Minimizing uncertainties in climate projections and water budget reveals the vulnerability of freshwater to climate change

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Highlights
- The multivariate technique corrects GCM biases and closes the water budget better
- Soil drainable porosities determine WS surplus or deficit and runoff relationships
- Land use types and climate change enhance WS deficit or surplus
- Additional moisture intake into basins does not always initiate surplus WS

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In brief
Food security and human sustainability are at risk due to rising water needs, especially in areas where resources are scarce. This work advances the knowledge of terrestrial water storage (WS) changes in a warming world by assessing the WS patterns using observations and climate experiments. The results show that different factors impact moisture movements in and out of basins. Climate change and land use type are major drivers in the observed trends and characteristics of WS surpluses or deficits.
Minimizing uncertainties in climate projections and water budget reveals the vulnerability of freshwater to climate change

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SUMMARY

Global water scarcity threatens agriculture, food security, and human sustainability. Hence, understanding changes in terrestrial water storage (WS) is crucial. By utilizing climate models, reanalysis, and satellite data, we demonstrate the effectiveness of the multivariate bias correction technique in facilitating precise WS representation while ensuring robust water budget closure. Historical data indicate seasonal changes, where forested basins exhibit a WS surplus in the December-January-February season, with a reversal in the June-July-August-September season. Non-forested basins display varied patterns influenced by geographical location and land use type. Future projections indicate increased June-July-August-September deficits in most Southern Hemisphere basins under the middle-road (SSP 245) scenario and wetter December-January-February conditions under the regional rivalry (SSP 370) scenario. Weather and climate systems governing WS vary by season and basin, resulting in inconsistent moisture intake into basins. These findings underscore the intricate interplay between moisture transport, land characteristics, and the resulting WS, highlighting the need to understand these complex interactions for effective regional water resource management strategies in changing climates.

SCIENCE FOR SOCIETY

Rising global temperatures will increase water in the atmosphere and diminish terrestrial water resources. Understanding changes in stored terrestrial water in surface or underground reservoirs is crucial for ecosystem and human sustainability. For example, modern agriculture often depends on groundwater and reservoirs, and water storage changes affect crop yield. Climate change will alter how much water is stored terrestrially; therefore, predicting these changes is crucial for adapting crops and other human water needs to changing water resources. Our findings reveal that warmer temperatures and shifting precipitation patterns can increase plant water consumption and evapotranspiration and reduce stored water. Stored water also depends on land use. For example, converting natural wetlands into urban areas reduces groundwater. The implications of warmer climates on water storage are region dependent, potentially exacerbating competition for water between human and natural ecosystems.
INTRODUCTION

Terrestrial water storage, hereafter called water storage (WS), is the ability of the environment to maintain an efficient water resource system through the interception, infiltration, and storage of precipitation through the canopy, litter, soil, and lake reservoir water bodies in space and time.1,2 WS boosts base flow in the age of precipitation through the canopy, litter, soil, and lake reservoir water bodies in space and time.1,2 WS boosts base flow in the age of precipitation through the canopy, litter, soil, and lake reservoir water bodies in space and time.1,2 WS boosts base flow in the age of precipitation through the canopy, litter, soil, and lake reservoir water bodies in space and time.1,2 WS boosts base flow in the age of precipitation through the canopy, litter, soil, and lake reservoir water bodies in space and time.1,2 WS boosts base flow in the age of precipitation through the canopy, litter, soil, and lake reservoir water bodies in space and time.1,2 WS boosts base 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the water budget approach in impact assessment due to the water budget closure problem. Numerical and climate models have been developed to overcome these complexities and to enhance our understanding of the Earth’s complex, nonlinear hydro-meteorological processes. These models also help address the emerging water budget closure problem arising from using different sources of datasets to balance the water budget.

Climate models provide efficient synopses in exploring water budget components (i.e., precipitation, runoff, evapotranspiration, and WS changes), which are challenging to monitor thoroughly on a global scale. However, general circulation models are unsuitable for impact research due to their poor resolution (inability to capture fine-scale details effectively) and their inadequate depiction of microphysical processes due to oversimplification of real-world features, which jointly magnify the inherent biases in global circulation models. Therefore, correcting these biases and investigating how well various correction strategies can mimic the signs of climate change are crucial. While bias correction (BC) methods have been widely employed to correct global circulation models meteorological variables, there remains uncertainty regarding their performance in correcting WS and how they address the water budget closure problem. Furthermore, the uncertainties linked to individual water budget components while estimating WS with the water budget approach limit their applicability in impact assessment. For example, evapotranspiration, a water budget component calculated using the water budget equation, accords well with estimates from remote sensing regarding the seasonal cycle but demonstrates more inter-annual variability and more significant magnitudes. In essence, inferring WS as a residual of other water components, without proper evaluation, could produce erroneous results due to inherent uncertainties associated with each component, lack of closure in the water budget model, and other drivers of WS change (e.g., LULC). Hence, the need to provide a critical understanding of the projected changes in WS characteristics and the roles of large-scale atmospheric processes and LULC using a synergy of climate model outputs, reanalysis dataset, and remote sensing observations is imperative and requires further attention in the context of a changing climate. Also, addressing the uncertainties and biases from different driving WS datasets is required to achieve accurate water budget closure.

