# Unraveling the Drivers of Water Shortage across Spatial Scales and Sectors in Colorado's West Slope River Basins

Sai Veena Sunkara[1], David Gold[2], and Patrick M. Reed[1]

[1]Cornell University
[2]Universiteit Utrecht Faculteit Geowetenschappen

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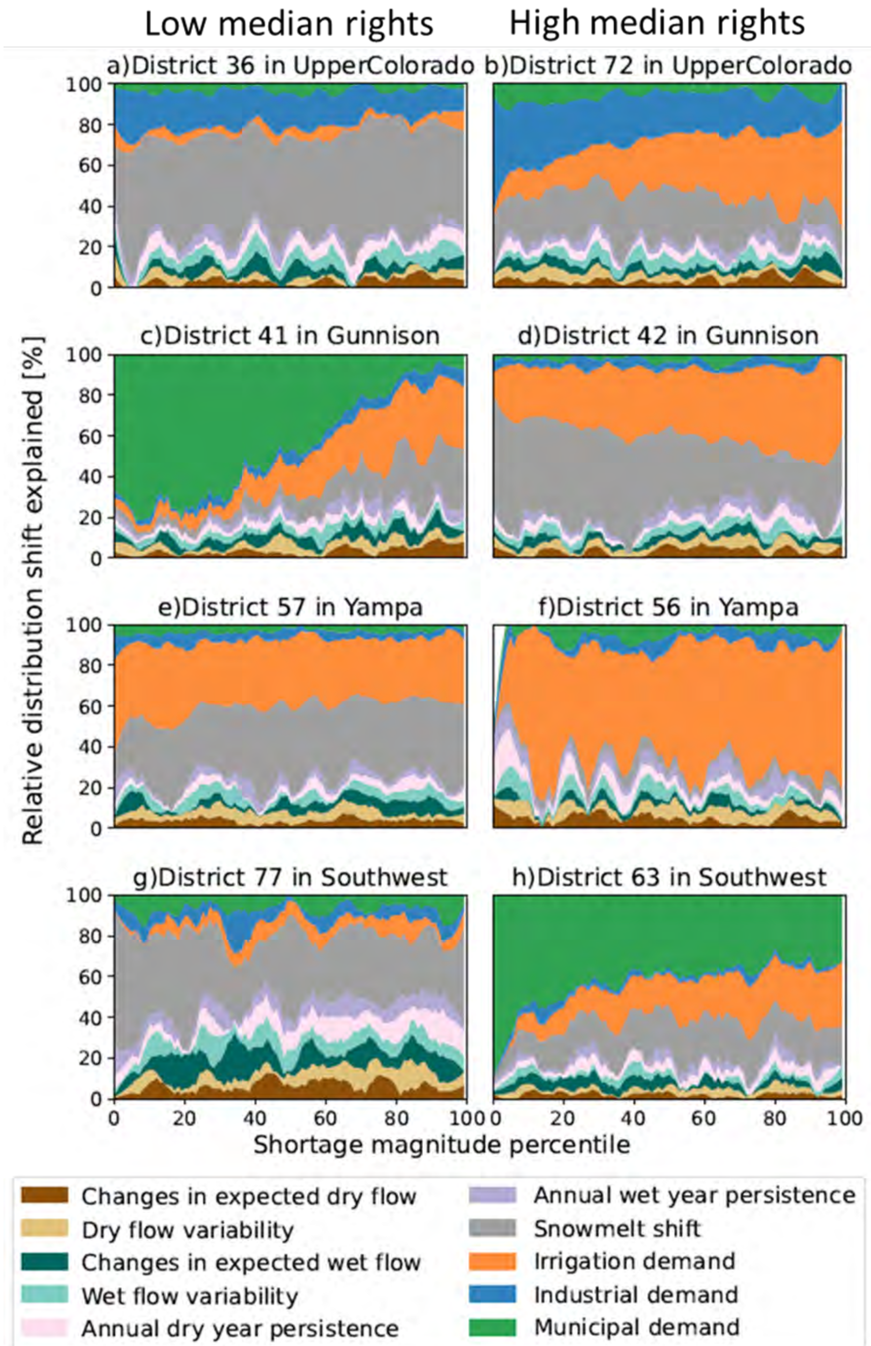
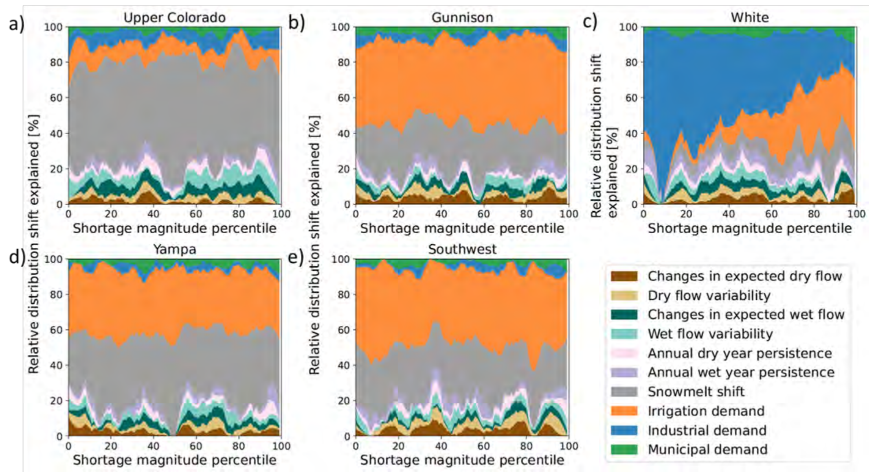
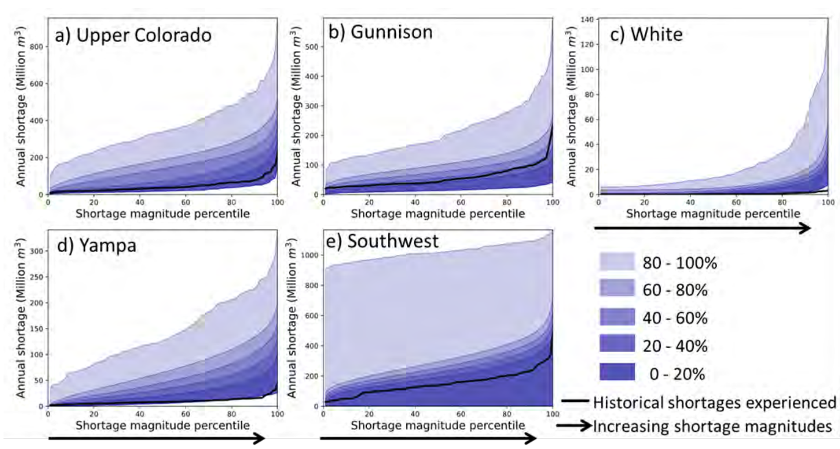
**Abstract**

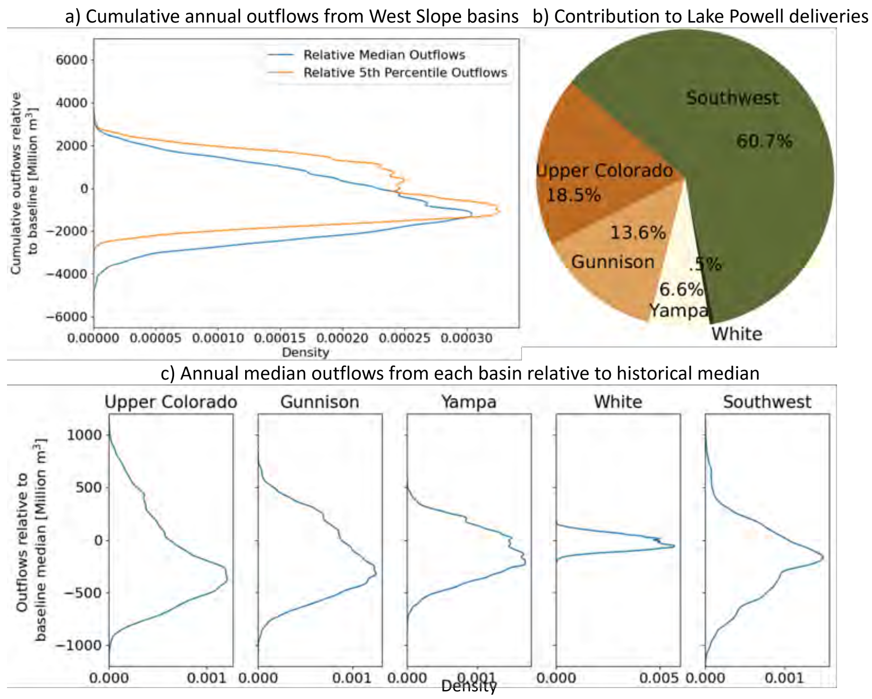
Colorado's West Slope Basins are a critical source of water for the Colorado River, contributing approximately 70% of the inflows to Lake Powell in a typical year. Whether these basins will face intensifying water shortages by mid-century remains highly debated due to deep uncertainties in future climate conditions, including the possibility of wetter or drier futures, persistence of severe drought, population growth, and evolving multisectoral water demands. Identifying the primary drivers of plausible mid-century water shortages is particularly challenging given the region's high internal climate variability, changing hydrology, and complex institutional framework governing water rights for thousands of users. This study integrates large-scale exploratory modeling with diagnostic sensitivity analysis to clarify the relative influence of uncertain natural and human drivers of water shortages in the West Slope basins. A multi-site Hidden Markov Model (HMM) is used to generate a wide range of synthetic streamflow scenarios representing plausible mid-century changes relative to the historical baseline. These stochastic hydrologic scenarios span both wetter and drier futures and are combined with projected demand changes across sectors. The resulting scenarios are simulated within Colorado's StateMod water allocation model to estimate water shortages at basin, district, and sectoral scales. Diagnostic sensitivity analysis reveals that the dominant drivers of shortages vary markedly by basin, district, major reservoir and sector. These findings provide actionable, scale-specific insights into the most influential factors shaping future water stress in Colorado's West Slope basins.



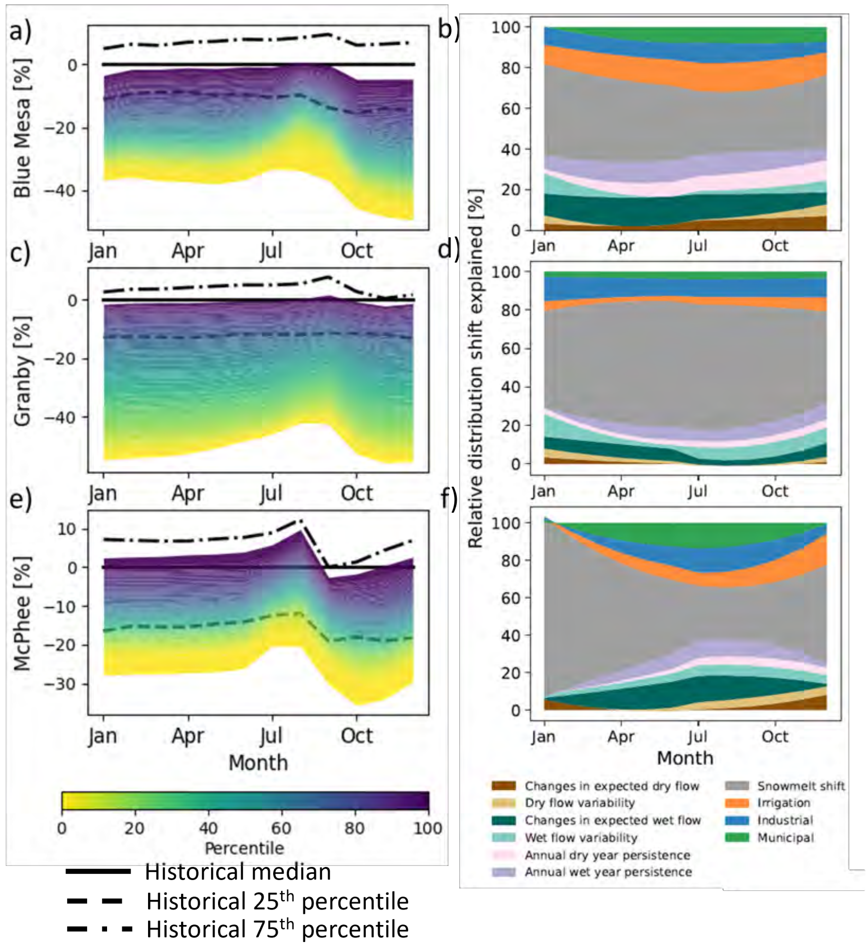
Low median rights
High median rights
a)District 36 in UpperColorado
b)District 72 in UpperColorado
c)District 41 in Gunnison
d)District 42 in Gunnison
e)District 57 in Yampa
f)District 56 in Yampa
g)District 77 in Southwest
h)District 63 in Southwest
Relative distribution shift explained [%]
Shortage magnitude percentile
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation demand
Industrial demand
Municipal demand

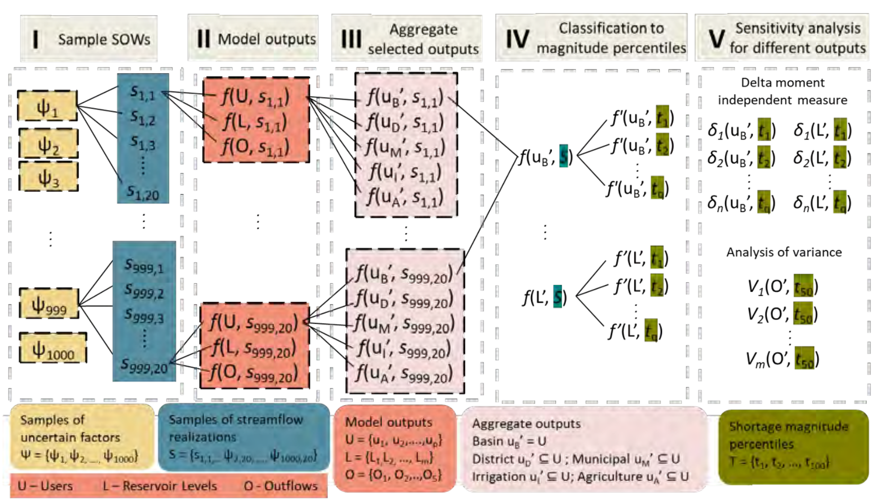

a) Upper Colorado
b) Gunnison
c) White
d) Yampa
e) Southwest
Relative distribution shift explained [%]
Shortage magnitude percentile
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation demand
Industrial demand
Municipal demand

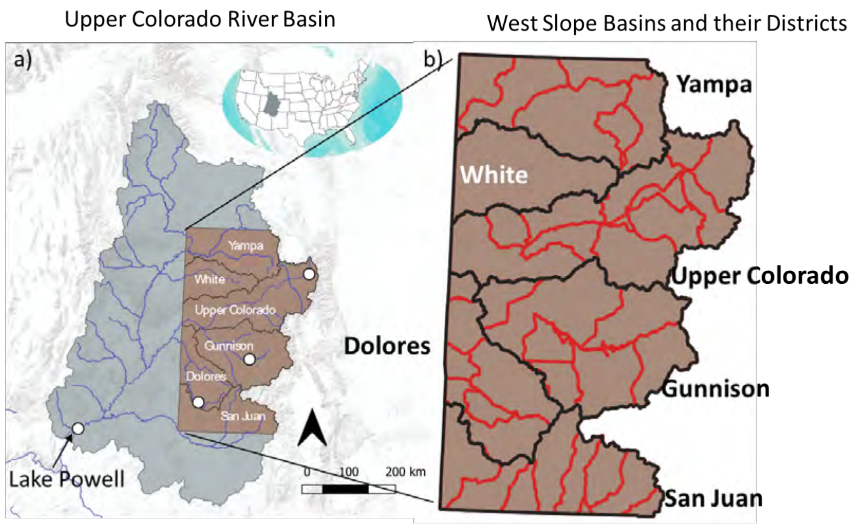

a) Upper Colorado
b) Gunnison
c) White
d) Yampa
e) Southwest
Annual shortage (Million $m^3$)
Shortage magnitude percentile
80 - 100%
60 - 80%
40 - 60%
20 - 40%
0 - 20%
Historical shortages experienced
Increasing shortage magnitudes

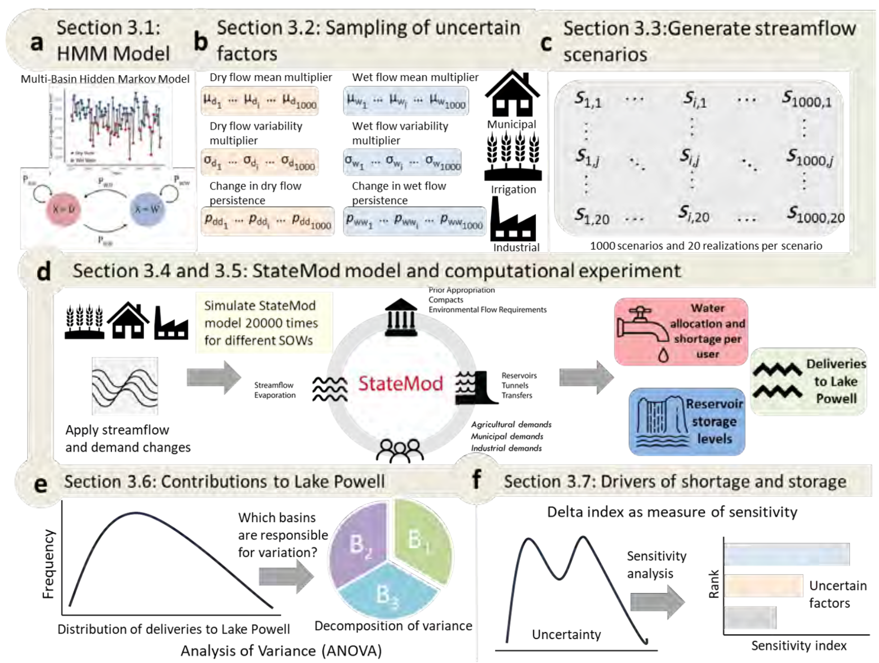


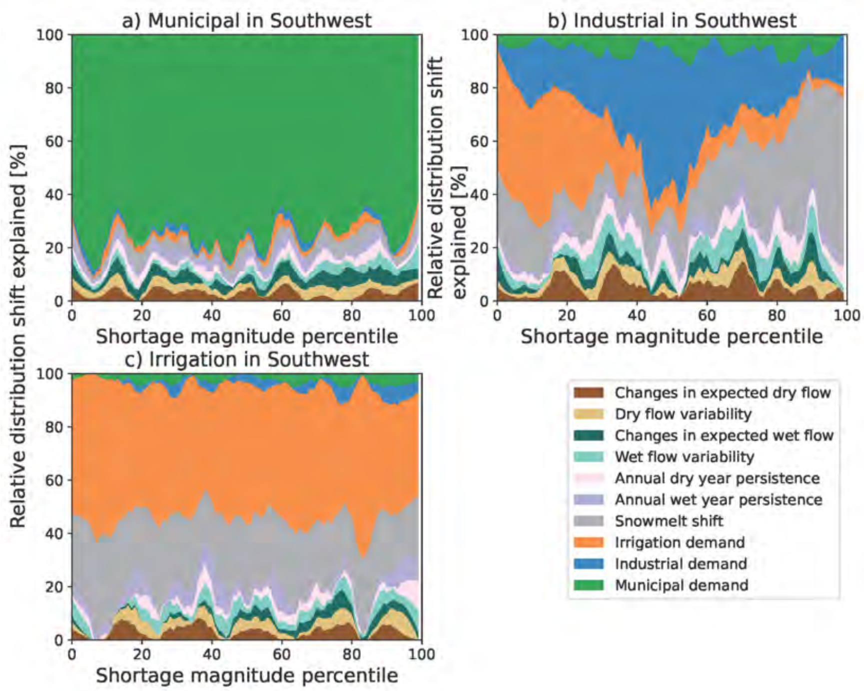
a) Cumulative annual outflows from West Slope basins
b) Contribution to Lake Powell deliveries
Relative Median Outflows
Relative 5th Percentile Outflows
Cumulative outflows relative to baseline [Million m³]
6000
4000
2000
0
−2000
−4000
−6000
0.00000 0.00005 0.00010 0.00015 0.00020 0.00025 0.00030
Density
Southwest
60.7%
Upper Colorado
18.5%
13.6%
Gunnison
.5%
6.6%
Yampa
White
c) Annual median outflows from each basin relative to historical median
Upper Colorado
Gunnison
Yampa
White
Southwest
Outflows relative to baseline median [Million m³]
1000
500
0
−500
−1000
0.000 0.001
0.000 0.001
0.000 0.001
0.000 0.005
0.000 0.001
Density


a)
b)
c)
d)
e)
f)
Blue Mesa [%]
Granby [%]
McPhee [%]
Relative distribution shift explained [%]
Jan
Apr
Jul
Oct
Month
Percentile
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation
Industrial
Municipal
Historical median
Historical 25th percentile
Historical 75th percentile


