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LETTER

# Assessing the complex influences of water management on hydrological drought characteristics in Texas

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## Abstract

The state of Texas in the United States is highly susceptible to drought. Its major rivers are subject to extensive water management (WM) activities in order to sustain multisectoral water demands, particularly during drought conditions. However, the impact of WM on the propagation dynamics and characteristics of hydrological drought (HD) in Texas remains unclear. To fill this gap, this study quantifies the influence of WM across 32 streamflow gauges along the mainstems of seven major rivers in Texas by comparing a variety of drought metrics under natural and managed conditions. Notably, we leveraged an extensive, naturalized streamflow dataset constructed by the Texas Commission on Environmental Quality, paired with gauge observations of managed conditions. Results indicate that at the multi-decadal scale, WM significantly reduced HD frequency across all seven rivers and at 81% of the gauges analyzed. Additionally, it increased the response timescale of HD across Texas' major rivers by a median of 2.5 months. Conversely, the average-event duration and severity increased in most locations. Temporal analysis reveals that the WM impact on HD varied seasonally, with attenuation effects during mid-summer and early fall and intensification effects during late winter and spring. Additionally, WM was found to greatly increase the spatial variability of HD characteristics across the region. These findings emphasize the complexity of WM effects on HD and the necessity for nuanced strategies in managing HD under WM influences.

## 1. Introduction

Drought can be a creeping or rapidly developing hazard characterized by deficiencies in precipitation (meteorological drought, MD), soil moisture (agricultural drought), and surface water or groundwater hydrological drought (HD), resulting in disparities between the supply and demand for socioeconomic activities (socioeconomic drought) (Mishra and Singh 2010, Hao and Singh 2015). Drought ranks as the disaster affecting the second-highest number of people worldwide from 2000 to 2019, with an average of over 70 million people impacted annually (Tsegai *et al* 2022), and has far-reaching impacts across various sectors such as water supply, energy production, and agriculture (Deb *et al* 2022, Zhang *et al* 2023, Ferencz *et al* 2024). There is evidence that climate change is altering drought patterns worldwide, thereby increasing the challenges in mitigation and adaptation (Cammalleri *et al* 2020, Gu *et al* 2023, Ullah *et al* 2023, Zhou *et al* 2023, Li *et al* 2024, Rastogi *et al* 2024). Additionally, drought is no longer solely a natural occurrence but has been profoundly influenced by complex human systems, posing new challenges for water resources management, environmental conservation, and societal resilience (Van Loon *et al* 2016, Van Oel *et al* 2018, AghaKouchak *et al* 2021, Kreibich *et al* 2023, Savelli *et al* 2023, Shah *et al* 2024).

The hydrological cycle has undergone significant alterations due to human activities, such as the widespread alteration of surface water flows and storage through reservoir operations and diversions of water from rivers and lakes. More than half of the world's major rivers are now regulated by dams (Nilsson *et al* 2005, Grill *et al* 2019). This impact is particularly pronounced in the US, where regulatory infrastructure has steadily expanded over time (Lehner *et al* 2011, Spinti *et al* 2023). Large infrastructural water projects play a crucial role in increasing water availability for multisectoral use. However, they have also brought adverse effects by disrupting the natural flow regime, impacting the magnitude and timing of streamflow (Salwey *et al* 2023). Consequently, these alterations can affect the characteristics of HD as well as drought propagation from MD to HD (Tijdeman *et al* 2018). Both positive and negative impacts of water management (WM) have been documented worldwide in the literature, varying with regions and seasons, as reviewed by Zhang *et al* (2022). For example, He *et al* (2017) showed that the 2014 drought in Southern California, US, was significantly alleviated through reservoir operations. Conversely, Xing *et al* (2021) found that HD was amplified in summer and fall but decreased in winter and spring in a reservoir-dominant basin in Northeast China. López-Moreno *et al* (2009) also found that the Alcántara reservoir near the border between Spain and Portugal amplified drought conditions downstream in the Portuguese part of the basin. Understanding how HD has been modified by human activities is crucial for effective water resources management, risk assessment, and adaptation strategies. It also aids in protecting ecosystems, mitigating social and economic impacts, and informing policy development and regulation.

Texas, the largest state in the contiguous US, stands out as an exemplary region to study the effects of WM on drought, due to its vulnerability to drought and significant WM practices (Nielsen-Gammon *et al* 2020). WM refers to the strategic planning, allocation, and regulation of water resources. In Texas, WM involves the widespread use of infrastructure (e.g. reservoirs) and institutional measures (e.g. water rights and regulations) to ensure reliable water supply under the variable and diverse climate conditions across the state, which include frequent droughts and floods. Over the past century, Texas has experienced several notable drought events, including the 1950–1957 drought, which ranks among the lengthiest drought on the record in Texas, and the 2011 drought, recognized in many regions as the most severe single-year drought in the state (Hoerling *et al* 2013). WM plays an essential role in Texas in enhancing the resilience of communities to water-related hazards and in supporting the availability of water for various human and ecosystem needs. For example, approximately 42% of the water used in the state in 2021 was sourced from reservoirs (Texas Water Development Board 2024a). Despite substantial and widespread WM in Texas, the WM influence on drought processes and propagation in this region has received limited attention. This knowledge gap serves as the primary motivation for this study.

Previous studies have explored WM's influence on drought in other areas, typically by comparing drought conditions under managed and unmanaged states using various methodologies, including observation-based, modeling-based, and hybrid observation-modeling approaches. Observation-based methods rely solely on observed streamflow and can be categorized into different sub-methods based on the properties of the streamflow measurements. Common observation-based approaches include the 'pre-post disturbance', 'paired catchment,' and 'upstream-downstream' methods. The 'pre-post disturbance' approach compares drought characteristics before and after WM interventions at the same location but during different time periods. To accurately assess the impact of WM, this method necessitates careful separation of the effects due to WM from those caused by natural climate variability (Lorenzo-Lacruz *et al* 2013, Wu *et al* 2018, Huang *et al* 2021). The 'paired catchment' approach compares droughts in two catchments with similar physical characteristics, where one serves as a control and the other as the disturbed catchment; however, finding suitable paired catchments can be challenging (Van Loon *et al* 2019, Brunner 2021). The 'upstream-downstream' approach compares HD downstream of a management point with those upstream, assuming the latter are unaffected (López-Moreno *et al* 2009, Rangecroft *et al* 2019). Uncertainty in this method arises from potential non-linear relationships between upstream and downstream gauging stations. The modeling-based methods quantify the anthropogenic influences by comparing simulated natural flow and disturbed flow (Firoz *et al* 2018, Yang *et al* 2020, 2024), with the natural flow serving as a reference that reflects what flow would be under natural conditions without human activities (Terrier *et al* 2021). Unlike the previously mentioned observation-based methods, this approach has the advantage of comparing drought characteristics at the same location within the same period, thereby minimizing confounding factors that can arise from comparing different time periods or locations. However, this method relies entirely on numerical simulations, which can introduce considerable uncertainties, particularly due to assumptions about WM that are not supported by empirical data (Zhao and Gao 2018, Abeshu *et al* 2023). The observation-modeling hybrid approach compares drought characteristics between observed streamflow and modeled natural flow (Van Loon and Van Lanen 2013, Liu *et al* 2024). This approach retains the advantages of the modeling-based methods by avoiding the pitfalls of comparing different time periods or locations, and it leverages observed streamflow data, thereby reducing some uncertainties from numerical simulations. However, it also has limitations, as it may attribute all discrepancies between the datasets solely to human activities, which can be misleading due to uncertainties introduced by the assumptions and parameterizations within the complex algorithms used in hydrological models to simulate naturalized flow.