Here, we investigate changes in WS by evaluating two BC techniques that aim to improve the representation of WS changes while reducing uncertainties in the water budget closure within the Coupled Model Intercomparison Project Phase 6 (CMIP6) global climate models (GCMs), reanalysis dataset and remote sensing observations. The improved representation of WS has significant implications for water resource management, ecological conservation, and climate change adaptation strategies. We observe that the multivariate BC approach improves WS representation and closes the water budget reasonably. This improvement offers a more precise representation of global terrestrial water changes within the CMIP6 GCMs for historical data and future projections. Hence, we utilize the information from multivariate BC outputs to achieve the following:

1. assess global WS changes to enhance our understanding of WS trends, projections, and seasonal characteristics under different climate change scenarios, including the middle of the road (SSP 245), regional rivalry (SSP 370), and fossil-fueled development (SSP 585) scenarios and
2. explore the potential influences of LULC, global wind systems, and water vapor transport on WS changes.

By investigating the intricate relationships among various factors, we establish that land use and land cover patterns, alongside moisture transport into and out of basins—regulated by global wind and pressure systems—exert significant influence on global terrestrial water changes.

RESULTS AND DISCUSSION

Method summary
We investigate long-term WS dynamics derived from the water budget equation and GRACE data. However, using univariate and multivariate BC approaches, we aimed to improve WS representation while reducing uncertainties in water budget closure within CMIP6 GCMs, reanalysis dataset, and remote sensing observations. The univariate quantile mapping BC strategy maps the source distribution quantiles to target distribution quantiles. In contrast, the multivariate BC techniques consider the whole multivariate dependency structures between several dependent and independent climate variables. The multivariate dependency structure shows the connections between each independent variable (e.g., precipitation and runoff) and each dependent variable (e.g., WS). Thus, the multivariate approach consistently corrects biases across multiple variables while the univariate method corrects each variable (e.g., evapotranspiration) independently. We conduct a comprehensive assessment of the accuracy of each GCM and BC method, employing various performance statistics. Our investigation includes estimating trends and examining the joint dependency structures among water budget variables. We employ self-organizing maps and Gaussian mixture models to enhance our understanding of classifying WS into surpluses and deficits. Additionally, we analyze the dynamics and trends of WS, considering the influence of different LULCs, large-scale climate events, and climate change scenarios.

Performance of BC methods and GCMs
Assessing the long-term average state of CMIP6 WS from 1959 to 2014 using the spatial root-mean-square error (RMSE) reveals discrepancies in the performance of different GCMs across various regions. For example, in the Amazon basin, the CMCC (Centro Euro-Mediterraneo sui Cambiamenti Climatici Earth System Model) 2 model exhibits an RMSE ranging from 10 to over 140 mm, while the UKESM (United Kingdom Earth System Modeling project (Low Resolution)) model ranges from 0 to 100 mm. The higher RMSE observed in the CMCC model, surpassing 140 mm in many tropical regions and highland areas like the Himalayas, indicates substantial deviations from the reference data. These deviations may be attributed to variations in land surface schemes, misrepresentation of vegetation and orography, unrealistic large-scale variability, and divergent internal variability between climate models and observations. Figure S1K validates the uncertainty from using varied water budget component datasets for estimating WS. The uncertainties range from 0 to 120 mm RMSE, especially in the tropics and mid-latitudes. Higher
RMSEs in Greenland can be attributed to the water budget equation’s inaccurate representation of frozen WS. Generally, for cold, snow-prone, and some polar regions, permafrost storage contributes to large RMSE.

The identified uncertainties were effectively addressed to ensure a comprehensive closure of the water budget. Additionally, a performance evaluation of the bias-corrected GCMs using the N-dimensional probability density function transform method (MBCN; Figure 1) reveals a significant reduction in biases compared with the uncorrected GCMs (Figure S2) across various time scales, including monthly, seasonal, and annual. Notably, the MBCN-corrected GCMs demonstrate monthly performance scores ranging from 0.0 to 2.1 for the RMSE between the reference and model output and the reference standard deviation (RSD). The RMSE varies from 0.0 to 27.0 mm, the median absolute error (MedAE) ranges from 0.0 to 17.0, and the relative absolute error (RAE) varies from 0.0 to 2.5. We observe similar tendencies in the quantile delta mapping (QDM)-corrected CMIP6 models (Figure S3). Conversely, the uncorrected CMIP6 models exhibit monthly RSR ranging from 1.1 to 5.0, RMSE ranging from 7.0 to 42.0 mm, MedAE ranging from 5.0 to 36.0, and RAE ranging from 1.18 to 5.5.

Following the BC, the models with the poorest performance on a global scale are MPILR (monthly), MRI (Meteorological Research Institute Earth System Model Version 2.0) and MIPLR (June-July-August-September [JJAS]), and MIPLR (December-January-February [DJF]). It is worth noting that the BC methods effectively reduced uncertainties in the water budget and improved the alignment between the bias-corrected WS derived from the water budget equation (bias-corrected WS [BCWS]) and the WS data reconstructed from the GRACE mission across all temporal scales (Figures 1 and S3). This is consistent with Xiong et al., who demonstrated improved accuracy of downscaled and bias-corrected climate model simulations relative to GRACE reference data over the Yangtze River Basin.

