Journal of Hydrology 656 (2025) 133029

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Time of emergence (TOE) of potential aridification in the western United States

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ARTICLE INFO

This manuscript was handled by A. Bardossy, Editor-in-Chief, with the assistance of Gerrit Schoups, Associate Editor

Keyword:
Time of Emergence
Total water storage
Climate Change
Aridity

ABSTRACT

Quantifying the timing of hydroclimatic changes due to global warming is crucial for water resources management. This study investigates the hydroclimatic changes based on the Time of Emergence (TOE) analysis in the western United States, with a focus on the impacts of climate change and aridification. Utilizing the Community Earth System Model Version 2 Large Ensemble (CESM2-LE), we investigate projected changes in temperature, precipitation, evapotranspiration, runoff, snow, and Total Water Storage (TWS). Despite precipitation increases in the future, our results project a robust decrease in TWS by the end of the 21st century, mainly driven by higher evapotranspiration and reduced snow. Total Water Storage, which is an integrated measure of all terrestrial hydrological processes, exhibits a more pronounced climate change signal compared to precipitation. Significant regional variations also emerge in the TOE of TWS, with states around the interior and high-elevation regions experiencing changes faster, as early as in the 2030 s, than those on the Pacific Coast or in southern regions. The study highlights the Upper Colorado River Basin as an emerging aridification hotspot, emphasizing the need for targeted research and adaptive water resource management strategies. This research underscores the importance of jointly considering TWS and the aridity index to comprehensively assess hydrologic regime shifts under global warming.

Plain Language Summary: Climate change is leading to shifts in temperature, rainfall, evapotranspiration, river flow, snow, and other factors. These changes collectively affect what we call the 'hydroclimate,' which includes changes in groundwater and aridity. Our study finds that as climate change progresses, there will be a noticeable decrease in groundwater, particularly in the interior states. Additionally, we observe an expansion of dry areas, especially in the Upper Colorado River Basin due to reduced snow. This information is crucial for policymakers who need to plan and prepare for future water resource management in the face of a warming climate.

1. Introduction

In light of the impacts of global warming, the hydroclimate of the western United States has undergone worrisome changes. Anthropogenic factors have contributed to worsening drought impacts since early as the 20th century (Marvel et al., 2019). A future with less to no snow, particularly in the mountainous areas, is anticipated and likely inevitable (Rhoades et al., 2022). This reduction in snow cover is not merely a loss of snow, it represents a broader change in water flux, impacting evapotranspiration (Hamlet et al., 2007), runoff (Berghuijs et al., 2014), and water storage, including surface water, groundwater, and soil moisture altogether, hence signifying a regime change in hydroclimate (Gergel et al., 2017). These changes also indirectly affect vegetation (Thorne et al., 2017), drought predictability (Livneh & Badger, 2020), and wildfires (Abatzoglou & Williams, 2016).

In a nutshell, the onset of climate change due to global warming is exacerbating aridity (Cook et al., 2004; Overpeck & Udall, 2020). In the western United States, there is evidence of heightened drought risk and a shift in the Aridity Index (AI) towards drier conditions (Greve et al., 2019). Historical data suggests that anthropogenic factors have contributed to the increased incidence of droughts in the 20th century (Marvel et al., 2019; Stevenson et al., 2022). Consequently,

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https://doi.org/10.1016/j.jhydrol.2025.133029
Received 2 August 2024; Received in revised form 13 January 2025; Accepted 24 February 2025
Available online 7 March 2025

understanding the timing of these changes in the hydrological regimes is crucial not only for predicting future climate patterns but also for developing effective response strategies (Lisonbee et al., 2022).

To address these challenges, this study utilizes the concept of the Time of Emergence (TOE), defined as the point at which signals of climate change become distinguishable from natural variability. The western United States is projected to experience the TOE of mega-droughts along the Pacific Coast and mega pluvial in the inland areas in the 21st century, based on the Representative Concentration Pathway 8.5 (RCP8.5) scenario (Stevenson et al., 2022). Filling this knowledge gap is crucial for understanding the TOE of hydrological regimes, which is essential in guiding regional adaptation strategies and informing policy and resource management decisions in anticipation of water shortfall. To date, only a technical document supporting the U.S. Forest Service 2010 Resources Planning Act (RPA) assessment has briefly discussed the TOE of potential aridification in the western United States with older-generation climate models (Greenfield & Nowak, 2013), making this study a necessity.

A key aspect of our analysis is examining the interplay between these hydroclimatic changes and a significant topographical feature. Section 2 details the data and methods employed in our research. Section 3 presents projections of long-term hydroclimatic changes across the United States, with a specific focus on the TOE in the western region. The paper concludes in Section 4 with final remarks and a discussion of our findings.

2. Data and method

2.1. Hydroclimate variables

Hydroclimate is a field that intersects hydrology and climate, necessitating the integration of a diverse set of variables for comprehensive analysis. Temperature plays a crucial role in affecting evaporation, transpiration, and the state of water. Next, there is precipitation, evapotranspiration, and runoff, which are directly linked to the surface water cycle and transport. These processes collectively offer a rudimentary estimate of changes in Total Water Storage (TWS). In the Community Earth System Model Version 2 Large Ensemble (CESM2-LE), the TWS includes canopy water, snow water, surface water, plant storage water, soil water, and river water. The variation in TWS, in addition to the previous changes, encompasses various components such as changes in groundwater, rivers, lakes, and snow. Our study, therefore, examines hydroclimate change using the following six variables: temperature, precipitation, evapotranspiration, runoff, snow, and TWS. Notably, TWS is a critical variable that integrates various hydroclimatic factors and reflects the total amount of water stored in a given area. An increase in precipitation and a decrease in runoff both contribute to an increase in TWS, while an increase in evapotranspiration and a decrease in snow—one of the key components of TWS—lead to its reduction. Thus, a decline in TWS is indicative of a reduction in overall water availability, signaling potential challenges in water resource management.