In this study, we employ an improved observation-modeling hybrid approach by using naturalized flow data from the Texas Commission on Environmental Quality (TCEQ) naturalized streamflow datasets, which were reconstructed primarily using observed data rather than relying on simulated processes. The naturalized flow was developed through an accounting method that adjusts observed streamflow by adding or subtracting human influences (e.g. reservoir operations, diversions) to/from observed streamflow, as detailed in section 2.1. A key strength of this method is its reliance on empirical measurements, such as streamflow observations and records of human WM activities, which reduces the uncertainties typically associated with comparing naturalized flow estimates from hydrological modeling to real-world observations.

The objective of our research was to quantify the impact of WM on drought propagation from MD to HD and characteristics of HD in major rivers across Texas. In section 2, we present the data and methods used to identify drought events, and approaches to quantify the human impacts. Section 3 presents the results and provides discussion regarding whether, how, and to what extent HD was influenced by WM. Section 4 summarizes conclusions from the findings.

## 2. Data and methods

### 2.1. Observed and naturalized streamflow

This drought analysis covers the mainstems of seven major rivers in Texas, and include the Nueces, San Antonio, Colorado, Brazos, Trinity, Neches, and Sabine Rivers. A total of 32 United States Geological Survey (USGS) streamflow gauges were selected for our analysis, as depicted in figure 1. These gauges were chosen based on two criteria: (1) at least 30 consecutive years of monthly data and (2) having upstream reservoirs, which represent the largest regulatory infrastructure of the region. The spatial configurations of the gauges nicely capture the longitudinal profile of each major river and are distributed across a broad spectrum of hydroclimatic conditions within the Texas-Gulf basin, spanning arid regions in the west to wet regions in the east, as indicated by the mean annual precipitation shown in figure 1. The drainage areas of these gauges range from 5424 $km^2$ to 103 580 $km^2$.

The observed streamflow at the USGS gauges, which represent regulated flow in the presence of WM, was retrieved from the National Water Information System using the data retrieval Python package developed by USGS (Hodson et al 2023). The retrieved data are at the daily scale and were aggregated to the monthly scale. Monthly naturalized streamflow was extracted from the input datasets used by the Water Rights Analysis Package (WRAP) of the Water Availability Modeling system (Wurbs and Hoffpauir 2012) developed by the TCEQ and its contractors, which serves as the foundation for the Texas water rights permitting programs (Wurbs 2005, 2021). The naturalized streamflow datasets from WRAP represent river flows in the absence of WM, which were estimated by adjusting the observed streamflow from USGS gauges accounting for factors including water storage in large reservoirs, reservoir evaporation, water supply diversions, and return flows. The general equation used for flow naturalization is as follows (Wurbs 2006, 2019, 2021, Texas Commission for Environmental Quality 2023):

$$\begin{aligned}\text{Naturalized Flow} &= \text{Gaged Flow}\\ &+ \text{Upstream Diversions}\\ &+ \text{Changes in Upstream Reservoir Storage}\\ &+ \text{Upstream Reservoir Evaporation}\\ &- \text{Upstream Return Flows.} \qquad (1)\end{aligned}$$

Upstream diversions, reservoir storage, and return flows were estimated using a combination of historical records, data from agencies such as the Texas Natural Resource Conservation Commission (TNRCC, now TCEQ), USGS, US Army Corps of Engineers, and the Texas Water Development Board (TWDB), along with estimates based on population data and information from individual water rights holders. Reservoir evaporation was calculated by multiplying the average reservoir surface area with net evaporation rates determined by subtracting precipitation from evaporation using gauge-based quadrangular data from TWDB. The naturalization process accounts only for WM activities, without addressing other factors that may influence streamflow, such as climate change and land use/land cover change.

The streamflow records for the 32 study sites vary due to differences in data availability and the initial impoundment date of upstream major reservoirs. For this analysis, we selected a common period of record for both regulated and naturalized streamflow data for each gauge (table S1). The detailed information for the selected gauges, including their latitude, longitude, drainage area, basin name, and analysis periods, is provided in table S1 in the supplementary material, and the USGS gauge ID for each gauge is shown on figure S1. The time series of naturalized and observed streamflow are presented in figure S2.