I Sample SOWs
II Model outputs
III Aggregate selected outputs
IV Classification to magnitude percentiles
V Sensitivity analysis for different outputs
Delta moment independent measure
Analysis of variance
Samples of uncertain factors
Samples of streamflow realizations
Model outputs
Aggregate outputs
Basin u_B' = U
Shortage magnitude percentiles
U – Users
L – Reservoir Levels
O - Outflows


Upper Colorado River Basin
West Slope Basins and their Districts
a)
b)
Yampa
White
Upper Colorado
Gunnison
Dolores
San Juan
Lake Powell
0
100
200 km


a Section 3.1: HMM Model
b Section 3.2: Sampling of uncertain factors
c Section 3.3:Generate streamflow scenarios
Multi-Basin Hidden Markov Model
Dry flow mean multiplier
Wet flow mean multiplier
Dry flow variability multiplier
Wet flow variability multiplier
Change in dry flow persistence
Change in wet flow persistence
Municipal
Irrigation
Industrial
1000 scenarios and 20 realizations per scenario
d Section 3.4 and 3.5: StateMod model and computational experiment
Simulate StateMod model 20000 times for different SOWs
Apply streamflow and demand changes
Streamflow
Evaporation
StateMod
Prior Appropriation
Compacts
Environmental Flow Requirements
Reservoirs
Tunnels
Transfers
Agricultural demands
Municipal demands
Industrial demands
Water allocation and shortage per user
Deliveries to Lake Powell
Reservoir storage levels
e Section 3.6: Contributions to Lake Powell
Frequency
Which basins are responsible for variation?
Distribution of deliveries to Lake Powell
Decomposition of variance
Analysis of Variance (ANOVA)
f Section 3.7: Drivers of shortage and storage
Delta index as measure of sensitivity
Sensitivity analysis
Uncertainty
Rank
Uncertain factors
Sensitivity index


a) Municipal in Southwest
b) Industrial in Southwest
c) Irrigation in Southwest
Relative distribution shift explained [%]
Relative distribution shift explained [%]
Shortage magnitude percentile
Shortage magnitude percentile
Shortage magnitude percentile
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation demand
Industrial demand
Municipal demand

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**Sai Veena Sunkara[1], David Gold[2], Patrick Reed[1]**

[1]School of Civil and Environmental Engineering, Cornell University, Ithaca, NY, USA
[2]Department of Physical Geography, Utrecht University, Utrecht, The Netherlands

**Key Points:**

- We present the largest exploratory modeling study of plausible mid-century hydrological and demand changes in Colorado's West Slope Basins.
- Projected deliveries to Lake Powell fall up to 52% below their baseline median making compliance with the Law of River Compact challenging.
- Magnitude-varying sensitivity analysis provides actionable basin, sector, and user specific insights on the drivers of water shortages.

Corresponding author: Sai Veena Sunkara, `ss4285@cornell.edu`

## Abstract

Colorado's West Slope Basins are a critical source of water for the Colorado River, contributing approximately 70% of the inflows to Lake Powell in a typical year. Whether these basins will face intensifying water shortages by mid-century remains highly debated due to deep uncertainties in future climate conditions, including the possibility of wetter or drier futures, persistence of severe drought, population growth, and evolving multisectoral water demands. Identifying the primary drivers of plausible mid-century water shortages is particularly challenging given the region's high internal climate variability, changing hydrology, and complex institutional framework governing water rights for thousands of users. This study integrates large-scale exploratory modeling with diagnostic sensitivity analysis to clarify the relative influence of uncertain natural and human drivers of water shortages in the West Slope basins. A multi-site Hidden Markov Model (HMM) is used to generate a wide range of synthetic streamflow scenarios representing plausible mid-century changes relative to the historical baseline. These stochastic hydrologic scenarios span both wetter and drier futures and are combined with projected demand changes across sectors. The resulting scenarios are simulated within Colorado's StateMod water allocation model to estimate water shortages at basin, district, and sectoral scales. Diagnostic sensitivity analysis reveals that the dominant drivers of shortages vary markedly by basin, district, major reservoir and sector. These findings provide actionable, scale-specific insights into the most influential factors shaping future water stress in Colorado's West Slope basins.


## Plain Language Summary

Colorado's West Slope basins contribute approximately 70% of inflows into Lake Powell, which is a critical storage impacting how water allocated across across the Upper and Lower Colorado River Basin. However, it is unclear whether the West Slope basins will experience more frequent and severe water shortages by the middle of the century. Future water availability depends on many uncertain factors, such as how hydrologic variability affects rainfall and snowpack, whether persistent droughts continue as well as population growth and future water demands. This study uses modeling to explore many possible future streamflow scenarios, ranging from wetter to much drier conditions, and combines them with possible changes in water demand from cities, agriculture, and industrial sectors. These scenarios are evaluated using Colorado's official water allocation model called StateMod to estimate shortages across basins, districts, reservoirs, and water-use sectors. Our results show that there is no single cause of future water shortages. Instead, the most important drivers vary spatially and by type of water use. This means water planning and adaptation strategies should be tailored to specific basins and users, rather than relying on a single generic strategy.

## 1 Introduction

Colorado's West Slope basins are crucial for understanding drought risk in the Colorado River Basin. As the alpine headwaters of the Colorado River, the West Slope basins are the source of nearly 70% of average annual deliveries to Lake Powell and, consequently, are highly influential in how water shortages propagate among downstream water users (CWCB, 2023). These basins are critical to the state of Colorado's $550-Billion economy (U.S. Bureau of Economic Analysis, 2025) by supporting irrigated agriculture, municipal and industrial water supply, hydropower production, and recreation. However, since the early 2000s , persistent drought in the West Slope and the broader Colorado River Basin has led to unprecedented water management challenges (Lukas & Payton, 2020; Udall & Overpeck, 2017; Wheeler et al., 2022). For most of the 21st century, consumptive water use has exceeded natural streamflow, leading to severe drawdowns in Lake Powell and threatening hydropower generation, agricultural production, and water supply (J. Schmidt et al., 2025). In response, the seven Colorado River Basin states are currently negotiating new operations guidelines scheduled to take effect in 2027. Understanding the opportunities and consequences of future management policies requires a comprehensive understanding of drought risk and its impacts across spatial and sectoral scales (Wheeler et al., 2022). This paper advances our understanding of how drought risks and their drivers in the West Slope basins may evolve by mid-century. To our knowledge, it represents the most comprehensive exploratory modeling analysis of the broad range of plausible mid-century changes in the region's hydrological conditions and multisectoral demands. Our analysis distinguishes how the West Slope basins' water shortages and their deeply uncertain drivers vary across scales (regional, basin, and local) and sectors (agricultural, municipal, and industrial demands), while accounting for the institutional complexity of their major infrastructure and water rights systems.

Characterizing drought vulnerability in the West Slope basins is challenging due to the complex interactions between the natural processes and human systems that emerge across a range of spatial and temporal scales (Hadjimichael et al., 2024). Thousands of representative water users withdraw water for irrigated agriculture, municipal supply, and industrial uses (CWCB, 2023). Water rights are governed by Colorado's Prior Appropriations doctrine, a complex legal hierarchy that creates complex and emergent dependencies among users in terms of how they are impacted by water shortages propagating through the region (Bruns et al., 2005; US Bureau of Reclamation, 2012). Reservoir operations alter the timing and magnitude of streamflows, shifting when and where water scarcity occurs (J. C. Schmidt, 2010). These human management decisions interact with natural hydrologic variability to shape local drought dynamics (AghaKouchak et al., 2021; Van Loon et al., 2016). Meanwhile, spatially compounding drought events can propagate across multiple sub-basins, magnifying regional impacts (Gold et al., 2024). Together, these multisectoral demands and potentially spatially compounding drought dynamics complicate risk assessment in the West Slope basins, requiring modeling approaches that capture their feedbacks across scales (Hadjimichael et al., 2024; Gold et al., 2024).

Quantifying drought risk in the West Slope basins is further complicated by uncertainty in future conditions. Paleoclimate reconstructions reveal that internal hydroclimatic variability in the Upper Colorado River Basin can generate droughts more prolonged and severe than any observed in the historical record, highlighting that the modern observation record is limited in capturing the full range of possible futures (Woodhouse et al., 2006; McCabe et al., 2024). Future changes in precipitation and temperature introduce substantial additional uncertainty. Mid-century streamflow projections span a wide range, encompassing scenarios with 40% declines in streamflows to those with nearly 25% increases relative to the baseline period from 2000-2020, driven by divergent assumptions and initial conditions across climate models (Udall & Overpeck, 2017; Hoerling et al., 2024). Human water demand adds yet another layer of complexity, with future changes in consumptive use varying by sector, scale, and location, depending on assumptions about population growth, land-use change, and per capita consumption patterns (Upper Colorado River Commission, 2016; CWCB, 2023).

The broad range of projections about future changes in streamflow and human demand are examples of "deep uncertainties" within the West Slope system (Quinn et al., 2020; Smith, 2022). Deep uncertainty occurs when stakeholders do not know, or cannot agree on, the probability distributions of system inputs, the system boundaries, or the drivers of key processes (Lempert et al., 2006; Moallemi et al., 2020; Kwakkel et al., 2016). Recently, exploratory modeling frameworks have shown promise in characterizing drought risk under deep uncertainty (Singh, 2023; Wu et al., 2025). These approaches address uncertainty through systematic computational experiments that use large ensembles of future conditions to explore the underlying drivers of vulnerability and to identify consequential future scenarios (Bankes, 1993; Moallemi et al., 2020; Reed et al., 2022). For example, Gold et al. (2024) used exploratory modeling to examine how internal variability and a middle-of-the-road projection of mid-century streamflow decline (7% relative to a 1970-2000 baseline) could influence future multisectoral drought vulnerability in the West Slope basins. Results highlighted that extreme events arising from stationary internal variability can cause spatially compounding drought impacts that exceed observed historical extremes. Moreover, their findings suggest that even a modest decrease in average annual streamflow may lead to unprecedented multisectoral challenges for local and regional water management.

While Gold et al. (2024) provided insights into the drought vulnerabilities within the West Slope basins, their analysis was limited to a single mid-century streamflow scenario (7% decline) that neglected basin-specific changes in water use demands and did not systematically quantify how the drivers of vulnerabilities vary across scales and sectors. This leaves several critical questions about drought vulnerability unanswered. First, what are the local and regional implications of the broader range of plausible streamflow changes (-30% to +20% changes) in the West Slope Basins? Second, which deeply uncertain characteristics of streamflow changes have the greatest influence on water shortage dynamics? The wide range of plausible future streamflow conditions may result from changes in mean annual streamflows, the variance of annual streamflows, streamflow timing (e.g., shifts in snowmelt patterns), or persistence (e.g., the likelihood of transitioning from dry periods to wet periods, or vice versa). The relative importance of each of these characteristics is unknown . Third, how do uncertain future changes in multisectoral water demand combine with changes in streamflow to influence local and regional drought vulnerabilities? Multisectoral water shortages are a function of nonlinear interactions between deeply uncertain future conditions. For example, Colorado's future irrigated acreage is expected to decline, yet rising temperatures may increase demand per acre, challenging our ability to map future vulnerabilities. Finally, how do the drivers of drought vulnerabilities in the West Slope basins differ across their hierarchy of users, sectors, and spatial scales (regional-to-local)?

To answer these questions, this study introduces an exploratory modeling framework that evaluates a broad array of plausible mid-century streamflow changes, coupled with a systematic sampling of plausible multisectoral water demands tailored to each West Slope basin. We pair our exploratory modelling experiments with a global sensitivity analysis to clarify the relative importance of the drivers of water shortages by basin, sector, and user (Saltelli et al., 2021; Reed et al., 2022; Razavi et al., 2025). Global sensitivity analysis has been widely applied in water resources systems to support model diagnostics, improve our understanding of complex systems, and support management decisions (Baroni & Francke, 2020; Razavi et al., 2021; Wagener & Pianosi, 2019). Among various approaches, the Delta Moment Independent Method (DMIM) is a kernel density estimation technique that is capable of accounting for distributional effects beyond solely the variance of outputs and computes a sensitivity index that accounts for input factors influence the entire output distribution of performance measures of interest (Borgonovo, 2007; Plischke et al., 2013; Kim & Ahn, 2025). Accounting for the inputs' effects on the entire output distribution makes DMIM particularly suitable for applications where understanding risks and extreme events is crucial, such as flood prediction, drought assessment, and water quality management (Borgonovo et al., 2012; Hadjimichael et al., 2020; Saltelli et al., 2004).

The DMIM has also been used for various modeling tasks such as calibration, parameter importance, and diagnostic analysis (Cohen & Herman, 2021; Haghnegahdar et al., 2017; Gupta & Razavi, 2018). For example, Hadjimichael et al. (2020) developed a global sensitivity analysis-centered diagnostic framework to explore water scarcity drivers in institutionally complex river basins. Applying the framework to a single subbasin in the West Slope, the authors revealed key uncertainties that drove vulnerability among individual water users and demonstrated how these vulnerabilities changed across water users. However, a comprehensive picture of how the drivers of drought vulnerability vary across scales and sectors has not been explored across all of the West Slope basins.

Although DMIM characterizes how input scalar variables influence model outputs of interest, the method does not provide insight into the relative influence of the individual West Slope subbasins on downstream deliveries. Given that the West Slope basins contribute unevenly to Lake Powell, quantifying the relative influence of each basin helps capture how basin-level uncertainties compound regionally. This regional understanding of uncertainty propagation is essential for evaluating the West Slope basin's overall ability to meet post 2026 delivery obligations currently under negotiation by the seven Colorado River Basin States. In this study, we employ an Analysis of Variance (ANOVA) approach on a large ensemble of simulated basin outflows to explore the relative influence of regional subbasins on Lake Powell deliveries. ANOVA-based decomposition enables partitioning of total output variance into basin's contributions, thereby identifying dominant controls on regional deliveries (Neter et al., 1996; Mokhtari & Frey, 2005). We use the regional ANOVA to complement the local DMIM analysis, to provide a holistic representation of drought vulnerability across spatial scales.

This study presents the most comprehensive multi-scale, multi-sectoral analysis of drought risk in Colorado's West Slope basins to date. Using 20,000 plausible mid-century future scenarios, encompassing over 2-Million simulated years, we clarify water shortage vulnerabilities and drivers in the West Slope basins using StateMod, Colorado's institutional water-allocation model. Our analysis reveals distinct differences in how plausible changes in streamflow characteristics and demands in combination with the region's significant internal variability yield water shortages across scales, sectors, and users. Our analysis highlights 1) the extent of reductions to deliveries to Lake Powell caused by plausible changes in future streamflow and multisectoral water demand; 2) the local to regional specific drivers of future drought vulnerability; and 3) the vulnerability of reservoir storage to future drought scenarios. The remainder of this paper details the methods used to generate these findings and presents a comprehensive exploration of the results.

## 2 Colorado's West Slope basins

The six West Slope basins of the Upper Colorado River Basin span 92,000 km$^2$ that captures 80% of Colorado's precipitation (much of it as snow). These basins irrigate 3,715 km$^2$ of farmland contributing \$1.4 billion annually, underpin more than \$5 billion in water-based recreation (Crespo et al., 2025; Sencan & Gray, 2025). Figure 1b shows the location of West Slope basins Upper Colorado, Gunnison, Yampa, White, San Juan, Dolores. In our analysis the San Juan and Dolores basins are modeled as single basin by CWCB for planning purpose and is referred to as "Southwest" basin in the remainder of this study. Each West Slope basin itself is partitioned into several distinct water districts, each responsible for administering local diversions, storage, and water-right priorities. The West Slope basins host more than 2,000 water users, many of which are small and geographically distributed, spanning municipal, industrial, and irrigation sectors. These users hold a highly diverse portfolio of water rights, with each entity possessing distinct decree volumes, priorities, and operational characteristics, resulting in complex and heterogeneous demand patterns across the region. Municipal water demands are influenced by changes in other drivers such as population, urban land use, and adoption of conservation measures. Industrial demands are driven by economic factors as growth and changes in industrial production. Irrigation demands are dependent on irrigation acreage, environmental conditions, implementation of efficiencies, and innovative technologies. Major reservoirs (e.g., Blue Mesa, McPhee, Lake Granby) operate under the doctrine of prior appropriation, balancing irrigation, municipal use, hydropower, recreation, flood control, and endangered-species flow targets. Blue Mesa, McPhee, Lake Granby are the largest reservoirs in the Gunnison, Dolores and Upper Colorado basins respec-

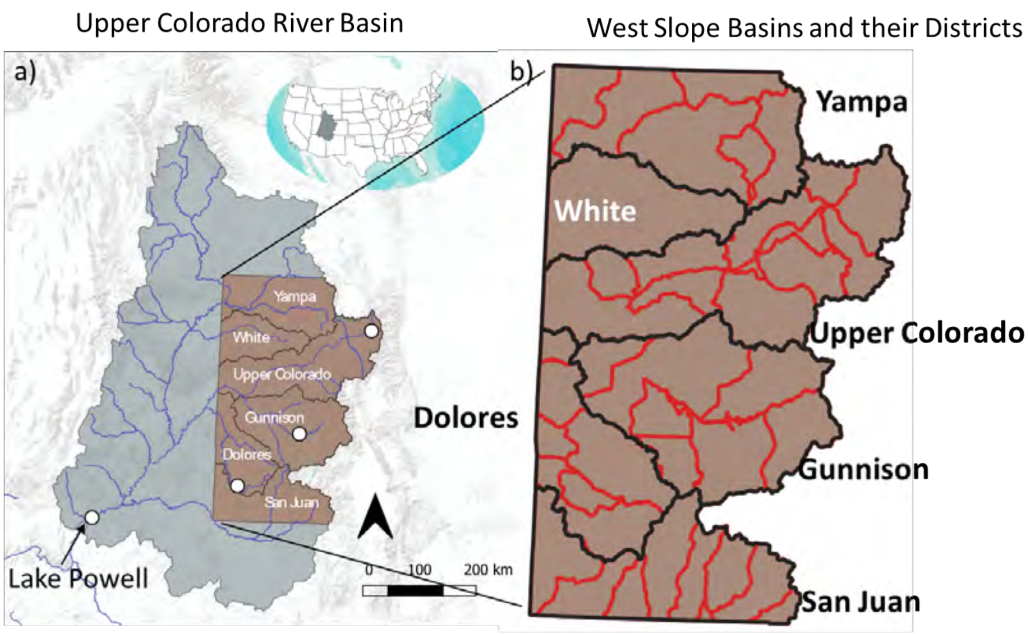


**Figure 1.** (a) A map of the Upper Colorado River Basin with the six West Slope Basins highlighted in brown. (b) Zooming into the six West Slope Basins each partitioned into water districts outlined in red.

tively that impact the water availability downstream of these reservoirs. Refer to Figure 1 for the location of these reservoirs. The outflows from the West Slope basins determine the deliveries to lower basin states. Under the framework of the Law of the River Compact of 1922 in the Colorado, the upper basin is obligated to ensure that sufficient water flows past Lees Ferry; the dividing point between the Upper and Lower Basins. Specifically, the upper basin must not deplete the river such that the flows are above an annual average of 9247 million $m^3$. By meeting these delivery requirements, the upper basin enables the lower basin states to use their full apportionment of the river's water under the Compact.