2.2. Data

The CESM2-LE provides more than 50 ensemble members, each with a 0.9° x 1.25° latitude-longitude grid resolution, covering a broad spectrum of variables. This dataset is based on CMIP6 scenarios, encompassing historical data from 1850 to 2014 and projections under the Shared Socioeconomic Pathway 3–7.0 (SSP370) from 2015 to 2100. The large ensemble allows for probabilistic derivation of future projections. We directly utilize monthly mean data for temperature, precipitation, evapotranspiration, runoff, snow, and TWS from CESM2-LE (Rodgers et al., 2021). Additionally, we employ other variables such as absorbed solar radiation, clear sky downwelling solar flux at the surface, downwelling solar flux at the surface, maximum and minimum temperatures, 2 m relative humidity, 10 m wind speed, and surface pressure to calculate reference evapotranspiration.

To validate CESM2-LE, this study uses the monthly Global Land Data Assimilation System (GLDAS) V2.0 Catchment Land Surface Model (Rodell et al., 2004) and the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) (Hersbach et al., 2020). GLDAS V2.0 Catchment, a land data assimilation system provided by NASA, is used for temperature, precipitation, evapotranspiration, runoff, snow, and TWS from 1948 to 2014, also with a 1° x 1° latitude-longitude grid. ERA5, a reanalysis dataset from ECMWF, supplies data for temperature, precipitation, evapotranspiration, runoff, and snow from 1940 to 2022, with a 0.25° x 0.25° latitude-longitude grid. Detailed information about all the data is shown in Table S1.

2.3. Time of emergence (TOE)

The TOE is determined as the timing at which the range of interannual variability crosses the future projection, meaning that the events that were extreme in the base period have become the normal events. Here, the TOE is calculated for temperature, precipitation, and evapotranspiration in the increasing direction, and for runoff, snow, and TWS in the decreasing direction. The TOE uses a single-threshold method, and the base period is from 1900 to 1999. The future projection was calculated by combining the historical linear trend with the future linear trend, and for the interannual variability, we used the method proposed by Thompson et al. (2015) rather than the standard deviation (Ryu et al., 2024). The interannual variability, as defined by Thompson, was calculated as shown in Equation (1), where the 't_c' represents the two-tailed 95 % confidence level, 'n_t' is the number of time steps, 'σ' denotes the standard deviation of the variable, '$g(n_t)$' refers to the standard deviation of time, and '$\gamma(n_t, r_1)$' is scaling factor derived from the lag-one autocorrelation (Thompson et al., 2015).

$$e = t_c n_t \sigma \gamma(n_t, r_1) g(n_t) \tag{1}$$

Here is an example of calculating the TOE in practice using a single grid cell (Fig. S1). First, the linear trend and interannual variability are determined for the period 1900 to 1999. Next, a linear projection for the future period from 2000 to 2100 is used to define the climate change signal, represented by the red line in Fig. S1. The previously calculated interannual variability is then used to define the range of interannual variability, shown by the grey range. Finally, the green point is identified as the TOE, where the climate change signal surpasses the range of interannual variability.

2.4. Aridity index (AI)

The AI is defined as the ratio of precipitation to potential evapotranspiration. Here, potential evapotranspiration is calculated in various ways and is also used as reference evapotranspiration (Xiang et al., 2020). Therefore, AI is calculated as the ratio of precipitation to reference evapotranspiration according to Zomer et al. (2022). The reference evapotranspiration is adopted using the FAO-56 Penman-Monteith method and is shown in Equation (2). In this equation, 'R_n' represents the net radiation at the crop surface, 'G' is the soil heat flux density, 'T_{avg}' denotes the average temperature, 'u_2' is the wind speed at 2 m, 'e_s' and 'e_a' are the saturation and actual vapor pressures, respectively, 'Δ' is the slope of the vapor pressure curve, 'γ' is the psychrometric constant, while 'r_s', and 'r_a' refer to bulk surface resistance and aerodynamic resistance, respectively.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_{avg}+273} u_2 (e_s - e_a)}{\Delta + \gamma\left(1 + \frac{r_s}{r_a}\right)} \tag{2}$$

Then, the AI is calculated as the ratio of annual mean precipitation to annual mean reference evapotranspiration, which is shown in Equation (3). Furthermore, the AI is divided into five climate classes: hyper-arid for values less than 0.03, arid for values between 0.03 and 0.2, semi-arid for values between 0.2 and 0.5, dry sub-humid for values between 0.5–0.65, and humid greater than 0.65 (Zomer et al., 2022).

$$AI = \frac{Annual\ mean\ precipitation}{Annual\ mean\ reference\ evapotranspiration} \tag{3}$$

3. Results and discussion

3.1. Historical and future changes

To depict regional features, we calculated the area average from the CESM2-LE. To validate CESM2-LE's performance, we compared its outputs with the GLDAS V2.0 Catchment data from 1948 to 2014 and the ERA5 reanalysis data from 1940 to 2022. These comparisons, illustrated in Fig. 1, show the annual anomaly time series of the six variables across two regions: the western United States comprising 11 states, and the Upper Colorado River Basin given its vital role in the region's water resource. The boundaries of each region are shown in Fig. S2. For snow, the annual anomaly time series is averaged from December to March (DJFM) each year. The green line and light green range are shown as the ensemble mean and double standard deviation range of the CESM2-LE, respectively. The GLDAS V2.0 Catchment in grey and ERA5 in black are plotted together. Our results indicate that CESM2-LE effectively captures the variability within one standard deviation when compared to the land data assimilation and reanalysis datasets.

We note that CESM2-LE does exhibit limitations in accurately simulating the recent trends of precipitation and evapotranspiration in the western United States. To further validate the observed decreasing trend in precipitation, we selected the seven ensemble members of CESM2-LE that exhibit the most decreasing trends in precipitation from 1986 to 2022, ranked by magnitude. The means and double standard deviation ranges of these ensemble members are illustrated in Fig. S3. The results indicate that the recent decreasing trend in precipitation is consistent across both models and observational data, yet the models predict an increase in precipitation towards the end of the 21st century. This suggests that the recent decreasing trend in precipitation over the western United States is likely influenced by decadal natural variability in the water cycle, which is largely driven by large-scale atmospheric circulations such as the El Niño-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the Interdecadal Pacific Oscillation (IPO) (Smith et al., 2015; Wang et al., 2012). Additionally, the decreasing trend in precipitation has been influenced by climate change driven by greenhouse gases, and studies have shown that the PDO has been affected by anthropogenic aerosols (Hoerling et al., 2019; Kuo et al., 2023; Lehner et al., 2018). Lastly, in the 21st century, precipitation is generally projected to increase, although it may decrease in some models (Li et al., 2021; Zhao et al., 2023).