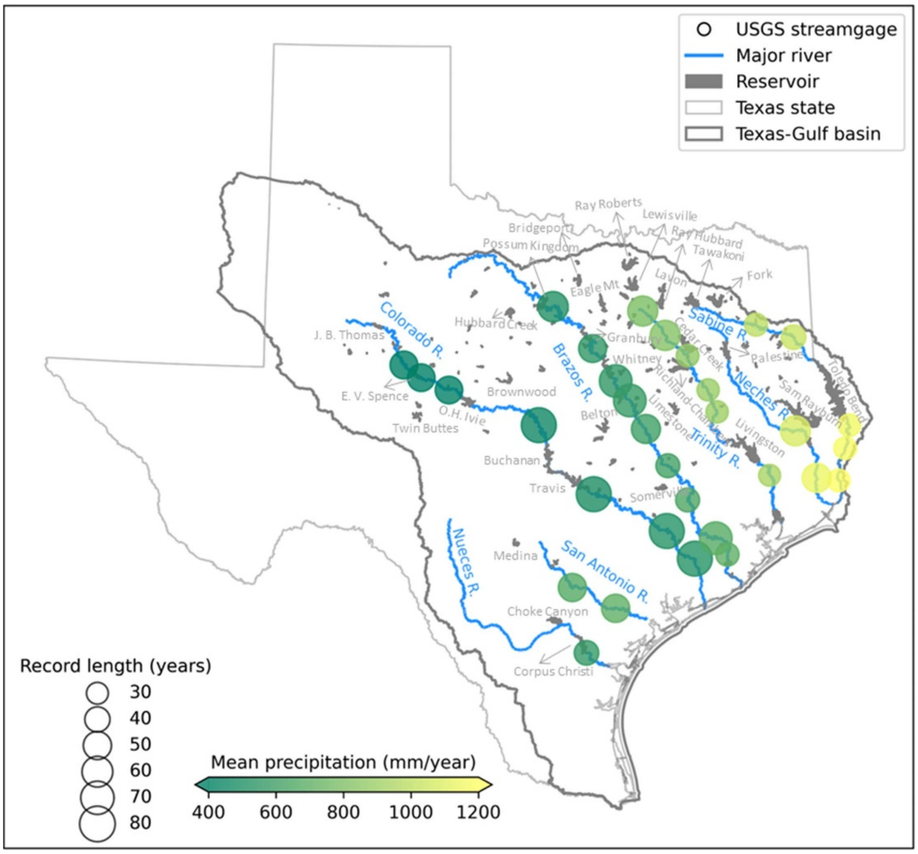


**Figure 1.** Locations of 32 USGS streamflow gauges distributed across the major rivers of the Texas-Gulf basin (HUC2 ID = 12), spanning the majority of Texas. The size of each point indicates the length of the streamflow and precipitation record used for analysis, while the color of each point represents the mean annual precipitation within the drainage area of each gauge. The blue lines represent the mainstems of the seven rivers (Nueces, San Antonio, Colorado, Brazos, Trinity, Neches, and Sabine). The gray polygons indicate the major reservoirs within the seven major river basins.

### 2.2. Precipitation

To characterize MD, this study employed monthly precipitation data sourced from the TWDB, available from January 1940 (Texas Water Development Board 2024b). This dataset has served as one of the principal sources for streamflow naturalization for Texas's WRAP. Therefore, using this precipitation data along with the WRAP naturalized flow ensures consistency in the analysis. The TWDB precipitation data is gridded into 92 one-degree grid cells covering Texas, and the monthly precipitation at each grid was computed as the mean of the measurements from precipitation stations using Thiessen networks (Wurbs 2021). In this study, average precipitation for each gauge was calculated as the area-weighted average across the entire upstream drainage area, ensuring that both local precipitation at the gauge and precipitation upstream within the basin were considered. The drainage area boundaries for each gauge were obtained from the Hydro Network-Linked Data Index developed by the USGS (Blodgett 2024). Additionally, since drought is assessed on a monthly scale, the time required for flow routing from upstream to downstream can be disregarded.

### 2.3. Drought events identification and drought characteristics

The standardized precipitation index (SPI) (McKee *et al* 1993) for precipitation and the standardized streamflow index (SSI) (Shukla and Wood 2008) for streamflow were utilized in this study as drought indicators. They are commonly used standardized anomaly indexes to characterize the level of drought or wet conditions relative to historical norms (Bachmair *et al* 2016, Tijdeman *et al* 2020, Zhang *et al* 2022). These two indices are also used by the TWDB for drought response and planning (Perry 2023). The calculation of these indices includes the following common steps: (1) compute accumulated precipitation or streamflow values over specific time periods (e.g. 1 month, 6 months). (2) Construct a cumulative distribution function (CDF) for the accumulated values, determining the probability of occurrence for different precipitation or streamflow levels. (3) Transfer the CDF into a standard normal distribution function to allow for fair and consistent comparison across different locations and time periods.

Prior studies have demonstrated the efficacy of the Gamma distribution in fitting precipitation data

(McKee *et al* 1995, Edwards and McKee 1997, Mishra and Singh 2009) and the lognormal distribution for streamflow across different climates in Texas (Rajsekhar *et al* 2013, 2015). Following these established practices, this study utilized the Gamma distribution to derive SPI, and the lognormal distribution for SSI for both observed and naturalized streamflow. Naturalized streamflow served as the benchmark for defining HD under natural condition. Both SPI and SSI were constrained within the range of $\pm 3.09$ (Guttman 1999).

Drought events were identified using the widely adopted run theory (Yevjevich 1967), with an SPI (SSI) threshold of $-0.5$. Drought duration of a single event was defined as the number of months with SPI (SSI) $< -0.5$, and drought severity was calculated as the absolute cumulative SPI (SSI) values during this period. Following Liu *et al* (2024), smaller drought events were merged into larger ones if the interval between these events was less than 3 months and the average SPI (SSI) during the interval was below 0.5. Consequently, the duration and severity of the larger event equated to the sum of the duration and severity of the smaller drought events.

### 2.4. HD response time and propagation rate

Persistent deficits in precipitation impact other elements of the water cycle, potentially leading to the propagation of MD into other components of the hydrological system (e.g. soil moisture, streamflow, groundwater storage). The propagation from MD to HD typically occurs with a delay, an emergent phenomenon in the hydrological system resulting from several underlying mechanisms (Changnon 1987, Van Loon 2013, Entekhabi 2023). Terrestrial water stored in soils, aquifers, lakes, snowpacks, and glaciers acts as buffers that can attenuate impacts of precipitation deficit on streamflow. However, as MD persists or as its severity increases, these buffers become depleted, eventually manifesting significantly below-normal streamflow. In managed river systems, human activities, such as WM practices—including operations of reservoirs—can modify the natural transition of drought signals within the water cycle. Therefore, the response time lag between MD and HD is due to the combined natural and human influences, which has been shown to vary with climatic factors, catchment characteristics, and management practices (Apurv and Cai 2020, Farahmand *et al* 2021, Yang *et al* 2024).

In this study, the widely used Pearson correlation analysis was employed to estimate drought response timescales (Barker *et al* 2016, Li *et al* 2022, Zhang *et al* 2022). This approach involves cross-correlating the SSI time series with a 1 month accumulation period (SSI-1) against SPI time series calculated over accumulation periods ranging from 1 to 24 months (SPI-$n$, where $n = 1, 2, \ldots, 24$). The SPI accumulation period that shows the highest correlation is identified as the response time. Because not every MD triggers a HD, the propagation rate of MD to HD was defined as the ratio of the number of MD events that resulted in HD events to the total number of MD events (Yang *et al* 2024). This propagation rate measures the sensitivities of HD to MD, with larger rates indicating greater sensitivity. A MD event that overlaps with the start month of the HD event was considered to trigger the HD. These corresponding MD and HD were defined as matched droughts, and the following analysis was conducted based on these matched droughts (Huang *et al* 2021, Liu *et al* 2024). To compare across gauges, the differences in response time and propagation rate between managed and natural conditions were normalized by the benchmark naturalized condition (Van Loon *et al* 2022).

