Supplement of

How well are we able to close the water budget at the global scale?

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Additional figures

**Figure S1.** Coefficient of variation between different sets of precipitation datasets. Satellite: TRMM, GPM, and GPCP. Observations: CPC, CRU, and GPCC. Reanalyses: ERA5 Land, JRA55, and MERRA2. Inter-category: mean of satellite, observations, and reanalyses.
Figure S2. Coefficient of variation between different sets of evapotranspiration datasets. Remote sensing: FLUXCOM, GLEAM, MOD16, and SSEBop. Land surface models: CLSM, Noah, and VIC with versions 2.0 and 2.1. Reanalyses: ERA5 Land, JRA55, and MERRA2. Inter-category: mean of remote sensing, LSMS, and reanalyses.
Figure S3. Coefficient of variation between different sets of runoff datasets. Land surface models: CLSM, Noah, and VIC with versions 2.0 and 2.1. Reanalyses: ERA5 Land, JRA55, and MERRA2. Inter-category: GRUN, mean of LSMs, and mean of reanalyses.
Figure S4. Distribution of the maximum NSE over all combinations in terms of basin area
Figure S5. Components of the water budget in the Amazon basin for the combination leading to the highest NSE.
Figure S6. Correlation between monthly values of GRACE TWSC and the budget reconstruction in the Amazon basin, with the combination leading to the highest NSE (NSE=0.92 and cyclostationary NSE=-1.28)
Figure S7. Components of the water budget in the Niger basin for the combination leading to the highest NSE
Figure S8. Correlation between monthly values of GRACE TWSC and the budget reconstruction in the Niger basin, with the combination leading to the highest NSE (NSE=0.94 and cyclostationary NSE=0.62)
Figure S9. Number of combinations yielding a positive cyclostationary NSE in each basin. Grey means that no combination achieved a positive value.
Figure S10. 132 basins with a maximum NSE larger than 0.8 or a maximum $NSE_c$ larger than 0.1. The distance between basins is the Euclidean distance between the vector of costs for each combination. The height of the U-shaped link is proportional to this distance. Basins are clustered to minimize the intra-cluster variance and colored basins are those selected to plot Fig. ??
Figure S11. Same as ?? but for evapotranspiration datasets.
Figure S12. The mean of the 10th highest NSE with combinations comprising the reference dataset is compared to the mean of the 10th highest NSE excluding the reference dataset. Yellow indicates basins where the reference dataset is similar to or better than others while blues show regions where it was significantly worse. Hatches show basins with a poor water budget closure (maximum NSE lower than 0.8 and maximum $NSE_c$ lower than 0.1).
Figure S13. Same as ?? but for runoff datasets.
**Figure S14.** The mean of the 10th highest NSE with combinations comprising the reference dataset is compared to the mean of the 10th highest NSE excluding the reference dataset. Yellow indicates basins where the reference dataset is similar to or better than others while blues show regions where it was significantly worse. Hatches show basins with a poor water budget closure (maximum NSE lower than 0.8 and maximum $NSE_c$ lower than 0.1).
Figure S15. Components of the water budget in the Mackenzie basin with all components from GLDAS2.2 CLSM (assimilating GRACE TWS)
**Figure S16.** Legend of Fig. S17, S18, S19, S20
Figure S17. Datasets appearing in combinations that satisfy a cost lower than 0.1 for each basin separately. The top line of each basin bar represents precipitations datasets. The left part of the bottom line is evapotranspiration datasets while the right part is runoff. The limit between ET and R is symbolized by a black line located proportionally to the portion of ET in the mean annual water cycle of the corresponding region, explaining while the bottom line may have a length different than 100%. Basins are ordered according to hierarchical clustering (dendrogram in Fig. S10). The color legend for datasets can be found in Fig. S16.
Figure S18. Following of Fig. S17
Figure S20. Following of Fig. S19
Additional tables
| Name             | Method                     | Period            | Spatial resolution | Reference                                      |
|------------------|----------------------------|-------------------|-------------------|------------------------------------------------|
| CPC Unified      | Rain-gauge                 | 1979 - present    | 0.5° x 0.5°       | Chen and Xie (2008)                            |
| CRU v4.04        | Rain-gauge                 | 1901 - 2019       | 0.5° x 0.5°       | Harris et al. (2020)                           |
| GPCP v.2.3       | Rain-gauge and satellite   | 1979 - present    | 2.5° x 2.5°       | Schneider et al. (2020)                        |
| GPM IMERG v.06   | Satellite                  | 2000 - present    | 0.1° x 0.1°       | Huffman et al. (2019)                          |
| TRMM (TMPA/3B43) | Satellite                  | 1998 - 2019       | 0.25° x 0.25°     | Huffman et al. (2007, 2010)                    |
| JRA55            | Reanalysis                 | 1958 - present    | ~0.5° x 0.5°      | Morin and Sahaibari (2019)                     |
| JRA55            | Reanalysis                 | 1981 - present    | 0.1° x 0.1°       | Kobayashi et al. (2015); Harada et al. (2016) |
| MERRA2           | Reanalysis                 | 1980 - present    | 0.625° x 0.625°   | Reichle et al. (2017)                          |
| PGF              | Rain-gauge, Satellite, and Reanalyses | 1948 - 2014            | 1.0° x 1.0°       | Sheffield et al. (2006)                        |
| MSWEP 2.8        | Rain-gauge, Satellite, and Reanalyses | 1979 - present                        | 0.1° x 0.1°       | Beck et al. (2019)                             |
### Table S2. Evapotranspiration datasets