Next, we analyzed the local changes across the study area. Fig. 2 displays a spatial comparison of hydrological changes over different eras. It contrasts the average values for three distinct periods: The first column represents the 1900 s climatology from 1900 to 1999, the second and third columns indicate the ratio of change for the recent and future 20-year climatologies with respect to the 1900 s, respectively. Changes in the direction of becoming drier are colored red. The most significant change is observed in snow, which has already declined by over 45 % in approximately half of the regions in the recent period. This decline is projected to encompass all regions by the end of the century, aligning with the anticipated low-to-no-snow future (Siirila-Woodburn et al., 2021).

Examining the TWS climatology of the western United States in the 1900 s, as shown in Fig. 2(p), reveals the distinct areas of water resources. The Central Valley of California, known for its substantial agriculture, is delineated by its high TWS. The water in this region has a mechanism of recharging back into the groundwater through aquifers (Meixner et al., 2016). On the other hand, the Upper Colorado River Basin, a region with a strong declining trend, has been reported to be at risk of water supply shortages due to climate change (Barnett & Pierce, 2009; McCabe & Wolock, 2007). Additionally, the Great Basin region is a water resource region highly correlated with snow, an endangered water resource as well (Shiozawa et al., 2023). However, CESM2-LE shows high values in the 1900 s for the Great Basin, which may be a model bias. Overall, the present TWS change in the western United States has shown a marked decrease relative to the past, a pattern expected to continue. This occurs despite projections of increased precipitation, suggesting that changes in snow and evapotranspiration might be offsetting the effects of precipitation, leading to less water being stored underground.

3.2. TOE of hydrological variables

Building on the presented analysis of hydroclimatic changes across the western United States, we now focus on the TOE, defined as the critical point at which changes exceed the range of interannual variability and establish a new norm. Fig. 3 shows the TOE for each grid, considering six variables, alongside topography in (a) as a reference. The grid where the TOE was identified in more than 32 of the 50 CESM2-LE ensembles is highlighted with a dot, providing significance for TOE frequency. Our results indicate that the TOE for temperature is expected to be reached in the early 21st century across most of the western United States, aligning with previous studies and thus validating our methodological approach (Lehner et al., 2017). For precipitation, the TOE is predominantly projected to occur after 2050. However, evapotranspiration has already surpassed the TOE, a finding to be approached cautiously due to the model's limitations in simulating this variable, as revealed in Fig. 1. Snow changes are most pronounced at higher altitudes, where snow is projected to reach the TOE by the 2030 s, starting their irreversible decline. Regions at lower elevations not showing a TOE for snow can be attributed to historically lower snow, as Fig. 2(o) indicates, such that even a 50 % or greater decrease in snowfall was predicted to fall within the interannual variability range, masking the long-term trend. Precipitation exhibits strong interannual variability, which complicates the detection of climate change signals and introduces uncertainty into the TOE analysis (Hawkins & Sutton, 2011; Martel et al., 2018). While snow is an important indicator, it alone is insufficient to provide a comprehensive description of hydrology.

Collectively, these results highlight and explain the TOE for TWS across different hydrologic unit code (HUC) regions (Fig. 4). In areas like the Great Basin (HUC16), which is predicted to have the early TOE for precipitation and the late TOE for evapotranspiration and snow, the TOE for TWS is delayed or nonexistent. Conversely, the early TOE for TWS in the Upper Colorado River Basin (HUC14) is evident in regions with notable historical snow and a relatively small increase in precipitation. This region suggests a robust link between decreasing snow levels and TWS. Interestingly, the Upper Colorado River Basin, despite its lower TWS climatology, shows a more pronounced decline, possibly due to its snowpack-driven hydrology.

A detailed regional analysis for the 11 western U.S. states is presented in Fig. 5. Here, the box plots show the distribution of TOEs for each variable and state, where the number in front of each box plot is the number of ensembles in which the TOE appeared out of 50 ensembles. A low number means that many ensembles will not reach the TOE within the 21st century.

Temperature exhibits a uniform TOE across all states with southern states reaching it faster than northern states, consistent with the results in Fig. 3 and the literature (Deser et al., 2016). In contrast, other hydroclimatic variables show significant variations in the timing and frequency of TOE occurrences. Precipitation TOEs are occurring in fewer ensemble members in southern states like California, Arizona, and New Mexico, indicating limited increases in future precipitation. On the other hand, the inland states' precipitation TOEs align with earlier research,

