**Text S1. Methods for estimating glacier water storage**

To be consistent with TWSA data, changes in glacier volume, , can be converted into changes in glacier water storage represented as equivalent water height (EWH), , through Eq. (S1):

, (S1)

where and refer to the density of ice and the area of pixel, respectively. The units for , , , and are m3, kg/m3, m2, and kg/m2 (equiv. to mm), respectively.

**Text S2. Methods for estimating permafrost water storage**

Changes in permafrost water storage, , can be indirectly estimated from changes in active layer thickness (ALT), , by applying Eq. (S2) (Xiang et al., 2016; Zou et al., 2022).

, (S2)

where is the porosity of soil and rock in the bottom of active layer and is set to 0.4352 m3/m3 (same as soil porosity of perennial land ice defined in JRA-55); and are the density of ice and water, respectively; is the ice content in the permafrost with an upper limit of 20% (Zhang et al., 2008); is the residual water content in the increased active layer and is determined to be 7.93% (Gouttevin et al., 2012).

**Text S3. Methods for estimating pixel-wise lake and reservoir water storage**

The temporal resolution of GLWS is near-monthly and was resampled to monthly by using linear interpolation. The water storage data are archived lake by lake instead of grid by grid. To allow for spatial analysis, we first identified the geographical locations of all grids intersecting with a given lake or reservoir at a 0.5º🞩0.5º resolution based on the vector boundaries derived from HydroLAKES dataset. Next, pixel-wise water storage for the given lake or reservoir can be obtained through Eq. (S3).

, (S3)

where and are the total water storage and area of the lake or reservoir, respectively; and are the allocated water storage and intersecting area of the th grid, respectively.

**Text S4. Principles of PSM simulation in CLSM**

Inspired by Famiglietti and Wood (1994), Koster et al. (2000) and Ducharne et al. (2000) proposed CLSM in 2000 by coupling a classic hydrological model, TOPMODEL (Beven and Kirkby, 1979), with the parameterization of surface energy and water fluxes from Mosaic LSM. Based on the concepts of TOPMODEL, the distribution of water table depth can be inferred from that of topographic index. Subsequently, the distribution of water table depth is applied to derive catchment deficit (CD), which is defined as the water amount required to saturate the entire catchment under the assumption that vertical moisture profile in the unsaturated zone arises from hydrostatic equilibrium. In addition, two variables that take into account non-equilibrium conditions are defined in CLSM, namely surface excess (SE) and root zone excess (RE). SE and RE quantify the deviations of surface soil moisture and root zone soil moisture, respectively, from the value implied by the equilibrium profile. Richards equation is used to solve the vertical water fluxes between CD, SE, and RE, which contribute to bringing the vertical moisture profile closer to the equilibrium profile (Gascoin et al., 2009).

**Text S5. Data processing of multi-source RZSM simulations**

The stratification of root zone is 0–100 cm for GLDAS CLSM and MERRA-2; 0–10 cm, 10–40 cm, and 40–100 cm for GLDAS Noah and FLDAS Noah; and 0–7 cm, 7–28 cm, and 28–100 cm for ERA5-Land. In terms of unit, RZSM is represented as water storage (kg/m2, equiv. to mm) in GLDAS Noah and GLDAS CLSM, volumetric water content (m3/m3) in FLDAS Noah and ERA5-Land, and relative moisture (%) in MERRA-2. To be comparable with PSM, RZSM should be quantified by water storage consistently. To this end, RZSM for GLDAS Noah and GLDAS CLSM was determined as the summation of water storage in different layers. As for FLDAS Noah and ERA5-Land, RZSM can be obtained through Eq. (S4) with FLDAS Noah as an example.

, (S4)

where and are the volumetric water content and thickness of the th layer, respectively. is the total number of soil layers. As for MERRA-2, relative soil moisture should first be converted into volumetric water content by multiplying by soil porosity derived from CLSM. was then calculated as the product of volumetric water content and root zone depth (100 cm), as shown in Eq. (S5).

