Recent global decline in endorheic basin water storages

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Endorheic (hydrologically landlocked) basins spatially concur with arid/semi-arid climates. Given limited precipitation but high potential evaporation, their water storage is vulnerable to subtle flux perturbations, which are exacerbated by global warming and human activities. Increasing regional evidence suggests a probably recent net decline in endorheic water storage, but this remains unquantified at a global scale. By integrating satellite observations and hydrological modelling, we reveal that during 2002–2016 the global endorheic system experienced a widespread water loss of about 106.3 Gt yr−1, attributed to comparable losses in surface water, soil moisture and groundwater. This decadal decline, disparate from water storage fluctuations in exorheic basins, appears less sensitive to El Niño–Southern Oscillation-driven climate variability, which implies a possible response to longer-term climate conditions and human water management. In the mass-conserved hydrosphere, such an endorheic water loss not only exacerbates local water stress, but also imposes excess water on exorheic basins, leading to a potential sea level rise that matches the contribution of nearly half of the land glacier retreat (excluding Greenland and Antarctica). Given these dual ramifications, we suggest the necessity for long-term monitoring of water storage variation in the global endorheic system and the inclusion of its net contribution to future sea level budgeting.

Global endorheic basins (Fig. 1a), in which surface flow is landlocked from the ocean, cover one-fifth of the Earth's land surface but nearly half of its water-stressed regions1. Many arid and semi-arid regions are inherently endorheic, with surface flow unable to break topographic barriers and retained in a landlocked storage that equilibrates through evaporation2. As surface flow is scarce in endorheic regions, water storage, particularly in sizable lakes, reservoirs and aquifers, becomes of vital ecological and social importance. Endorheic water storage can be maintained only if the system fluxes, chiefly through precipitation, evaporation and groundwater exchanges, remain in a delicate balance. However, recent climate change, notably warming and drying in many arid/semi-arid regions3–5, has triggered observable perturbations to the endorheic water balance, intensified further by human water withdrawals, damming and diversions4–6. Regional evidence of storage declines has been seen for decades in desiccating lakes (for example, the Aral Sea and Great Salt Lake)3,4, retreating glaciers (for example, Tibetan and Amu Darya)4,10, depleting aquifers (for example, Arabian and Persian)11, suggesting a likely enduring decline of the total terrestrial water storage (TWS) within the global endorheic system.

In the mass-conserved hydrosphere, a net endorheic water deficit not only aggravates water stress in endorheic regions, but also imposes the same amount of water surplus on the exorheic system, where surface flow reaches the ocean. Therefore, a persistent TWS decline in global endorheic basins signifies a potential source of sea level rise (SLR). The rate of SLR averaged at ~1.9 mm yr−1 during the past half century7, and increased to ~3.4 mm yr−1 in the current millennium despite occasional hiatuses due to El Niño–Southern Oscillation (ENSO)8–10. About 65–80% of the recent decadal SLR was attributed to ocean thermal expansion (~1.1–1.4 mm yr−1) and ice-sheet mass loss in Greenland and Antarctica (~1.1–1.3 mm yr−1). The other ~20–35% was induced by the net TWS change that integrates mountain glacier and ice cap (GIC) loss, groundwater depletion, reservoir impoundment and mass changes in other stores (for example, lakes, soil and permafrost)11–13. Some of these TWS changes, however, were assessed without a discrete consideration of endorheic and exorheic origins, which may overestimate their individual impacts on the sea level budget. For example, glacial meltwater that originates from endorheic basins produces no direct excess discharge to the exorheic system14, and reservoirs in endorheic basins do not detain runoff that otherwise drains to the ocean. Owing to observation changes, studies that explicitly assessed endorheic contributions are limited to major terminal lakes that are often considered as basin-wide integrators of climatic and hydrological conditions15–17. Particular emphases were given to the strikingly desiccating Aral Sea and the world’s largest endorheic lake, the Caspian Sea, where the water level has shown cyclic fluctuations but an overall lowering since the end of the Little Ice Age (~2 cm yr−1)18. Budget changes in these two lakes and their affected groundwater, if a complete loss to exorheic regions via vapour transfer is assumed, contributed a potential SLR of ~0.1–0.2 mm yr−1 at recent decadal