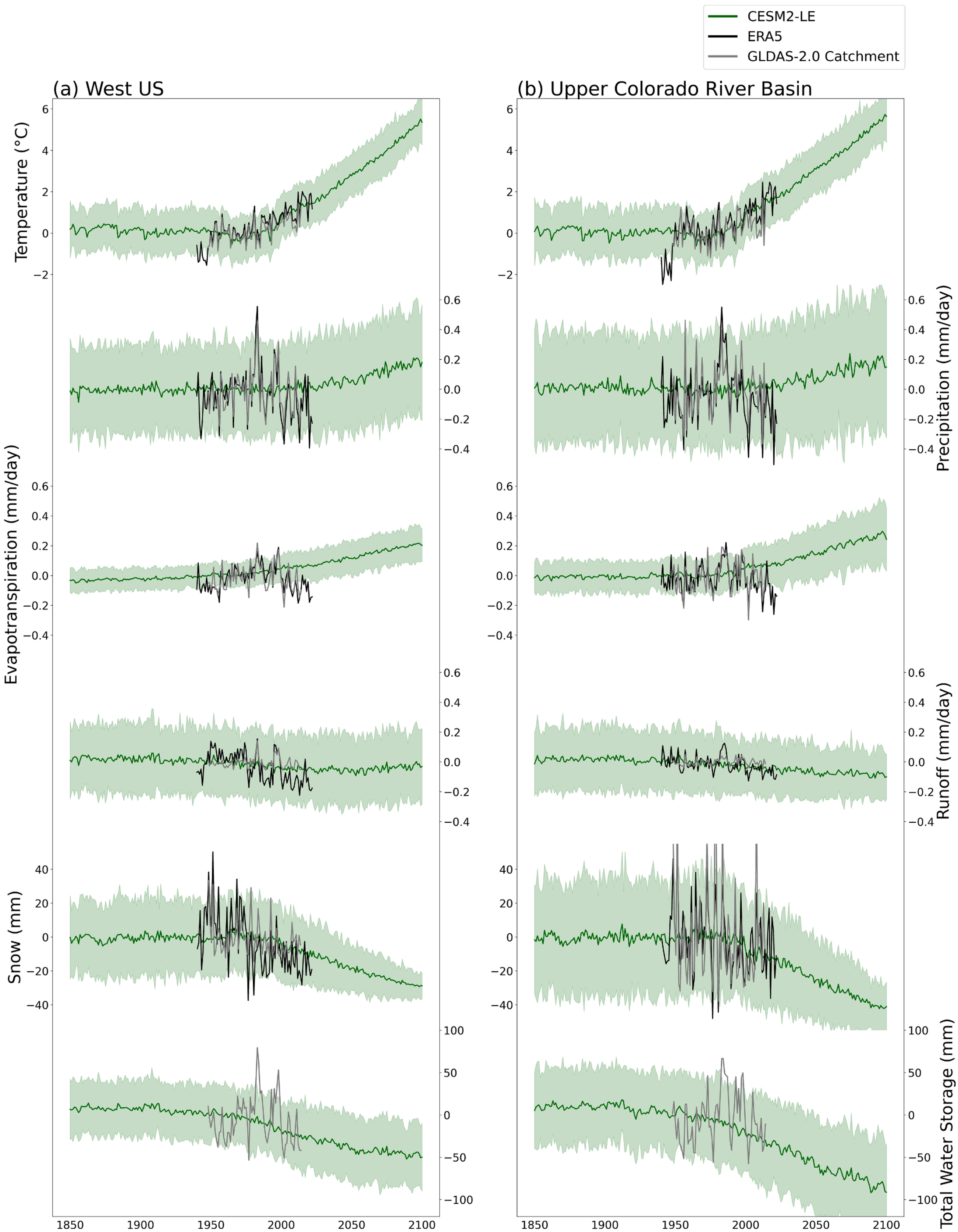

Fig. 1. Anomaly time series from 1850 to 2100 of temperature (TREFHT, K), precipitation (PRECT, m s^{-1}), evapotranspiration (QFLX_EVAP_TOT, mm H2O s^{-1}), runoff (QRUNOFF, mm s-1), snow (H2OSNO, mm), and TWS (TWS, mm). For clarity, all variables have been scaled to the units indicated on the y-axis labels in the figure. The green line is 50 ensembles means CESM2-LE and the light green shaded area is a range of double standard deviation. The black and grey line is the GLDAS V2.0 Catchment and ERA5, respectively. (a) is the western US, and (b) is the Upper Colorado River Basin region. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

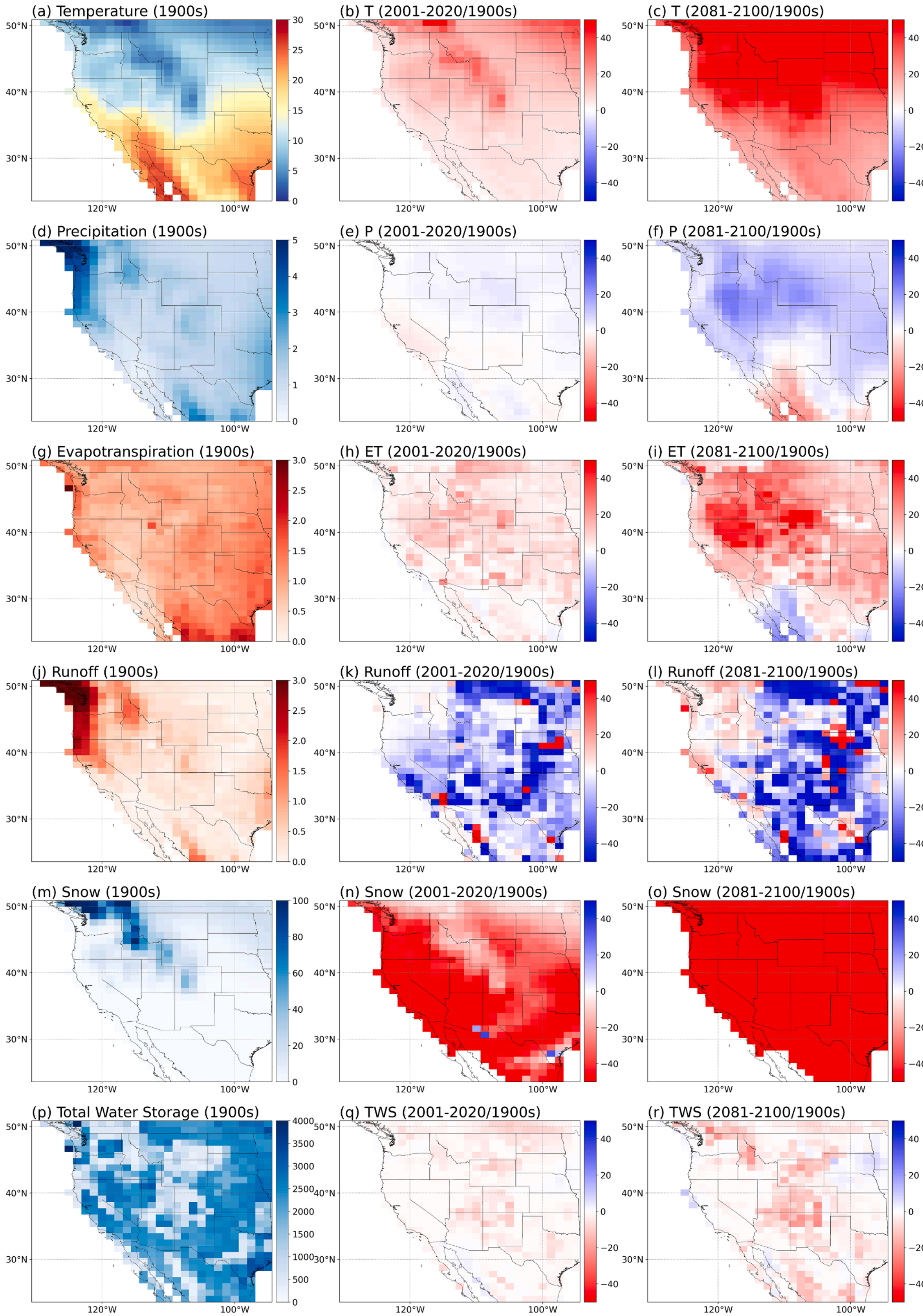

Fig. 2. Past climatology across the United States and current and future changes from the past. The first column is 100-year climatology from 1900 to 1999, second column is changing ratio for 20-year climatology from 2001 to 2020 to 20-year climatology from 1900 s, and third column is changing ratio for 20-year climatology from 2081 to 2100 to 20-year climatology from 1900 s. The unit for the first column is the same as the unit of each variable in Fig. 1, while the unit for the other columns is percentage (%). The first to sixth rows are, in order, temperature (TREFHT), precipitation (PRECT), evapotranspiration (QFLX_EVAP_TOT), runoff (QRUNOFF), snow (H2OSNO), and TWS (TWS).