## 3. Results and discussion

### 3.1. Change in drought propagation characteristics

*3.1.1. Response time of HD to MD*

The cross-correlation between the SSI-1 and various timescale of SPI for each gauge is presented in figure S3. Comparison of the HD response time between the natural and managed conditions (figure 2) suggests that WM significantly delayed HD across Texas's major rivers, with 27 out of 32 gauges (84%) experiencing an increase in the response time, while the remaining 5 gauges were unchanged. Under natural conditions, the median response time among the gauges was 2.5 months, while in the presence of WM, it increased to 5 months, with the median relative change being 83%. Additionally, the spatial variability of the response has increased, as indicated by the larger range of the interquartile of the response time from regulated *Q* in figure 2(b).

The largest increases in response time were found at gauge 08 158 000 in the lower Colorado River, gauge 08 093 100 in Brazos River, and gauge 08 026 000 in Sabine River. These three gauges are located immediately downstream of the Lake Travis, Whitney Lake, and Toledo Bend Reservoir, respectively (figure 1). Each of these reservoirs is the largest for its respective river in terms of storage capacity, supporting that larger reservoirs provide greater buffers against the propagation from MD to HD. This finding aligns with conclusions from previous studies. For instance, Huang *et al* (2021) reported that the construction of the Three Gorges Dam, the world's largest power station in terms of installed capacity, has led to increasing propagation time from MD to HD by 0.5, 1.67, and 2 months in the upper, middle, and lower region. Lorenzo-Lacruz *et al* (2013) also found a significant positive correlation between the

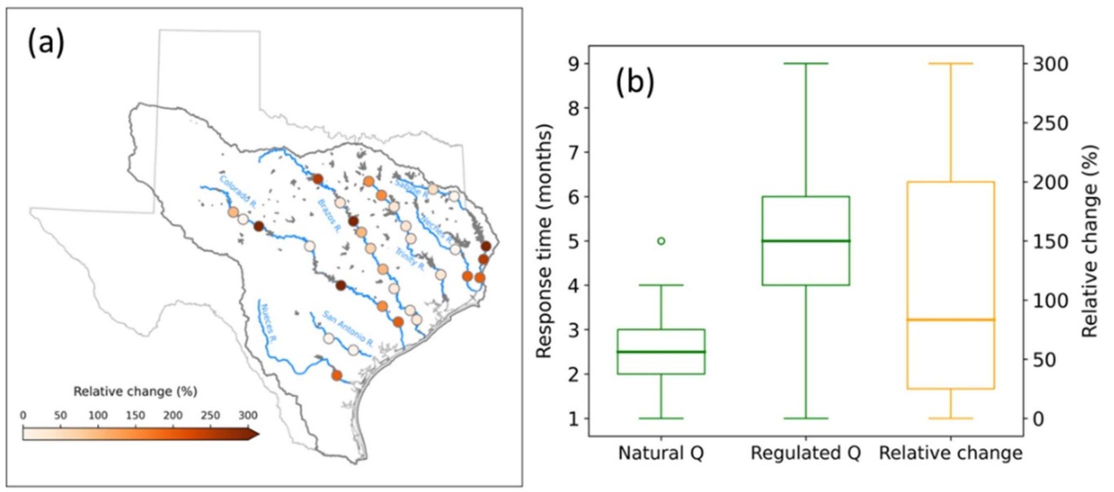


**Figure 2.** (a) Relative change in response time of HD to MD between natural and managed conditions. (b) Boxplot illustrating the variability of response time under natural condition, managed condition, and their relative changes.

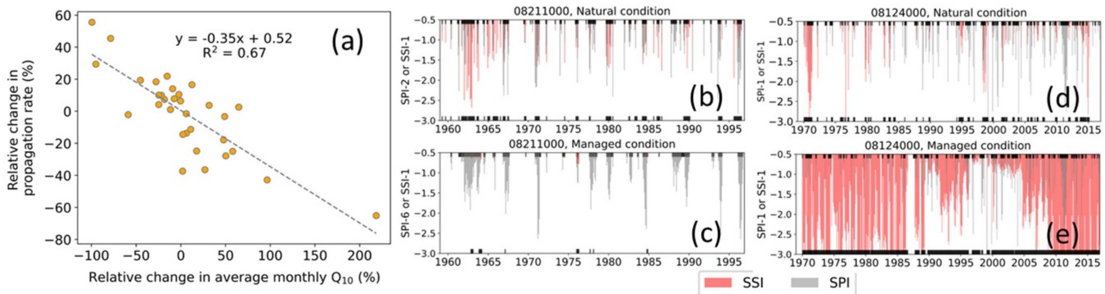


**Figure 3.** (a) Relationship between the relative change in propagation rate and the relative change in average monthly 10-percentile streamflow ($Q_{10}$). Identified HD and MD at gauge 0821 100 in the Nueces River under (b) natural and (c) managed conditions, and at gauge 08 124 000 in the Colorado River under (d) natural and (e) managed conditions. The number ($n$) in SPI-$n$ indicates the monthly response time of HD to MD. The lengths of the heavy black lines indicate the duration of MD (top axes) and HD (bottom axes) event in panels (b)–(e).

reservoir storage capacity and HD response time scale.

It is noted that the maximum correlation found between the SPI and SSI, based on regulated streamflow at gauge 08 124 000 in the upper Colorado River downstream of the E. V. Spence Reservoir (figure S1), did not pass the significance level of $p < 0.05$. To understand this, we analyzed monthly flow percentiles, including the 10th percentile exceedance probability flow ($Q_{10}$) and median flow ($Q_{50}$) to characterize flow patterns. It was found that $Q_{10}$ and $Q_{50}$ for managed flows at this gauge decreased by 99% and 93%, respectively, representing the largest decreases among all gauges for these flow percentiles. The heavy regulation of the E. V. Spence Reservoir likely largely disrupted the streamflow response to precipitation. It also likely contributed to the substantial increase in the HD response time at gauge 08 126 380, which is located further downstream of gauge 08 124 000, with the response time increasing from 2 months to 8 months.