## 3 Exploratory Modeling and Sensitivity Analysis Methodology

This study contributes a diagnostic exploration of how water shortages in the West Slope basins may evolve by the mid-century and clarifies the dominant human or natural drivers of these changes across multiple spatial scales and sectors. Using exploratory modeling and sensitivity analysis, we examine how water users at various scales respond to the natural variability of the hydroclimatic system and the deep uncertainties surrounding plausible changes in multisectoral demands and future drought extremes. We first employ a multi-basin two-state Gaussian Hidden Markov Model (HMM) (Figure 2a; (Gold et al., 2024)) to capture the internal variability of the hydroclimatic system in the West Slope basins (Section 3.1). We use HMM to generate an ensemble of synthetic streamflows that preserve the spatial and temporal correlation structures within and across the basins and accurately represent the hydrological extremes of the historical record. Building from Hoerling et al. (2024), we explore deeply uncertain changes to mid-century streamflows (drier or wetter), and snowmelt timing by adjusting the HMM parameters of the streamflow generator derived from historical streamflow data to align with the broad range future changes (Section 3.2, Figure 2b). In addition, we explore changes in multisectoral human water demands associated with developments in the West Slope basins by perturbing water demands to reflect plausible mid-century changes (CWCB, 2023). We use these generated ensembles of synthetic streamflows and uncertain demands as inputs to the StateMod water allocation model used by the state of Colorado in major planning efforts (Section 3.3, Figure 2c). We explore the regional impacts of deeply uncertain future conditions by evaluating changes in cumulative deliveries to Lake Powell from the five West Slope basins as these deliveries affect the water availability in the Lower Colorado River basin. We use ANOVA to quantify the contribution of individual basins to the variability in outflows to Lake Powell (Section 3.5, Figure 2d). We examine the impacts of deeply uncertain futures on regional reservoirs by exploring how temporal storage dynamics change across the ensemble of plausible mid-century multisectoral demands and hydroclimatic extremes. We then explore the main drivers of changes in storage dynamics using the DMIM sensitivity analysis method. Finally, we explore water shortages and their drivers by examining shortages across basins, water districts, and sectors. Applying DMIM we conduct a magnitude-varying sensitivity analysis (Hadjimichael et al., 2020) to assess the relative influence of multiple sources of uncertainty on water shortages of varying magnitudes (Section 3.6, Figure 2e). This analysis highlights emerging vulnerabilities and identifies the key driving factors in water shortage.

### 3.1 Multi-basin Hidden Markov Model

We use a multi-basin, two-state Gaussian Hidden Markov Model (HMM) to generate synthetic streamflows for the West Slope basins, designed to better capture internal variability and also hydrologic extremes within the system while preserving spatial and temporal correlations within and across basins (Gold et al., 2024). We chose this as a streamflow generator for two reasons. First, two-state hidden Markov models have been demonstrated to effectively represent hydrologic extremes and persistence across sub-basins of the Upper Colorado River and West Slope basins (Bracken et al., 2014; Quinn et al., 2020; Gold et al., 2024; Nowak et al., 2012). Second, parameters within two-state Gaussian HMMs can be adjusted to emulate plausible streamflow shifts consistent with climate model projections (Quinn et al., 2020). The historical streamflows at the outlet nodes of the West Slope basins are highly correlated. In our multibasin HMM, we preserve this correlation by using a common state (wet or dry) for a given year across all five basins. The likelihood of state changes for all basins is determined by a single, shared 2x2 transition matrix. We then employ the Viterbi algorithm to classify each year in the historical record as either wet or dry.

Our HMM defines separate Gaussian distributions fit to naturalized log-annual flows at each basin outlet, assuming two states (wet and dry). The distributions for wet and dry states each have a mean vector of length five and a 5x5 covariance matrix, which together describe the joint variability among the basins. For further details on the wet and dry state characteristics of the historical record across the West Slope basins, see Figure S1 of this paper's supporting information. The mean vectors, covariance matrices, and the probability of transitioning between states were all the HMM parameters estimated using the Expectation-Maximization algorithm defined in "hmmlearn" Python library (Lebedev, 2015) using data from 1938 to 2013 to focus on recent conditions while excluding an earlier wet period. Refer to Gold et al. (2024) for more details of the parameter estimation and validation of Markov properties. We then generate annual streamflows, a sequence of hidden climate states (wet or dry) using the transition matrix that are sampled from a multivariate distribution corresponding to the current state, preserving spatial and temporal correlation across basins. Finally, the simulated log-flows are exponentiated to return to flow units (Figure S1d summarizes the process of generating synthetic streamflows). After simulating annual flows at the outlet nodes of the West Slope basins, we apply a modified Nowak et al. (2010) disaggregation method to generate flows at multiple nodes within each basin (Quinn et al., 2020).

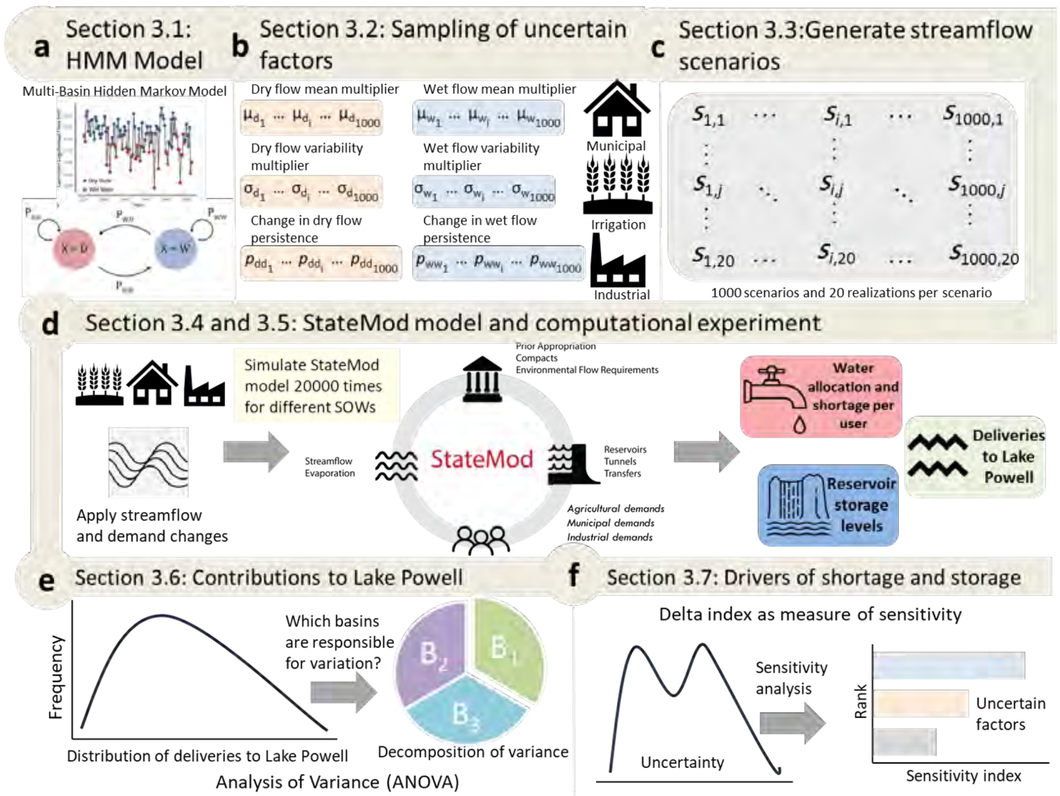


**Figure 2.** Overall methodology of this study. (a) Multi-basin Hidden Markov Model (HMM) with two states, defined by state-dependent multipliers and transition probabilities used to simulate hydrologic scenarios. (b) Uncertain input factors are sampled, including HMM parameters (mean multipliers for wet and dry states, variability multipliers, and transition probabilities); as well as demand factors across municipal, irrigation and industrial sectors. (c) Streamflow scenarios are generated for 1,000 combinations of uncertain factors, each with 20 realizations to represent internal hydrologic variability. (d) The StateMod water allocation model is run for each scenario to simulate key outputs such as basin-level deliveries, water allocations, and reservoir storage levels. (e) ANOVA is used to decompose variance in cumulative deliveries to Lake Powell, quantifying the contribution of each West Slope basin under varying hydrologic futures. (f) Sensitivity analysis to identify the dominant uncertain drivers influencing shortages and reservoir storage across all scenarios.

| Hydrologic factors | LB | UB |
|---|---|---|
| Log-space dry flow mean (m3) multiplier | 0.98 | 1.01 |
| Log-space dry flow standard deviation multiplier | 0.75 | 1.25 |
| Log-space wet flow mean (m3) multiplier | 0.98 | 1.01 |
| Log-space wet flow standard deviation multiplier | 0.75 | 1.25 |
| Change in dry-to-dry transition probability | -0.3 | 0.3 |
| Change in wet-to-wet transition probability | -0.3 | 0.3 |
| Demand factors | | |
| Irrigation demand multiplier Colorado | 0.76 | 1.14 |
| Industrial demand multiplier Colorado | 0 | 2.35 |
| Municipal demand multiplier Colorado | 1.29 | 1.72 |
| Irrigation demand multiplier Gunnison | 0.69 | 1.2 |
| Industrial demand multiplier Gunnison | 0 | 2.4 |
| Municipal demand multiplier Gunnison | 1.12 | 2.01 |
| Irrigation demand multiplier Southwest | 0.9 | 1.37 |
| Industrial demand multiplier Southwest | 1.7 | 2.07 |
| Municipal demand multiplier Southwest | 1.09 | 2.61 |
| Irrigation demand multiplier Yampa | 1.01 | 1.79 |
| Industrial demand multiplier Yampa | 1.42 | 1.79 |
| Municipal demand multiplier Yampa | 0.8 | 1.98 |
| Irrigation demand multiplier White | 0.69 | 1.38 |
| Industrial demand multiplier White | 1.87 | 23.68 |
| Municipal demand multiplier White | 0.7 | 1.84 |

### 3.2 Sampling of Uncertain Factors

For this exploratory assessment, we create a large ensemble of uncertain factors, representing changes in hydrology (drier and wetter conditions), and human water demands across municipal, industrial, and irrigation water users. These deeply uncertain factors are defined to reflect the future plausible changes in the West Slope basins. Table 1 outlines the 21 uncertain factors considered in this study. The hydrologic factors relate to parameters of the HMM model (section 3.1) and snowmelt shift. The demand uncertain factors pertain to multi-sectoral demands within each West Slope basin. We generate 1000 parameter combinations of deeply uncertain factors using Latin Hypercube Sampling (LHS) across the ranges shown in Table 1 (McKay et al., 2000). LHS is an efficient method for exploring multidimensional parameter spaces, providing improved coverage under the assumption of parameter independence and uniform distributions. For each uncertain factor combination $\psi$, 1000 streamflow realizations are also generated, sampling the internal variability. Out of 1000, 20 realizations are selected using the quantile technique for the drought index in this analysis (see supporting information S1 for details). The selected ranges are based on insights from relevant literature and prior studies focused on the West Slope basins. More details in the following subsections. The sample size was determined based on prior studies of the main stem of the Upper Colorado River, indicating it is large enough to capture the impacts of the sampled factors (Quinn et al., 2020; Hadjimichael et al., 2020).

#### *3.2.1 Plausible mid-century changes in hydrologic conditions*

We explore plausible mid-century changes in hydrologic conditions by adjusting the parameters of the HMM. As detailed in section 3.1, we use a two-state multi-site HMM to generate synthetic streamflows. We adjust six parameters (first six parameters listed in Table 1) to represent changes in the frequency, severity, and persistence of both dry and wet years. We modify these HMM parameter estimates using multipliers (the first four parameters) and changes to state transition probabilities. For example, applying the log-space annual dry flow mean multiplier shifts the mean of the distribution of the generated dry flows to the left or right (i.e., making the entire distribution of dry flows drier or wetter). Applying the log-space dry flow standard deviation multiplier increases or reduces the spread of dry flows. For instance, using a log-space multiplier on the dry/wet flow mean shifts the entire distribution of simulated dry/wet flows lower (multiplier less than 1) or higher. Adjusting the log-space standard deviation multiplier changes the variability of dry flows by expanding or narrowing the distribution. Modifying the transition probabilities alters the persistence of each state, increasing or decreasing the likelihood of remaining in dry or wet conditions. The ranges of the HMM parameters were selected to reflect plausible changes of streamflow projections from 220 members of large ensemble simulations that also include CMIP6 projections that align with mid-century projections (Hoerling et al., 2024; Figure S2 of Supporting Information). Refer to supplementary information S2 for more details on the projections data.

Along with increase or decrease in streamflows, warmer temperatures projected in the West Slope basins are projected to change snowmelt timing resulting in earlier peak runoff (Heldmyer et al., 2023; Milly & Dunne, 2020). Therefore, we also include snowmelt timing as a binary factor, representing scenarios with and without a one-month earlier shift in snowmelt. This is implemented by shifting spring peak flows 30 days earlier, following the approach of Hadjimichael et al. (2020), and is consistent with projections under various climate forcing scenarios (Kao et al., 2023; Hegewisch et al., 2023). Overall, the HMM generator enables exploration of a wide range of characteristics for changing mid-century hydrologic conditions including flow magnitude, variability, and persistence. It provides a direct means of understanding how internal variability and changes in hydrology shape plausible future drought extremes.

#### *3.2.2 Plausible changes in multi-sectoral demands*

Colorado's population is expected to grow from 5.4 million to 7.5 million by 2050, directly impacting municipal water demand when estimated using gallons per capita per day (CWCB, 2023). Historical data indicate a decline in per capita water use, driven by efficiency improvements; for example, per capita demand dropped by 5% between 2008 and 2015 (CWCB & CDWR, 2016; Board, 2015). Industrial water demand is also projected to rise with population growth, particularly from sectors such as thermoelectric power generation, snowmaking, and other high-volume users. Despite conservation efforts that lower per capita use, projections still indicate increased unmet demand for municipal and industrial users especially during dry years, where baseline conditions show no shortages. Agricultural businesses contribute $47 billion to Colorado annually, and demand is driven by irrigation acreage (Colorado Legislative Council Staff, 2023). The state projects a decline in irrigated acreage, but demand increases with rising temperatures (CWCB, 2023). In the baseline scenario, around 20% of irrigation demand is unmet, and this gap worsens under future conditions. The demand projections vary by basin and are outlined in the CWCB (2023), developed with input from diverse stakeholder groups, including the Interbasin Compact Committee, basin roundtables, and the Outreach Working Group.

The basin-specific projections inform the range of multisectoral demand multipliers listed in Table 1, tailored to the West Slope basins. For each basin, the lower and upper bounds of these multipliers are derived by comparing the maximum and minimum demand projections across scenarios as percentage deviations from the baseline. Recognizing the uncertainty in future water demands, especially given the conflicting projections across sectors, we explore increases and/or decreases in municipal, industrial, and irrigation demands. These scaling factors are applied uniformly across all users within each sector. The anticipated rise in irrigation demand during dry years when evapotranspiration increases and streamflows reduces is captured by imposing a negative correlation between irrigation demands and generated streamflows.

Although the Upper Colorado Basin accounts for only about 6% of the state's population, it is projected to experience growth of 48% to 88% from 2015 to 2050. As a result, municipal water demand is expected to increase across all scenarios. Urbanization is likely to impact the region's agricultural communities, with an estimated 14,000 acres of irrigated land expected to be converted to urban use. This reduction in irrigated acreage may lead to a decrease in overall irrigation demand. However, rising temperatures associated with climate change are expected to increase diversion demands, potentially offsetting the effects of land loss. In the Gunnison Basin, population growth is the primary driver of increased water demand. In contrast, agricultural demands are expected to decline due to a reduction in irrigated acreage and the adoption of water conservation technologies. The Southwest basin is projected to experience substantial population growth ranging from 16% to 161% between 2015 and 2050 which is expected to drive significant increases in municipal and industrial water demand. With limited urbanization, the agricultural sector is projected to face growing shortages due to changes in water availability resulting from hydrological uncertainty. Agriculture remains the dominant water use in Yampa and White basins, with increase in irrigated acreage and their demands. As different basins are projected to evolve distinctly, applying tailored multisectoral demand changes enhances the assessment of system vulnerabilities, highlighting the value of the large exploratory modeling experiment contributed in this study.

### 3.3 StateMod

In this study, we utilize StateMod to capture the complex human and natural dynamics of the West Slope basins. StateMod is a component of the Colorado Decision Support System (CDSS), developed by Colorado Water Conservation Board (CWCB) and Colorado's Division of Water Resources (Malers et al., 2000; Parsons & Bennett, 2006). StateMod is a comprehensive and widely used tool for water planning and allocation in Colorado, that captures key river basin dynamics, reservoir storages and their operations, as well as water rights, agreements, and exchanges that shape highly resolved user level diversions. StateMod captures the institutional complexity of Colorado's prior appropriation doctrine by simulating each user's consumptive use, evaluating water availability across thousands of users, and imposing reservoir operation rules in accordance with water availability, demands and storage targets. For the West Slope basins, separate StateMod models have been developed for the Upper Colorado, Gunnison, Yampa, White, and Southwest basin.