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Aside from regional evidence, the overall magnitude and spatial pattern of endorheic TWS decline have not been quantified at a global scale, and its net contribution to recent SLR remains unclear. Here we determine the mass changes in TWS throughout the world’s endorheic basins and the potential impact on SLR during the early twenty-first century. Our monitored TWS is the vertical integration of all water forms on and below the continental surface, where net mass changes were inverted from time-variable gravity fields observed by NASA’s Gravity Recovery and Climate Experiment (GRACE) satellites. We used the monthly mass anomalies during April 2002 through March 2016, from the Jet Propulsion Laboratory mass concentration block (mascon) solution. This solution isolated TWS signals by removing the noise from the solid earth and improved spatial resolution over conventional spherical-harmonic solutions. Monthly mascon anomalies were rescaled to 173 endorheic units (Fig. 1a), each aggregated from refined landlocked watersheds until the size exceeded a mascon. Scaled endorheic mass changes were partitioned into the contributions of surface water, soil moisture and groundwater to contrast the possible attributions in different regions. We implemented an ensemble of multiple hydrological models (Supplementary Table 1) to derive monthly anomalies in soil moisture and part of surface water compartments, such as snowpack and plant canopies. The modelled surface water anomalies were further corrected by storage variations in major lakes/reservoirs estimated from altimetric and/or optical satellite observations (Supplementary Figs. 1–10) and mass changes in GIC derived from stereo imagery (Supplementary Fig. 11 and Supplementary Tables 2 and 3). By subtracting the corrected anomalies in the land water content from the net TWS changes, we disaggregated the groundwater contribution from those of surface water and soil moisture. Detailed data processing and uncertainty analysis are given in Methods.
Net endorheic storage loss and impacts on sea level

Our results confirm a widespread TWS decline within the global endorheic system during the studied 14 years (Fig. 1). Net water loss prevails in about three-quarters of the endorheic units in area (23.2 out of 31.8 million km\(^2\)) or number (129 out of 173), agglomerated particularly along the water-stressed subtropical ridge in Central Asia, the Middle East and northern Africa (Fig. 1a). In total, the global endorheic system has undergone a net storage change of \(-106.32 \pm 11.70\) Gt yr\(^{-1}\) (uncertainties are in the 95% confidence intervals). This is about twice the rate of concurrent TWS changes from the entire exorheic region \((-58.44 \pm 27.75\) Gt yr\(^{-1}\), excluding Greenland and Antarctica), although the endorheic area is only one-fifth of the global land-mass (Fig. 1b,c). Although the signature in exorheic TWS anomalies is closely linked to ENSO-driven climate variability (Fig. 2), with prominent positive/negative TWS anomalies during La Niña/El Niño events, endorheic anomalies appear less sensitive to such interannual modulations (Supplementary Fig. 12 and Supplementary Table 4 give other climate oscillations). This contrast highlights the possible significance of longer-term climate conditions (for example, multidecadal variability and anthropogenic warming) and direct human water management and Supplementary conditions (for example, multidecadal variability and anthropogenic warming) and direct human water management and Supplementary Table 4 give other climate oscillations). This contrast highlights the possible significance of longer-term climate conditions (for example, multidecadal variability and anthropogenic warming) and direct human water management and Supplementary Information.

Regional variation and links to climate and human actions

Despite a net global decline, the change of endorheic TWS exhibits an intriguing regional variation. On the one hand, our map of TWS trends for individual endorheic units (Fig. 1a) shows exacerbated water scarcity in many of the world’s drought hotspots. These include not only drainage basins under intense human influences, such as those of the Caspian Sea, Aral Sea, Lake Urmia, Balkhash Lake and Great Salt Lake, but also remote or sparsely populated deserts in Africa (for example, Sahara), Central Asia (for example, Taklamakan and Gobi), the Middle East (for example, Arabian), South America (for example, Atacama), western United States (for example, Great Basin and Mojave) and western Australia (for example, Great Sandy and Gibson). TWS declines in these hotspots accentuate the evident impact of recent meteorological drought on arid/semi-arid regions, which is often intertwined with human-induced evaporative loss through surface water diversion, damming and groundwater abstraction. On the other hand, water losses across most of the endorheic land-mass contrast markedly with water gains in the Inner Tibetan Plateau (ITP), eastern Australia, Sahel, Great Rift Valley, Kalahari Desert (southern Africa) and northern Great Basin and Great Plains (North America). However, these water gains are more spatially constrained and are dominantly induced by natural variability (Supplementary Information).

To contrast regional variation further, we group global endorheic basins by continent and climatic similarities into six primary zones (Fig. 3a), with TWS anomalies and changing trends compared in Fig. 3b–h and Table 1. Approximately two-thirds of the global endorheic water loss \((-73.64 \pm 7.74\) Gt yr\(^{-1}\)) stems from Central Eurasia, the largest zone, which covers one-third of the endorheic land-mass. Water loss within Central Eurasia generally weakens along an eastward gradient, as illustrated in four secondary zones. Over half of the total zonal loss is concentrated on the Caspian Sea Basin alone, 10% on the Aral Sea Basin (including nearby watersheds that receive transbasin diversions) but largely balanced out by the water gain in ITP, and the other \(-40%\) from across the remaining basins. Monthly TWS anomalies in Central Eurasia exhibit a strong monotonic decline since 2005, despite an earlier increase linked to the rise of the Caspian Sea level\(^{13}\), and a water gain in ITP that persisted for more than a decade (Fig. 3h).