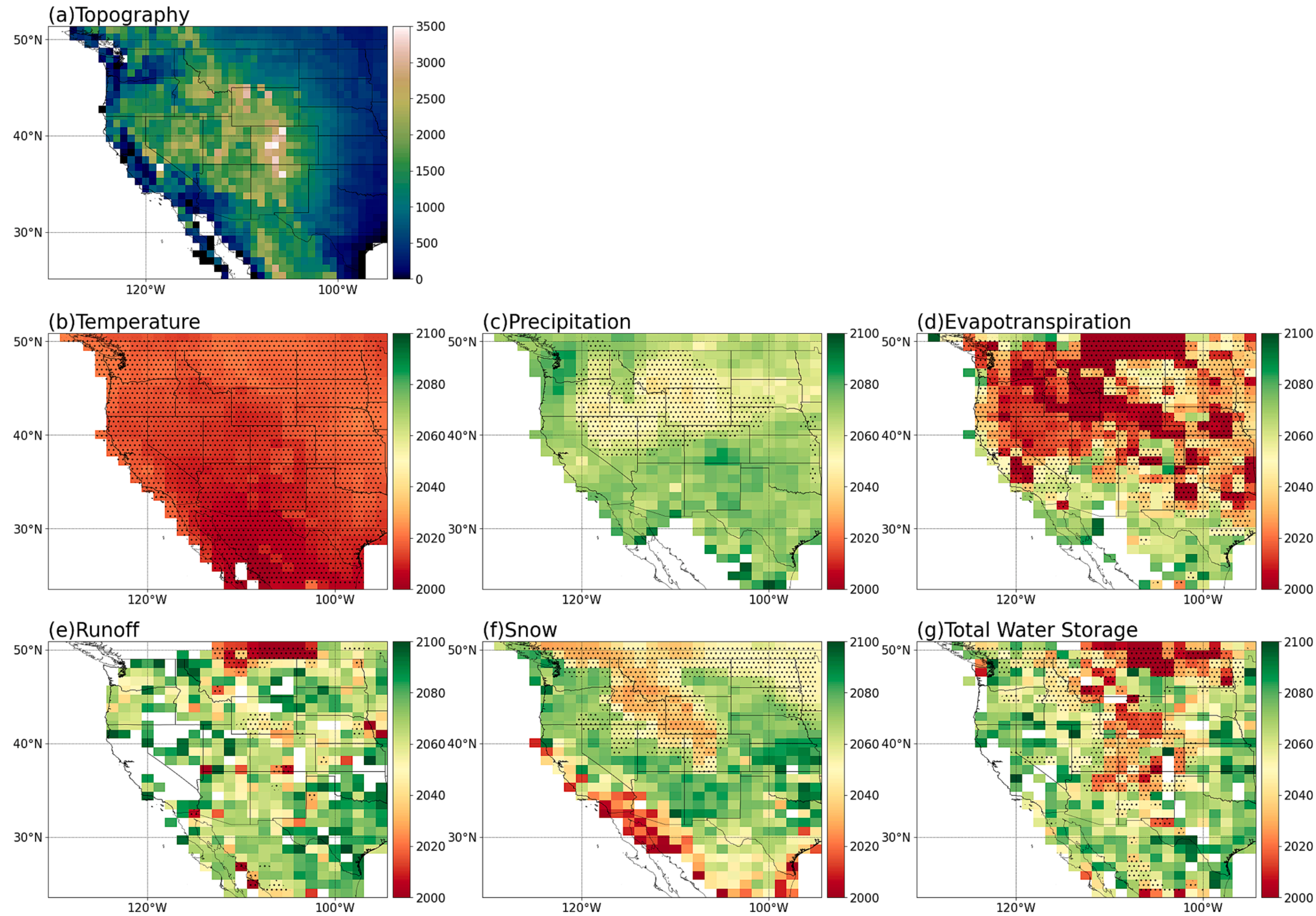

Fig. 3. The TOE map with six variables. (a) is a topography of the western United States. (b) – (g) are, in order, Temperature, Precipitation, Evapotranspiration, Runoff, Snow, and TWS, with the dotted area representing grids that occurred at least 32 times out of the 50 ensembles.

suggesting precipitation TOEs will manifest within the interior of the western United States (Nguyen et al., 2018). Evapotranspiration shows an already passed or sooner TOE at norther and inland states like Montana, Wyoming, and Idaho, with a delayed TOE at southern and closer to the Pacific Coast. This means that the impact of water storage reduction is greater in inland higher-elevation states. Notably, the TOE for snow occurs in more than 70 % of ensembles in seven states, excluding Oregon, California, Arizona, and New Mexico. It is uniformly present across all ensembles in five high-elevation inland states (Montana, Wyoming, Colorado, Idaho, and Utah), occurring faster than in other states. This pattern highlights the disparity in hydroclimatic impacts between the interior West and coastal/southwest regions.

These hydrological variations illustrate that the TOE of TWS by state also distinguishes between the interior and the coastal/southwestern regions. As evidenced in Fig. 3, the inland states of Wyoming, Montana, and Colorado demonstrate faster TOEs compared to other states, indicating a quicker response of TWS to hydroclimatic changes. Furthermore, California, Nevada, and Oregon show TOEs of TWS in less than 20 % of the ensemble members, highlighting a distinct hydrological behavior characterized by a large amplitude in natural variability. The TWS's positive response to precipitation and negative reaction to evapotranspiration and snow loss more distinctly delineate the hydroclimatic differences between the inland and coastal/southwestern regions of the western United States.