, (S5)

**Text S6. Methods for obtaining ensemble estimation through BTCH**

Taking RZSM as an example, the ensemble estimation can be obtained through Eq. (S6) and Eq. (S7).

, (S6)

, (S7)

where is the total number of datasets to be integrated (=5 for RZSM); is the weight of the th dataset; is the error variance of the th dataset.

**Text S7. Evaluation metrics of RF models**

, (S8)

, (S9)

, (S10)

where is the th PSM value simulated by CLSM; is the th PSM value predicted by RF; is the average of all . Higher R2 and lower rRMSE indicate greater explanatory power and accuracy of the RF model.

**Text S8. Component contribution ratio**

To quantify the contribution of a given individual storage component to the interannual variability of TWS, the component contribution ratio (CCR) proposed by Kim et al. (2009) was employed, as shown in Eq. (S11) and Eq. (S12).

, (S11)

, (S12)

where denotes the mean absolute deviation (MAD) of an individual storage component (e.g., canopy water storage); is the long-term mean of during the study period; is the number of years; is the number of storage components.

**Text S9. Discussion on the influence factors of PSM modelling**

In the RF-based modelling of CLSM-simulated PSM, CLSM-simulated RZSM achieved the highest importance among the four predictors across 97.17% of global grid cells (Fig. S2), implying the feasibility of improving PSM simulations by optimizing RZSM. Despite this, CLSM-simulated RZSM outperformed other RZSM products only in 16.10% of global grid cells (Fig. S3). The optimal RZSM product was characterized by strong spatial heterogeneity without any dominant patterns, which underscored the significance of integrating multi-source RZSM simulations for PSM prediction. Furthermore, the relative importance of RZSM varied with climate conditions. Specifically, it was more important in humid regions than in drylands as illustrated by scaled importance (Fig. S4). This implied the weaker correlation between RZSM and PSM in drylands, which explained the lower R2 of RF models in drylands mentioned in Sect. 4.1.2, given that RZSM was the foremost predictor of PSM. We attributed the differences across climatic zones to the higher susceptibility to decoupling of RZSM and PSM in drylands, which was consistent to Carranza et al. (2018) who identified decoupling of surface and subsurface SM under arid conditions with in situ data.

For the remaining 2.83% of global grid cells, NDVI emerged as the dominant predictor variable for PSM modelling in most regions, accounting for 2.08% of global grid cells in total. Specifically, NDVI exhibited predominant impacts on PSM dynamics in the band between the Sahara Desert and the Congo Basin, the east coast of Africa, eastern South America, and northern Australia (Fig. S2). Interestingly, this spatial pattern closely aligned with the global distribution of deep-rooted regions predicted by Schenk and Jackson (2005) via climate-based model, highlighting the critical role of vegetation activity in regulating regional water storage variability. To further investigate the relationship between vegetation and water storage, the spatiotemporal variations of the sole vegetation-associated TWS component, i.e., canopy water storage (CWS), were analyzed (Fig. S5). However, the spatial pattern of CWS failed to match that of the variable importance of NDVI. The reason may be that CWS cannot adequately represent vegetation water storage, which was not quantified in this study due to its markedly smaller magnitude of variation compared to other components at the global scale (Rodell et al., 2005). Building on these findings, we suggest that vegetation water storage should be underscored in the hotspots of vegetation-PSM interactions to enhance the understanding of regional water storage evolution in future studies.