For each basin, CDSS developed baseline datasets to simulate the historical period 1909–2013 (105 years), representing the current infrastructure and institutional water rights context. The StateMod results from this dataset are referred to as the historical baseline throughout this manuscript. This data set was developed by superimposing historical diversions data on naturalized flows, monthly reservoir storage, and return flows on historical streamflow USGS gauge observations. This comprehensive representation enables simulation of water supply, allocation, and reservoir operations in response to user demands, while accounting for water rights and operational policies specific to each basin. Under Colorado's prior appropriation doctrine, each water right is tied to a specific location on the stream and assigned an administrative number, which determines its legal priority and the decreed water it is allowed to divert based on seniority. The model's manual is available for each basin that contains additional information on data development and historical model simulations (CWCB & CDWR, 2016).

### 3.4 Measures of Vulnerability Across Spatial and Temporal Scales

StateMod computes water deliveries to each user (U), reservoir storage levels (L), and basin outflows (O) under each ensemble realization (Figure 2d). The first metric of focus is consumptive use shortage of an user U, defined as the difference between a user's consumptive water demand and the actual supply available to meet that demand (i.e., unmet demand).

$$shortage_{u,y,i,j} = Demand_{u,y,i,j} - Supply_{u,y,i,j} \tag{1}$$

Where $\mathrm{Demand}_{u,y,i,j}$ is the consumptive water demand of user $u$ for scenario $s_{i,j}$, where $i \in (1, N)$ represents the $N$ deep-uncertainty samples and $j \in (1, M)$ represents the $M$ realizations within each sample. The variable $y$ varies at the annual scale, $y \in (1, 105)$, for the 105 years defined in each scenario. Annual shortages are computed from the monthly values simulated using StateMod. $\mathrm{Supply}_{u,y,i,j}$ is the supply delivered to user $u$, and $\mathrm{Shortage}_{u,y,i,j}$ is the corresponding shortage.

In our analysis, we sum consumptive use shortages all users within each basin to understand spatially compounding impacts of shortage on the State of Colorado.

$$shortage_{uB,y,i,j} = \sum_{u=1}^{ub} shortage_{u,y,i,j} \tag{2}$$

Where $\mathrm{shortage}_{uB,y,i,j}$, is the cumulative water shortage across all users in the basin B. B represents the West Slope basins.

For our second metric, we sum the consumptive-use shortages across all institutionally administered water districts to identify districts that are vulnerable to changes in baseline conditions. This is computed similarly to equation 2, with users varying for each district D (Figure 3 III). Additionally, we find shortages or unmet demand across sectors, including agriculture, municipal, and industrial users. This is computed similarly to equation 2, with users classified as agriculture (A), municipal (M), and industrial (I). We compute the shortages across basins, districts, and sectors, and use the results to explore the distribution of shortage magnitudes across the ensemble and evaluate key percentiles. This allows us to characterize not only the average impacts but also the likelihood of more severe shortage outcomes.

$$f(t) = \inf\{\, a : F(a) > t \,\} \tag{3}$$

Where inf is the greatest lower bound of shortages, which is the smallest value of a such that the cumulative distribution of F(a) reached at least t. t varies from 0 to 100

Our final metric, reservoir storage, focuses on the reservoir levels in the region's three largest reservoirs, Blue Mesa, Lake Granby, and McPhee in Gunnison, Upper Colorado and Southwest basin respectively. We examine the percentiles of each reservoir across ensembles and compare storage levels with the historical median assuming current operating policies. These results can inform policymakers when developing future reservoir operating policies.

### 3.5 Exploring the Drivers of Vulnerability

We evaluate the relative influence of West Slope basins on deliveries to Lake Powell by analyzing deliveries from the five major contributing basins: Upper Colorado, Gunnison, Yampa, White, and Southwest (Figure 2e). This analysis addresses how inter-basin variability, along with hydrologic and demand uncertainty, affects Lake Powell inflows, a key driver of Powell's operations and lower Colorado basin requirements (Udall & Overpeck, 2017). We quantify each basin's influence by applying a variance partitioning approach using ANOVA, a widely used statistical method in hydrology to attribute variability in a response variable to multiple sources (Mokhtari & Frey, 2005; Tang et al., 2007). We use the F-test as a statistical measure to assess the significance of differences in responses due to individual parameters and their interactions (Archer et al., 1997). Larger F-values indicate greater influence and higher sensitivity of a parameter or interaction on the output. The p-value for the F-statistic, represents the probability of observing the calculated F-statistic (Supporting information table T2) or a more extreme one if the null hypothesis were true. We get a low p-value of 0.0 (¡ 0.05) suggests the observed differences among group means are statistically significant, leading to the rejection of the null hypothesis and acceptance of the alternative that at least one mean is different. In the ANOVA, a linear additive model is applied with deliveries to Lake Powell as the response variable, as expressed in Equation 5

$$\textbf{Deliveries to Lake Powell} = \mathbf{f}(\mathbf{O_{UC}} + \mathbf{O_{Gunnison}} + \mathbf{O_{Yampa}} + \mathbf{O_{White}} + \mathbf{O_{Sanjuan}}) \quad (4)$$

Where, O represents the outflows relative to the historical baseline median from each basin as defined in the subscripts as the West Slope basins with UC abbreviated for Upper Colorado basin. We use the sum of the squares (SS) from the ANOVA test relative to total sum of squares to quantify the uncertainty by each basin ($V_m$, Figure 3V) and to identify which basin (denoted by m) is more strongly associated with the uncertainty quantified for deliveries to Lake Powell.

$$\mathbf{V}_m = \frac{\mathbf{SS}_m}{\sum_{i=1}^{5} \mathbf{SS}_i} \quad (5)$$

### 3.6 Magnitude varying sensitivity analysis

We utilize the DMIM to identify the factors that influence variability of drought vulnerability. The DMIM analysis is an empirical density-based global sensitivity analysis technique that evaluates how uncertain factors influence the entire distribution of a model's output or the response variable, by capturing higher order interactive effects rather than focusing solely on mean or variance (Figure 2f). This method has proven effective in addressing complex and highly nonlinear water resource applications (Chaney et al., 2015; Hadjimichael et al., 2020; Lau et al., 2023). For each uncertain factor (described in Section 3.2), the method computes a delta index, which quantifies the expected change in the output distribution when that uncertain factor varies; normalized to allow comparisons across factors (Borgonovo, 2007; Plischke et al., 2013). This makes DMIM useful for capturing sensitivity across the full range of outcomes considering higher moments of statistics. The method is moment-independent, allowing it to detect sensitivity that may affect skewness, tails, or multimodal behaviors in the output distribution. In this study, we implement DMIM using the SALib library in Python (Herman & Usher, 2017). We also include a control variable with no influence on the model to verify that the Delta method assigns negligible sensitivity to avoid bootstrap noise. We apply the DMIM to assess the relative contributions of uncertain factors including HMM parameters, snowmelt shift and multi-sectoral demand changes to variability in water shortages and reservoir storage levels.

As explained in section 3.4, the output variables are discretized based on the percentiles of the distribution f(u,t). We perform the magnitude-varying sensitivity analysis for multiple output variables, including shortage magnitude aggregated across basins, districts and sectors. We also conduct this analysis for variation in reservoir storage levels for the three major reservoirs Lake Granby, McPhee and Blue Mesa in Upper Colorado, Southwest and Gunnison basins respectively. This analysis provides insights on under what circumstances adaptation may be most needed by identifying which uncertain input factors contribute most to the variability observed in these output metrics.

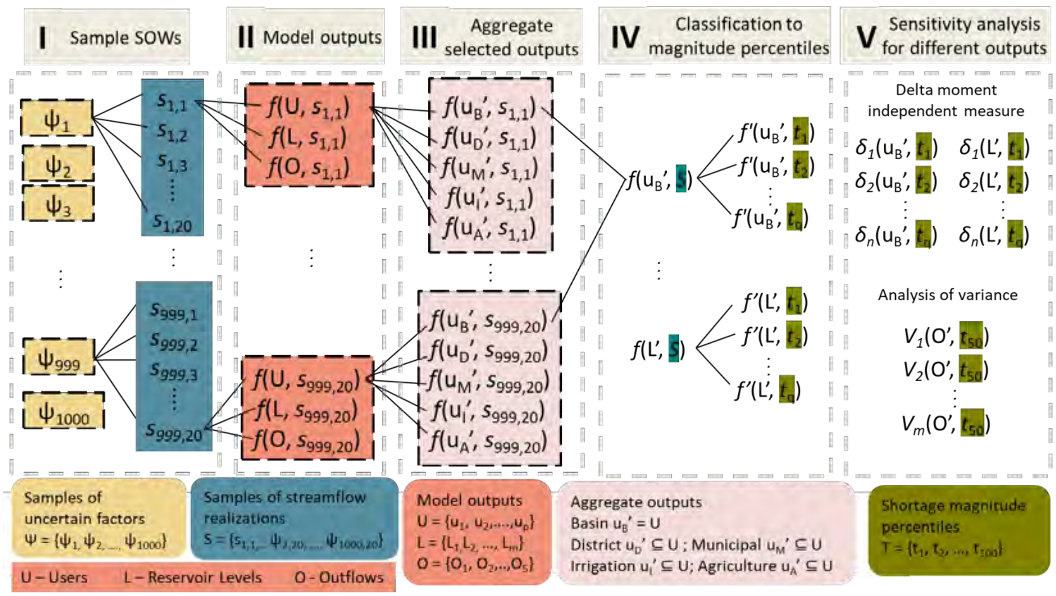


**Figure 3.** Experimental design of this study. (I) Sampling of states of the world (SOWs) from uncertain factors ($\psi$) along with the generation of streamflow realizations to capture internal variability (s), that is, 20 streamflows for each sample $\psi$. (II) Simulation of model outputs using StateMod; shortages for all users in the basin (U), reservoir storage levels (L) and outflows from each basin (O) across all streamflow realizations (S). (III) Aggregation of selected outputs into relevant categories for the corresponding users (basin-wide B, district D, municipal M, industrial I, agriculture A). (IV) Classification of outputs into magnitude percentiles (T). (V) Sensitivity analysis to identify dominant factors impacting different performance outputs. Color coding highlights distinct components: uncertain inputs (yellow), streamflow samples (blue), model outputs (orange), aggregated metrics (pink), and shortage percentiles (green).

### 3.7 Computational Experiment

In this study, we apply StateMod to simulate water allocation in Colorado's West Slope Basins. To the best of our knowledge, this is the largest exploratory modeling experiment ever conducted for the West Slope basins that systematically samples across plausible changes in mid-century hydrologic conditions and basin-specific demands. To characterize the uncertainty in future hydrologic and demand conditions, we generate 1000 combinations of uncertain input factors, denoted as $\psi$ (Figure 3I). These input sets include changes to HMM parameters, snowmelt shift and multi-sectoral demands. For each sampled SOW $\psi$, we generate 20 stochastic realizations of streamflow (s, Figure 3I), capturing internal variability. In total, 20,000 independent simulations were performed, each representing a 105-year period, yielding an aggregate of 2.1 million simulated years across all scenarios. These 2.1 million years are simulated using StateMod as described in section 3.3 to generate a range of system outputs (Figure 3 II). Model outputs are generated for each user in the West Slope basins and then aggregated at multiple levels, including basin, district, and sector (Figure 3 III). To analyze extreme conditions, we compute magnitude percentiles for these aggregated outputs (Figure 3 IV) and conduct sensitivity analyses (Figure 3 V) based on these results to identify the uncertain factor drivers. This was executed on National Energy Research Scientific Computing Center (NERSC) Perlmutter system using a total of 1000 cores distributed across 10 computer nodes.

# 4 Results and discussion

## 4.1 West Slope deliveries to Lake Powell

As discussed in the Introduction, the West Slope basins play a vital role in the Colorado River system by contributing approximately 70% of the annual water deliveries to Lake Powell (US Bureau of Reclamation, 2020; Gold et al., 2024). Figure 4 provides a broader understanding of how the West Slope annual deliveries could plausibly change by the mid-century based on the exploratory ensemble. Figure 4a shows the distributions of the differences between cumulative West Slope annual deliveries to Lake Powell for the sampled mid-century scenarios and the historical 105-year baseline record. The panel compares the resulting distributions of differences for the 5th and 50th percentiles of cumulative annual deliveries across the exploratory ensemble's 20,000 scenarios, each of which is composed of 105-years of monthly streamflows (see Figure S3 for the distribution of all sampled scenarios). So as an example in Figure 4a, the 5th percentile distribution captures the relative changes in the cumulative annual West Slope 5th percentile deliveries for the historical baseline's 105-year record versus the corresponding 5th percentile deliveries attained across each of the 105-year records that compose the 20,000 scenarios sampled in the exploratory ensemble. The 5th percentile deliveries represent low annual delivery volumes to Lake Powell that are exceeded in 95% of years within the 105-year record. Similarly, the median (50th percentile) deliveries represent annual volumes that are exceeded in 50% of simulated 105-years.

In Figure 4a, the relative 5th percentile distribution indicates a higher frequency of reduced cumulative deliveries to Lake Powell in low-flow or drought conditions, with the peak of distribution remaining below zero with a maximum reduction of 3062 million $m^3$. For context, this represents a 52% decrease in deliveries compared to the historical baseline's 5th percentile deliveries. Under the Colorado River's Law of the River Compact (Section 2), the Upper Basin is must ensure that flows at Lees Ferry are above an annual average of 9247 million $m^3$. A 52% reduction in deliveries at the 5th percentile distribution would equal about 3% of this required volume, which would significantly constrain deliveries to the Lower Basin states. In Figure 4a, the median distribution of Lake Powell deliveries (50th percentile) shows an overall reduction in outflows, suggesting that many scenarios result in heightened risks to Lake Powell deliveries. The peak of this distribution has a reduction of 1061 million m3 Lake Powell deliveries compared to the historical median. This corresponds to approximately 12% reduction of the compact annual average volume (of 9247 million m3). This suggests that, even with the inclusion of the substantially wetter futures sampled in the exploratory ensemble, the West Slope basins routinely face reduced deliveries, increasing challenges for meeting the requirements of the Colorado River Compact.

Our results are corroborated by Wang et al. (2022) who document significant historical reductions in deliveries to Lake Powell when comparing 1981-2010 to and 2001-2020 reference periods. The cumulative deliveries to Lake Powell reflect differing contributions from the individual West Slope basins. Understanding how each West Slope basin influences the annual deliveries under varying hydrologic and demand conditions is important for informing effective water management strategies for the Upper Colorado River basin. Consequently, in Figure 4b, we formally quantify the relative contributions of the West Slope basins to the variance in cumulative annual deliveries to Lake Powell compared to the historical median using an ANOVA variance decomposition. Figure 4b presents the fraction of variance in annual West Slope deliveries to Lake Powell attributed to each basin. The Southwest Basin contributes 60.7% of the total variance in West Slope deliveries, followed by Upper Colorado (18.5%), Gunnison (13.6%), Yampa (6.6%), and White (0.5%). These results highlight the Southwest Basin as a dominant driver of variability in deliveries to Lake Powell and, consequently, as a key basin influencing water availability for the Lower Colorado basin states. This finding is somewhat unexpected given that the Upper Colorado Basin contributes the highest median out-

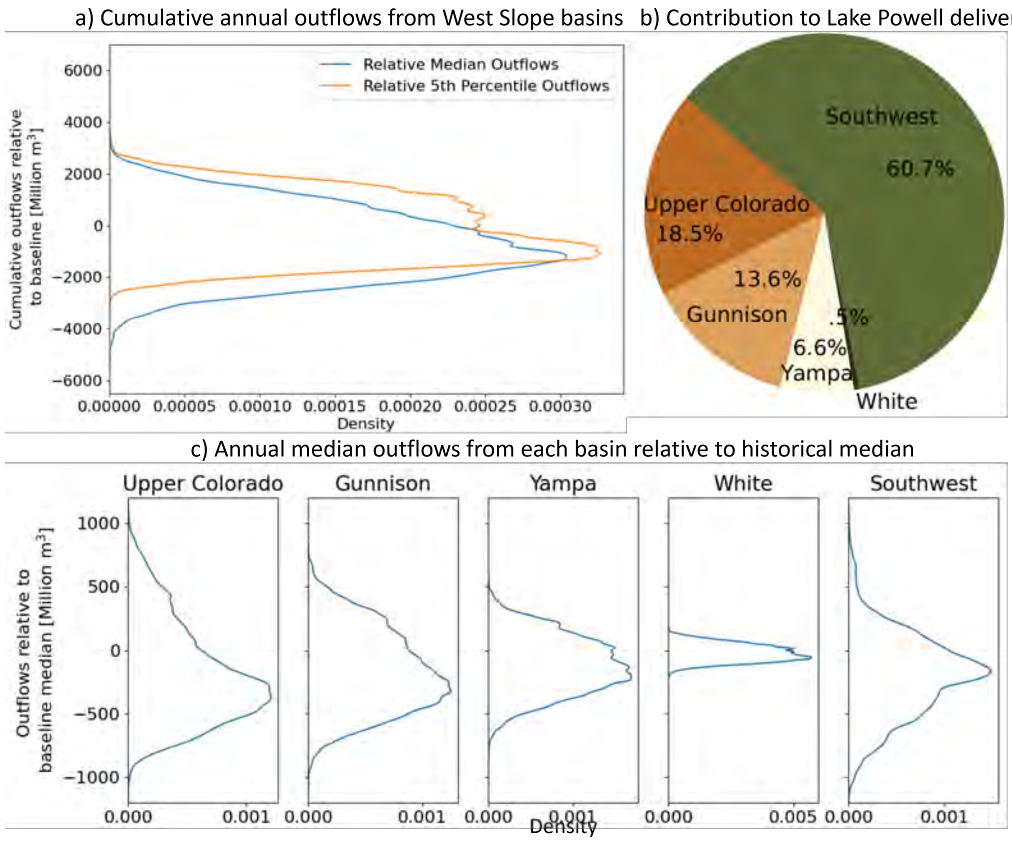


**Figure 4.** a) Density plots show the distribution of cumulative annual outflows (in million $m^3$) from the West Slope basins under all scenarios relative to historical baseline. (b) Pie chart illustrates the relative contribution of each basin to the variance of total annual West Slope outflows from ANOVA analysis under all sampled scenarios. (c) Density plots for difference in median annual outflows relative to historical median for each of the West Slope basins.

flows (in terms of magnitude) compared to the Southwest; however, the Southwest shows a markedly stronger sensitivity to the hydrologic and demand conditions sampled in this study's exploratory experiment (Section 3.2).