*3.1.2. Propagation rate from MD to HD*

Propagation rate quantifies the proportion of MD events that lead to HD events. Regionally, the average propagation rates showed only a marginal increase from 0.72 to 0.74 under managed condition. However, a strong negative correlation ($R^2 \approx 0.7$) was observed between the relative change in propagation rate and the relative change in low flow (represented by average monthly $Q_{10}$), with an approximately linear relationship (figure 3(a)). This robust relationship suggests that enhancing low flow helps reduce the sensitivity of hydrological systems to MD. The largest shifts occurred at gauge 08 211 000 in the Nueces River and gauge 08 124 000 in the Colorado River. Figures 3(b) and (c) illustrate the identified MD and HD under natural and managed conditions for gauge 08 211 000, while figures 3(d) and (e) display the same for gauge 08 124 000. The vertical color bars indicate the SPI or SSI values during drought months, and the heavy black lines mark the duration of each MD (top axes) and HD (bottom axes) event in panels (b)–(e).

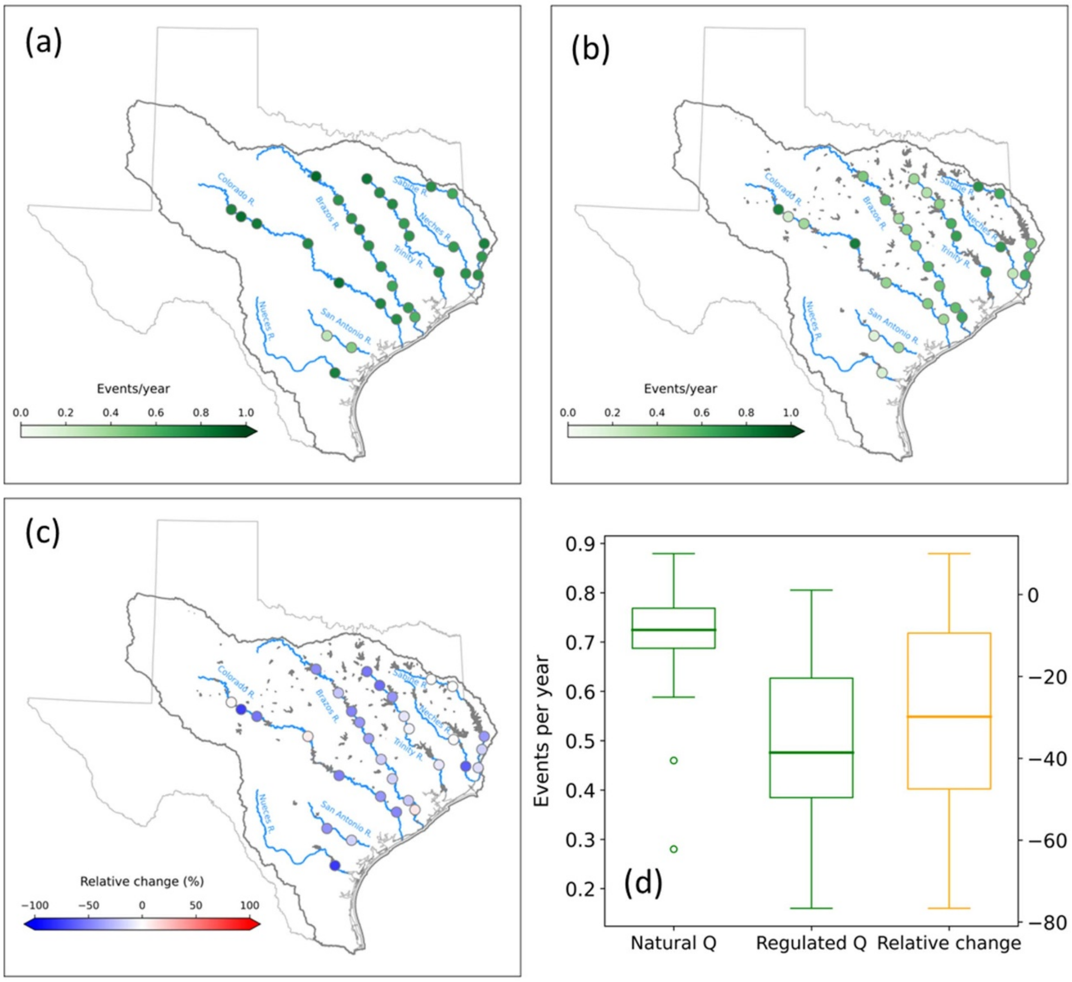


**Figure 4.** Spatial distribution of the HD frequency under (a) natural condition, (b) managed condition, and (c) their relative change. (d) Boxplot illustrating the range of variability in HD frequency under natural condition, managed condition, and their relative change.

The propagation rate at gauge 08 211 000 decreased dramatically from 68% to 24% with WM, a relative change of 65%, alongside a significant increase in low flow by 218%. Conversely, the propagation rate at gauge 08 211 000 increased from 63% to 99%, a relative change of 56%, corresponding to a 99% decrease in low flow.

## 3.2. Change in HD characteristics

### 3.2.1. Frequency

HD frequency refers to the number of HD events during the study periods at each gauge. Given the variability in the periods of record among the gauges, the total drought frequency was normalized by the number of years of available records in each gauge, allowing for comparison across gauges. Figures 4(a)–(c) map the average frequency (events/year) under natural condition, managed condition, and their relative changes. Results indicate a substantial decrease in frequency across all seven rivers and at most gauges, with 26 out of the 32 gauges (81%) experiencing a decline ranging from 5% to 77%, while 6 gauges show a slight increase or remain unchanged. The median frequency per year decreased from 0.72 to 0.48, with a median relative change around −30% from figure 4(d).