**Table S1. Consideration of non-groundwater components in previous studies.**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Reference | Study area | glaciers | permafrost | lakes and reservoirs | surface runoff | snow | canopy water | soil moisture |
| Yi et al. (2016) | China | 🞩 | 🞩 | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 |
| Lv et al. (2021) | China | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🗸 |
| Zhao et al. (2023) | China | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🗸 |
| Lin et al. (2020) | Lhasa River Basin | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 | 🞩 | 🗸 |
| Zhu and Zhang (2022) | Yangtze River Basin, Yellow River Basin | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🗸 |
| Liu et al. (2023) | northwest China | 🞩 | 🞩 | 🗸 | 🗸 | 🗸 | 🗸 | 🗸 |
| Peng et al. (2021) | Central Asia | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🗸 |
| Forootan et al. (2017) | the Middle East | 🞩 | 🞩 | 🗸 | 🞩 | 🗸 | 🗸 | 🗸 |
| Nikraftar et al. (2024) | the Middle East | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🞩 | 🗸 |
| Shin et al. (2021) | Nepal | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🗸 | 🗸 |
| Montecino et al. (2016) | Northern Chile | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 | 🞩 | 🗸 |
| Sproles et al. (2015) | Canada | 🞩 | 🞩 | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 |
| Zhu et al. (2022) | Canada | 🞩 | 🞩 | 🞩 | 🞩 | 🗸 | 🞩 | 🗸 |

**Table S1 (continued). Consideration of non-groundwater components in previous studies.**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Reference | Study area | glaciers | permafrost | lakes and reservoirs | surface runoff | snow | canopy water | soil moisture |
| Muskett and Romanovsky (2011) | Alaska | 🞩 | 🞩 | 🞩 | 🗸 | 🞩 | 🞩 | 🞩 |
| Wang et al. (2022) | North America | 🞩 | 🞩 | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 |
| Xanke and Liesch (2022) | Euro-Mediterranean region | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🞩 | 🗸 |
| Muskett and Romanovsky (2009) | Arctic | 🞩 | 🞩 | 🞩 | 🗸 | 🞩 | 🞩 | 🞩 |
| Lin et al. (2022) | Arctic | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🞩 | 🗸 |
| Jin and Feng (2013) | Global | 🞩 | 🞩 | 🞩 | 🗸 | 🗸 | 🗸 | 🗸 |
| Xiang et al. (2016) | Tibetan Plateau | 🗸 | 🗸 | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 |
| Zhang et al. (2017) | Tibetan Plateau | 🗸 | 🗸 | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 |
| Zou et al. (2022) | Tibetan Plateau | 🗸 | 🗸 | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 |
| Fan et al. (2023) | northern Himalayas | 🗸 | 🗸 | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 |
| Li et al. (2023) | China | 🗸 | 🞩 | 🗸 | 🗸 | 🗸 | 🗸 | 🗸 |
| Liu et al. (2020) | Asia and eastern Europe | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 | 🗸 | 🗸 |
| Wang et al. (2018) | global endorheic basins | 🗸 | 🞩 | 🗸 | 🞩 | 🗸 | 🗸 | 🗸 |

**Table S2. Interannual trends in igGWSA, GWSAnoGLA, and GlacierWSA in glacier-covered regions.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Region | igGWSA | GWSAnoGLA | GlacierWSA | Region | igGWSA | GWSAnoGLA | GlacierWSA |
| Global | −0.19\*\* | −4.03\*\* | −3.85\*\* | Region 10 | 0.58\*\* | 0.30\*\* | −0.28\*\* |
| Region 1 | 4.92\*\* | −8.87\*\* | −13.79\*\* | Region 11 | 1.40\*\* | −0.07 | −1.47\*\* |
| Region 2 | 1.41\*\* | 0.04 | −1.36\*\* | Region 12 | −0.04 | −0.64\*\* | −0.60\*\* |
| Region 3 | 3.28\*\* | −10.01\*\* | −13.30\*\* | Region 13 | 0.32\*\* | −0.35\*\* | −0.66\*\* |
| Region 4 | 4.99\*\* | −8.82\*\* | −13.81\*\* | Region 14 | 0.63\*\* | −0.61\*\* | −1.24\*\* |
| Region 5 | −18.79\*\* | −24.72\*\* | −5.92\*\* | Region 15 | 0.58\*\* | −1.53\*\* | −2.10\*\* |
| Region 6 | 12.49\*\* | −7.78\*\* | −20.27\*\* | Region 16 | 0.37\*\* | 0.08 | −0.29\*\* |
| Region 7 | 7.86\*\* | −7.16\*\* | −15.03\*\* | Region 17 | 2.25\*\* | −2.37\*\* | −4.62\*\* |
| Region 8 | 1.73\*\* | 0.47\* | −1.27\*\* | Region 18 | 1.54\*\* | 0.15 | −1.38\*\* |
| Region 9 | −1.42 | −10.36\*\* | −8.95\*\* |  |  |  |  |

Note: Unit: cm/yr. \* indicates significance at the 0.05 level. \*\* indicates significance at the 0.01 level.