Furthermore, there is compelling evidence of comparable statistical properties between the monthly GRACE data and the MBCN-BCWS (Figure 2) that validate the reduction in uncertainty at the basin scale. The breadth of each density curve corresponds to the estimated frequency of data points within an area.
Comparing the peaks, troughs, and tails of these density curves allows us to assess similarities or discrepancies in the data series. A broad density curve suggests a high frequency of values within a particular range, while a narrow density curve indicates a lower occurrence of values in that range. We observe notable similarities in the properties of the density curves and no significant alterations in the mean values across all basins (p > 0.05). This lack of significant mean changes between the GRACE data and the BCWS underscores the effectiveness of the BC method in accurately addressing water budget errors arising from utilizing water budget variables from diverse sources. In general, multivariate BC can effectively enhance the consistency, precision, and dependability of climate model simulations, while reducing the uncertainties arising from water budget closure. Furthermore, the Student’s t test statistic at a 95% confidence level is used to evaluate GRACE and MBCN-BCWS data, and the analysis indicates no statistically significant difference in the annual WS for most models across various regions (Figure S4). Consequently, the CMIP6 multimodel ensemble mean (Figure S4C) and INM (Institute for Numerical Mathematics CM5) (Figure S4D) demonstrate the overall best performances. Even though single-model, initial-condition, large ensembles quantify uncertainty from the model’s internal variability, that single model may be an inadequate approximation of reality. In contrast, multimodel ensembles generate climate simulations with identical forcing across multiple models to quantify epistemic uncertainties. Therefore, conducting thorough model evaluation and implementing BC is crucial when utilizing either of the two ensemble approaches for impact assessment. Therefore, we use the CMIP6 multimodel ensemble mean (ENS) (Multi-model ensemble mean of the previous nine models) in the subsequent sections after establishing the overall robustness in the previous analyses.

**Joint dependency structure and partial correlation**

Ensuring that the ENS and BC methods can accurately capture and preserve the dependency structures among water budget variables, such as precipitation, actual evapotranspiration, and runoff, is crucial. However, the QDM-corrected ENS fails to preserve the dependency between WS and actual evapotranspiration for all continents (Figure S5A). In contrast, the MBCN-corrected ENS maintains this dependency, with values close to zero observed for every continent (Figure S5B). On the other hand, the uncorrected ENS cannot retain the dependency structure between WS and other variables (Figure S5C). A higher RMSE generally indicates a more remarkable inability of the model to preserve the joint dependency structure among the variables. We also show that the bias-corrected ENS effectively preserves the partial correlation between WS and precipitation (Figure S6). However, the uncorrected ENS fails to replicate this relationship, particularly in Asia and North America, potentially leading to mischaracterizing basins such as the Volga, Ob, Lena, and Mississippi (Figure S6C). Generally, the reference dataset and the
MBCN bias-corrected ENS have a positive partial correlation between WS and precipitation across all basins (Figures S6B and S6D). This positive correlation between WS and precipitation, along with the predominantly negative correlation with actual evapotranspiration, can be influenced by changes in temperature. As the temperature rises, more moisture is introduced into the atmosphere through evapotranspiration, propelling a precipitation event via moisture convergence at lower altitudes and resulting in heavier precipitation. Therefore, more water is available because of the high intensity and flow of the recent precipitation event; hence, the positive correlation between WS and precipitation and the majorly negative correlation with evapotranspiration in the reference and MBCN bias-corrected ENS.

Moreover, both the QDM-corrected and uncorrected ENS demonstrate inadequate performance in evaluating the correlation between WS and runoff (Figures S6A and S6C). This inadequacy stems from inherent biases within the uncorrected CMIP6 models, compounded by the limitations of QDM in rectifying biases sequentially across all variables. Hence, the association among the variables is missing during QDM corrections. Conversely, MBCN preserves the multivariate dependence structure reasonably well. Generally, small precipitation amounts and high evaporative demand can result in low WS. Likewise, high precipitation and low evaporative demand can cause low evapotranspiration and high WS, aiding rapid soil recharge. Also, a high volumetric water content threshold is required for runoff activation in deeper tropical soil layers. Increased precipitation over tropical soils with high drainable porosities keeps the volumetric water content at saturation. When the saturation threshold at lower soil depths is exceeded, the extra water flows to the upper levels, satisfying the field capacity, and runoff begins. On the other hand, drainable porosity declines with depth in temperate soils due to increases in bulk density, triggering a quick rise in the water table and accelerating shallow lateral subsurface flow; hence, the positive partial correlation between runoff and WS.

**Historical WS trends and future projections**

The analysis of the WS annual trend (Figure S7) reveals notable differences between the uncorrected ENS and the reference dataset. In the historical period, the uncorrected ENS overestimates the trends in most basins. For instance, the reference dataset indicates predominantly negative trends ranging between −25 and 0 mm/decade in basins such as the Amazon, Chad, and Colorado (Figure S7A). However, the uncorrected ENS classifies these trends as ranging between −5 and 15 mm/decade (Figure S7B). In contrast, the MBCN-corrected ENS satisfactorily replicates these observed trends (Figure S7C). These trends are consistent with past studies, including over China, where similar negative trends have been reported. The significance of the observed trends varies across basins, with the corrected ENS consistently detecting more accurate and significant trends than the uncorrected ENS. Therefore, the MBCN-corrected ENS proves reliable for effectively illustrating future trends in WS. Under the shared socioeconomic path (SSP) 245 scenario, significant negative trends are observed in some parts of the Amazon, Paraná, Nile, and Volta basins (Figure S7D). These negative trends are further intensified under the SSP 370 and 585 climate change scenarios. The trends for different seasonal classifications (JJAS and DJF) are also evaluated and are consistent with the reference data, demonstrating the accuracy of MBCN-corrected ENS.

Furthermore, analyzing multiple-period trends for selected basin averages (Figure 3) reveals magnitude and trend significance variations during the JJAS season. Specifically, the Yangtze River basin exhibits mixed trends in the historical period, as seen in the JJAS single-period trend (Figure S9). However, the negative trends observed in the multiple-period analysis are statistically significant (Figure 3A I). For instance, the Yangtze River basin manifests a positive but non-significant trend of 7 mm/decade from 1959 to the later 30-year period (along the y axis). In contrast, the 56-year period indicates a non-significant −2 mm/decade trend. Additionally, future projections from 2057 to 2070, under the SSP 245 scenario, exhibit predominantly positive trends (Figure 3B I). However, under SSP 585, although significant trends are absent, we observed a greater number of positive trends than the SSP 245 scenario (Figure 3D I).