3.3. Aridification in the western United States

According to the future changes in the hydrological climate discussed above, both evapotranspiration and precipitation are increasing, which means that the current dry or wet climate may change. To analyze these collective changes, we categorized the climate of the western United States into five classes using the AI, following the methodology of Zomer et al. (2022). The regions and states with changes in AI class were then examined.

As illustrated in Fig. 6, which was analyzed similarly to Figs. 2 through 5, it is evident that most areas in the western United States were semi-arid in the 1900 s (Fig. 5a). By the end of the 21st century, as shown in Fig. 6(c), a further decrease in AI suggests increased aridity, particularly in interior states like Colorado, Utah, Arizona, and New Mexico, exacerbating their existing arid conditions. Conversely, the Great Basin region and northern states like Wyoming and Montana are projected to transition towards more humid conditions by the century's end. These spatial patterns are similar to previous research (Park et al., 2018) and are also similar to the precipitation patterns observed in Fig. 2; this is because the AI index heavily depends on precipitation changes.

Furthermore, Fig. 6(d) – (g) calculate the timing of shifts in AI climate classification towards either aridity or humidity. The change in AI's climate classification, which is appeared to change at the end of the 21st century, seems to be strongly associated with precipitation patterns. For instance, regions with significant increases in precipitation are shifting towards a wetter AI climate class, whereas those with smaller increases are trending drier. Intriguingly, California exhibits both drying and wetting trends, as evidenced in Fig. 5(h) and (i), when analyzed by state. Additional analysis by the HUC region (Fig. S13) further clarifies the results, indicating that the TOE has already occurred in the direction

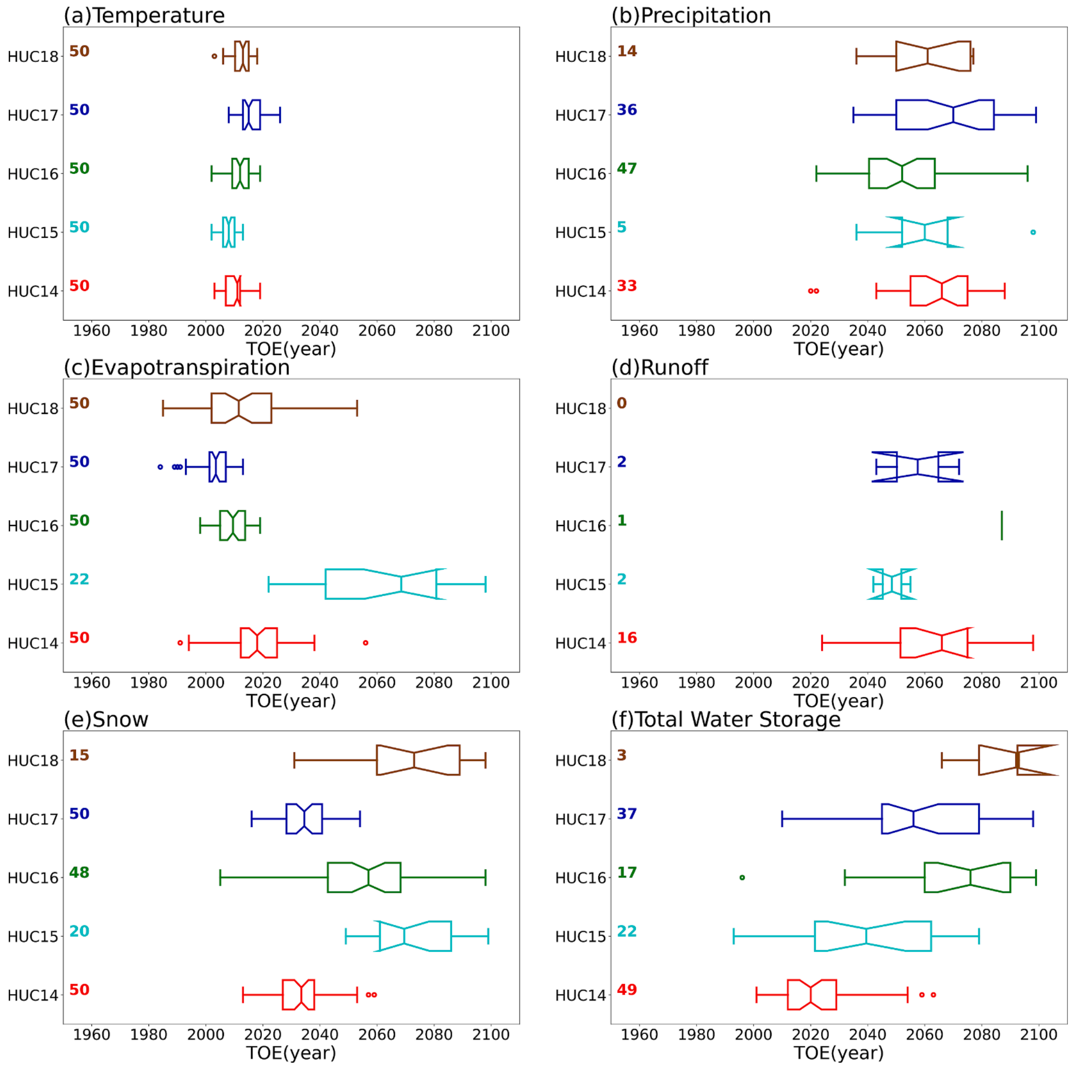

Fig. 4. The 5 HUC regions' TOE in 11 western US states. The numbers for each state represent the number of occurrences out of 50 ensembles. (a) – (f) are, in order, Temperature, Precipitation, Evapotranspiration, Runoff, Snow, and TWS.

of wetting in the California basin (HUC18). On the other hand, the Upper Colorado River Basin (HUC14) appears to have become drier, but only in 16 ensembles and with large uncertainties. In addition, the Lower Colorado River Basin (HUC15), which appears to have seen little change in precipitation, is projected to change in a drier direction in six ensembles, though in only a few cases. Overall, this suggests that future changes in AI classification are heavily influenced by variations in precipitation.

