sigma$ operator indicates a standard deviation sampled across all available years and medium-scale study basins.

Despite some evidence for significant large-scale correlation between $\theta$ and $S$ (Abelen and Seitz, 2013; Abelen et al., 2015), there are viable reasons for scepticism regarding the application of Eqs. (4)–(6) to a water budget application. First, due to the extremely shallow vertical support of PM-based surface soil moisture retrievals, it is uncertain if $d\theta_{PM}/dt$ actually provides an effective linear proxy for $dS/dt$. Second, even if such a linear relationship can be established, it is unclear if the ratio $\sigma (dS_{GR}/dt) / \sigma (d\theta_{PM}/dt)$ in Eq. (6) provides a robust calibration coefficient to convert surface soil moisture variations into annual variations in $S$. These theoretical concerns are addressed below.

![Figure 4](https://www.hydrol-earth-syst-sci.net/21/1849/2017/)

**Figure 4.** For the 16 medium-scale basins listed in Table 2, the annual time series of raw $P - Q - E_T$ (solid black line) and $P - Q - E_T$ obtained by assuming flux closure over the 8-year period of record (dashed red line). Values of the microwave-based $dS_{PM}/dt$ proxy are also plotted (solid blue line).

4.2 Evaluation of proxy assumptions and calibration

Figure 4 plots (annual) variations of $P - Q - E_T$ and $dS_{PM}/dt$ for all 16 medium-scale basins listed in Table 1. See Sect. 3 for the rationale behind the selection of these particular basins. The large plotted departures (from zero) seen for $P - Q - E_T$ confirm that interannual variations in $S$ play a significant role in the application of Eq. (1) at an annual timescale.

In addition, consistently negative $P - Q - E_T$ estimates are observed within several medium-scale basins (see, e.g., basins #5, #8, #9, and #12 in Fig. 4). Because these basins cannot be directly resolved by GRACE, it is difficult to confirm whether this tendency is real (i.e., a decadal-scale trend in storage) or an artefact of the summed impact of multiple long-term measurement biases in independent $P$, $Q$, and $E_T$ products. However, based on the large-basin analysis presented in Sect. 3, the latter appears more likely. Therefore, annual $P - Q - E_T$ values are de-biased by subtracting out (on a basin-by-basin basis) the 8-year annual mean of $P - Q - E_T$ (see dashed line in Fig. 4). The impact of this assumption on subsequent results will be discussed below.

Our primary goal is to determine the potential for explaining observed annual $P - Q - E_T$ variations in Fig. 4 using the microwave-based $dS_{PM}/dt$ proxy introduced above and empirically evaluating the assumptions – expressed in Eqs. (4)–
feasible parameterization strategies will be required to fix their values. To this end, Fig. 5b plots the sampled correlation between $d\theta_{PM} / dt$ and $dS_{GR} / dt$ as a function of $W_{DEC}$, $W_{NOV}$, and $W_{OCT}$. Note that monthly weighting values which maximize this correlation in Fig. 5b also tend to maximize the correlation between $d\theta_{PM} / dt$ and $P - Q - E_T$ in Fig. 5a. Based on Fig. 5b, the maximum correlation between $d\theta_{PM} / dt$ and $dS_{GR} / dt$ is found at $W_{OCT} = 0.4 \text{ [-]}$, $W_{NOV} = 0.5 \text{ [-]}$, and $W_{DEC} = 0.1 \text{ [-]}$. These (spatially and seasonally fixed) weighting values will be used for all subsequent calculations of $d\theta_{PM} / dt$ via Eq. (4). The relative lack of weight applied to December surface soil moisture retrievals is likely reflective of frozen soil moisture conditions at this time and the need for $dS / dt$ anomalies to be lagged in time with respect to superficial surface soil moisture variations. Adding monthly-averaged $\theta$ retrievals from September ($\theta_{PM, Sep}$) into Eq. (4) – so that end-of-year $\theta_{PM}$ was calculated using a 4-month weighted-average product – produced essentially no change to Fig. 5.