### 3.2.2. Cumulative duration and severity

Cumulative drought duration is defined as the total number of months under HD within the period of analysis, either under the natural or managed condition. Similarly, cumulative drought severity denotes the absolute value of the cumulative SSI below the threshold of −0.5, under natural or managed condition. To compare across gauges with varying periods of records, the cumulative drought duration and severity were normalized by the number of years of available records at each gauge. Notably, both the cumulative duration and severity in HD decreased in more than half of the gauges with WM (figure 5). Under natural condition, both the drought duration and severity exhibited much less variability among the gauges compared to managed condition, particularly the drought severity, as shown in figure 5(d). The median duration per year among the gauges

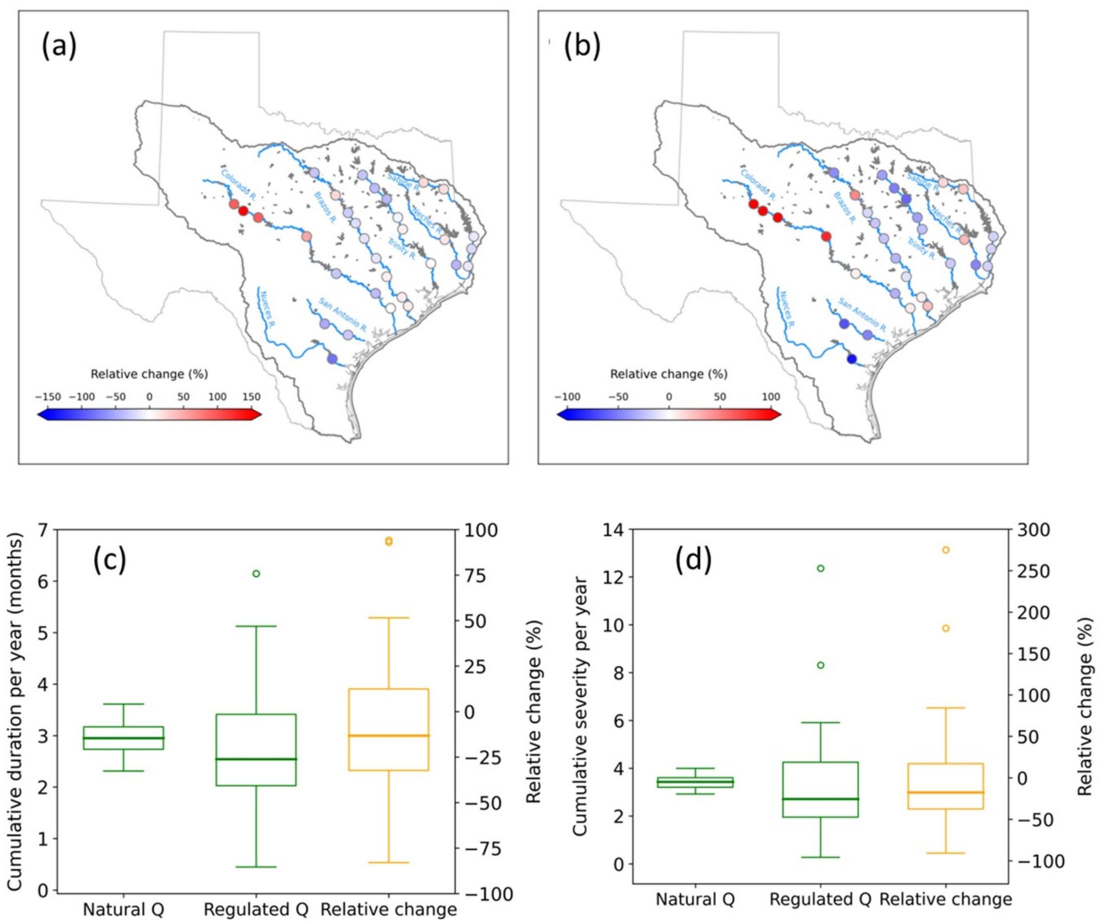


**Figure 5.** Spatial distribution of the relative change in (a) cumulative duration and (b) cumulative severity of HD; boxplots illustrating (c) the cumulative drought duration per year and (d) cumulative severity per year under natural condition, managed condition, and their relative change. Outliers at $y = 10.2$ in regulated $Q$ and $y = 290.2\%$ in relative change in (c), and $y = 22.4$ in regulated $Q$ and $y = 645.8\%$ in relative change in (d) were excluded from the figure to enhance visualization.

decreased from 2.9 months to 2.5 months, and the severity per year decreased from 3.5 to 2.7. However, for some locations, WM led to large (>50%) increases or decreases in both duration and severity, highlighting spatially varied impacts of WM on drought.

The upper Colorado River upstream of Lake Buchanan experienced the most pronounced exacerbation of HD in terms of both cumulative duration and severity under managed condition. A clear demonstration of this exacerbation can be seen when comparing figures 3(d) and (e) for gauge 08 214 000. To investigate the cause, we analyzed four gauges at this section of the river (08 123 850, 08 124 000, 08 126 380, 08 147 000), which are under the influence of three major reservoirs (storage capacity $\geqslant$ 5000 acre-feet at normal operating level) including J.B. Thomas, E.V. Spence, and O.H. Ivie Reservoirs. These reservoirs have permitted water supply storage capacities of 204 000, 488 760, and 554 340 acre-feet, accounting for 26.8% of the total permitted storage capacity of the 29 existing major reservoirs in the Colorado River basin (Wurbs 2022). However, the median fullness of these reservoirs is merely 15%, 23%, and 48% within the analysis period, respectively. The need to conserve storage in these reservoirs for reliable water supply resulted in very limited water released downstream, leading to significant declines in streamflow compared to the natural condition. Under managed condition, the average monthly $Q_{50}$ decreased by 50%, 93%, 78%, and 30% at these locations, representing the most substantial reductions among all sites. Similarly, WM reduced low flow even more significantly, with average monthly $Q_{10}$ reduction of 79%, 99%, 95%, and 45%, respectively. The substantial degree of water regulations at these reservoirs, particularly their reduction in streamflow, led to the largest increase in cumulative drought time (93%, 290%, 94%, and 52%) and cumulative severity (180%, 646%, 275%, and 84%) among all the gauges. In contrast, the largest reduction in cumulative duration and cumulative severity occurred at gauge 08 211 000 in Nueces River, which is directly downstream of Lake Corpus Christi. The cumulative duration and cumulative severity declined by 83% and 91%, respectively.