Figure 4c shows the distributions of median outflows relative to the historical median for each of the West Slope basins. When the values that compose these distributions fall below zero, they indicate reduced deliveries to Lake Powell that would impact its storage levels and deliveries to the lower basin. Though the exploratory ensemble's sampled scenarios include wetter futures with up to 30% increases in streamflow relative to the historical baseline period (give dates of baseline here), many of the basins' outflows are significantly reduced with the peaks of their distributions on the negative side of Figure 4c's scale. The increasing risks of reductions in Lake Powell's storage are similar to those projected in other studies (Gold et al., 2024; J. C. Schmidt et al., 2023). The Upper Colorado and Southwest basin exhibit the widest ranges of variability, spanning more than ±1000 Million $m^3$ differences in deliveries to Lake Powell, suggesting that they are the primary West Slope basins impacting deliveries. This is equivalent to 11% of (of 9247 million $m^3$) the average annual deliveries of the Law of the River Compact. The Gunnison and Yampa basins also display considerable spread, though with somewhat narrower distributions, while the White River basin shows very limited variability, contributing relatively minor deviations from baseline conditions. The reductions in deliveries intensify toward the lower tails of the distribution for the Upper Colorado, Gunnison, and Southwest basin, with reductions relative to the historical median of 1177, 1065, and 2678 million $\mathbf{m^3}$, respectively. Overall, results clarify how the West Slope basins influence deliveries to Lake Powell, with the Southwest and Upper Colorado basins being the most dominant contributors.

### 4.2 Variation in Reservoir Storages and Dominant Driving Factors

While Section 4.1 focused on potential changes in deliveries to Lake Powell from the West Slope basins, those deliveries are directly influenced by reservoir operations and their storage levels within the basins (Sakas, 2021; Wheeler et al., 2019). Declining reservoir storage levels threaten water supply reliability, increase vulnerability during drought, and limit flexibility when managing water supply given hydrologic and demand uncertainties. Figure 5 illustrates variation in monthly reservoir storage and their dominant driving factors across the three largest reservoirs in the West Slope basins Blue Mesa (Gunnison), Granby (Upper Colorado), and McPhee (Southwest). The panels are divided into two main groups: the left column figures (a, c, e) show reservoir storage change relative to the historical median at monthly time steps, while the right column figures (b, d, f) show the relative contributions of the uncertain factors in driving variability in the reservoirs. The color scales in panels (a), (c), and (e) represent the percentiles of monthly reservoir storage, calculated across the 1,000 samples of deeply uncertain factors. Lighter colors (as yellow) correspond to lower storage levels (drier conditions), while darker colors (blue) indicate higher storages (wetter conditions) compared to historical baseline. The dashed lines mark the historical 25th and 75th percentiles. The solid black line represents the historical median. The Blue Mesa Reservoir located in the Gunnison basin (Figure 5a) exhibits a notable summer-to-fall seasonal decline in storage beginning around July, with levels reaching their lowest between October and December. This post-July drop is driven by peak irrigation demands, further exacerbated by declining inflows during late summer. Granby Reservoir and McPhee reservoir (Figure 5c, e) show a similar seasonal pattern, with storage decreases beginning in summer months and with prolonged low levels lasting into the fall. This trend reflects changes to water availability upstream from diversions and multi-sectoral demands, combined with reduction in snowmelt contributions. Granby at the mouth of the Gunnison River is heavily dependent on the snowmelt contributions and the majority of runoff occurs during spring snowmelt.

Across all three reservoirs, the projected median storage levels are below historical median ($\tilde{1}0 - 20\%$) with storage levels declining during the late-summer to early-fall (July – Oct). During the drought years, the worst storages (below 10th percentiles) drop to 40–55% below the historical median for Blue Mesa and Granby comparable to the severe drawdowns observed during the 2002 drought, when reservoirs approached critically low levels. During wet periods, the storages are close to historical median with no significant increases reflecting increased multisectoral demands that offset potential gains from higher inflows. Overall, the low storage levels below the historical median present significant challenges, which are particularly concerning given the wide range of sampled scenarios include instances with much wetter projected mid-century conditions. Even with these much wetter future conditions, Figure 5a, c, and e results show systematic reductions in storage compared to the historical median. The reduction in storage levels is also consistent with the previous studies on reservoirs of the Colorado River Basin (Simeone et al., 2024; Goble, 2016). Notably, during the extreme drought year of 2002, Lake Granby was drawn down to its dead storage, showing how low-flow conditions can rapidly deplete storage.

Given the projected declines in major reservoir storages, the next step is to understand which deep uncertain factors are driving these changes. We use the DMIM to identify the most dominant uncertain factors that influence reservoir storage variability, pro-

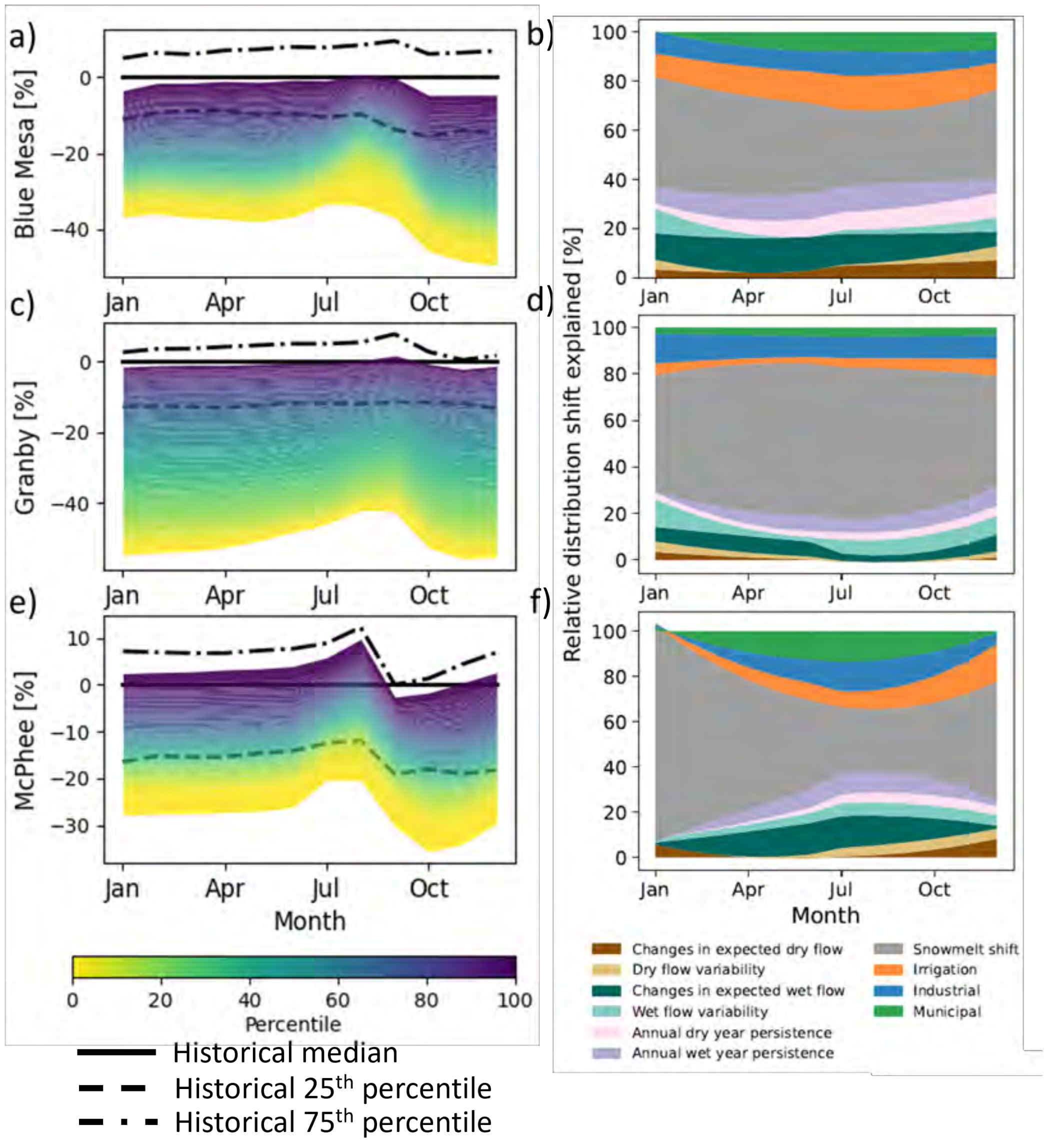


**Figure 5.** Variation in monthly reservoir storage (a, c, e) and their dominant factors (b, c, f) of the West Slope's three largest reservoirs, Blue Mesa (Gunnison), Lake Granby (Upper Colorado), and McPhee (Southwest). The variation in reservoir storage is shown in percentage change in storage from the historical median relative to the reservoir capacity. The colors represent the percentiles of monthly storage across 1000 SOWs. The historical median monthly reservoir storage is the line drawn at zero and the 25th and 75th percentile historical storage for each month are shown in dashed and dashed-dot lines. The dominant factors impacting storage in the reservoirs are shown in b) Blue Mesa, c) Lake Granby and d) McPhee reservoirs. Each color represents the uncertain factors described in Table 1. The colors in the legend are listed in the order that they are plotted, from bottom, up.

viding helpful insights that can inform management strategies (Figure 5 b, d, f). Each of the right-hand panels in Figure 5 corresponds to the reservoir to its left, showing the percentage of relative distribution shift contributed by each of the uncertain factors effects in driving changes in monthly storage variability. Across all of the reservoirs, the projected 30-day shift in the timing of snowmelt is the dominant factor throughout the year. All three reservoirs are highly sensitive to changes in snowmelt timing, especially during spring and summer as reservoir operations are defined as a function of inflow. This also indicated the impacts of extreme dust-on-snow events shifting snowmelt runoff (Neff et al., 2008; Deems et al., 2013). Other studies have also demonstrated the importance of snowmelt timing shifts in the Upper Basin, which in turn has downstream impacts on the Lower Colorado River Basin (Milly and Dunne, 2020; Clow, 2010). For Blue Mesa reservoir (Figure 5b ), beyond the effects of snowmelt timing shift, irrigation demand (orange) and annual wet year persistence (light purple) also play a role in reservoir storage fluctuations. These factors represent sectoral water use and an increase in the frequency of above-average inflows (wet years) in the Upper Gunnison basin. In our exploratory scenarios, irrigation demands range up to a 20% increase (Table 1). While persistent wet years can result in increased inflows to the reservoir, changing seasonal irrigation demands can reduce upstream contributions before they reach the reservoir. For the McPhee Reservoir, multisectoral demand-related factors emerge as dominant drivers, reflecting substantial demand increases of 37–161% (Table 1). Changes in expected wet flows, and annual wet year persistence also influence storage variability during the late-summer to early-fall recession period (July–October), when snowmelt contributions diminish and streamflows decline. During this time, reservoir storage is shaped by the combined pressures of reduced inflows and elevated sectoral demands. For water managers, Figures 5b, d, and e provide evidence that managing storage variability must consider the complex coupled responses betweeen natural hydrology and evolving sectoral water demands.

Overall, Figure 5 presents the temporal reservoir storage dynamics with snowmelt timing shifts as the dominant driving factor. The degree to which other human water use demand factors influence storage variability varies significantly by the reservoir and its source West Slope basin. While reservoir operations and their storages play a critical role in managing the water supply, they do not fully encompass the diversity of water uses and users at the broader basin scale. In the next section, we explore the shortage vulnerabilities across the cumulative users within each of the West Slope basins.

### 4.3 Basin-wide Shortages

Our analysis of basin-wide shortages provides insights into how the exploratory ensemble's scenarios influence cumulative user-level water deficits in each of the West Slope basins. The West Slope basins include a diverse range of users, each with distinct water rights, priorities, and demands. Shortages are defined as the difference between users' demands and actual supply. Water supply allocations are based on the prior appropriation doctrine and vary across complex interactions across the basins' hydrologic, institutional and infrastructure elements. These elements are accounted for explicitly in our examination of each of the basin's consumptive use shortages in Figure 6 given their representation in StateMod simulations of sampled scenario outcomes. Figure 6 shows the percentile varying changes in the magnitudes and frequencies of cumulative annual water shortages experienced by the West Slope basins' users across the 20000 scenarios explored in this study. In each panel, shortages across the ensemble of scenarios are compared with the cumulative distribution of historical annual shortage magnitudes (black line). The y-axis represents the magnitude of annual shortage, while the x-axis shows its non-exceedance probability. The blue shaded areas indicate the frequency of each shortage magnitude's occurrence across the sampled scenarios, with lighter shades corresponding to higher frequencies. In Figure 6, for each of the 20000 scenarios, water shortages for individual users are aggregated annually within each basin based on 105 years of monthly simulations. For each scenario sampled this produces a cumulative distribution of an-

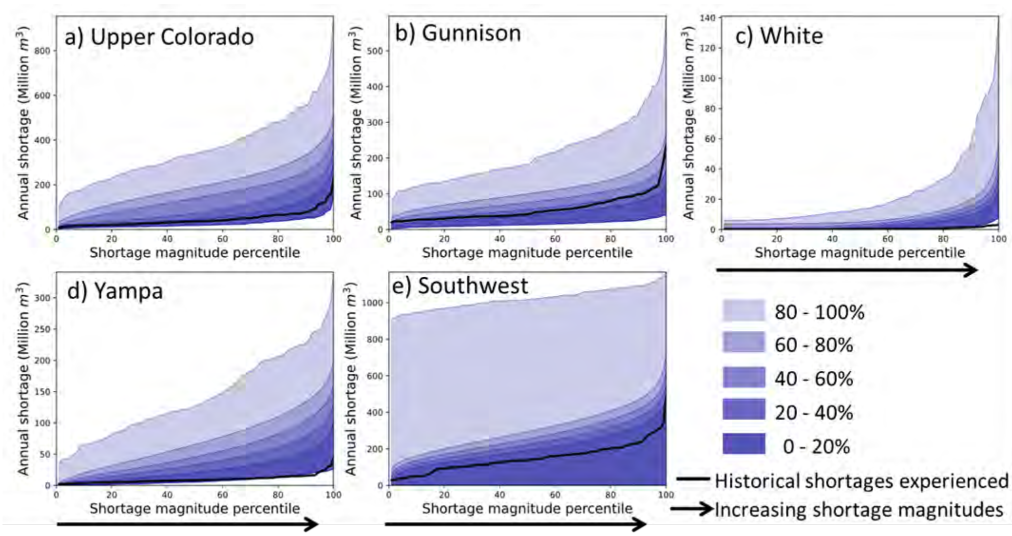


**Figure 6.** Percentile-varying impacts on cumulative annual shortage magnitude and frequency for the West Slope Basins. Each panel represents shortages experienced by each basin: (a) Upper Colorado, (b) Gunnison, (c) Yampa, (d) White, and (e) Southwest. The black line in every panel indicates the percentage of time each annual shortage magnitude was experienced historically by each basin. The shaded areas represent the frequency with which these magnitudes of shortage are experienced at each percentile across the simulated ensemble. The direction arrow on the x-axis represents the direction of increasing shortage magnitudes. Figure style adapted from Hadjimichael et al. (2020b).

nual shortage values for each basin (i.e., 20000 annual cumulative shortage distributions). Figure 6 shows the ranges of shortage magnitudes that emerge for each percentile of the annual cumulative distributions analyzed. Additionally, in Figure 6 the frequencies of shortages are defined as the percentage of scenarios where the shortage magnitude is below the respective percentile magnitude across all 20000 scenarios. The frequencies provide a direct visual understanding of how the annual shortage magnitude results are distributed across the exploratory ensemble.

The historical shortages (black line) are reduced in magnitude compared to the modeled scenarios and fall within the lower frequency 0 - 20% zones in the exploratory ensemble for the Upper Colorado, White, Yampa and Southwest basin. The implication of this result is that sampled future mid-century conditions result in more frequent and severe shortages than have occurred historically. Comparing the historical median shortage magnitudes at the 50th percentile, we find that for most of the basins these relatively modest observed shortage levels occur infrequently in the 0–20% frequency zone for the sampled mid-century scenarios, with the exception of Gunnison. For the Gunnison, its historical median shortage magnitudes occur more frequent 20 –40% range of the sampled scenarios. This indicates that, despite the inclusion of a substantial number of wetter scenarios with sampled instances that have reduced sectoral demands, the West Slope basins experience increased shortage magnitudes that are well beyond their historical medians in majority of the exploratory ensemble's scenarios. This highlights a significant mid-century vulnerability for the region.

The five West Slope basins have significant differences in both the magnitude and frequency of their annual water shortages (Figure 6). Increases in annual shortage magnitudes (higher values on the y-axis) in Figure 6 arise from different sampled scenarios where challenging years within their 105-year sequences contribute to extreme shortages (Figure S4). The specific scenarios contributing to the most extreme annual shortages vary across the West Slope basins. The Southwest basin (Figure 6e) is the most vulnerable followed by Upper Colorado (Figure 6a), with consistently high shortage magnitudes across a wide range of percentiles. The variance in the magnitude of shortages differs across the ensemble, with higher percentiles exhibiting greater variability than lower percentiles. This variability also differs across the basins , with the Southwest showing the highest variance. Additionally, the variance in shortage magnitude is not uniform but changes across the various shortage frequencies within the ensemble. Though the hydrological changes are similarly sampled across basins, differences in water demands and user rights lead to distinct cumulative effects in each basin. For all West Slope basins, shortages occurring with 80–100% frequency demonstrate the largest variance relative to other frequencies, highlighting the variability in large magnitudes of shortages associated with extreme conditions. Although the historical demands of the Southwest basin are similar to those in the Upper Colorado, the basin's projected future demands are significantly higher for irrigation and municipal development (see Table 1). Historical shortage comparisons of the Upper Colorado and Southwest users contributing the highest total shortages in their respective basins show that no single user is responsible for basin-wide shortages (Figure S5). Rather, it is the cumulative effect across users that drives the severity of shortages, both in magnitude and frequency (Figure 6a, e). The Gunnison (Figure 6b) basin has the third highest shortage magnitudes, while the White (Figure 6c) and Yampa basins (Figure 6d) show the lowest overall shortage magnitudes. Next, we investigate the key drivers of these vulnerabilities.

### 4.4 Dominant Factors Driving Shortages in the West Slope Basins

Figure 7 illustrates which factors dominantly influence the cumulative annual shortages in each of the West Slope basins across their magnitude percentiles. The y-axis indicates the relative distribution shift (%) of each uncertain factor derived from the DMIM, illustrating the sensitivity of annual shortages to each factor across different shortage magnitude percentiles on the x-axis. For each of the 1,000 sampled deep uncertain factor combinations in the exploratory ensemble, we simulate 20 replicate realizations of 105-year monthly sequences for each of the West Slope basins using StateMod. The 20 replicates are designed to explicitly account for internal hydroclimatic variability. For each deep uncertain sample, we compute the median consumptive use shortage across the 20 realizations at each shortage magnitude percentile (ranging from 0 to 100). This median value aids in accounting for the influence of internal variability. We then calculate the DMIM indices at each shortage magnitude percentile across the 1,000 sampled deep uncertain factor combinations. These DMIM indices for each percentile identify how different deep uncertain factors shape water shortage outcomes across the range of small to extreme shortages. The earlier snowmelt shift (shown in grey) emerges as a key hydrologic factor influencing shortage magnitudes across a range of percentiles, in the Upper Colorado, Gunnison, Yampa, and Southwest basin (Figure 6a, b, d, e). The dominance of snowmelt timing over the demand factors in the Upper Colorado River Basin indicates a heightened sensitivity to changes in water supply, particularly in relation to shifting seasonality. A one-month advance in peak runoff, as simulated by the snowmelt shift parameter, reflects trends toward hotter and drier conditions. This not only alters the timing of water availability but also reduces the buffering role of snowpack as a natural storage system, thereby increasing vulnerability to prolonged drought conditions. Recent studies corroborate the potential for significant reductions in water availability due to changes in snow conditions (e.g., increased extreme dust on snow events) as influenced by projected increases in temperature and evapotranspiration (Bass et al., 2023; Milly & Dunne, 2020; Deems et al., 2013).