The parameterization of $W_{OCT}$, $W_{NOV}$, and $W_{DEC}$ alone is sufficient if $d\theta_{PM} / dt$ is to be interpreted solely as a linear proxy for relative interannual variations in $dS / dt$; however, interpretation of $d\theta_{PM} / dt$ as an absolute measure requires the additional parameterization of $K_{PM}$ (mm) in Eq. (5) to transform $d\theta_{PM} / dt$ into a $dS / dt$ estimates with units of (mm yr$^{-1}$) (i.e., $dS_{PM} / dt$). Figure 6 shows the impact of $K_{PM}$ in Eq. (5) on the root-mean-square difference (RMSD) between $dS_{PM} / dt$ and $P - Q - E_T$. Results are obtained by lumping annual results for all years within all medium-scale basins listed in Table 2, and the assumption that $K_{PM}$ is fixed in both space and time. The plotted horizontal line plots the interannual standard deviation of $P - Q - E_T$ – which is equivalent to the RMSD accuracy achievable by assuming $dS / dt = 0$ in Eq. (1). This baseline is improved upon by a wide range of $K_{PM}$ values. However, the absolute accuracy of the $dS_{PM} / dt$ proxy is maximized near $K_{PM} = 900 \text{ mm}$.

The $K_{PM}$ estimation approach in Eq. (6) is based on the assumption that this optimal value can be obtained via a simple variance matching approach applied to $d\theta_{PM} / dt$ and $dS_{PM} / dt$. Applying Eq. (6) (in a lumped manner to all years and all medium-scale basins in Table 2) leads to a value of $K_{PM} = 1150 \text{ mm}$, which is reasonably close to the optimal value of $K_{PM} = 900 \text{ mm}$. It is also well within the broad range of $K_{PM}$ which improves upon a baseline of neglecting $dS / dt$ entirely (see Fig. 6).

It should be noted that the parameterization strategies presented above involve direct comparison between (relatively) high-resolution $\theta$ products obtained from microwave remote sensing with lower-resolution GRACE-based $dS_{GR} / dt$ retrievals (which have been trivially re-sampled to capture a basin-scale mean). Despite the inability of GRACE retrievals to spatially resolve the medium-scale basins considered here, Figs. 5 and 6 suggest these comparisons are still able to yield useful calibration information. However, it is possible that resolution inconsistencies between GRACE and
AMSR-E may have a degrading impact on results. One strategy for resolving this scale inconsistency is to first degrade the spatial resolution of the AMSR-E $\theta$ field to match the ~200,000 km$^2$ GRACE resolution prior to applying the calibration approach outlined in Figs. 5a and 6. However, attempts to do this (via smoothing of the AMSR-E $\theta$ fields using a 2-dimensional Gaussian filter) actually led to a small decrease in the quality of the $W_{\text{Oct}}$, $W_{\text{Nov}}$, $W_{\text{Dec}}$, and $K_{\text{PM}}$ calibration. This implies that, despite their resolution differences, direct comparisons between AMSR-E and GRACE products appear to offer the most viable calibration approach.

4.3 Microwave-based closure evaluation

Utilizing the calibrated $W$ and $K_{\text{PM}}$ derived in Sect. 4.2 leads to the $d\delta_P/\delta t$ values plotted in Fig. 7. Each point in the scatter plot represents one annual value within a single medium-scale basin. Our microwave-based $d\delta_P/\delta t$ proxy product has a linear correlation with independently acquired $P - Q - E_T$ values of 0.71 [-], which is statistically significant (one-tailed, at 99% confidence) even after allowances have been made for over-sampling in both time and space (see Sect. 2.3). Note that all calibrated parameters ($W$ and $K_{\text{PM}}$) are constant in both space and time and therefore cannot provide a spurious source of skill for $d\delta_P/\delta t$ temporal variations. In addition, all calibration is against GRACE-based $d\delta_G/\delta t$ and $P - Q - E_T$ fields are used solely for the purpose of independent verification.

While $P - Q - E_T$ derived in medium-scale basins cannot be directly validated against GRACE-based $d\delta_G/\delta t$ retrievals (due to the ground resolution of GRACE being much coarser than the size of the medium-scale basins), the significant correlation in Fig. 7 strongly suggests that they are adequately representing the net annual flux of water into and out of the medium-scale basins. A slight reduction in correlation (from 0.71 to 0.62 [-]) is found when $P - Q - E_T$ is not corrected to close water balance over the 8-year study period. Likewise, replacing ALEXI $E_T$ with NOAH-based $E_T$ leads to another (very) slight reduction in correlation in Fig. 7 (from 0.71 to 0.69 [-]). However, it should be stressed that, in all cases, the correlation between $d\delta_G/\delta t$ and plotted $P - Q - E_T$ remains statistically significant (one-tailed, at 95% confidence). See Fig. 4 for $d\delta_P/\delta t$ time series results within individual medium-scale basins.