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multiple decades but has decelerated since ~2013. The TWS in the vast desert zone of Sahara and Arabia underwent a continuous decrease throughout 2002–2016, resulting in the other one-third of the net global loss (−33.10 ± 3.57 Gt yr⁻¹). A marked storage decline also prevailed in Dry Andes and Patagonia (−9.61 ± 1.96 Gt yr⁻¹), but has slowed down and partially reversed since 2012. Net water losses in Australia and Western North America are less dramatic (−4.05 ± 4.86 and −2.53 ± 2.00 Gt yr⁻¹, respectively) due to spatial dipole and short-term fluctuations. For instance, Australia’s Millennium Drought was temporarily alleviated by La Niña-induced precipitation anomalies in the eastern region (for example, the Great Artesian Basin) during 2010–2012. Water declines in the latter three zones sum up to another 15% of the net global endorheic loss, which is, however, counteracted by the water gain in Great Rift Valley/Southern Africa (GRVSA, 16.60 ± 2.28 Gt yr⁻¹).

**Contributions of different water storage components**

The net TWS changes aggregate the contributions of different hydrological components (Fig. 4 and Table 1). The net global endorheic loss during the past 14 years is attributed to comparable declines in surface water (36.08 ± 9.89%), soil moisture (26.36 ± 7.46%) and groundwater (37.56 ± 16.57%), but such contributions result from highly unequal partitions among zonal TWS changes. In Central Eurasia, surface water loss outweighs that of soil moisture and is more than double that of groundwater (Fig. 4c). The prominent surface water loss can be observed by the recent shrinkage of many large lakes across Central Asia and the Middle East (for example, Aydar, Aral Sea, Bosten, Caspian Sea, Khyargas, Tengiz and Urmia (Supplementary Fig. 2)). In particular, over 70% of the global endorheic surface water loss was induced by the level drop in the Caspian Sea (~6.8 cm yr⁻¹). Another ~11% was caused by the desiccation of the Aral Sea (~1,041.7 km² yr⁻¹) despite the compensation of excess discharge from warming-induced glacier melting (Supplementary Figs. 5–8 and Supplementary Table 5). Surface water losses in these two basins coincided with a drying climate (deficient precipitation and rising temperature (Supplementary Fig. 13o–r)), along with intensive water diversion (for example, from the Volga River, Amu Darya and Syr Darya) for irrigation, which supplemented moisture supplies for evapotranspiration. Diversion-based irrigation may have also increased the regional return flow and resulted in possible groundwater recharge despite the overall soil moisture loss (Fig. 4d,e). In contrast, increasing precipitation and, to a lesser extent, warming-induced glacier loss led to the evident lake expansion in ITP (Supplementary Fig. 13s,t and Supplementary Table 5), where surface water surplus explains over 80% of the net TWS gain (Fig. 4f). As water relocation from glaciers to lakes does not alter the endorheic system storage, the increasing net precipitation (that is, precipitation minus evapotranspiration) is the primary contributor to the net TWS gain, which is in line with recent literature. Surface freshwater is critically limited in the remaining endorheic zone of Central Eurasia (Fig. 4g), where groundwater withdrawal easily exceeds the natural recharge. Similar to river diversion, groundwater depletion might enhance evapotranspiration by cumulatively transferring water from aquifers to the surface, which explains 68% of the zonal TWS loss.

A greater dominance of groundwater depletion to net TWS loss is seen in Australia (Fig. 4h) and Sahara and Arabia (Fig. 4j),
where endorheic basins often retain aridic and groundwater becomes the only permanent water source. In Sahara and Arabia, for instance, annual groundwater depletion (−33.23 ± 4.37 Gt yr\(^{-1}\)) matches the rate of the zonal TWS loss. Our estimate is similar to that of Richey et al.\(^7\) (about −29 ± 6 Gt yr\(^{-1}\) during 2003–2013) if one sums up their estimated depletions of major aquifers, which include Arabian Aquifer, Nubian Aquifer, Northwestern Sahara, Murzuk-Djado Basin, Taoudeni-Tanezrouft Basin and Lake Chad Basin, although these authors did not correct the modelled surface anomalies by lake storage changes (for example, a minor increase in Lake Chad). In addition to the unsustainable human water withdrawals, groundwater declines in these desert zones may result from vadose capillary fluxes that transport water from aquifers to compensate for soil moisture loss\(^3\). Such declines are in sharp contrast to the groundwater gain in GRVSA (16.54 ± 2.70 Gt yr\(^{-1}\) (Fig. 4i)), which indicates persistent recharge as a result of excess precipitation (Supplementary Fig. 13i,j).