In additional to snowmelt timing shifts, irrigation demand is also a key driver of shortages in the Gunnison, White, Yampa and Southwest basin (Figure 7b-e) . The mag-

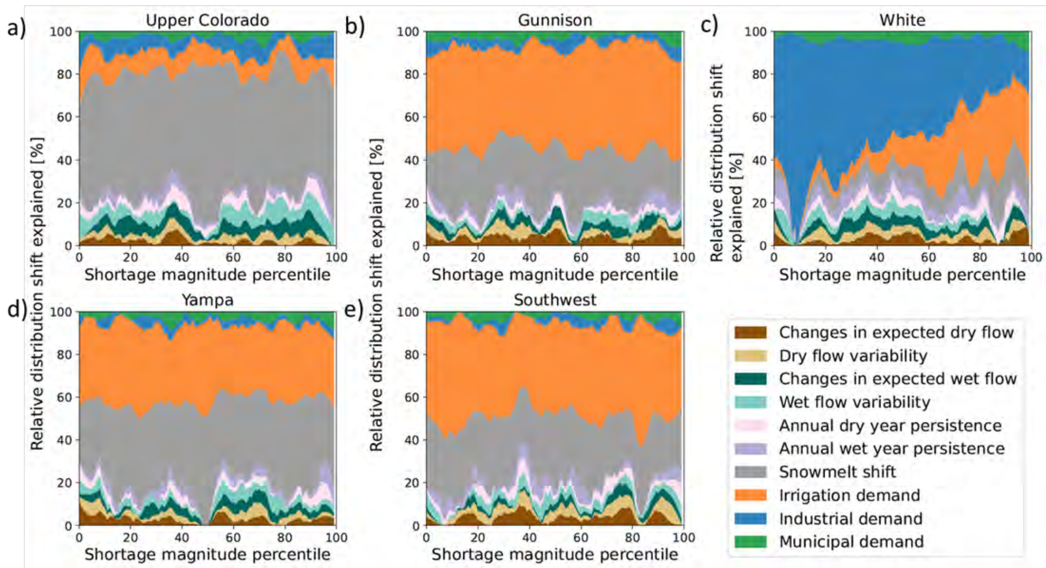


**Figure 7.** Percentile-varying sensitivity indices of shortage magnitude for the West Slope basins. X-axis represents the shortage magnitude percentile with increasing in shortage magnitude from 0 to 100. Y-axis represents the percentage of contribution by each uncertain factor. Each panel presents the magnitude-varying sensitivity indices attributed to each factor, for the shortages experienced by (a) Upper Colorado, (b) Gunnison, (c) White, (d) Yampa, and (e)Southwest. The colors in the legend are listed in the order that they are plotted, from bottom, up.

nitude of historical annual irrigation demands is at least 10 times the municipal or industrial demands. These basins are particularly sensitive to changes in their overall water demands (irrigation, industrial, municipal demand), with the hydrologic factors that impact water availability playing a secondary role. This dominance reflects not just the magnitude of agricultural demand shortages but the way they shape basin-wide shortages through nonlinear interactions with hydrologic variability and water rights. For example, under low-flow conditions, senior right holders with high irrigation withdrawals upstream strongly influence how downstream shortages emerge. Notably, these results for the Gunnison, White, and Yampa differ from those observed in the Upper Colorado Basin (Figure 7a), where snowmelt shift is a dominating factor. The relative importance of changes in expected dry or wet year flows, their variability and persistence vary across different basins and shortage percentiles. Beyond shifts in snowmelt timing and human water use demands, variations in shortage magnitude are strongly shaped by differences in dry flow persistence. This reflects the region's potential for sustained multi-year extreme droughts.

In contrast to the other basins, White Basin's (Figure 7c) shortages are strongly influenced by industrial demands, although their relative importance decreases as the magnitude percentile of shortages increases (larger magnitude percentiles implies extreme shortages). This result is linked to the projected high industrial growth in the basin as development in oil and natural gas industry among other small industrial users (Colorado Water Plan, 2025), which reflect ongoing and planned developments in the basin, as outlined in the Colorado Water Plan such as new energy infrastructure. Under extreme shortage conditions, water management strategies in the White Basin need to prioritize reductions in irrigation demands as well as and their interactions with changes in the basin's hydrologic regimes, rather than focusing primarily on industrial use. Irrigation demand does not appear as a dominant factor at lower shortage magnitude percentiles because many irrigation rights in the White Basin were appropriated as early as 1880, granting them senior priority. As a result, small deviations from the historical baseline still allow these senior rights to be satisfied. However, under a broader range of scenarios particularly those involving extreme drought, reduced water availability leads to significant shortages, even for senior rights holders.

Across the West Slope basins, the drivers of water shortage exhibit notable spatial variability. While some basins share similar dominant factors (e.g., snowmelt shift for Upper Colorado and Yampa; irrigation demands for Gunnison and Southwest), the relative importance of these factors differs by basin. For instance, in the Gunnison basin, irrigation demand exerts the strongest influence under moderate shortage conditions, whereas in the White, irrigation demand becomes more influential when the shortage severity increases. This variation reflects differences in basin hydrology, diverse water users and their rights, underscoring the need for basin-specific strategies when assessing and managing shortage risks. The findings from Figure 7 are based on cumulative shortages across all users within each basin. However, when shifting from basin scale to the scale of individual water districts, it is important to understand how shortage patterns change and if their dominant uncertain factors become more heterogenous. In the next section, we explore these differences at district-level to understand how different users shape regional vulnerabilities.

### 4.5 Dominant Factors across water districts

Figure 8 illustrates how the dominant drivers of uncertainty (deep uncertain factors) vary across different magnitudes of water shortage for two representative districts in each of the West Slope basins. The districts were selective to be representative of the diversity of their most sensitive deep uncertain factors and to capture differences across water rights. The results in Figure 8 draw on the detailed user information within the StateMod models of the West Slope basins that include information on allocation seniority, and the amount of water allocated to the user. We classify the selected districts into "junior rights" (Figure 8b, d, f, h) and "senior rights" (Figure 8a, c, e, g). In short, districts with senior rights in Figure 8 indicate those with a high priority in allocation (Refer to Figure S6 for information of administration rights of users across all districts). This targeted analysis highlights the diversity among districts within the same West Slope basin, revealing significant differences in the dominant factors driving their water shortages.

Water shortages for the District 36 in the Upper Colorado basin (Figure 8a) are largely controlled by the 30-day snowmelt shift (in grey color), the relative effect of which is reduced when looking at the representative junior rights District 72 (Figure 8b). District 36, which holds senior water rights, is primarily dependent on water availability to divert and meet its demands. In contrast, District 72, with junior water rights, is influenced by both water availability and administrative water rights. Within District 72, even when water is available, users with junior rights may not receive allocations due to priority limitations. In such instances, demand factors such as irrigation, municipal and industrial become more dominant than shifts in snowmelt timing in driving shortages. At the basin level for the Upper Colorado (Figure 7), snowmelt timing shift emerged as a key factor influencing shortages. However, this changes at the district scale. For example, in District 72, which holds junior water rights, irrigation demand becomes the dominant driver under extreme shortages. This indicates that even when water is available, institutional constraints can result unmet demand causing demand factors to dominate water shortages more than hydrologic factors like snowmelt timing. These findings illustrate that district-scale analysis yields insights that may be masked at the basin level, emphasizing the importance of having a highly resolved spatial scale as well as capturing institutional complexity evaluating water shortage drivers.

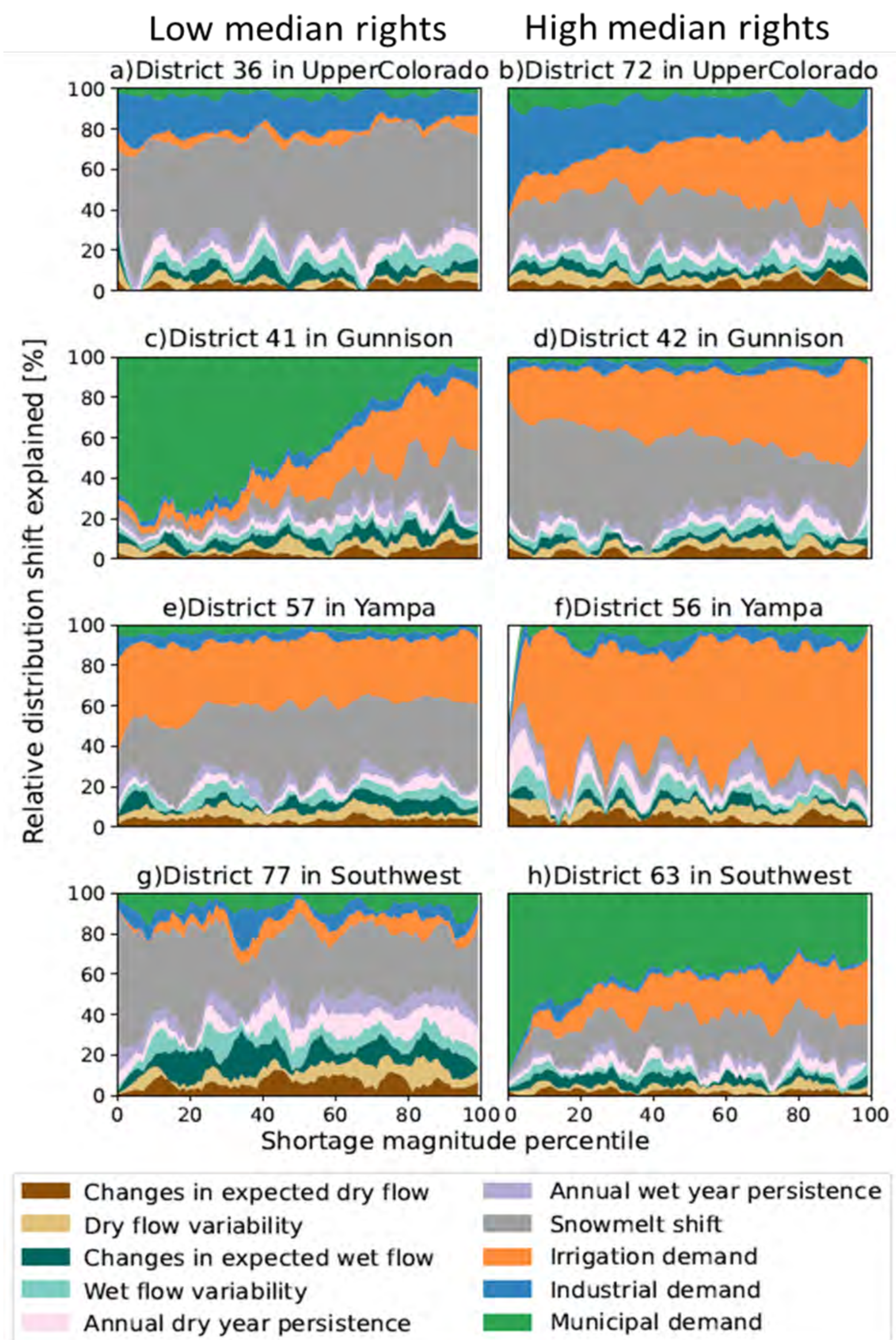


**Figure 8.** Percentile-varying sensitivity indices of magnitude percentile varying shortage for two selected water districts from each West Slope basin. X-axis represents the shortage magnitude percentile with increasing in shortage magnitude from 0 to 100. Y-axis represents the percentage of contribution by each uncertain factor. Each panel presents the magnitude-varying sensitivity indices attributed to each factor, for the shortages experienced by (a)District 36 and (b) District 72 in Upper Colorado, (c) District 41 and (d) District 42 in Gunnison, (e) District 57 and (f)District 56 in Yampa, (g) District 77, and (h) District 63 in Southwest. The colors in the legend are listed in the order that they are plotted, from bottom, up.

Across the selected districts in the Gunnison, Southwest, and Yampa basins shown in Figure 8, multi-sectoral demand factors and snowmelt timing shift consistently emerge as the two most influential drivers of water shortages. However, the relative importance of these factors shifts with the severity of shortages and their priority of allocation. In District 41 (Gunnison, Figure 8c), as shortage magnitudes increase, irrigation demand becomes increasingly influential, while the role of municipal demand diminishes under extreme shortages. In District 41, municipal demands are much smaller in magnitude compared to irrigation demands, consequently they play a more significant role at lower shortage percentiles. This pattern contrasts with District 42 (Figure 8d) of the Gunnison Basin, where municipal demand contributes even less, reflecting the lower decreed municipal volumes among water users in that district. Selected districts from Yampa and Southwest also show differences across districts that vary with shortage magnitude percentiles. For districts with junior right users, however, shortages across different extremes are driven more by multisectoral demand changes than by hydrology. A comparable pattern is seen in District 72 of the Upper Colorado, where institutional constraints can lead to unmet demand, and demand-side factors play a greater role than hydrologic ones. Figure 8 also highlights that there are district specific and significant interactive effects across the hydro-climatic factors such as mean wet and dry year flows, variability of wet and dry conditions, and persistence of wet and dry years. The White basin is not administered through districts but rather as a single basin and therefore is not included in Figure 8. Overall, this section highlights the complexity of how the drivers of district-scale water shortages vary with institutional and regional differences. The next section explores water shortage controls from a multi-sectoral perspective across the West Slope basins.

### 4.6 Dominant Factors across Sectors

Colorado state's economy is strongly water dependent across its key agricultural, municipal, and industrial sectors (Richter et al., 2024). While water districts in the West Slope basins are organizing units of governance and management of water resources, the region's competing sectoral demands significantly influence water use beyond their boundaries. Municipal, industrial, and agricultural users are distributed in the complex network of water use, each with potentially different deeply uncertain driving factors shaping water shortages. We illustrate these sectoral differences for the Southwest basin in Figure 9 (other West Slope basins in Figure S7-S10). This basin plays a critical role in shaping inflows to Lake Powell (Figure 4) and supports a diverse range of water users under institutionally complex water transfers (Redsteer et al., 2013; Mullane, 2025). These characteristics make the Southwest basin particularly well suited to highlight how dominant deep uncertain factors vary across municipal, industrial, and agricultural water demand users (Figure 4). Not surprisingly, the municipal sector (Figure 9a) is dominated by municipal demand (in color green), which consistently explains around 70%-90% of the changes in shortage magnitude across all percentiles. Two municipal users hold the most senior water rights among more than 1000 users in the Southwest basin, suggesting that municipal shortages are driven more by demand than by hydrologic variability. As demands increase , even users with high priority experience water shortages at the mid-century. This highlights the need for urban water supply planning to incorporate strategies such as demand management and increases in water use efficiency to address future uncertainties.

The industrial sector (Figure 9b) shows a much more heterogeneous distribution of uncertain factors. While industrial demand (blue) and irrigation demand (orange) are the major factors for small magnitudes of shortage; the contribution of hydrological factors along with snowmelt shift increases for more extreme shortages. This indicates that industrial water shortages are influenced by both direct demand and hydrologically driven changes in water supply, with the relative importance of these drivers shifting across hydrologic conditions and shortage magnitude percentiles. For smaller shortage magnitudes, irrigation demand emerges as the dominant factor. Irrigation typically peaks during the

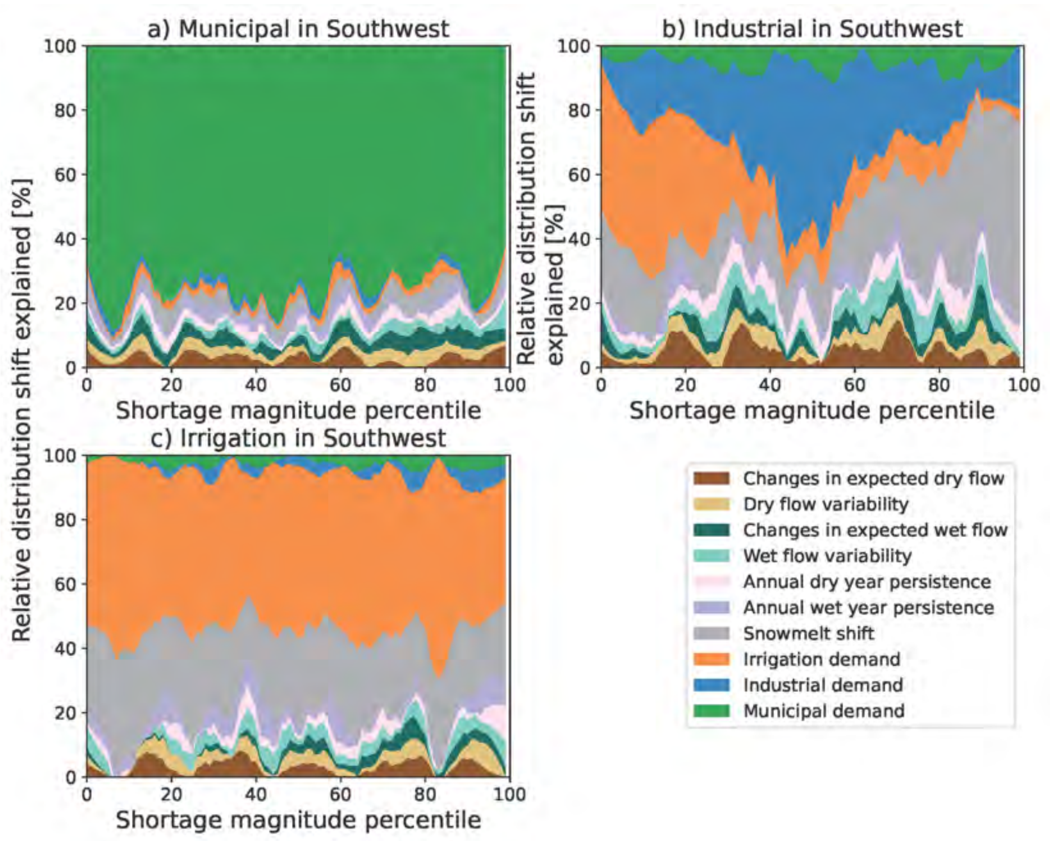


**Figure 9.** Percentile-varying sensitivity indices of shortage magnitudes across different sectors in Southwest basin. X-axis represents the shortage magnitude percentile with increasing in shortage magnitude from 0 to 100. Y-axis represents the percentage of contribution by each uncertain factor. Each panel presents the magnitude-varying sensitivity indices attributed to each factor, for the shortages experienced by (a) Municipal, (b) Industrial and, (c) Irrigation sector. The colors in the legend are listed in the order that they are plotted, from bottom, up.

summer and fall season, which coincides with periods of reduced reservoir storage (Figure 5). In addition, water demands are higher in summer months for industries (e.g., thermoelectric power generation). At median shortages, industrial demand itself plays a more direct role in driving its own shortages, reflecting increased thermoelectric water use as a key growth factor in the basin. Under extreme shortages, however, snowmelt timing becomes the primary driver, with earlier and reduced runoff exacerbating water supply limitations and amplifying the severity of industrial shortages. This pattern highlights the sector's increasing vulnerability to hydrologic variability, particularly under dry scenarios (CWCB, 2023).