**Table S3. Interannual trends in igGWSA, GWSAnoPER, and PWSA in permafrost zones.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Region | igGWSA | GWSAnoPER | PWSA | Region | igGWSA | GWSAnoPER | PWSA |
| Global | 0.08\* | −0.36\*\* | −0.44\*\* | North Asia | 0.30\*\* | −0.14 | −0.44\*\* |
| North America | −0.52\*\* | −0.89\*\* | −0.36\*\* | Tibetan Plateau | 1.70\*\* | 0.63\*\* | −1.08\*\* |
| Europe | 1.86\*\* | 1.04\*\* | −0.82\*\* |  |  |  |  |

Note: Unit: cm/yr. \* indicates significance at the 0.05 level. \*\* indicates significance at the 0.01 level.

**Table S4. Interannual trends in igGWSA, GWSAsimplified, and LRWSA in giant lakes.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Lake | igGWSA | GWSAsimplified | LRWSA | Lake | igGWSA | GWSAsimplified | LRWSA |
| Global | −0.19\*\* | −0.35\*\* | −0.11 | Malawi | 2.60\*\* | −1.32\*\* | −3.92\*\* |
| Caspian Sea | 0.77\* | −4.82\*\* | −5.58\*\* | Great Slave | −0.66\* | −0.74\*\* | −0.09 |
| Great Lakes of NA | −1.74\* | 0.99\*\* | 2.72\*\* | Winnipeg | −0.30 | 0.68\*\* | 0.98 |
| Victoria | −1.45 | 1.56\* | 3.01\*\* | Ladoga | −0.78 | 0.39\* | 1.17 |
| Tanganyika | −0.53 | 0.39 | 0.92 | Balkhash | −1.40\* | −0.04 | 1.36\* |
| Baikal | 0.68\*\* | −0.70\*\* | −1.38\*\* | Aral Sea | 11.46\*\* | −1.15\*\* | −12.60\*\* |
| Great Bear | −0.09 | −0.13\*\* | −0.03 | Lakes of Tibetan Plateau | −2.31\*\* | 0.04 | 2.62\*\* |

Note: Unit: cm/yr. \* indicates significance at the 0.05 level. \*\* indicates significance at the 0.01 level.

**Table S5. Interannual trends in igGWSA, GWSA200, and GWSA289 in deep-soil areas.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Region | igGWSA | GWSA200 | GWSA289 | Region | igGWSA | GWSA200 | GWSA289 |
| Mississippi | −0.08 | −0.08 | −0.03 | Congo | 0.06 | −0.24\*\* | 0.53\*\* |
| Volga | −0.24\* | −0.37\*\* | −0.16\*\* | Songhua-Liaohe | −0.06 | −0.07 | 0.39\* |
| Ob | 0.03 | −0.06 | 0.22\*\* | Pampas | −0.08 | −0.16 | 0.69\*\* |
| Loess Plateau | −0.83\*\* | −0.99\*\* | −0.42\*\* | Ganges-Brahmaputra | −1.09\*\* | −1.25\*\* | −1.24\*\* |

Note: Unit: cm/yr. \* indicates significance at the 0.05 level. \*\* indicates significance at the 0.01 level.