On the other hand, the Amazon basin exhibits significant negative trends for all years under all future SSPs (Figures 3B–3D, ii). Notably, there are some positive trends during drought episodes (in the 1970s) in the Lake Chad basin (Figure 3A, iii). This can be attributed to the rising groundwater table despite prolonged droughts, a phenomenon popularly called the Sahelian paradox. This also enhances vegetation recovery during that period. In addition, the warming of the northern Atlantic Ocean and the Mediterranean Sea positively impacts the Lake Chad basin by boosting the meridional convergence of external moisture at low levels. As a result, the region experiences increased precipitation and a partial rebound of rainfall after drought episodes. Similarly, positive WS trends can be attributed to increased soil moisture content due to increasing rainfall intensity from the intensification of the low-level jet in the area. However, the local moisture recycling rate, regulated by planetary flow patterns coupled with the El Niño-Southern Oscillation, significantly impacts annual precipitation fluctuations in the basin. Figure S9 illustrates the single-period trend for the DJF season, noting consistent negative trends in the Amazon, Paraná, and Nile basins for the historical and all future scenarios.

**WS and LULC classification**

Following the initialization, competition, collaboration, self-organization, and clustering adaptation mechanisms of the WS self-organizing maps (SOMs), we classified the WS into 11 units (Figure 4). In the historical JJAS, basins such as the Amur and Volta witness an extreme WS surplus. Moreover, LULC type is also an important factor in WS representation. For example, basins with a high proportion of forest cover (Amazon, Congo, and Volga; Figure 5) are generally linked with a WS deficit in the JJAS period. This can be attributed to less precipitation reaching the ground due to tree canopies and increased evapotranspiration due to active tree transpiration and higher leaf area. Hence, the recharge appears to be slower. Also, lower temperatures, limited water availability from frozen soil or reduced precipitation, snowfall interception, and decreased leaf area index can prevent high evapotranspiration rates thereby maintaining WS in DJF. It is important to note that the WS deficit in forested basins varies depending on forest type. For example, broadleaf forests facilitate more WS deficit than other vegetation types (cf. Figures 4A and 5). Additionally, the type of vegetation, its height,
and its density are key factors that significantly influence the accumulation and interception of snow and precipitation.65

On the other hand, basins with a high proportion of combined grassland, shrubland, and barren land are linked with JJAS WS surplus (e.g., Volta and Ob). However, shrublands in the polar basins (e.g., Yukon, Kolyma) aid more WS deficit in the JJAS season. In general, leaf area increases precipitation and snow interception, but tall shrubs promote snow trapping.65 Furthermore, the WS classification is reversed for many basins during the DJF season (Figures 4B and 5). This suggests that the WS modifications are not based solely on LULC type but also on seasonal differences in climate dynamics.

In the future JJAS under SSP 245, most basins in the Southern Hemisphere will experience more intense WS deficits. At the same time, North Africa will reverse from a slight surplus (Figure 4A) to a severe WS deficit (Figure 4C). It is worth noting that, under SSP 370 JJAS, several basins, like the Kolyma, that previously experienced WS deficits during the historical period show a shift in signals during the future period. Therefore, further investigation is needed to understand the underlying mechanism behind these dynamic patterns.

On the other hand, most tropical basins show a northward shift of the WS surplus under SSP 585. Notably, most basins in the Southern Hemisphere get drier, while basins just above the equator get wetter, confirming the “dry gets drier and wet gets wetter” paradigm.41 For future DJF seasons, the WS surplus recovers in the tropics, shifting farther north under SSP 585, while the extreme WS deficit is more pronounced under SSP 245. Most Southern Hemisphere basins witness wetter conditions under SSP 370 compared with SSP 245 and 585. Because CMIP6 model projections incorporate future LULC dynamics, changes in future LULC could be essential in WS future classifications.

**WS and climate dynamics**

Given the established WS feedback from LULC, a critical emphasis lies in comprehending the impact of climate dynamics on WS. Figure 6 shows the seasonal, long-term average state of wind fields, WS, and geopotential height in the lower and mid-troposphere from 1959 to 2014. Investigating the Northern-Hemispheric tropical African expanse reveals a strong lower tropospheric southwesterly monsoon wind from the Atlantic
Ocean during JJAS (Figure 6A), carrying moisture inland. This is accompanied by a monsoon trough centered on the Sahel, a weak ridge across the Mediterranean Sea, and southward moisture transport (Figure 7A). This favors the wetting of this region, thereby stimulating WS surplus in JJAS (Figure 4A).

Furthermore, the southwestern monsoon pushes moisture up to around 18°C (Figure 6A), while southward moisture transport from the Mediterranean Sea dominates the larger expanse of the Sahel (Figure 7A). In the mid-troposphere, there is a Saharan high to the west, favoring the intensification of the African easterly jet (AEJ) (Figure 6C). This increases the magnitude of the southward moisture transport westward from the Mediterranean Sea by around 80 kg/m²/s (Figure 7A). On the other hand, moisture transport from the Atlantic Ocean, orchestrated by the southwestlies, is limited to the lower troposphere (Figure 6A). As a result, the lower tropospheric southwestern monsoon governs WS dynamics in the southern Volta, southern Chad, and southern Nile basins.