The irrigation sector (Figure 9c) displays distinctly different factors compared to the other two sectors, where irrigation demand (orange) is the dominant driver. Snowmelt shift also contributes across the magnitude percentile range, though to a lesser degree than irrigation demand. Hydrologic uncertainty such as expected dry/wet flow changes and flow variability have a secondary influence. This highlights a system in which irrigation-related decisions such as cropping patterns, land use shifts from urbanization, and adoption of water-efficient technologies serve as the primary drivers of water stress, particularly during severe shortages. While changes in altered snowmelt timing intensify the problem, managing agricultural demand is critical in the basin to deal with shortage. In the Southwest basin, water conservation initiatives for irrigation demands and increased funding for resilient infrastructure are being implemented, particularly as water supplies for one federally recognized tribe were reduced to just 10% of their normal allocation in 2021 (Colorado water plan progress report, 2025).

Overall, the dominant factors vary significantly between sectors. Municipal shortages are driven by demand alone, whereas industrial and irrigation sectors are more sensitive to both hydrologic and demand factors. Snowmelt timing becomes a more important factor in the industrial and irrigation sectors, particularly during high-magnitude shortages (Figure 9b, c). This suggests that seasonal shifts in water availability are increasingly relevant in assessing the shortages across sectors; this also applies for the basin and district scales as presented in the previous sections. While the discussion is for Southwest basin, similar patterns of sectoral sensitivity to uncertain factors are observed across other West Slope basins (Figure S7 – S10), with notable differences outlined in Supplementary material S3. In summary, different basins respond uniquely to uncertainties, with sectoral impacts varying based on basin-specific hydrologic and demand conditions.

## 5 Conclusions

This study presents the most comprehensive multi-scale, multi-sectoral analysis of drought risk in Colorado's West Slope basins. We combine exploratory analysis with sensitivity analysis to identify drivers of water shortage vulnerabilities in the West Slope basins using StateMod, Colorado's institutional water-allocation model. Our analysis reveals distinct differences in how plausible changes in streamflow characteristics and demands in combination with the region's significant internal variability yield water shortages across spatial scales, and sectors. Uncertainties across the basins can produce up to a 52% reduction in low-flow deliveries to Lake Powell relative to the historical baseline, with the Southwest basin contributing the largest share of this variability. Although this study explored a broad range of significantly wetter and drier scenarios for mid-century streamflows, our results show a consistent trend that major West Slope reservoir storages are vulnerable to declines that are 40–55% below their historical medians, underscoring the severity of potential drawdowns. We further quantify basin-specific differences in the magnitude and drivers of shortages, highlighting the roles of snowmelt timing, increasing human water demands, and the persistence of low-flow conditions, all of which vary substantially across basins.

Future work will extend this analysis by examining user-level drivers of shortages without spatial aggregation, allowing investigation across different administrative rights. This approach will enable a clearer understanding of how shortages and their underlying drivers propagate spatially within individual water districts and how these dynamics differ across districts. Given the large ensemble of 20,000 simulated scenarios, future research could also focus on identifying and characterizing scenario storylines, building on recent advances in scenario discovery methods (e.g., (Hadjimichael et al., 2024)). These narratives could be further enriched through co-production with diverse stakeholders in the West Slope basins, ensuring that scenario interpretations align with decision-making. Finally, an important avenue for future research is to move beyond traditional scenario discovery toward identifying causal relationships between shortage drivers and shortage magnitudes, and to assess how these causal effects vary spatially. Such advances would provide deeper insights into the mechanisms driving water shortages and improve the relevance of scenario-based analyses for water management and planning.

## Open Research Section

StateMod (Version 15.0) was developed by CDSS and is publicly available from `https://cdss.colorado.gov/software/statemod` (CWCB & CDWR, 2016). Instructions for replicating the computational experiment, data processing code, and figure generation can be found at `https://doi.org/10.5281/zenodo.8388003` (Sunkara et al., 2026b). All data for this work, including input data, raw output, and final results, can be found at `https://doi.org/10.57931/3012850` (Sunkara et al., 2026a).

## Conflict of Interest disclosure

The authors declare there are no conflicts of interest for this manuscript.

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**Figure 1.**

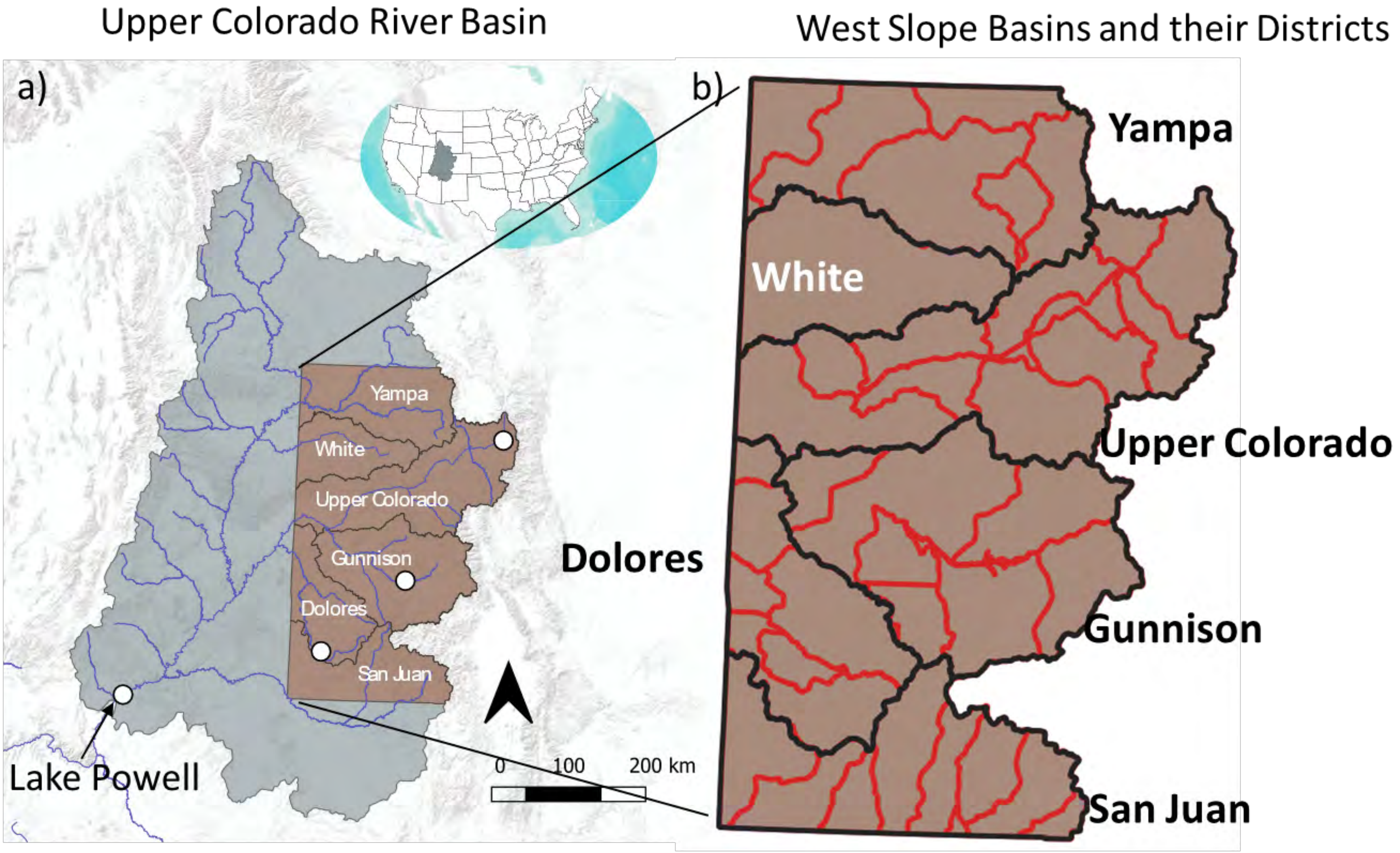

Upper Colorado River Basin
West Slope Basins and their Districts
a)
b)
Yampa
White
Upper Colorado
Gunnison
Dolores
San Juan
Lake Powell
0
100
200 km
Yampa
White
Upper Colorado
Dolores
Gunnison
San Juan

**Figure 2.**

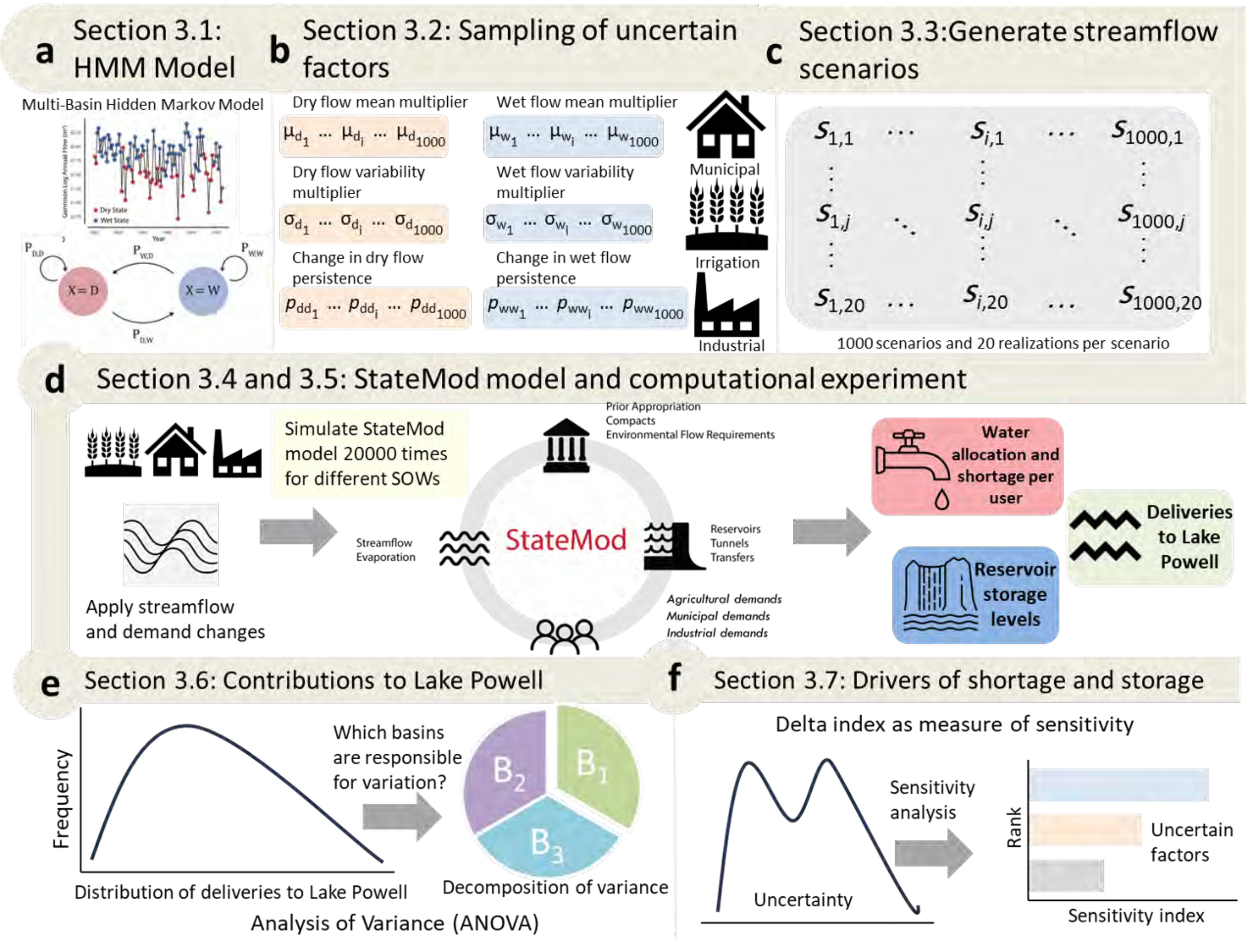
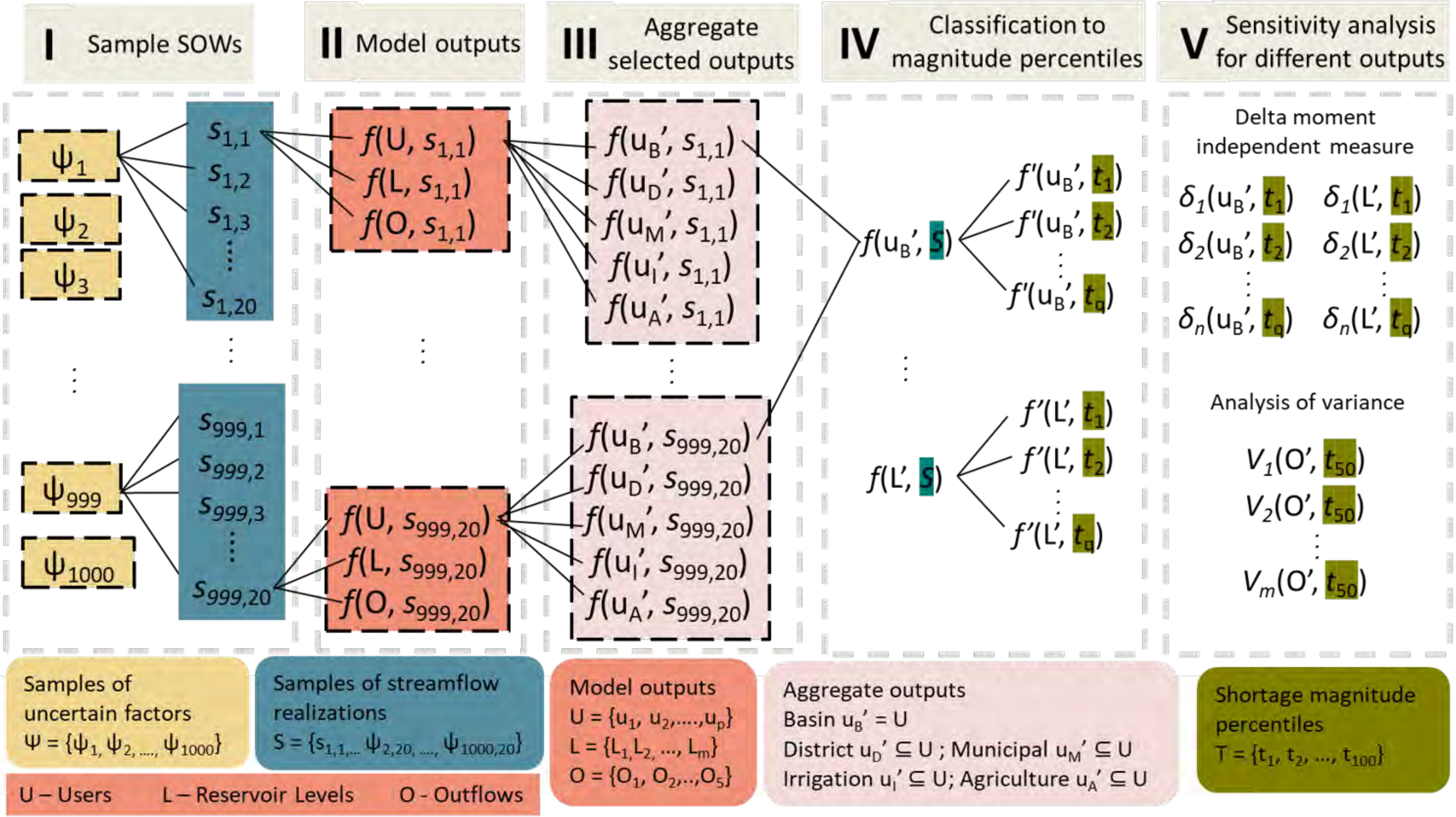

a
Section 3.1: HMM Model
Multi-Basin Hidden Markov Model
Dry State
Wet State
Year
X = D
X = W
b
Section 3.2: Sampling of uncertain factors
Dry flow mean multiplier
Wet flow mean multiplier
Dry flow variability multiplier
Wet flow variability multiplier
Change in dry flow persistence
Change in wet flow persistence
Municipal
Irrigation
Industrial
c
Section 3.3:Generate streamflow scenarios
1000 scenarios and 20 realizations per scenario
d
Section 3.4 and 3.5: StateMod model and computational experiment
Simulate StateMod model 20000 times for different SOWs
Prior Appropriation
Compacts
Environmental Flow Requirements
Streamflow
Evaporation
StateMod
Reservoirs
Tunnels
Transfers
Agricultural demands
Municipal demands
Industrial demands
Apply streamflow and demand changes
Water allocation and shortage per user
Deliveries to Lake Powell
Reservoir storage levels
e
Section 3.6: Contributions to Lake Powell
Frequency
Distribution of deliveries to Lake Powell
Which basins are responsible for variation?
Decomposition of variance
Analysis of Variance (ANOVA)
f
Section 3.7: Drivers of shortage and storage
Delta index as measure of sensitivity
Uncertainty
Sensitivity analysis
Rank
Uncertain factors
Sensitivity index

**Figure 3.**



I Sample SOWs
II Model outputs
III Aggregate selected outputs
IV Classification to magnitude percentiles
V Sensitivity analysis for different outputs
ψ1
ψ2
ψ3
ψ999
ψ1000
s1,1
s1,2
s1,3
s1,20
s999,1
s999,2
s999,3
s999,20
f(U, s1,1)
f(L, s1,1)
f(O, s1,1)
f(U, s999,20)
f(L, s999,20)
f(O, s999,20)
f(uB′, s1,1)
f(uD′, s1,1)
f(uM′, s1,1)
f(uI′, s1,1)
f(uA′, s1,1)
f(uB′, s999,20)
f(uD′, s999,20)
f(uM′, s999,20)
f(uI′, s999,20)
f(uA′, s999,20)
f(uB′, S)
f′(uB′, t1)
f′(uB′, t2)
f′(uB′, tq)
f(L′, S)
f′(L′, t1)
f′(L′, t2)
f′(L′, tq)
Delta moment independent measure
δ1(uB′, t1) δ1(L′, t1)
δ2(uB′, t2) δ2(L′, t2)
δn(uB′, tq) δn(L′, tq)
Analysis of variance
V1(O′, t50)
V2(O′, t50)
Vm(O′, t50)
Samples of uncertain factors
Ψ = {ψ1, ψ2, ...., ψ1000}
Samples of streamflow realizations
S = {s1,1,... ψ2,20, ...., ψ1000,20}
Model outputs
U = {u1, u2,....,up}
L = {L1,L2, ..., Lm}
O = {O1, O2,..,O5}
Aggregate outputs
Basin uB′ = U
District uD′ ⊆ U ; Municipal uM′ ⊆ U
Irrigation uI′ ⊆ U; Agriculture uA′ ⊆ U
Shortage magnitude percentiles
T = {t1, t2, ..., t100}
U – Users L – Reservoir Levels O - Outflows