4.4 Downscaling evaluation

An important follow-on question is the degree to which the skill demonstrated in Fig. 7 enhances our ability to track $dS/\delta t$ in medium-scale basins above and beyond existing GRACE products. To this end, Fig. 8a plots annual GRACE-based $d\delta_G/\delta t$ versus $P - Q - E_T$ for all medium-scale basins. Since the ground resolution of GRACE is significantly coarser than the size of these basins, it is unfair to evaluate $d\delta_G/\delta t$ based on these comparisons. However, despite this severe resolution penalty, $d\delta_G/\delta t$ still manages to correlate relatively well (i.e., a linear correlation of 0.66 [-]) with independently acquired estimates of annual $P - Q - E_T$. The tendency for skill in GRACE-based $d\delta_G/\delta t$ to persist even at these (sub-resolution) scales implies that annual $dS/\delta t$ fields in this region contain spatial auto-correlation at length scales finer than the GRACE spatial resolution. However, it should be stressed that the use of GRACE-based $d\delta_G/\delta t$ fields at these spatial resolutions is...
not recommended and applied here only to define a baseline upon which to evaluate the benefits of subsequent downscaling using microwave-based $d\Delta P_{\text{PM}} / dt$ estimates.

To this end, Fig. 8b plots the relationship between annual $P - Q - E_T$ and $d\Delta S / dt$ estimates obtained via a simple downscaling strategy based on the direct averaging of annual $d\Delta S_{\text{GR}} / dt$ and $d\Delta S_{\text{PM}} / dt$ estimates for each medium-scale basin. Relative to GRACE-only results presented in Fig. 8a, this simple downscaling strategy leads to a significant improvement in the degree of correlation with independent $P - Q - E_T$ values. Specifically, this correlation is increased from 0.66 [−] for the GRACE-only $d\Delta S_{\text{GR}} / dt$ case in Fig. 8a to 0.77 [−] for the case of averaging $d\Delta S_{\text{GR}} / dt$ and $d\Delta S_{\text{PM}} / dt$ in Fig. 8b. Application of a Fisher $z$-transformation and the effective degree sample size calculation presented in Sect. 2.3 confirms that this increase in correlation is statistically significant (two-tailed, at 95% confidence).

In order to further examine geographic trends in results, Fig. 9 evaluates $d\Delta S_{\text{PM}} / dt$, $d\Delta S_{\text{GR}} / dt$, and downscaling results (based on the simple linear averaging of $d\Delta S_{\text{PM}} / dt$ and $d\Delta S_{\text{GR}} / dt$) obtained individually for each medium-scale basin in Table 2. Results are shown for both the linear correlation and absolute RMSD match with annual $P - Q - E_T$ variations. It is reasonable to expect that the accuracy of microwave-based $\theta$ retrievals, and thus their value as the basis of $d\Delta S / dt$ estimates, should progressively degrade for higher-numbered study basins (which generally have wetter climates and denser vegetation coverage – see Fig. 1).

Therefore, it is somewhat surprising that no clear trend between basin land cover and the relative performance of the microwave-based $d\Delta S_{\text{PM}} / dt$ proxy is discernible in Fig. 9. However, $d\Delta S_{\text{PM}} / dt$ results demonstrate relatively poor accuracy for the furthest northern (and most heavily cultivated) basin (i.e., basin #7) and for the wettest basin (i.e., basin #16). The downscaled results (based on the simple averaging of $d\Delta S_{\text{PM}} / dt$ and $d\Delta S_{\text{GR}} / dt$) generally produce results which are superior to the isolated application of either $d\Delta S_{\text{PM}} / dt$ or $d\Delta S_{\text{GR}} / dt$; however, basin-to-basin variations are large and metric values for individual basins are impacted by considerable sampling errors.