| Name              | Method                           | Period     | Spatial resolution | Reference                                      |
|-------------------|----------------------------------|------------|--------------------|------------------------------------------------|
| GLDAS2.0 CLSM2.5  | Land surface model               | 1948 - 2014| 1.0° x 1.0°        | Li et al. (2020a); Koster et al. (2000)        |
| GLDAS2.1 CLSM2.5  | Land surface model               | 2000 - 2020| 1.0° x 1.0°        | Li et al. (2020a); Koster et al. (2000)        |
| GLDAS2.2 CLSM2.5  | Land surface model               | 2003 - 2020| 0.25° x 0.25°      | Li et al. (2019, 2020a)                        |
| GLDAS2.0 NOAH3.6  | Land surface model               | 1948 - 2014| 1.0° x 1.0°        | Beaudoin et al. (2019); Chen et al. (1996)    |
| GLDAS2.1 NOAH3.6  | Land surface model               | 2000 - 2020| 1.0° x 1.0°        | Beaudoin et al. (2019); Chen et al. (1996)    |
| GLDAS2.0 VIC4.1.2 | Land surface model               | 1948 - 2014| 1.0° x 1.0°        | Beaudoin et al. (2020); Liang et al. (1994)   |
| GLDAS2.1 VIC4.1.2 | Land surface model               | 2000 - 2020| 1.0° x 1.0°        | Beaudoin et al. (2020); Liang et al. (1994)   |
| FLUXCOM           | Machine learning (remote sensing only) | 2001 - 2015| 0.5° x 0.5°        | Jung et al. (2019)                             |
| GLEAM v3.3a       | Priestley-Taylor                 | 1980 - 2018| 0.25° x 0.25°      | Martens et al. (2017); Miralles et al. (2011) |
| MOD16             | Penman-Monteith                  | 2000-2015  | 0.5° x 0.5°        | Mu et al. (2011)                               |
| SSEBop            | Surface energy balance           | 2003 - 2020| 0.5° x 0.5°        | Senay et al. (2013)                            |
| ERA5 Land         | Reanalysis (Penman-Monteith)     | 1981 - present| 0.1° x 0.1°      | Muñoz-Sabater (2019)                          |
| JRA55             | Reanalysis (JMA Simple Biosphere SiB) | 1958 - present| 0.5° x 0.5°      | Kobayashi et al. (2015); Harada et al. (2016) |
| MERRA2            | Reanalysis (Penman-Monteith)     | 1980 - present| 0.5° x 0.625°     | Gelaro et al. (2017)                          |
Table S3. Components of the mean annual water cycle in Pacific islands

|          | P (mm/year) | ET (mm/year) | R (mm/year) |
|----------|-------------|--------------|-------------|
| SEPIK    | 3390 ± 653  | 1404 ± 223   | 2116 ± 597  |
| MAMBERAMO| 3578 ± 851  | 1340 ± 227   | 2406 ± 756  |
| MAHAKAM  | 3163 ± 356  | 1359 ± 272   | 1911 ± 529  |
| KAPUAS   | 3666 ± 204  | 1366 ± 266   | 2339 ± 480  |