地图

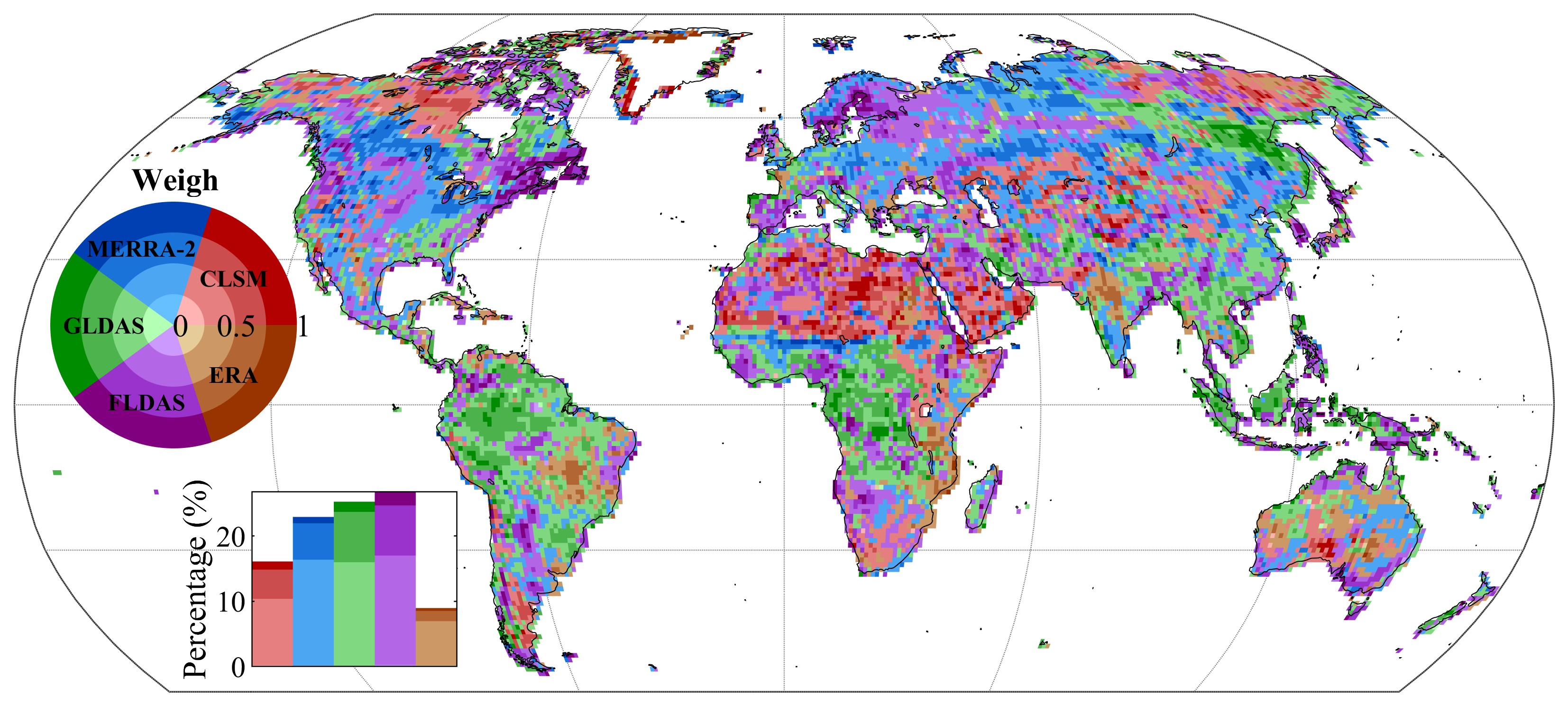
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**Figure S1. Soil depth information defined in GLDAS VIC model.**

地图

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**Figure S2. Map of dominant predictor variable for PSM modelling.**



**Figure S3. Map of the optimal RZSM dataset.**

图表, 条形图

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**Figure S4. Scaled importance of predictor variables for PSM modelling in humid regions and drylands. Note: Scaled importance was derived by setting the value of RZSM to 1 and proportionally scaling the values of other variables.**