In Western North America, a climate-induced soil moisture decrease (Supplementary Fig. 13c,d) dominates the net TWS loss (Fig. 4i). Meanwhile, studies\(^5,31,39\) suggest that human activities, such as irrigation and mining, are crucial causes of the surface water decline in Great Salt Lake (−0.20 Gt yr\(^{-1}\), consistent with −0.17 Gt yr\(^{-1}\) in Wurtsbaugh et al.\(^3\)) and Salton Sea\(^4\) (−0.11 Gt yr\(^{-1}\)) (Supplementary Fig. 2), which accounts for 12% of the zonal TWS loss. The contribution is more evenly partitioned among surface, soil and aquifers in Dry Andes and Patagonia (Fig. 4k), where a quarter of the net TWS loss stems from the shrinkage of Lakes Titicaca, Poopó and Mar Chiquita (Supplementary Fig. 2). Such concurrent losses in multiple water stores imply an extensive impact of the recent precipitation deficit (Supplementary Fig. 13e,f) and human activities on South America’s endorheic hydrology\(^5,34,42\).

**Implications for global water cycle**

Our findings reveal the recent decadal TWS decline in global endorheic basins, which largely outweighs the concurrent TWS change in the exorheic region. Although exorheic TWS modulates the sea level by directly affecting runoff to the ocean, it is also subject to natural variability of the climate system (for example, ENSO at multiyear timescales) that augments or suppresses the delivery of water from the ocean\(^5,14\). Another perspective, we show that endorheic TWS, albeit limited in quantity, can dominate the variation in global TWS at decadal timescales. This decadal loss in endorheic TWS suggests that recent climate conditions, in conjunction with direct human activities, resulted in a substantial vapour outflow from the continental interiors. The consequential water surplus to the exorheic system might be acting as a non-negligible source of SLR. Limited by the available TWS observations, our calculated trend may not imply a secular signal beyond the studied GRACE era. Nevertheless, this decadal endorheic loss is in line with satellite-observed decreases in surface water extents since ~1980\(^1,31\), model-simulated increases in water stress over the past half century\(^42,43\) and reported declines in water volumes of major saline lakes over the past ~40 years\(^5\), all predominantly in arid/semi-arid regions. Under the latest climate change scenarios, the reversal of such a net decline in the next half/one century seems uncertain given the projected decreases in precipitation, soil moisture and discharge but increases in potential evaporation, drought duration and water stress in many endorheic regions\(^15,44–48\).
Apart from a widespread net TWS loss, we quantify that the loss prevails comparably in all three primary hydrological stores (surface, soil and aquifers). However, their relative contributions vary among endorheic zones, which results from a strong spatial heterogeneity in flux–storage interactions and responses to climate and water management. As detailed in Methods and Supplementary Information, our partitioning of TWS losses relies on a synergy of multimodel ensemble and satellite observations, and emphasizes different components in the water cycle rather than attributions to natural variability versus secular forces. Despite uncertainties, our analysis exemplifies a critical effort towards the decoupling of climate–human influences on the recent TWS shift from endorheic to exorheic systems. This analytical decoupling is essential to project and manage water stress in arid-semi-arid regions under future climate change. Given such dual ramifications both to regional water sustainability and to global SLR, we thereby suggest a continued understanding of long-term TWS variation in global endorheic basins, and an explicit inclusion of its net contribution (such as by the Intergovernmental Panel on Climate Change) in future sea level budgeting.

Online content
Any methods, additional references, Nature Research reporting summaries, source data, statements of data availability and associated accession codes are available at https://doi.org/10.1038/s41561-018-0265-7.

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**Author contributions**
J.W. and C.S. conceived the presented study and performed the analysis. Y.S. initiated the separation of endorheic and exorheic basins. F.B. contributed to data analysis of glacier mass changes. Y.W. and H.M.S. provided model simulations and contributed to water balance analyses. F.Y. participated in model validations and lake storage analysis. J.W., J.T.R. and C.S. developed and conducted the assessment of mascon rescaling uncertainties, with constructive feedback from Y.W. and F.Y. Y.W., G.M.M., J.S.F. and H.M.S. contributed to data analysis of the separation of endorheic and exorheic basins. F.B. contributed to data analysis of glacier mass changes. Y.W. and H.M.S. provided model simulations and contributed to water balance analyses. F.Y. participated in model validations and lake storage analysis. J.W., J.T.R. and C.S. developed and conducted the assessment of mascon rescaling uncertainties, with constructive feedback from Y.W. and F.Y. Y.W., G.M.M., J.S.F. and H.M.S. and R.A.M. provided critical insights on method design and result interpretation. J.W. wrote the initial draft of the paper, with substantial contributions from all authors.