Distinctly, regions like the Upper Colorado River Basin are experiencing both the aridification and a TOE for reduced TWS. Conversely, the Great Basin shows the non-existent of a TOE in TWS and a trend towards a more humid direction of AI climate change. These areas are believed to be affecting from the increase in precipitation. Intriguingly, Wyoming, Montana, and Idaho are witnessing a TWS decrease alongside a shift towards a wetter AI climate class due to enhanced precipitation, yet also displaying a TOE for reduced TWS. This paradox suggests that despite the precipitation increase, the reduction in TWS is more pronounced due to a significant rise in evapotranspiration and a reduction in snow. In summary, it is anticipated that TWS, influenced by multiple hydrological factors, will align with AI directionality; however, regions with marked influences from snow and evapotranspiration are expected to become wetter but experience a reduction in water availability.

On one hand, it is possible that the increase in AI is an overestimate due to uncertainties, including potential evapotranspiration (Greve et al., 2019). It has also been suggested that the current drying may be part of a long-term drying trend driven by variability rather than direct climate change, but that anthropogenic factors may accelerate this process (Cook et al., 2004). Moreover, future TOEs of AI have been predicted (Park et al., 2018), with aridification across North America and record drought in the southwestern United States (Lisonbee et al., 2022; Overpeck & Udall, 2020).

4. Conclusions

The findings of this study, projecting a permanent decrease in TWS in the Western United States by the end of the 21st century, call for timely and targeted research efforts. Our study highlights significant regional variations in the TOE of TWS across the western United States. The findings suggest that interior and mountain states are projected to encounter changes in TWS faster compared to coastal and southern states. Applying TWS as a measure effectively mitigates the substantial noise in precipitation and evapotranspiration data, providing a clearer view of hydrological shifts. Additionally, we employed a distinct AI, separate from TWS, to assess the trends towards drying or wetting across the western United States, predicting a future increase in aridity within the Upper Colorado River Basin. However, aridity or aridification may be best represented by both AI and TWS to capture the essence of dismissing water resources.

While TWS and the AI both serve to elucidate hydrological changes,

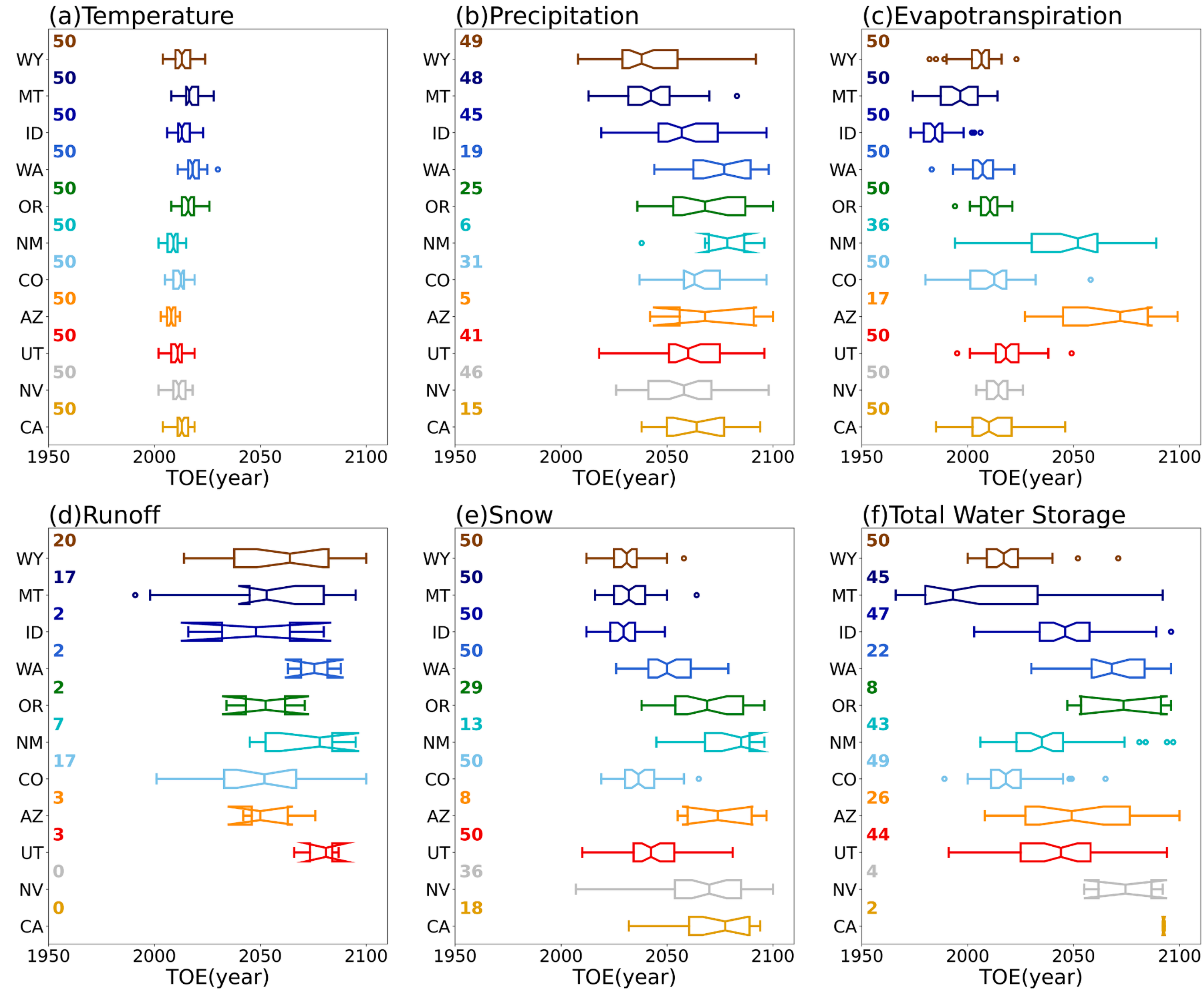

Fig. 5. The TOE in 11 western US states. Same layout as Fig. 4.

they represent different aspects of water dynamics—TWS relates to water supply capacity. In contrast, AI pertains to the region's land climate. By examining and comparing these two metrics, we identified regions with converging trends: the Great Basin, which is anticipated to become wetter without impacting water storage, and the Upper Colorado River Basin, which is expected to face drying conditions and water storage challenges. Notably, in regions like Idaho, Wyoming, and Montana, where evapotranspiration and snow impacts compete with precipitation impacts, these areas are predicted to become wetter and have water storage challenges. Each region has different trends and futures predicted, and each will require different future responses.