In contrast, the weak ridge in the lower troposphere, AEJ (Figure 6A) and the Saharan high in the middle troposphere regulate moisture intake in the northern Chad and northern Nile basins. The Nile basin has substantial moisture influx from the northern, eastern, and southern boundaries, while the western boundary is the export channel (Figure 7A). The intensity of the northward moisture fluxes at the southern boundary is greater than that of the inward moisture fluxes at the northern boundary or the outward moisture fluxes at the western boundary. This suggests that the leading cause of the high water vapor content during JJAS is the northward moisture flux linked to the Indian monsoon (Figures 6A and 7A). This demonstrates that the Indian Ocean is one of the crucial sources of moisture for the rising moisture content in this basin. The cutoff highs and the tropical cyclones around Madagascar (Figure 6A) and low-level jet (Figure 6B) in the lower troposphere redirect substantial moisture from the Indian Ocean away from Madagascar and East Africa toward the Nile basin (Figure 7A). Nevertheless, this phenomenon triggers the displacement and intensification of the low-level jets in DJF, notably toward the southern regions of Madagascar (Figure 6B). This displacement results in abundant moisture inflow, closely associated with atmospheric rivers from the Indian Ocean into the southern Congo basin in DJF (Figure 7B).
more moisture is available from atmospheric rivers, this does not always translate to surplus WS due to different LULC classes, atmospheric river characteristics, and landfall zones. Generally, the increased greenhouse warming from abundant moisture increases temperature. As a feedback, waterbodies lose more water due to higher evaporation, thereby increasing atmospheric moisture content.

The Amazon basin primarily receives inflow from its northeastern boundary during the JJAS period. In contrast, the other boundaries predominantly experience strong outflows (Figure 7A). Interestingly, the substantial outflows from the Amazon’s southern boundary, which result in a WS deficit in the Amazon basin, play a pivotal role as inflow for the Paraná basin, thereby leading to a WS surplus in Paraná (Figures 4 and 6). This robust outflow from the Amazon subsequently continues toward the southern boundary of the Paraná basin. The South America coastal jet (Figure 6C) dominates the moisture inflow and outflow (Figure 7A), while the low tropospheric anti-cyclonic vortex (Figure 6A) regulates the direction of flow over these basins. During DJF, the easterly crosses northern Australia, causing rapid moisture inflow from the western Pacific Ocean (Figure 7B). However, the low tropospheric low-pressure center (Figure 6B) and mid-tropospheric high-pressure center (Figure 6D) associated with this region during this period converge the moisture in northern Australia, paving the way for a robust westward outflow toward northwestern Australia (Figures 6B and 7B).

The dominant northward moisture inflow into the Yangtze and Amur basins in JJAS (Figure 7A) is from the South China Sea, aided by the low-level ridge and strong monsoon wind (Figure 6A). However, the Bay of Bengal, a low-level trough, and a mid-level jet (Figures 6B and 6D) are prominent in the northward moisture influx into the Yangtze and the moisture cutoff to the Amur in DJF (Figure 7B). Additionally, the Asian westerly jet (Figure 6D) and low-level high-pressure center in central Asia (Figure 6B) strengthen the transport of the northward-flowing moisture from the Arabian, Mediterranean, and Red Seas toward the Volga and Ob during DJF (Figure 7B), thereby enhancing the WS surplus in these months (Figure 4B).

We note higher moisture transport values over subtropical continents in both hemispheres. However, we observe a maximum landfalling atmospheric river on the western coast of the Atlantic, where high sea surface temperatures support a faster evaporation rate, supplying moisture to the atmosphere and promoting its subsequent transit to other places. This area is a crucial moisture pool for North Atlantic Ocean atmospheric rivers landfalling on the western European coast, northeastern American coast, Iceland, and Greenland. It is important to note that large atmospheric rivers are not synonymous with high precipitation extremes, as many

Figure 5. Land use and land cover classes
We reclassified the International Geosphere-Biosphere Program (IGBP) type 1 scheme global land use and land cover (LULC) dataset identifying 11 natural vegetation classes, three developed and mosaicked land classes, and three non-vegetated land classes into 12 distinct categories based on their similarity intervals to enhance interpretability. The black polygons represent river basins. LULC type is a crucial factor influencing WS changes. Basins with more forest cover (e.g., Amazon and Congo) consistently display a WS deficit during the historical JJAS period (Figure 4). The WS deficit within forested basins varies based on the specific forest type. Broadleaf forests exhibit higher WS deficits than other vegetation types (refer to Figure 4A for a detailed comparison). Basins dominated by grassland, shrubland, and barren land (e.g., Volta and Ob) consistently show a WS surplus during JJAS (Figure 4). These findings highlight the intricate relationship between LULC characteristics and WS patterns, highlighting the need for region-specific WS management strategies.
non-atmospheric river events have been associated with more extreme precipitation occurrence. More importantly, enhanced moisture drives the fast warming of the near-surface temperature, thus accelerating evaporation, which could potentially lead to more WS surplus. Moreover, this also depends on other dynamic factors, like the origin of the transport and the area of landfall.

**Conclusion**

We investigate global WS using bias-corrected CMIP6 GCMs. Our findings demonstrate that the MBCN BC technique effectively reduces biases in GCMs, preserves the dependency structure of WS variables (e.g., precipitation, evapotranspiration, and runoff), and achieves satisfactory water budget closure, offering a versatile methodology for the climate and hydrology research community. However, it is worth noting that the complexity of the MBCN method makes it time consuming and computationally demanding. Nevertheless, it is essential to conduct robust evaluations to ensure that the various WS properties are preserved while solving the water budget problem. This is crucial for maintaining accuracy in WS representativeness. For instance, QDM-corrected WS successfully maintains the quantity of WS but cannot preserve its dependency structure with other water budget variables. In general, multi-variate BC can effectively enhance the consistency, precision, and dependability of climate model simulations while reducing the uncertainties arising from water budget closure.