**Competing interests**
The authors declare no competing interests.

**Additional information**
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Methods

Defining endorheic regions. Endorheic basin extents were mainly acquired from a total of 48,813 landlocked watersheds identified in the 15 hydroSHEDS drainage basin data set1 (Supplementary Fig. 14a). Their spatial patterns are overall consistent with the depiction in the Global Drainage Basin Database17,18. Among minor discrepancies, ten watersheds landlocked in ITP, Manchuria, Siberia and western United States were captured only in Global Drainage Basin Database (Supplementary Fig. 14a), and thus included to supplement hydroSHEDS. These watersheds were aggregated into three enumeration scales: (1) 173 endorheic units (Fig. 1b), appearing as a 3-5-degree or larger mascons in size of a 3-degree spherical cap (~100,000,000 km²), (2) ten endorheic zones (Fig. 3a), which include six primary zones in the continental level and four secondary zones within Central Eurasia and (3) the entire global endorheic system, that is, the aggregated extent of all landlocked basins. Each endorheic unit, as further illustrated in Supplementary Fig. 14b, is a single landlocked watershed if its size exceeds a mascon, or an agglomeration of landlocked/nearby watersheds if their total area exceeds a mascon. These units exclude sporadic landlocked watersheds smaller than a mascon and substantially detached from major endorheic clusters (black areas in Fig. 1a). The secondary zones of the Caspian Sea Basin and the Aral Sea Basin (Fig. 3a) include several surrounding endorheic watersheds to compensate for the GRACE signal leakage from the Caspian Sea and the Aral Sea. The Aral Sea Basin also integrates nearby endorheic watersheds that receive transbasin diversions from the Amu Darya and the Syr Darya.

Calculating endorheic TWS changes. GRACE-observed monthly anomalies of equivalent water thickness (EWT) from April 2002 to March 2016 in the JPL-3 degree equal-area C20 solution (JPL-RLSM version 2)8,19,20 were rescaled to each enumeration level (unit, zonal and global) by an area-weighted scaling, M = Σm/m'Σm, where M denotes a monthly anomaly for any enumeration region, m, the original anomaly in each mascon i that intersects with this region and a, the intersection area. The desasonalized time series M with (monthly climatology removed) was used to calculate the TWS trend by best-fit linear regression. The RL05M solution provides 0.5-degree gain factors simulated by the Community Land Model27. However, this model lacks surface water compartments (for example, lakes and glaciers) and human processes, and the least-squares correction in the factor derivation tends to be dominated by the annual cycles of land water storage variations. Despite a partial recovery of the signal at the time scale of the mascon, the gain factors may not be suitable for calculating TWS trends at submascon resolution. For these reasons, they were not applied in our rescaling process. Instead, rescaling-induced uncertainties were accounted for in our estimated zonal and global trends.

Specifically, uncertainties (εm) of monthly M in each enumeration region were propagated from the measurement errors (ε) associated with original mascon data and the rescaling uncertainties (εr) induced by signal leakage in fringe mascons. Similar to M, a monthly εm was calculated as ∑m/m'Σm, where ε denotes the provided data uncertainty for each mascon i that intersects with this region. To infer ε, we computed the intersection area (ai) as a proportion (P) of each mascon (Supplementary Fig. 15). A fringe mascon is indicated by a value of P between 0 and 1 (hereafter the internal fringe portion). For each month, we first calculated the average of the EWT trend in the mascon polygon (available under a unit of mascon) by a step of 0.05 and calculated the average anomaly (M) in the full mascons with P ≥ 0.5, until i = 0 (that is, all the fringe mascons are included). In this way, M gradually picks up the missing signal within this endorheic region as the internal fringe portion decreases. Meanwhile, it absorbs increasing signal leakage as the external fringe portion expands. The variance of M, therefore, reflects the uncertainty of signal scaling at submascon resolution. Given this logic, the standard deviation in the array of M, (Supplementary Fig. 16) was used as a measure of this monthly ε. The time series εm and the variation of residuals from the trend fitting were then propagated to infer a 95% confidence interval of the TWS trend using a Monte Carlo method, as in Wang et al.55.