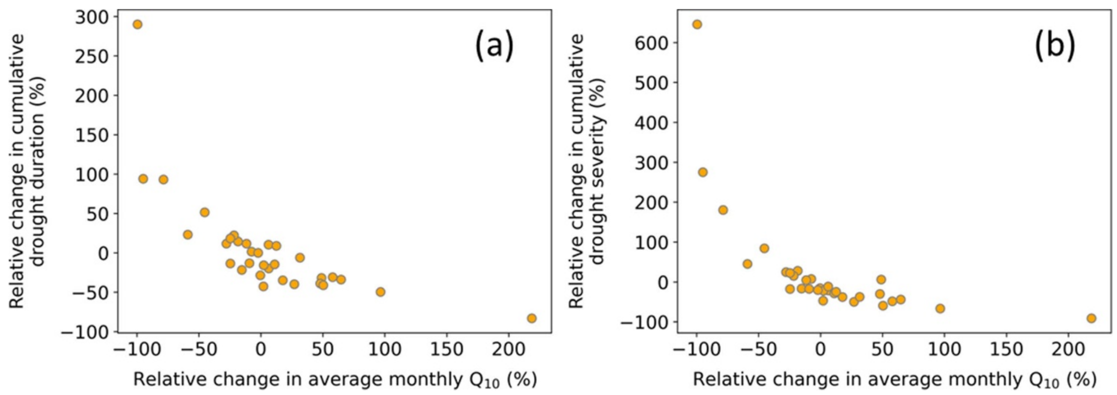


**Figure 6.** Relationship between changes in average monthly $Q_{10}$ and changes in cumulative HD duration (a) and severity (b).

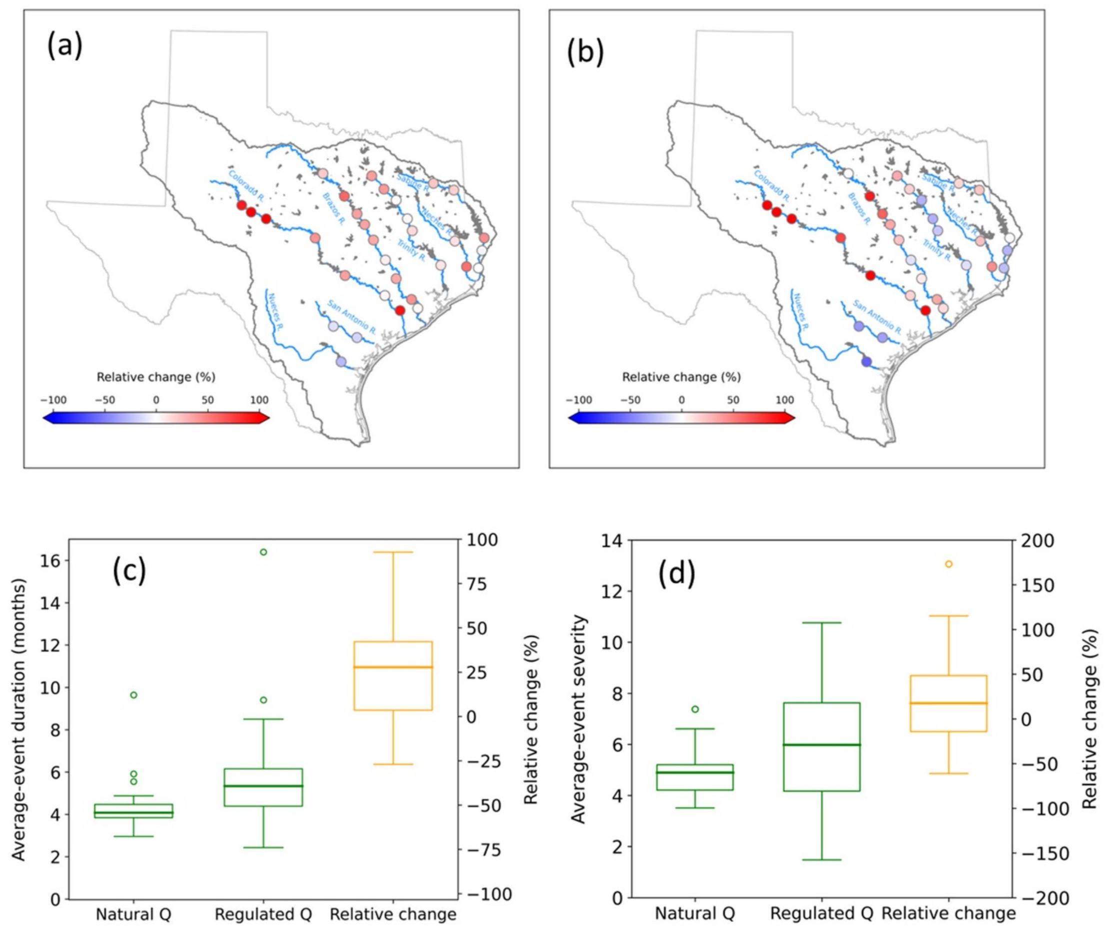


**Figure 7.** Spatial distribution of the relative change in (a) average-event duration and (b) average-event severity of HD; boxplots illustrating (c) the average-event duration and (d) average-event severity under natural condition, managed condition, and their relative changes. Outliers at $y = 51.5$ in regulated Q, $y = 1499.4\%$ and 320.3% in relative change in (c), $y = 107.35$ and $y = 32.97$ in regulated Q, $y = 2958.4\%$ and 712.1% in relative change in (d) were excluded from the figure to enhance visualization.

Our analysis identified a clear correlation between management's effect on average monthly $Q_{10}$ and the change in cumulative drought duration and severity (figure 6). Changes in cumulative duration and severity display a negative correlation with changes in $Q_{10}$, similar to the effect on propagation rate (figure 3(a)) but with a non-linear relationship. The non-linearity is evident as the slope of the fitting line becoming steeper with more negative change in $Q_{10}$, which suggests a more complex relationship between WM and its impact on HD.

### 3.2.3. Average-event duration and severity

Average-event duration and severity are defined as the mean values of HD duration and severity across all individual drought events. As shown in figure 7, most