Despite an expected increase in precipitation, the predicted decline in TWS due to increased evapotranspiration and reduced snow necessitates a deeper investigation into the regional water balance dynamics. This aspect is particularly interesting for a large water body like the Great Salt Lake in Utah, where the TWS trend seems contradictory to the lake's drastic decline. Increased water use and reduced resilience due to anthropogenic factors have been suggested as contributing causes of this phenomenon (Hassan et al., 2023; LaPlante et al., 2024), underscoring the importance of considering anthropogenic influences in future research. Additionally, to assess the uncertainty of a single model, the analysis was conducted using 50 and 25 ensemble members of MIROC6 and CanESM5, respectively, yielding similar results (Figure is not shown). This approach helps to validate our findings. Furthermore, although not discussed in detail here, soil moisture is an important component of TWS, and a simple analysis shows that while it behaved similarly in the past, it appears to be increasingly influenced by other variables, such as snow, in the future (Fig. S5). Future studies should evaluate soil moisture, as it is a key component of TWS. Incorporating a broader range of variables will provide a more comprehensive and robust understanding, reduce uncertainty, and enhance our knowledge of regional hydroclimatic changes.

CRediT authorship contribution statement

Jihun Ryu: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Shih-Yu Wang:** Writing – review & editing, Software, Investigation, Funding acquisition, Conceptualization. **Jee-Hoon Jeong:** Writing – review & editing, Conceptualization. **Hyungjun Kim:** Writing – review & editing, Conceptualization. **Jin-Ho Yoon:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

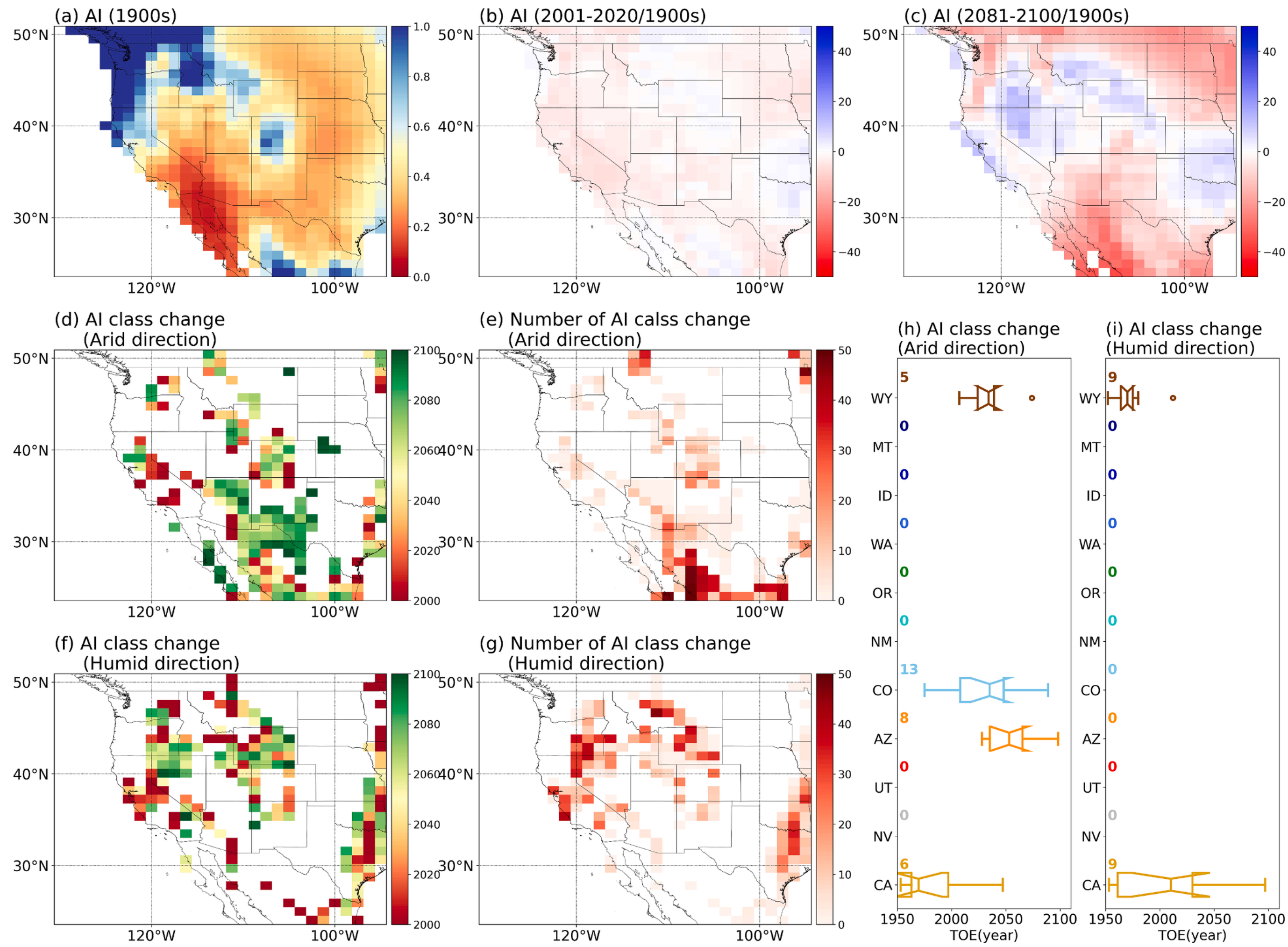

Fig. 6. A comprehensive analysis of the AI. (a) – (c) are same as Fig. 2, (d) – (e) are the change timing and number of times in the ensemble that the AI climate class changes in the arid direction, (f) – (g) are the change timing and number of times in the ensemble that the AI climate class changes in the humid direction, and (h) – (i) are same as Fig. 4.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is funded by the National Research Foundation of Korea under NRF-2021R1A2C1011827 and the Brain Pool program under RS-2023-00283239, the Korean Meteorological Agency under the grant KMI2018-07010, and Korea Environment Industry & Technology Institute(KEITI) through "Climate Change R&D Project for New Climate Regime.", funded by Korea Ministry of Environment(MOE) (RS-2022-KE002160).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2025.133029.

Data availability

Data will be made available on request.

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