It is possible to replicate the $d\Delta S_{\text{PM}} / dt$ approach applied to the medium-scale basins for the larger-scale basins listed in Table 1. However, large-scale $d\Delta S_{\text{PM}} / dt$ proxies calculated in this way (not shown) are significantly less accurate than GRACE-based $d\Delta S_{\text{GR}} / dt$ results, and there is no indication that a microwave-based $d\Delta S_{\text{PM}} / dt$ proxy can consistently improve upon the relative accuracy of annual $d\Delta S / dt$ in large basins beyond what is already possible via the utilization of existing GRACE-based $d\Delta S_{\text{GR}} / dt$. As a result, the added benefits of a microwave-based $d\Delta S_{\text{PM}} / dt$ proxy appear to be limited to basins which cannot be directly resolved by GRACE.
5 Discussion

PM-based estimates of surface soil moisture capture only soil water storage variations occurring within the couple of centimeters of the vertical soil column and cannot directly detect storage dynamics occurring in deeper layers of the unsaturated zone – to say nothing of even deeper variations in groundwater storage or reservoir storage. However, despite this severe theoretical limitation, PM surface soil moisture retrievals ($\theta$) appear to retain significant value as an indicator of relative interannual variations in $P - Q - E_T$ (see e.g., Fig. 7). This implies that, at least at an annual timescale and for certain conditions, unobserved components of $dS / dt$ are sufficiently correlated with observable trends in surface soil moisture such that $\theta$ retrievals may serve as a potential proxy for variations in total terrestrial water storage. Given the difference of 2 orders of magnitude in the spatial resolution of microwave-based $\theta$ (1000 km²) versus gravity-based (200 000 km²) $dS / dt$ estimates, the microwave-based proxy appears to enhance our existing ability to close the terrestrial water budget within the medium scale (2000–10 000 km²) basins listed in Table 2 (Fig. 8).

Intuitively, the ability of surface $\theta$ retrievals to capture (much deeper) $dS / dt$ variations is likely due to the tendency for (non-anthropogenic) variations in $dS / dt$ to be forced, in a “top-down manner”, by atmospherically driven anomalies in $P$ and $E_T$. In this simple conceptual model, variations in surface soil moisture provide a leading indicator of these anomalies as they are propagated downward into deeper hydrologic storage units (Chagnon, 1987; Entekhabi et al., 1992; Swenson et al., 2008). However, it must be stressed that this conceptual model is likely to break down for a number of cases. For example, storage variations due to direct groundwater pumping (Rodell et al., 2009), particularly when associated with increased surface soil moisture via irrigation, will almost certainly confound the ability of $\theta$ retrievals to effectively capture $dS / dt$. Likewise, it is difficult to imagine microwave-based $\theta$ providing an effective representation of $dS / dt$ due to large changes in reservoir storage and/or river system management. Finally, even in cases lacking significant anthropogenic modifications of the hydrologic cycle, the relationship between soil moisture and groundwater memory is known to vary significantly as a function of climate (Lo and Famiglietti, 2010). Some modes of soil moisture–groundwater interactions are almost certainly inconsistent with the application of Eqs. (4)–(6). Therefore, additional study is required to better understand the geographic limitations of $dSPM / dt$ as a credible $dS / dt$ proxy.

The geographic scope of this study was limited by two considerations. First, the evaluation analysis required access to sufficiently accurate annual $P - Q - E_T$ time series to serve as an independent benchmark for microwave-based $dSPM / dt$ estimates. As discussed in Sect. 2, this requirement restricts the geographic domain over which the analysis can currently be conducted. Second, the long-term AMSR-E LPRM soil moisture dataset utilized in the analysis has known limitations within areas of moderate and/or dense vegetation cover. Datasets based on lower-frequency L-band observations are currently being produced but will require 2 or 3 more years (beyond 2017) to match the temporal length of the existing AMSR-E data record. However, once longer-term L-band datasets become available, they will enable the expansion of this analysis into more densely vegetated areas.

Our decision to calculate annual flux quantities using a calendar year (i.e., 1 January to 31 December) approach is admittedly arbitrary. This choice may impact the accuracy of $dSPM / dt$ proxy estimates due to seasonal variations in the availability and accuracy of remotely sensed soil moisture retrievals acquired from PM remote sensing (due to, e.g., vegetation phenology and/or the presence of snow or frozen soils). In order to directly examine this issue, results in Fig. 8 were re-generated using a 1 September to 31 August annual time period. Relative to earlier 1 January to 31 December results, this new annual definition resulted in less skill for both estimates of interannual storage change (i.e., a reduction in correlation from 0.66 to 0.39 (−) for $dS_{GR} / dt$ results in Fig. 8a and from 0.77 to 0.54 (−) for the simple average of $dSPM / dt$ and $dS_{GR} / dt$ in Fig. 8b). However, the relative improvement seen when incorporating $dSPM / dt$ remained statistically significant (two-tailed, at 95% confidence). The reason for the reduction in performance is unclear; however, the added value of the microwave-based $dSPM / dt$ retrievals appears to be robust regardless of whether the fixed annual period is defined to end during the summer (31 August) or the winter (31 December). A more detailed sensitivity analysis involving a more continuous range of annual end dates is possible; however, it is complicated by the relatively small number of annual cycles currently available for this analysis and thus the tendency to significantly change temporal sampling supports when accommodating changes in the definition of an annual period.