The first value is the mean annual cycle averaged over all datasets while the second one is the standard deviation of mean annual values over all datasets.
Table S4. Components of the mean annual water cycle in equatorial rain forest/monsoon basins in South America

|Basin| P (mm/year) | ET (mm/year) | R (mm/year) |
|-----|-------------|--------------|-------------|
|MAGDALENA| 2339 ± 650 | 1157 ± 216 | 1373 ± 498 |
|CUYUNI| 2051 ± 269 | 1395 ± 223 | 766 ± 327 |
|ESSEQUIBO| 2121 ± 251 | 1314 ± 217 | 946 ± 405 |
|MARONI| 2312 ± 247 | 1406 ± 269 | 885 ± 364 |
|AMAZON| 2177 ± 172 | 1251 ± 196 | 958 ± 251 |
|ORINOCO| 2269 ± 289 | 1237 ± 200 | 1090 ± 315 |

The first value is the mean annual cycle averaged over all datasets while the second one is the standard deviation of mean annual values over all datasets.
Table S5. Values of NSE and cyclostationary NSE using GRDC as the only runoff dataset compared to the maximum over all other runoff datasets.

| Basin name   | maximum $NSE$ with all sources of runoff | maximum $NSE$ with GRDC runoff | maximum $NSE_c$ with all sources of runoff | maximum $NSE_c$ with GRDC runoff | months among 2003-2014 with available runoff data (in %) |
|--------------|-----------------------------------------|---------------------------------|-------------------------------------------|---------------------------------|--------------------------------------------------------|
| AMAZON       | 0.90                                    | 0.98                            | -1.49                                     | 0.49                            | 100.0                                                  |
| AMUR         | 0.59                                    | 0.90                            | 0.46                                      | 0.87                            | 31.9                                                   |
| CONGO        | 0.86                                    | 0.87                            | 0.18                                      | 0.22                            | 66.0                                                   |
| DANUBE       | 0.90                                    | NaN                             | 0.63                                      | NaN                             | 0.0                                                    |
| LENA         | 0.83                                    | NaN                             | -0.23                                     | NaN                             | 0.0                                                    |
| MACKENZIE    | 0.89                                    | 0.91                            | -0.01                                     | 0.19                            | 100.0                                                  |
| MISSISSIPPI  | 0.93                                    | 0.94                            | 0.47                                      | 0.53                            | 84.4                                                   |
| OB           | 0.92                                    | 0.96                            | 0.23                                      | 0.61                            | 66.0                                                   |
| ORANGE       | 0.34                                    | 0.20                            | 0.20                                      | 0.03                            | 100.0                                                  |
| PARANA       | 0.90                                    | 0.90                            | 0.69                                      | 0.68                            | 95.0                                                   |
| VOLGA        | 0.92                                    | 0.94                            | 0.45                                      | 0.58                            | 66.0                                                   |
| YANGTZE      | 0.75                                    | NaN                             | 0.21                                      | NaN                             | 7.1                                                    |
| YELLOW RIVER | 0.74                                    | NaN                             | 0.50                                      | NaN                             | 7.1                                                    |
| YENISEY      | 0.92                                    | 0.94                            | 0.27                                      | 0.41                            | 74.5                                                   |
| YUKON        | 0.90                                    | 0.93                            | 0.11                                      | 0.36                            | 100.0                                                  |

From the large basins used in Li et al. (2020b), only those with an area matching the discharge area from GRDC gauge stations were selected. The maximum $NSE$ (resp. $NSE_c$) with GRDC runoff was computed over combinations of P and ET from all available datasets, and R from GRDC measurements in basins with at least 66% of months available. In basins with less available months, NaN refers to no computation. The two other columns are the maximum over the 1694 combinations of all P, ET, and R datasets.
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