Additionally, we establish that WS dynamics are influenced by geographical area, LULC type, and climate dynamics that affect moisture movement in and out of basins. It is important to note that additional moisture intake into basins does not always lead to surplus WS due to various local-scale impacts, different LULC classes, atmospheric river characteristics, and landfall zones. Furthermore, we observe varied trends in WS across different basins, with the corrected model revealing more significant and accurate trends than the uncorrected CMIP6 multimodel ensemble mean. Under SSP 245, the future JJAS season exhibits more severe deficits in most basins in the Southern Hemisphere, while basins in North Africa experience a notable shift from a slight WS surplus to a severe WS deficit compared with the historical period. In contrast, under SSP 585, there is a northward shift in WS surplus in most tropical basins. Notably, basins in the Southern Hemisphere experience drier conditions under SSP 245, while African basins just above the equator become wetter across all climate scenarios compared with the historical period. For the future DJF season, the WS surplus in the tropics recovers and shifts farther north under SSP 585, while a severe WS deficit remains evident under SSP 245. Under SSP 370, most basins in the Southern Hemisphere exhibit wetter conditions compared with the historical period.

These findings offer insight into how ecological and human systems dependent on these WS dynamics could be affected.
Conserved water is crucial in lake and wetland systems, agriculture, shallow groundwater recharge, and irrigation. WS dynamics greatly influence associated ecological and social structures, including wetland maintenance, groundwater replenishment, lake health, irrigation scheduling, and improved water management in agriculture. The projected deficits or surpluses in WS due to climate change will impact water supply and may enhance or imperil the efficiency of hydrological and agricultural systems. Policymakers can consider the effects of WS dynamics when formulating climate change adaptation or mitigation strategies for different subsystems. Furthermore, sustainable land management approaches that promote ecosystem services and safeguard biodiversity should also be supported.

**EXPERIMENTAL PROCEDURES**

**Resource availability**

**Lead contact**

Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Wen Zhou (wen_zhou@fudan.edu.cn).

**Materials availability**

This study did not create any new or distinctive materials.

**Data and code availability**

The CMIP6 data and codes are publicly available through the Earth System Grid Federation at [http://esgf.llnl.gov/](http://esgf.llnl.gov/).

The CRU reference data are publicly available at [https://crudata.uea.ac.uk/cru/data/hrg/#info](https://crudata.uea.ac.uk/cru/data/hrg/#info).

The reconstructed GRACE data are publicly available at [https://doi.org/10.6084/m9.figshare.7670849](https://doi.org/10.6084/m9.figshare.7670849).

The Global Runoff Ensemble (GRUN) reference data are publicly available via [https://doi.org/10.6084/m9.figshare.9228176](https://doi.org/10.6084/m9.figshare.9228176).

The JRA55 reference data are publicly available at [https://rda.ucar.edu/datasets/ds628.1/](https://rda.ucar.edu/datasets/ds628.1/).


The code used in this manuscript is deposited and freely available at [https://github.com/cyndyfem/One-Earth-Paper.git](https://github.com/cyndyfem/One-Earth-Paper.git) and publicly available as of the publication date.

The original and unprocessed climate data used for this study are available in Adeyeri.176

Upon request, the lead contact will provide any extra data necessary to reanalyze the data described in this study.

**Variables**

Our analysis centers on nine CMIP6 models and their ensemble means for the historical (1959–2014) and future (2045–2100) periods (Table S1). The monthly reference dataset for precipitation and temperature is based on the Climate Research Unit (CRU) series.78 The reconstructed changes in terrestrial WS68 from the GRACE are used to evaluate WS from the water budget equation and bias correct the climate models. The reconstructed GRACE data are publicly available at [https://doi.org/10.6084/m9.figshare.7670849](https://doi.org/10.6084/m9.figshare.7670849).

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**Figure 7. WS and vapor transport**

Shown are long-term average states from 1959 to 2014 of WS changes (mm) (background) and integrated vapor transport (IVT; kg/m/s) in vectors during the historical (A) JJAS and (B) DJF seasons. Negative IVT means southward moisture transport, while positive IVT means northward moisture transport. The black polygons represent river basins, and the background is WS changes. See Figure S5 for basin names. Comprehending the dynamics of moisture transport is integral for understanding the movement of moisture into and out of basins. For example, during JJAS, the increased moisture content in the Nile basin is supported by the northward moisture transport from the Indian Ocean. This underscores the importance of the Indian Ocean as a primary moisture source for improving moisture conditions in the Nile basin. While atmospheric rivers contribute to increased moisture availability, this does not uniformly lead to excess WS due to variations in land use and land cover, differing features of atmospheric rivers, and the locations where they land. This complexity is evident in the southern boundary of the Amazon, where substantial outflows result in a WS deficit. However, these outflows are a significant inflow for the Paraná basin, contributing to the Paraná basin WS surplus during JJAS. These observations highlight the intricate relationship between moisture transport, land characteristics, and resulting WS dynamics in basins. It emphasizes the need for a thorough understanding of these complex interactions to effectively manage water resources in different regions.
WS change
The water budget equation is initiated with three meteorological variables: precipitation, actual evapotranspiration, and runoff. This is given as
\[
\frac{dS}{dt} = J - ET - Q \tag{Equation 1}
\]

where \(S\) is the total WS change over time, \(J\) is the precipitation, \(ET\) is the actual evapotranspiration, and \(Q\) is the runoff.