To further evaluate our estimated TWS changes, we determined how the EWT trend in each region changes from its endorheic interior to its periphery. This was done by calculating the linear trend in monthly M, with a gradually lowered t, as shown in Supplementary Fig. 17 (blue profiles). For each region under a non-decline, a rising profile implies that the rate of water loss tends to weaken as one moves away from the endorheic interior. If we assume that this pattern is also true at submascon scales, the magnitude of EWT decline in the internal portion of a fringe mascon would be greater than that in the external portion. Our signal scaling is based on a simple area partitioning of the fringe mascons that reflect the actual water loss in the peripheral endorheic areas (where signals of weaker decline leak into the internal portions), which leads to an overall conservative TWS trend for this enumeration region. This case applies to the entire endorheic system and to most zones that experienced TWS declines. The exception in Dry Andes and Puna (Supplementary Fig. 17c) is probably attributable to the complex endorheic boundary (Supplementary Fig. 15a) and the leakage of stronger EWT declines from the eoxerich Andes. In the Aral Sea Basin, fully enclosed mascons are found in the Amu Darya and Syr Darya regions (Supplementary Fig. 15c), but the most significant water loss occurred in the Aral Sea. This explains the weak initial decline (when P = 1 (Supplementary Fig. 17j) in this region. As P continues to decrease, the EWT trends are overall stable (Supplementary Fig. 17i, big black profile) despite the increased leakage of water loss signals over the Aral Sea (Supplementary Fig. 17b, blue profile). Similarly, a decreasing profile for any region under a net TWS gain implies that our estimated TWS increase is probably underrated. This is seen in the GRVSA (Supplementary Fig. 17e) and ITP (Supplementary Fig. 17f). However, as their total water gain accounts for a small proportion (~17%) of the total water loss in the other regions, our reported net TWS decline in global endorheic basins is overall conservative (Supplementary Fig. 17a).

Although our results did not apply the mascon set of 0.5-degree gain factors, their impact was assessed by comparing EWT trends calculated with versus without the gain factors for each endorheic zone (black and red profiles in Supplementary Fig. 17). As an inclusion of gain factors was already accounted for in our rescaling at submascon resolution, the EWT trends at each t were calculated from the average anomalies within the intersected or internal mascon portions (where P ≥ 0.5). The profiles illustrate how EWT trends between the two solutions (with and without gain factors) increasingly differ as more incomplete mascons are included in the rescaling. The two solution profiles appear highly consistent in each zone, and their divergence is enclosed by the 95% confidence intervals induced by the inherent mascon data errors (transparent shades). Therefore, including the gain factors will make no significant difference to the estimation of global/zonal TWS trends.

Estimating lake storage changes. We calculated storage changes in 142 large watersheds (a total area of ~540,000 km² (Supplementary Figs. 1 and 2)) that account for ~75% of the lakes/reservoirs in area and ~98% in volume across endorheic basins26,28. Level time series during our study period were collected from multimission altimeter observations (for example, Envisat, Jason, TOPEX/Poseidon and SARAL/AltiKa), as archived in the Database for Hydrological Time Series of Inland Water (https://dahiti.dgfi.tum.de/en), the HydroWeb2 (http://hydroweb.theia-land.fr) and the United States Department of Agriculture G-REALM (www.pecad.fas.usda.gov/cropexplorer/global reservoir). Hypsometry was considered for 38 (87% in area) of the 142 lakes, where level-area functions for the eight largest lakes (7%) were calibrated in this study using time-variable inundation areas mapped from MODIS (Moderate Resolution Imaging Spectroradiometer) imagery (250-m MOD09Q1) (Supplementary Figs. 3–10) and the level-area functions for the other 30 lakes (8%) were retrieved from the HydroWeb. For each of these 38 lakes, time series volume anomalies were calculated as the integrals of the hypsometric function from the average water level, and the mean volume seasonality was further removed for linear trend fitting. Volume anomalies in each of the remaining 104 lakes (13%) were approximated by water level time series that were assumed to vary with a static inundation area mapped from Landsat imagery acquired during 2008–2009 (representing the middle-stage extent during our study period) using methods in Sheng et al.54.

Multiple error sources were identified to propagate the uncertainties of lake volume anomalies, which were then used to infer the 95% confidence intervals for lake storage trends by the Monte Carlo method27 (as for TWS trends). For the eight lakes with calibrated hypsometries, error sources include (1) level uncertainties provided in the altimetric data, (2) mapping errors for the inundation areas, estimated from a relative bias of 5% in MODIS-based large waterbody extraction61 and related hypsometries, calculated as the mean square error of each fitted level-area function (Supplementary Figs. 3–10). For each of the remaining 134 lakes, the trend confidence interval was propagated from source (1), and another error term that attempts to reflect the overall uncertainty due to the unknown fitting errors in the hypsometries retrieved from HydroWeb (for the 30 lakes), the ignored lake area variation (for the other 104 lakes) and gaps in the acquired level time series. We quantified this error term to be 14% (95% confidence interval) of each lake storage trend, inferred from the eight lakes for which storage trends estimated using HydroWeb hypsometries or only water levels were validated against the estimates using our calibrated hypsometries. For the other smaller waterbodies for which storage changes were unquantified in our study, we considered that, in total, they generate a 95% uncertainty of 10 Gt yr⁻¹. If the lake volume change is assumed to be proportional to the lake area (akin to a simple bucket model in which water budget variations reflect precipitation–evaporation residuals multiplied by the bucket cap size), we have one-third of the net annual water loss in our studied 142 lakes to be ~10 Gt yr⁻¹. This uncertainty was partitioned to different endorheic zones by their total small waterbody areas.