图表

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**Figure S5. (a) Map of contribution ratio of canopy water storage (CWS) to TWS variability (unit: %). (b) Map of the multi-year (2000–2019) average of CWS (unit: cm). (c) Map of the interannual trend in CWS (unit: e-04 cm/yr). The three maps consistently revealed that the hotspots of CWS variability were located in tropical rainforest regions, encompassing the Amazon Basin, the Congo Basin, and Southeast Asia. The three maps were made based on the ensemble data of CWS simulations from four LSMs, i.e., GLDAS Noah, GLDAS CLSM, GLDAS VIC, and ERA5-Land. (d) The spatial Pearson's correlation coefficients between the four single-source data and the ensemble data for both multi-year average and interannual trend. \*\* indicates significance at the 0.01 level. The spatiotemporal patterns of CWS revealed by the four single-source data were all highly consistent with the ensemble data, indicating the high robustness of map a, b, and c.**

**References**

Beven, K. J. and Kirkby, M. J.: A physically based variable contributive area model of basin hydrology, Hydrol. Sci. Bull., 24, 43–69, https://doi.org/10.1080/02626667909491834, 1979.

Carranza, C. D. U., van der Ploeg, M. J., and Torfs, P. J. J. F.: Using lagged dependence to identify (de) coupled surface and subsurface soil moisture values, Hydrol. Earth Syst. Sci., 22, 2255-2267, https://doi.org/10.5194/hess-22-2255-2018, 2018.

Ducharne, A., Koster, R. D., Suarez, M. J., Stieglitz, M., and Kumar, P.: A catchment-based approach to modeling land surface processes in a general circulation model 2. Parameter estimation and model demonstration, J. Geophys. Res.: Atmos., 105, 24823-24838, https://doi.org/10.1029/2000jd900328, 2000.

Famiglietti, J. S. and Wood, E. F.: Multiscale modeling of spatially-variable water and energy-balance processes, Water Resour. Res., 30, 3061-3078, https://doi.org/10.1029/94wr01498, 1994.

Fan, L., Kuang, X., Or, D., and Zheng, C.: Streamflow composition and water "imbalance" in the Northern Himalayas, Water Resour. Res., 59, e2022WR034243, https://doi.org/10.1029/2022wr034243, 2023.

Forootan, E., Safari, A., Mostafaie, A., Schumacher, M., Delavar, M., and Awange, J. L.: Large-scale total water storage and water flux changes over the arid and semiarid parts of the Middle East from GRACE and reanalysis products, Surv. Geophys., 38, 591-615, https://doi.org/10.1007/s10712-016-9403-1, 2017.

Gascoin, S., Ducharne, A., Ribstein, P., Carli, M., and Habets, F.: Adaptation of a catchment-based land surface model to the hydrogeological setting of the Somme River basin (France), J. Hydrol., 368, 105-116, https://doi.org/10.1016/j.jhydrol.2009.01.039, 2009.

Gouttevin, I., Krinner, G., Ciais, P., Polcher, J., and Legout, C.: Multi-scale validation of a new soil freezing scheme for a land-surface model with physically-based hydrology, Cryosphere, 6, 407-430, https://doi.org/10.5194/tc-6-407-2012, 2012.

Jin, S. and Feng, G.: Large-scale variations of global groundwater from satellite gravimetry and hydrological models, 2002-2012, Global Planet. Change, 106, 20-30, https://doi.org/10.1016/j.gloplacha.2013.02.008, 2013.

Kim, H., Yeh, P. J. F., Oki, T., and Kanae, S.: Role of rivers in the seasonal variations of terrestrial water storage over global basins, Geophys. Res. Lett., 36, L17402, https://doi.org/10.1029/2009gl039006, 2009.

Koster, R. D., Suarez, M. J., Ducharne, A., Stieglitz, M., and Kumar, P.: A catchment-based approach to modeling land surface processes in a general circulation model 1. Model structure, J. Geophys. Res.: Atmos., 105, 24809-24822, https://doi.org/10.1029/2000jd900327, 2000.