Due to the uncertainties related to water budget closure, especially from using different data sources, the WS generated from the climate models during the historical period is bias corrected and evaluated against the reconstructed changes in WS\ref{31} of the GRACE mission (GRACE-REC). The GRACE missions have delivered unparalleled global estimates of monthly WS anomalies. However, due to their relatively short temporal span (\(\approx 20\) years), GRACE observational outputs are insufficient for evaluating the long-term trends of WS. As a result, we use the reconstructed GRACE products,\ref{83,84} which employ statistical models in training GRACE observations to backcast previous climate-driven changes in WS using daily and monthly meteorological information. In contrast to conventional hydrological models that individually represent water reservoirs such as snow and soil moisture, typically yielding a single model run, GRACE-REC directly reconstructs total WS changes and incorporates numerous ensemble members, thereby enabling a comprehensive assessment of predictive uncertainty.\ref{50} To assess the accuracy of these data-driven WS estimates, several studies\ref{19,41,83,84} have independently evaluated GRACE-REC and ascertained its accuracy and robustness. GRACE-REC is provided at a spatial resolution of 0.5° from 1901 to the present.

BC
A quantile-dependent correction function between the model simulation or water budget WS quantities and the observations quantities is used in the univariate quantile mapping (QM) BC technique. With this function, the simulated data are converted into bias-corrected data. The underlying presumption is that models can accurately predict the variable’s quantiles, or ordered categories, for both the past and future periods.\ref{33,34,35,47} To preserve the relative or absolute quantile changes, QM1 modifies the modeled values by the observed values at the exact quantiles, subsequently estimating the relative or absolute quantile changes between the calibration and future periods. Consequently, multiplying these relative changes by the bias-corrected values generates the bias-corrected future projections.\ref{33,42,43}

While preserving the anticipated changes in the simulated quantities, multivariate BC employs the QM technique to adjust the marginal distributions of the climate model simulations. The multivariate rescaling approach is applied to modify the joint multivariate dependence structure between different dependent variables during multivariate BC.\ref{52} The multivariate BC method using the N-dimensional probability density function transformation (MBCN) expands the N-dimensional probability density function transformation algorithm with QDM.\ref{34,35} Both QDM and MBCN are used in this study.

The QDM transfer function is given as follows.\ref{33}

The relative change in quantiles between the calibration and projected periods (\(t\)) for conservative variables is given as
\[
\Delta\left(\xi_{mc}\right) = \frac{F_{m\rho}^{-1}\left[\xi\left(t\right)\right]}{F_{mc}^{-1}\left[\xi\left(t\right)\right]} \tag{Equation 2}
\]

The relative change in quantiles between the calibration and projected periods (\(t\)) for non-conservative variables is given as
\[
\Delta\left(\xi_{nc}\right) = \frac{F_{m\rho}^{-1}\left[\xi\left(t\right)\right]}{F_{mc}^{-1}\left[\xi\left(t\right)\right]} \tag{Equation 3}
\]

The non-exceedance probability (\(\xi\)) associated with variable \(x\) at time \(t\) is given as
\[
\xi\left(t\right) = F_{m\rho}^{-1}\left[\xi_{m\rho}\left(t\right)\right] \tag{Equation 4}
\]

\(x_{m\rho}(t)\) is the climate model value \(m\) within the projection period \(p\), and \(F_{m\rho}^{-1}\) is the time-dependent cumulative distribution function (CDF) of the climate model projection \(x_{m\rho}\). Using a 30-year moving window, \(x_{m\rho}\) is calculated based on the empirical CDF. \(F_{m\rho}^{-1}\) is the simulations’ inverse CDF during the calibration periods.

The model’s \(\xi\) quantile is bias corrected from observations across the calibration period:
\[
\bar{\xi}\left(t\right) = F_{mc}^{-1}\left[\xi\left(t\right)\right] \tag{Equation 5}
\]

where \(\bar{\xi}\) is the bias-corrected quantile.

The inverse CDF during the calibration period, \(F_{mc}^{-1}\), is calculated from observation \(x_{mc}\).

The final bias-corrected model projection \(x_{mc}\) at time \(t\) is given as
\[
x_{mc}\left(t\right) = \bar{\xi}\left(t\right)\Delta\left(t\right), \text{ for conservative variables} \tag{Equation 6}
\]
\[
x_{nc}\left(t\right) = \bar{\xi}\left(t\right)\Delta\left(t\right), \text{ for non-conservative variables} \tag{Equation 7}
\]

The MBCN method incorporates a QDM approach to enhance the N-dimensional probability density function transformation method by leveraging information from the variables \(x_{m\rho}, x_{mc}\), and \(x_{nc}\). These variables undergo a rotational transformation, and the absolute changes described in Equations 6 and 7 are applied to each rotated \(x_{m\rho}, x_{mc}\), and \(x_{nc}\). Subsequently, the rotated \(x_{m\rho}, x_{mc}\), and \(x_{nc}\) are transformed to \(x_{m\rho}^{\Delta\left(t\right)}\), \(x_{mc}^{\Delta\left(t\right)}\), and \(x_{nc}^{\Delta\left(t\right)}\). This iterative process continues until \(x_{m\rho}^{\Delta\left(t\right)}\) converges to \(x_{mc}\). Additionally, the ordinal rankings of each column in \(X_{m\rho}\) are adjusted to align with the ordinal rankings of the corresponding elements in each column of \(X_{mc}\).