Estimating glacier mass changes. Changes in glacier mass balance were estimated for three secondary zones in Central Eurasia (ITP, the Aral Sea Basin and Others (Fig. 4a)) that contain ~98% of the total glacier extent in global endorheic basins (Supplementary Fig. 11). Our estimations were based on the 30 m gridded data set of glacier surface elevation (h) changes (hereafter dh/dt) from 2000 to 2016 in High Mountain Asia (HM A). The rates of dh/dt were derived by fitting a linear regression through time series of co-registered digital elevation models (DEMs) constructed from ASTER stereoimages during 2000–2016. Details are given in Brun et al.51.
We obtained 132 dh/dt maps (in a 1° grid with estimation uncertainties) that cover the endorheic HMA. Pixels over non-glacierized regions were masked by the Randolph Glacier Inventory 6.0. Over the glacierized regions, pixels with absolute dh/dt rates above 50 m yr\(^{-1}\) were excluded as noise. Similar to others\(^{1,39,40}\), glacier-hypsometry averages were used to represent the average dh/dt for region-wide units. To reduce the uncertainty due to the spatial heterogeneity of glacier changes, we divided the glacierized areas into several subregions\(^{41,42}\), which include northwestern ITP, southern ITP, Qilian Mountains, Kunlun Mountains within the Tarim Basin, southern Tian Shan, northern Tian Shan, the Pamirs and the remaining areas. Glacierized areas in each subregion were considered as one virtual contiguous ice body, with the glacier hypsometry calculated using 100 m elevation bands discretized by the ALOS (Advanced Land Observing Satellite) World 3D-30m DEM\(^{43}\). For each elevation band, dh/dt pixel values were filtered to the level of three normalized absolute deviations relative to the median of the elevation band. The dh/dt values were averaged for each elevation band, and the rate of volume change was calculated as the sum of the mean dh/dt multiplied by the glacier area in this band. The volume change was converted into mass multiplied by the glacier area in this band. The volume change was converted into mass assuming a conversion factor of 850±60 kg m\(^{-3}\) (ref. 44) and a negligible difference between the rates in 2000–2016 and 2002–2016. Glacier mass change rates for different elevation bands were then subtotalled to secondary endorheic zones (Supplementary Table 2).

Besides the above-mentioned secondary zones in Central Eurasia, small clusters of glaciers scatter in the Caspian Sea Basin (726 km\(^2\) or 0.02% of the zonal area), Dry Andes and Patagonia (438 km\(^2\) or 0.03%) and Western North America (177 km\(^2\) or 0.01% of the zonal area) (Supplementary Fig. 11 and Supplementary Table 3). By referring to previous studies of glacier changes around these zones\(^{45-48}\), glacier mass changes may only account for miniscule portions of the zonal TWS declines (where glacial changes are largely underlying the TWS change uncertainties (Supplementary Table 3)). For this reason, glacier mass changes in these zones were not explicitly quantified, and instead considered as modelled snow water equivalent (SWE) variations over their glacierized regions.

Partitioning net TWS changes. We partitioned GRACE-observed net TWS changes into surface water, soil moisture and groundwater contributions through a comprehensive synergy of model simulations and satellite observations. Given that some of the frequently used large-scale hydrological models lack surface water and groundwater compartments\(^{49,50}\), we relied on hydrological models only to simulate monthly anomalies in soil moisture, SWE and canopy water. Storage trends in major waterbodies and GIC were derived from multimission satellite measurements (above) and then combined with modelled SWE and canopy water trends to calculate net surface water change (Supplementary Table 5). Eventually, the groundwater contribution was separated as the residual between GRACE-observed TWS change and the estimated surface water and soil moisture changes.

Similar to some existing studies\(^{51,52}\), we considered two widely applied global hydrological models (WGHM\(^{53-56}\) and PCR-GLOBWB\(^{57}\)) and five land surface models (LSMs) from the Global Land Data Assimilation System (GLDAS) (CLM, Mosaic, Noah, VIC and CLSMM) to simulate monthly changes in SWE, canopy water and soil moisture during 2002–2016 (Supplementary Table 1 gives the model descriptions). To account for model discrepancies induced by different climate forcing and parameterizations, we followed a typical ensemble approach, in which the seasonally averaged model time series were averaged to represent monthly anomalies and standard deviations among the model time series as ensemble uncertainties. As the available modelling period for CLSM and PCR-GLOBWB discontinues after 2014, their time series were not included in the calculation of ensemble means. Instead, we compared their time series with the ensemble means from the other five models during 2002–2014, and used the monthly differences to further expand the ensemble uncertainties.