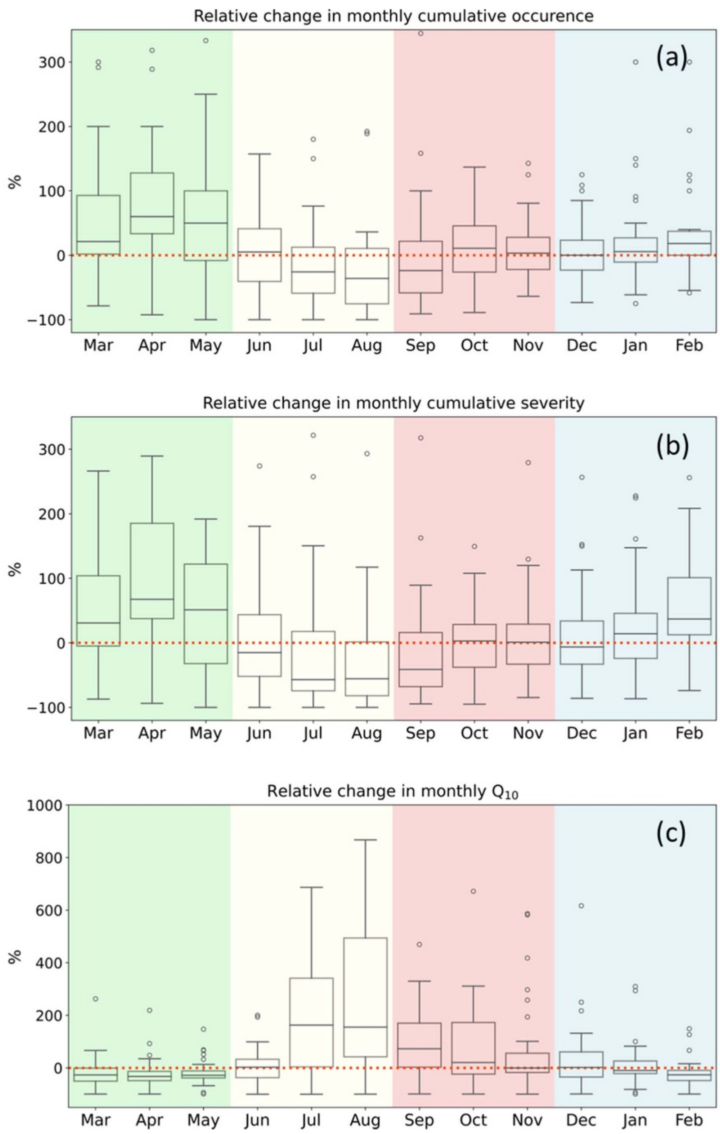


**Figure 8.** Boxplots illustrating the relative change in (a) monthly cumulative occurrence, (b) monthly cumulative severity of HD, and (c) monthly $Q_{10}$ under the natural and managed conditions. The background color indicates the four seasons.

gauges experienced longer and more severe average events in the presence of WM, despite some of these gauges showing decreasing cumulative drought duration and severity. Particularly, all gauges along the Colorado, Brazos, Trinity, and Neches rivers exhibited longer average-event durations. Moreover, all gauges along the Colorado River exhibited more severe average events, underscoring the particularly adverse influence of WM on HD characteristics within this basin. Conversely, there are five gauges (the lone gauge in the Nueces River, two gauges in the San Antonio River, and the two most downstream gauges in the Sabine River) where HD was reduced for all four metrics: cumulative duration, cumulative severity, average-event duration, and average-event severity. The variability in average-event duration and severity also exhibited greater fluctuation among gauges under WM compared to natural condition, mirroring the patterns observed in cumulative duration and severity.

*3.2.4. Temporal variations of WM impacts*

To understand the temporal characteristics of WM impacts, an analysis was conducted to calculate the relative changes in monthly cumulative occurrence and severity of HD for each gauge under natural and managed conditions, as presented in figures 8(a) and (b). The monthly cumulative occurrence of HD is defined as the total number of years in the dataset where the SSI is less than −0.5 for a specific month. Similarly, the monthly cumulative severity is defined as the cumulative severity of HD across years for a specific month.

The impact of WM on drought characteristics varied notably across months in Texas. Generally, late winter and spring (February to May) was more prone to drought under managed condition compared to natural condition, with greater occurrence and higher severity, as indicated by the significant deviation of the median change from zero. However, WM alleviated drought in mid-summer and early fall

(July – September). These seasonal variations in the impact of WM on drought resulted from the seasonality of WM impacts on streamflow. Figure 8(c) presents the relative change in monthly $Q_{10}$, indicating that low flow significantly increased from July to September in the presence of WM, especially in July and August, with median changes of 163% and 155% across gauges, respectively. Conversely, there is a notable decrease in low flow from February to May. The seasonality of WM impacts reflects WM strategies to store streamflow in reservoirs during late winter and spring when demand is lower and to release water during periods of high demand and low streamflow in mid-summer and early fall.

## 4. Conclusions

In this study, we investigated the impact of WM on HD characteristics and the dynamics of MD propagation to HD across major rivers in the state of Texas, using paired measurements of streamflow, naturalized streamflow, and precipitation data. The findings indicate an increase in the response time of HD to MD in most gauges, and a negative linear relationship between the change in drought propagation rate and the alteration in monthly low flow. This suggests that higher low flow due to WM activities reduce the likelihood of MD evolving into HD, while negative impacts to low flow increase propagation potential.

Our analysis revealed that WM led to a decrease in HD frequency in most gauges, and alleviated long-term cumulative HD duration and severity at more than half of the gauges. This can be attributed to the seasonal variation in WM's impact on droughts, with monthly occurrence and severity of HD generally increasing in cooler months (February to May with higher flow and lower demand) while decreasing in warmer months (July to September with lower flow and higher demand). Overall, the effectiveness of WM in alleviating drought conditions during warmer months surpassed its adverse effects in cooler months, contributing to a decrease in frequency and the long-term cumulative duration and severity of HD. In contrast, the average-event duration and severity of HD increased. Specifically, every gauge along the Colorado River experienced longer average-event duration and greater severity, emphasizing the substantial adverse impact of WM on some individual drought events within this basin.

The multifaceted impacts of WM revealed in this study highlight the importance of comprehensive assessment of WM influence on HD. The spatial variability of drought propagation and characteristics of HD significantly increased with the implementation of WM activities, emphasizing the need for tailored drought mitigation and adaptation strategies for different locations, as well as illustrating the need for caution when characterizing the effect of WM at only a small number of locations in a region as is typically done in the literature. The complex effects of WM revealed in this study could also motivate a critical reflection on current WM practices in Texas, especially considering the adverse impacts observed. Future studies could delve into the specific mechanisms and WM operations that contribute to these adverse effects on HD. This would provide a more detailed understanding of how different WM practices impact drought characteristics and potentially help inform better management strategies.

The naturalized flow used in this study was developed by adjusting historical gauged streamflow data to remove the impacts of human activities. This approach leverages a substantial amount of empirical data, providing a more data-driven foundation compared to traditional modeling methods. However, complete records of human influences are not always available, and the complexity of accurately capturing all such influences introduces inherent uncertainties into these adjustments. Consequently, the risk of incorrectly attributing all discrepancies between the naturalized flow and gauged flow solely to human activities cannot be entirely eliminated due to these uncertainties. Future research could explore alternative methods or additional data sources to refine these adjustments and reduce uncertainties.

## Data availability statement

The data that support the findings of this study are openly available at the following URL: https://github.com/IMMM-SFA/Yao_et_al_2024_ERL.

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