Performance statistics for GCMs
The performance of BC methods and GCMs is based on seasonal, monthly, and annual timescales and is investigated using the MedAE, RMSE—observation standard deviation ratio (RSR),\ref{70,88} RAЕ, and RMSE.

\(RSR\) is the ratio of the RMSE between the reference and model output and the reference standard deviation.\ref{70,88} This is given as
\[
RSR = \frac{RMSE_{reference}}{SD_{reference}} = \frac{\sqrt{\frac{\sum_{i=1}^{n} \left[Y_{reference} - \bar{Y}_{reference}\right]^2}{n}}}{\sqrt{\frac{\sum_{i=1}^{n} \left[Y_{reference} - Y_{mean}\right]^2}{n}}} \tag{Equation 8}
\]

RSR ranges from 0, which denotes zero residual variation or RMSE, indicating an accurate model simulation, to a significant positive number, suggesting an imperfect model.

\(MedAE\)

The MedAE resists outliers. Given that \(\hat{y}\) is the model output of the \(n\) sample, and \(y\) is the reference, MedAE estimated over \(n\) samples is defined as
\[
MedAE\left(y, \hat{y}\right) = \text{median}\left(|y_{1} - \hat{y}_{1}|, ..., |y_{n} - \hat{y}_{n}|\right) \tag{Equation 9}
\]

\(RAE\)

The RAE normalizes the total absolute error by dividing it by the total absolute error of the predictor. The resulting RAE index can range from 0 to infinity, where 0 indicates the ideal scenario:
\[
RAE_{y} = \frac{\sum_{i=1}^{n} |model_{y} - reference_{y}|}{\sum_{i=1}^{n} |reference_{y} - Y_{mean}|} \tag{Equation 10}
\]

where \(model_{y}\) is the value predicted by individual model \(y\) for record \(u\) out of \(n\) records, and \(reference_{y}\) is the reference value for record \(u\).

Trends and dependency structure
WS variables are subjected to the modified Mann-Kendall (MMK) trend test,\ref{19,41,83,84} while Sen’s estimator\ref{23,33,90} is used to estimate the magnitude of the trends. Also, a 30-year multiple-period trend\ref{33} is used to examine the
trends over different timescales. This method depicts trends throughout various timescales, considering each trend’s unique characteristics from its inception to its conclusion. The joint dependency structures are estimated from the RMSE of the correlation coefficients between WS and other water budget variables.

**Self-organizing maps and WS classifications**

The SOM, an artificial neural network technique, organizes training data input space into a two-dimensional discrete grid. One neuron in the grid is assigned to each chunk of data, and the distance between neurons indicates how similar the chunks are. Based on the distribution of the weight vectors, the SOM method groups the training datasets into a two-dimensional grid representing several clusters. After that, SOM partitions into clusters by taking data samples from each stratum. As a result, the datasets with equal variance and bias are grouped as one. We employ the partitioning around medoids (PAM) algorithm to determine the optimal clustering classification in the reduced feature space, guided by the gap statistics. With the gap statistic, the total within-cluster variance is compared with what would be predicted by a reference null distribution for various values of the number of clusters. The gap statistics’ maximum value, which indicates that the data have been well clustered and that the clusters are well separated, is the ideal. Utilizing the gap statistics prevents the data from being over- or underfitted.

Additionally, we employ the expectation maximization algorithms of Gaussian mixture models (GMM) with different covariance structures for parameter estimation of the SOM nodes, while the spatially explicit priors maintain the spatial heterogeneity to validate the PAM-generated clusters. This approach facilitates the organization of SOM nodes into distinct groups. We select the best GMM using the Bayesian Information Criterion (BIC). Therefore, we adopt the GMM with the lowest BIC value for clustering the SOM nodes. Leveraging the SOM and GMM, we generate 11 WS classification units. More information regarding the interface between SOM and GMM can be found in Adeyeri et al.

**LULC classification**

Land Cover Type v.6 of the MODIS (MCD12Q1) categorizes land cover based on distinct thematic categories. The International Geosphere-Biosphere Program (IGBP) type 1 land cover scheme identifies 17 land cover categories comprising 11 classes of natural vegetation, three classes of developed and mosaicked land, and three classes of non-vegetated land. We reclassify the IGBP land cover classes into 12 distinct classes based on interval similarity. Reclassification through interval similarity entails grouping data into intervals and assigning a consistent new value to all data points within each interval. This approach merges comparable land use types during land use reclassifications, streamlining data analysis, and simplifying interpretation.

**Atmospheric river dynamics**

We adopt the vertically integrated vapor transport (IVT) to understand the dynamics of water vapor movement in and out of a particular domain. IVT is defined as

\[
IVT = \frac{1}{g} \int_{p_{top}}^{p_{surface}} q \bar{V} dp
\]

where \(g\) is the gravitational constant, \(\bar{V}\) is the horizontal wind vector, \(q\) is the specific humidity, \(p_{surface}\) is the pressure at the surface, and \(p_{top}\) is the pressure at the top of the atmosphere.

**SUPPLEMENTAL INFORMATION**

Supplemental information can be found online at https://doi.org/10.1016/j.onear.2023.12.013.

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**AUTHOR CONTRIBUTIONS**

O.E.A., conceptualization, software, resources, data curation, methodology, scripting, investigation, formal analysis, visualization, writing – original draft, review, and validation; W.Z., review, supervision, validation, funding acquisition, resources, and project administration; C.E.N., validation, review, and editing; X.W., supervision; K.A.I., validation, writing – review, editing; P.L., review and editing.

**DECLARATION OF INTERESTS**

The authors declare no competing interests.

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