Li, Q., Pan, Y., Zhang, C., and Gong, H.: Quantifying multi-source uncertainties in GRACE-based estimates of groundwater storage changes in mainland China, Remote Sens., 15, 2744, https://doi.org/10.3390/rs15112744, 2023.

Lin, H., Cheng, X., Zheng, L., Peng, X., Feng, W., and Peng, F.: Recent changes in groundwater and surface water in large Pan-Arctic river basins, Remote Sens., 14, 607, https://doi.org/10.3390/rs14030607, 2022.

Lin, L., Gao, M., Liu, J., Wang, J., Wang, S., Chen, X., and Liu, H.: Understanding the effects of climate warming on streamflow and active groundwater storage in an alpine catchment: the upper Lhasa River, Hydrol. Earth Syst. Sci., 24, 1145-1157, https://doi.org/10.5194/hess-24-1145-2020, 2020.

Liu, Q., Xu, Y., Chen, J., and Cheng, X.: Multi-source satellite reveals the heterogeneity in water storage change over northwestern China in recent decades, J. Hydrol., 624, 129953, https://doi.org/10.1016/j.jhydrol.2023.129953, 2023.

Liu, X., Feng, X., Ciais, P., and Fu, B.: Widespread decline in terrestrial water storage and its link to teleconnections across Asia and eastern Europe, Hydrol. Earth Syst. Sci., 24, 3663-3676, https://doi.org/10.5194/hess-24-3663-2020, 2020.

Lv, M., Ma, Z., and Yuan, N.: Attributing terrestrial water storage variations across China to changes in groundwater and human water use, J. Hydrometeorol., 22, 3-21, https://doi.org/10.1175/jhm-d-20-0095.1, 2021.

Montecino, H. C., Staub, G., Ferreira, V. G., and Parra, L. B.: Monitoring groundwater storage in northern Chile based on satellite observations and data simulation, Bol. Cienc. Geod., 22, 1-15, https://doi.org/10.1590/s1982-21702016000100001, 2016.

Muskett, R. R. and Romanovsky, V. E.: Groundwater storage changes in arctic permafrost watersheds from GRACE and in situ measurements, Environ. Res. Lett., 4, 045009, https://doi.org/10.1088/1748-9326/4/4/045009, 2009.

Muskett, R. R. and Romanovsky, V. E.: Alaskan permafrost groundwater storage changes derived from GRACEand ground measurements, Remote Sens., 3, 378-397, https://doi.org/10.3390/rs3020378, 2011.

Nikraftar, Z., Parizi, E., Saber, M., Hosseini, S. M., Ataie-Ashtiani, B., and Simmons, C. T.: Groundwater sustainability assessment in the Middle East using GRACE/GRACE-FO data, Hydrogeol. J., 32, 321-337, https://doi.org/10.1007/s10040-023-02717-3, 2024.

Peng, Q., Wang, R., Jiang, Y., Li, C., and Guo, W.: The change of hydrological variables and its effects on vegetation in Central Asia, Theor. Appl. Climatol., 146, 741-753, https://doi.org/10.1007/s00704-021-03730-w, 2021.

Rodell, M., Chao, B. F., Au, A. Y., Kimball, J. S., and McDonald, K. C.: Global biomass variation and its geodynamic effects: 1982-98, Earth Interact, 9, 1–19, https://doi.org/10.1175/ei126.1, 2005.

Schenk, H. J. and Jackson, R. B.: Mapping the global distribution of deep roots in relation to climate and soil characteristics, Geoderma, 126, 129-140, https://doi.org/10.1016/j.geoderma.2004.11.018, 2005.

Shin, S., Pokhrel, Y., Talchabhadel, R., and Panthi, J.: Spatio-temporal dynamics of hydrologic changes in the Himalayan river basins of Nepal using high-resolution hydrological-hydrodynamic modeling, J. Hydrol., 598, 126209, https://doi.org/10.1016/j.jhydrol.2021.126209, 2021.