Several studies noticed that the amplitude of soil moisture variation from WGHM is substantially lower than those of other models\(^{57-59}\), which is also seen in our studied endorheic basins (Supplementary Fig. 18). To avoid possible biases in trend calculation, WGHM was excluded from the ensemble of soil moisture anomalies, but was used to derive additional ensemble uncertainties with CLSM and PCR-GLOBWB. We also assumed that during the studied GRACE era, direct irrigation impacts on soil moisture were regional and limited to seasonal timescales, and did not considerably alter the interannual soil moisture trends at zonal/global scales (Supplementary Information). Our modelled soil moisture anomalies were validated against in situ measurements from the Soil Climate Analysis Network (SCAN; www.wcc.nrcs.usda.gov/scan) in endorheic North America (Supplementary Fig. 19). For most SCAN stations, deseasonalized soil moisture time series from measurements and models show significant correlations, and the discrepancies between their interannual trends are within the 95% confidence intervals. Detailed validations are provided in Supplementary Information, Supplementary Figs. 20 and Supplementary Table 6.

As previously described, our glacier mass changes were based on detected elevation changes from stereocorrelated time series DEMs\(^{41}\). These changes include the contributions of both alpine glaciers and snowpack. To avoid double-counting, we replaced modelled SWE over glacierized endorheic HMA by satellite-observed glacier mass changes. This replacement also minimized the influence of modelled SWE errors that are often amplified in alpine environments\(^{5,60}\). To further validate the modelled SWE changes in other regions, we selected endorheic North America with high-quality SWE estimates from the Snow Data Assimilation (SNODAS) product (Supplementary Information). The time series of modelled and SNODAS anomalies show evident differences in magnitude, but agree fairly well in interannual trend (with a discrepancy insignificant to the confidence intervals (Supplementary Fig. 21)). Although this validation is limited in North America, the amount of water stored in the snowpack and canopies in endorheic basins is relatively small. This is reflected by the combined loss of SWE and canopy water (3.6±1.90 Gt yr\(^{-1}\)), which contributes <4% of the global endorheic TWS loss (Supplementary Table 5). Thus, the influence of SWE modelling uncertainties on our TWS partitioning is probably minuscule.

Assessing TWS responses to climate forcing. Climate impacts on TWS changes were assessed by exploring (1) the correlations between annual net TWS changes and total precipitation and (2) the trends in monthly temperature anomalies, for the global endorheic system and each endorheic zone (Supplementary Fig. 13). We emphasized TWS changes in response to precipitation on an annual basis to remove the influence of correlations dominated by seasonal variation. We calculated temperature trends to assess recent warming in endorheic regions and to facilitate the discussion of warming-induced glacier retreat and the possible enhancement of potential evapotranspiration. Note that evapotranspiration responds to radiative and aerodynamic variables in addition to temperature\(^{52}\), so we do not claim that warming alone necessarily caused the observed TWS loss. However, as existing glacier-evapotranspiration data do not adequately account for the impact of open surface water, the response of TWS changes to actual evapotranspiration was not explored.

To account for uncertainties in climate variables, we retrieved the monthly means of precipitation and temperature anomalies during 2002–2016 from multiple observation/assimilation sources. Sources of precipitation data include the Climate Prediction Centre Merged Analysis of Precipitation (CMAP)\(^{61}\) (www.esrl.noaa.gov/psd/data/gridded/data.cmap.html), the Global Precipitation Climatology Center (GPCC) precipitation\(^{62}\) (total full v7 (www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html), the Global Precipitation Climatology Project (GPCC)\(^{63}\) (www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html) and the Precipitation Reconstruction over Land\(^{64}\) (www.esrl.noaa.gov/psd/data/gridded/data.precl.html) data set. As the merged analysis and reanalysis precipitation data trend to show evident uncertainties over ITP\(^{65}\), its precipitations were acquired from a 0.25° gridded observation data set\(^{66}\) provided by the National Climate Center of China Meteorological Administration. Sources of temperature data include the NOAA Global Surface Temperature\(^{67}\) (www.esrl.noaa.gov/psd/data/gridded/data.noaaglobtemp.html), the Berkeley Earth Surface Temperature\(^{68}\) (http://berkeleyearth.org/data) and mean surface air temperature from the GLDAS LSMS.

Code availability. All analytical codes generated in this paper are available from the corresponding author upon request.

Data availability

Calculated water storage changes in global endorheic regions are distributed through PANGAEA (https://doi.org/10.1594/PANGAEA.89895). Storage changes in major lakes and reservoirs are available upon reasonable request to the corresponding author. Glacier mass change data are available through Nature Geoscience article https://doi.org/10.1038/NGEO2999.

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