The targeting of annual variations in $S$ is motivated by the need to address important questions surrounding interannual variations in the hydrologic cycle. However, a natural extension of this work is the application of $dSPM / dt$ at a finer timescale. In theory this is possible; however, a seasonally varying $W$ and/or $K_{PM}$ parameterization would likely be required for $dSPM / dt$ to accurately capture monthly variations in total water storage. Given that monthly $dSPM / dt$ variations are commonly dominated by a fixed seasonal cycle, it is then challenging to discern whether any apparent skill in monthly $dSPM / dt$ variations is real or simply an artefact of over-fitting a seasonally varying parameterization. As a result, the objective validation of a monthly $dSPM / dt$ proxy will require the availability of longer $dSPM / dt$ and $P - Q - E_T$ datasets capable of supporting mutually exclusive calibration and validation time periods.
6 Conclusions

Advances in the remote sensing of $E_T$ currently afford an opportunity to independently verify other annual components of the terrestrial water budget—including changes in terrestrial water storage ($dS/\text{dr}$). Confirming recent work with GRACE, results demonstrate the importance of $dS/\text{dr}$ for closing the annual water budget. In particular, GRACE-based $dS_{GR}/\text{dr}$ estimates appear to provide a reliable source of such information within large-scale river basins with relatively low annual snowfall totals and anthropogenic management (Figs. 2–3). In addition, for basins smaller than the 200 000 km$^2$ GRACE spatial resolution, estimates of $dS_{PM}/\text{dr}$ derived from PM remote sensing and Eqs. (4)–(6) also demonstrate clear value for providing annual closure information (Fig. 7). Given that PM-based soil moisture retrievals are available at substantially finer spatial resolution than gravity-based retrievals of $dS/\text{dr}$, this opens up the strong possibility of using microwave-based surface soil moisture retrievals to downscale gravity-based $dS/\text{dr}$ retrievals (Fig. 8).

The retrieval of the microwave-based $dS_{PM}/\text{dr}$ proxy is based on two—somewhat ad hoc—assumptions expressed in Eqs. (4)–(6) which claim that (1) $dS_{PM}/\text{dr}$ obtained via Eq. (4) has a linear underlying relationship with $dS/\text{dr}$ and (2) the constant of proportionality in the relationship can be derived via variance matching between microwave- and gravity-based estimates of $dS/\text{dr}$. These assumptions are directly supported by empirical results presented in Figs. 5 and 6. Nevertheless, it should be stressed that theoretical support for Eqs. (4)–(6) is still quite weak, and it is relatively easy to imagine cases in which these assumptions would be expected to fail (see Sect. 5). Therefore, additional validation work over a wider variety of conditions is certainly required. Likewise, an objective intercomparison between this approach and earlier downscaling approaches based on higher-resolution land surface model output (e.g., Reager et al., 2015; Wan et al., 2015) is warranted.

In addition to isolating potential value in microwave-based $dS_{PM}/\text{dr}$ estimates, water balance results presented here also provide confidence regarding our ability to capture annual variations in $dS/\text{dr}$ via Eq. (1) and flux observations. In particular, both annual $dS_{GR}/\text{dr}$ and $dS_{PM}/\text{dr}$ estimates exhibit a statistically significant correlation against independent annual $P - Q - E_T$ values within the medium-scale basins examined here (Fig. 7). Terrestrial $E_T$, in particular, is commonly perceived to represent a weak link in the characterization of Eq. (1). However, based on results presented here, it appears that ALEXI-based $E_T$ products over CONUS are now sufficiently accurate (at least in a relative interannual sense) for annual $E_T$ estimates to be used as a viable constraint to infer the accuracy of other water budget components. This is a marked improvement over the calculation of $E_T$ as a balance residual and opens the door to the fuller use of Eq. (1) as a diagnostic tool for various water balance products.

Data availability. All yearly, basin-averaged data products used in this analysis are available upon request from the corresponding author.

Competing interests. The authors declare that they have no conflict of interest.

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