Sproles, E. A., Leibowitz, S. G., Reager, J. T., Wigington, P. J., Jr., Famiglietti, J. S., and Patil, S. D.: GRACE storage-runoff hystereses reveal the dynamics of regional watersheds, Hydrol. Earth Syst. Sci., 19, 3253-3272, https://doi.org/10.5194/hess-19-3253-2015, 2015.

Wang, H., Xiang, L., Steffen, H., Wu, P., Jiang, L., Shen, Q., Li, Z., and Hayashi, M.: GRACE-based estimates of groundwater variations over North America from 2002 to 2017, Geod. Geodyn., 13, 11-23, https://doi.org/10.1016/j.geog.2021.10.003, 2022.

Wang, J., Song, C., Reager, J. T., Yao, F., Famiglietti, J. S., Sheng, Y., MacDonald, G. M., Brun, F., Schmied, H. M., Marston, R. A., and Wada, Y.: Recent global decline in endorheic basin water storages, Nat. Geosci., 11, 926-932, https://doi.org/10.1038/s41561-018-0265-7, 2018.

Xanke, J. and Liesch, T.: Quantification and possible causes of declining groundwater resources in the Euro-Mediterranean region from 2003 to 2020, Hydrogeol. J., 30, 379-400, https://doi.org/10.1007/s10040-021-02448-3, 2022.

Xiang, L., Wang, H., Steffen, H., Wu, P., Jia, L., Jiang, L., and Shen, Q.: Groundwater storage changes in the Tibetan Plateau and adjacent areas revealed from GRACE satellite gravity data, Earth Planet. Sci. Lett., 449, 228-239, https://doi.org/10.1016/j.epsl.2016.06.002, 2016.

Yi, S., Wang, Q., and Sun, W.: Basin mass dynamic changes in China from GRACE based on a multibasin inversion method, J. Geophys. Res.: Solid Earth, 121, 3782-3803, https://doi.org/10.1002/2015jb012608, 2016.

Zhang, G., Yao, T., Shum, C. K., Yi, S., Yang, K., Xie, H., Feng, W., Bolch, T., Wang, L., Behrangi, A., Zhang, H., Wang, W., Xiang, Y., and Yu, J.: Lake volume and groundwater storage variations in Tibetan Plateau's endorheic basin, Geophys. Res. Lett., 44, 5550-5560, https://doi.org/10.1002/2017gl073773, 2017.

Zhang, T. J., Barry, R. G., Knowles, K., Heginbottom, J. A., and Brown, J.: Statistics and characteristics of permafrost and ground-ice distribution in the Northern Hemisphere, Polar Geogr., 31, 47-68, https://doi.org/10.1080/10889370802175895, 2008.

Zhao, K., Fang, Z., Li, J., and He, C.: Spatial-temporal variations of groundwater storage in China: a multiscale analysis based on GRACE data, Resour. Conserv. Recycl., 197, 107088, https://doi.org/10.1016/j.resconrec.2023.107088, 2023.

Zhu, Q. and Zhang, H.: Groundwater drought characteristics and its influencing factors with corresponding quantitative contribution over the two largest catchments in China, J. Hydrol., 609, 127759, https://doi.org/10.1016/j.jhydrol.2022.127759, 2022.

Zhu, Y., Myint, S. W., Schaffer-Smith, D., Sauchyn, D. J., Xu, X., Piwowar, J. M., and Li, Y.: Examining ground and surface water changes in response to environmental variables, land use dynamics, and socioeconomic changes in Canada, J. Environ. Manage., 322, 115875, https://doi.org/10.1016/j.jenvman.2022.115875, 2022.

Zou, Y., Kuang, X., Feng, Y., Jiao, J. J., Liu, J., Wang, C., Fan, L., Wang, Q., Chen, J., Ji, F., Yao, Y., and Zheng, C.: Solid water melt dominates the increase of total groundwater storage in the Tibetan Plateau, Geophys. Res. Lett., 49, e2022GL100092, https://doi.org/10.1029/2022gl100092, 2022.