**Figure 4.**

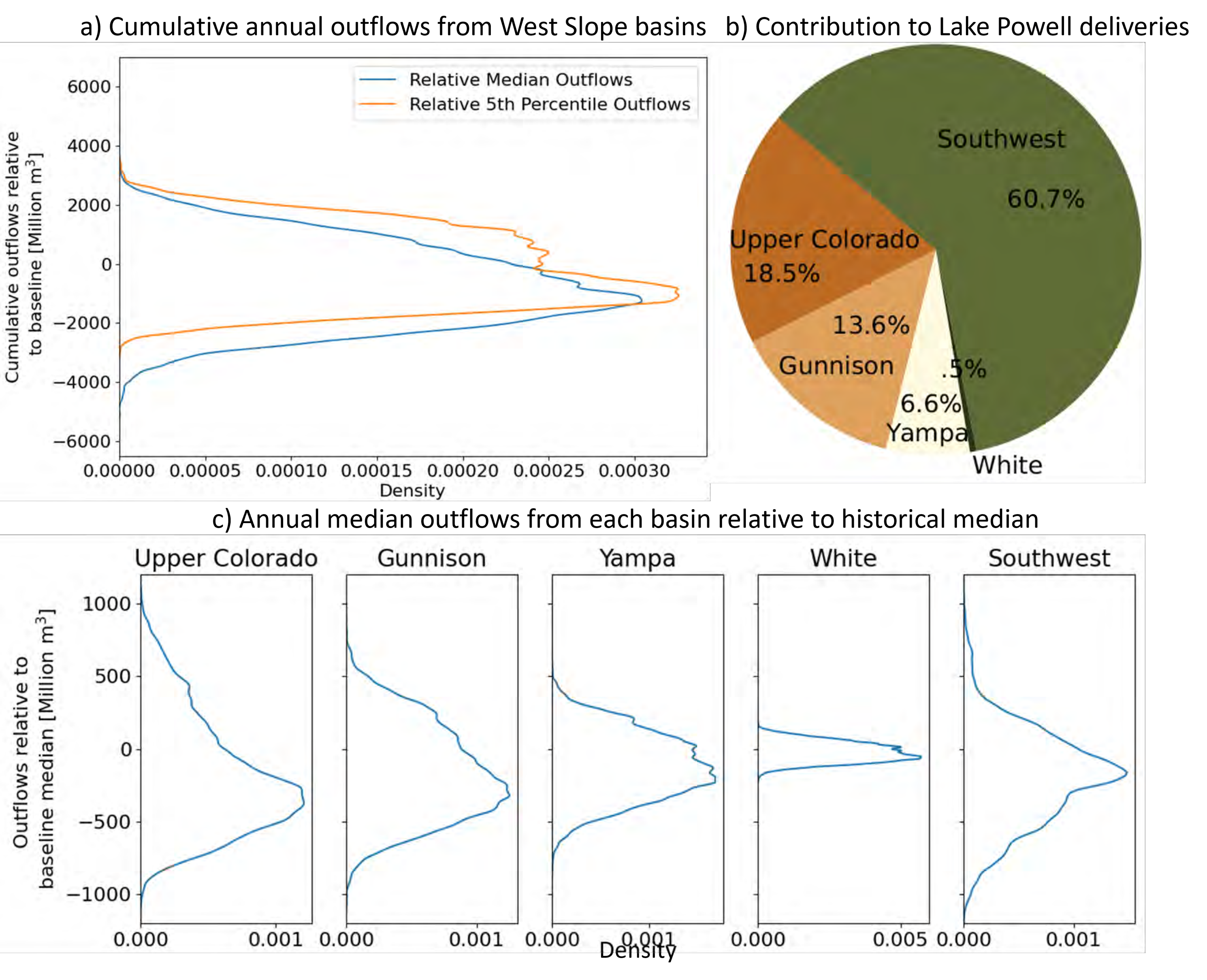
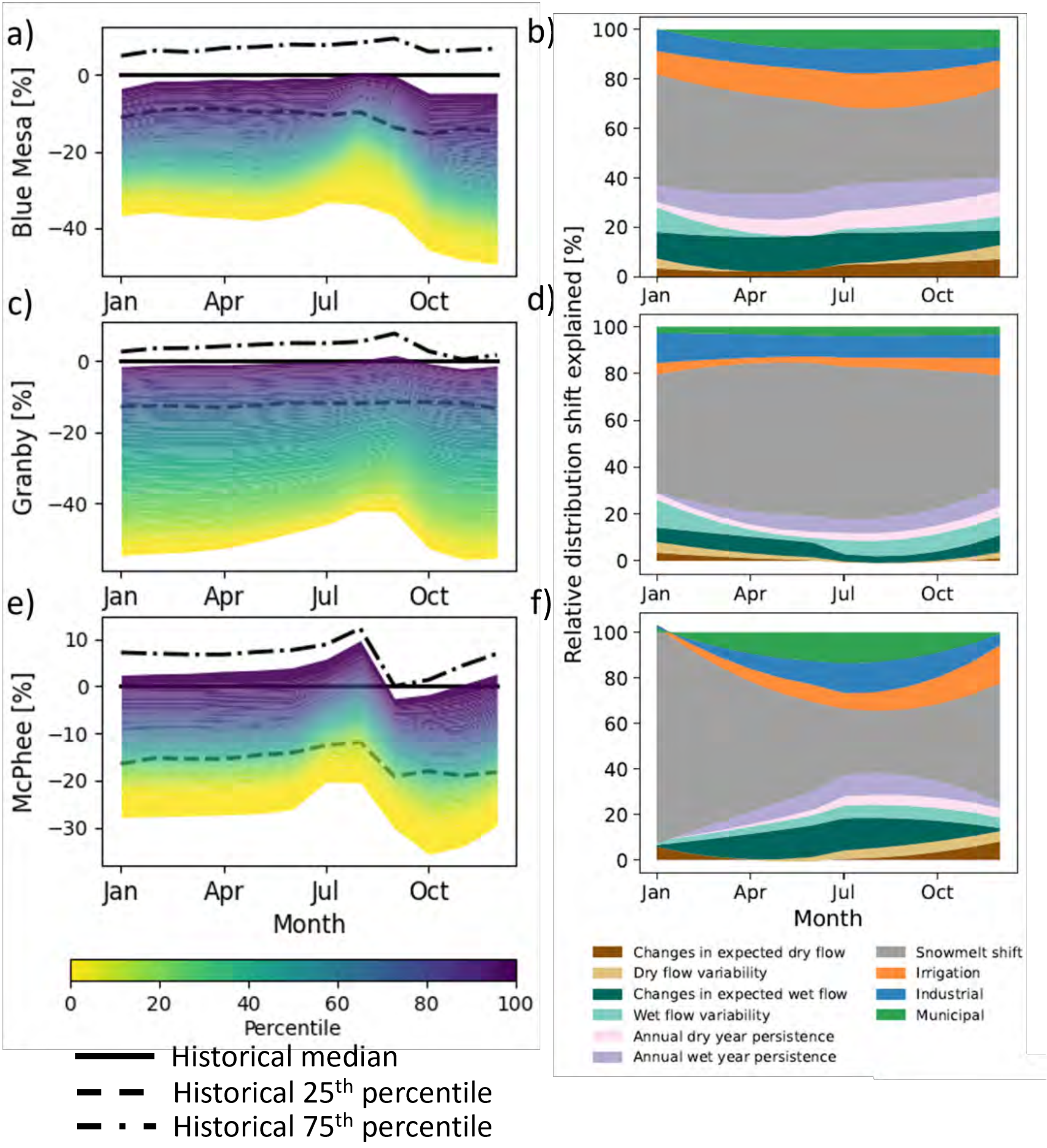
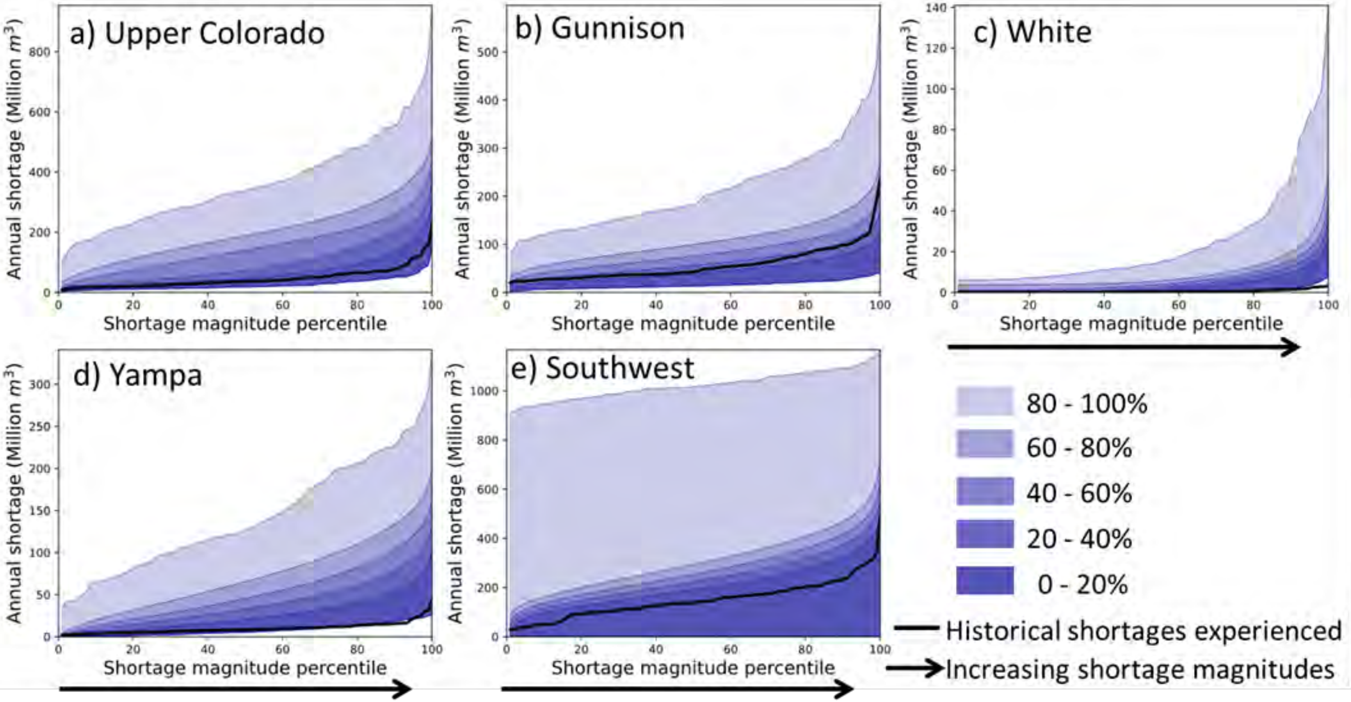

a) Cumulative annual outflows from West Slope basins
Relative Median Outflows
Relative 5th Percentile Outflows
Cumulative outflows relative to baseline [Million m3]
6000
4000
2000
0
−2000
−4000
−6000
0.00000
0.00005
0.00010
0.00015
0.00020
0.00025
0.00030
Density
b) Contribution to Lake Powell deliveries
Southwest
60.7%
Upper Colorado
18.5%
13.6%
Gunnison
.5%
6.6%
Yampa
White
c) Annual median outflows from each basin relative to historical median
Upper Colorado
Gunnison
Yampa
White
Southwest
Outflows relative to baseline median [Million m3]
1000
500
0
−500
−1000
0.000
0.001
0.005
Density

**Figure 5.**



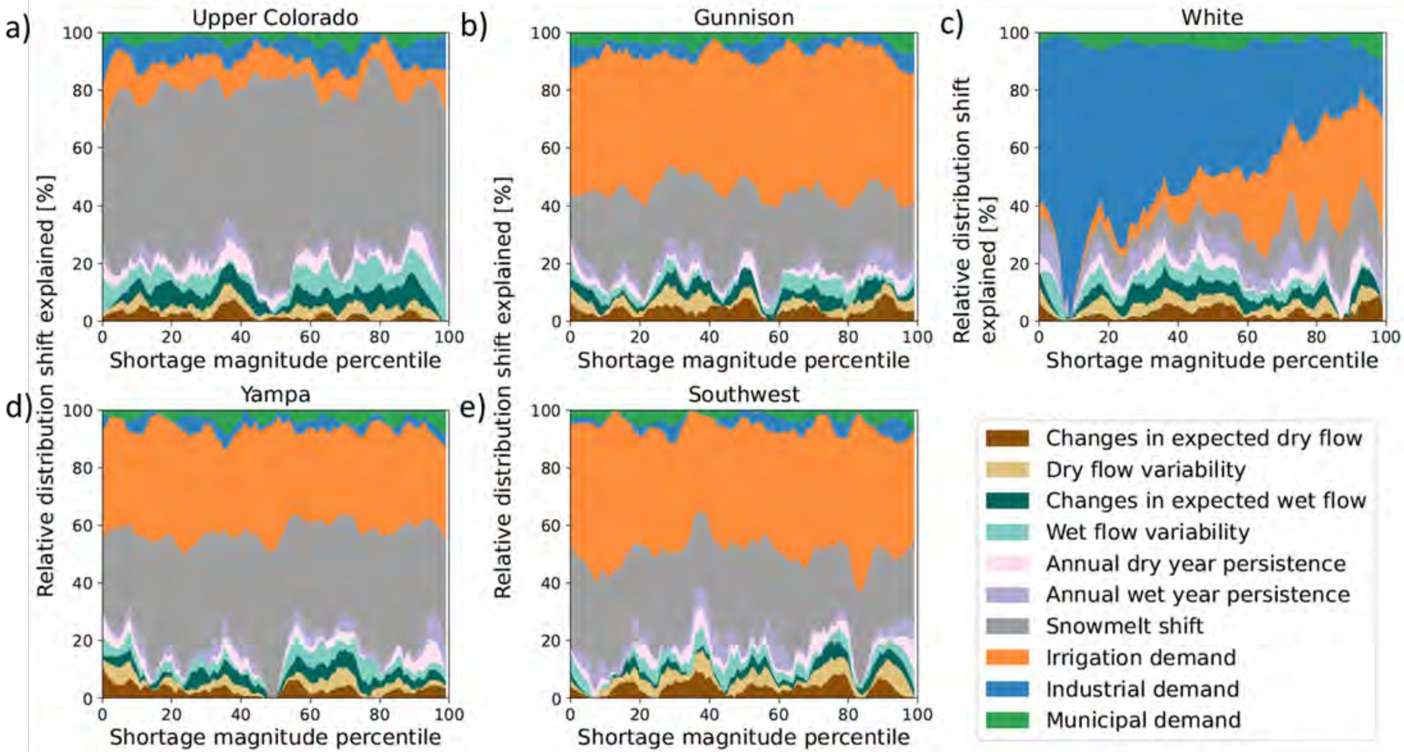
a)
b)
c)
d)
e)
f)
Blue Mesa [%]
Granby [%]
McPhee [%]
Relative distribution shift explained [%]
Jan
Apr
Jul
Oct
Month
Percentile
0
20
40
60
80
100
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation
Industrial
Municipal
Historical median
Historical 25th percentile
Historical 75th percentile

**Figure 6.**



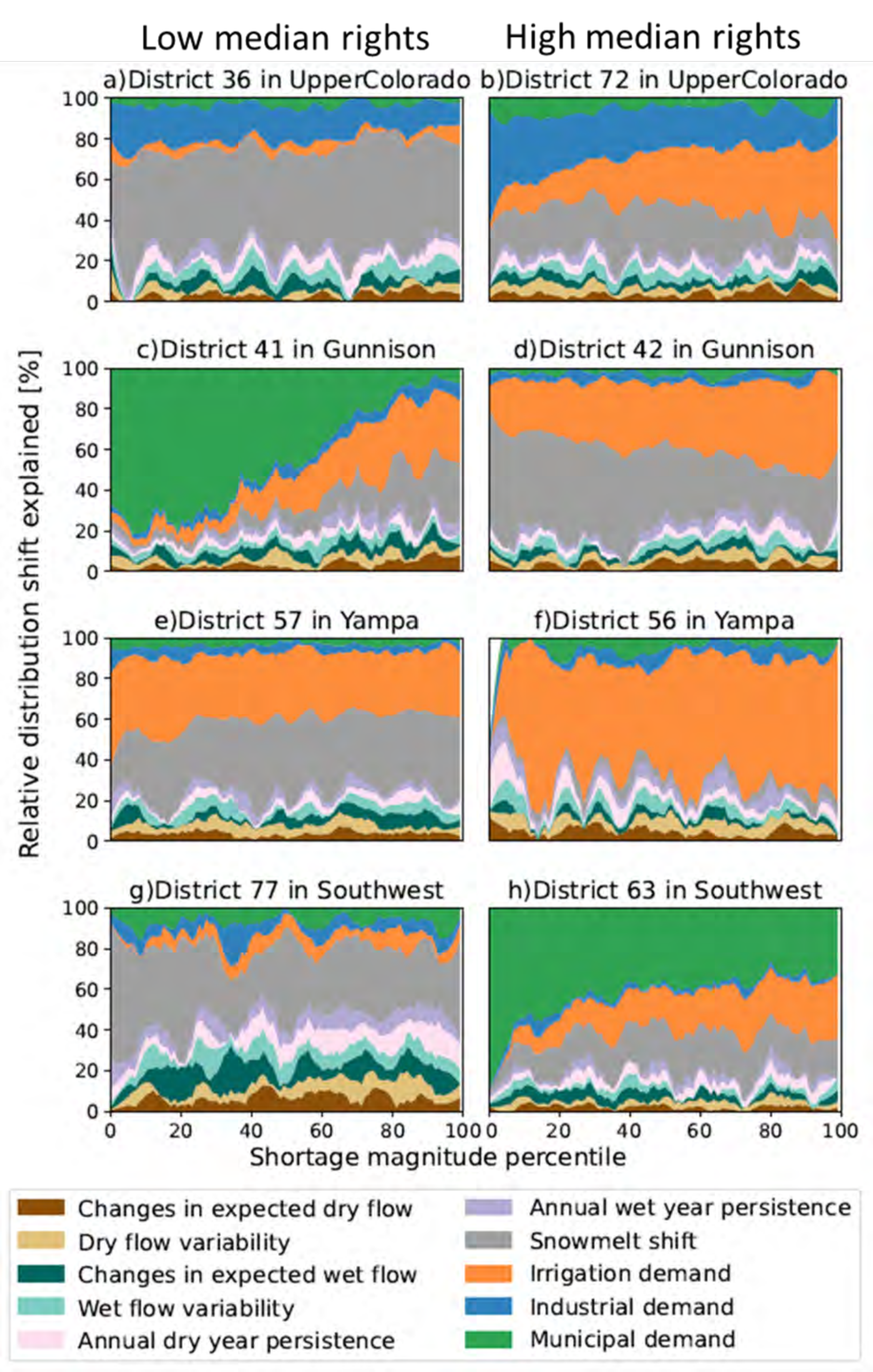
a) Upper Colorado
b) Gunnison
c) White
d) Yampa
e) Southwest
Annual shortage (Million $m^3$)
Shortage magnitude percentile
80 - 100%
60 - 80%
40 - 60%
20 - 40%
0 - 20%
Historical shortages experienced
Increasing shortage magnitudes

**Figure 7.**



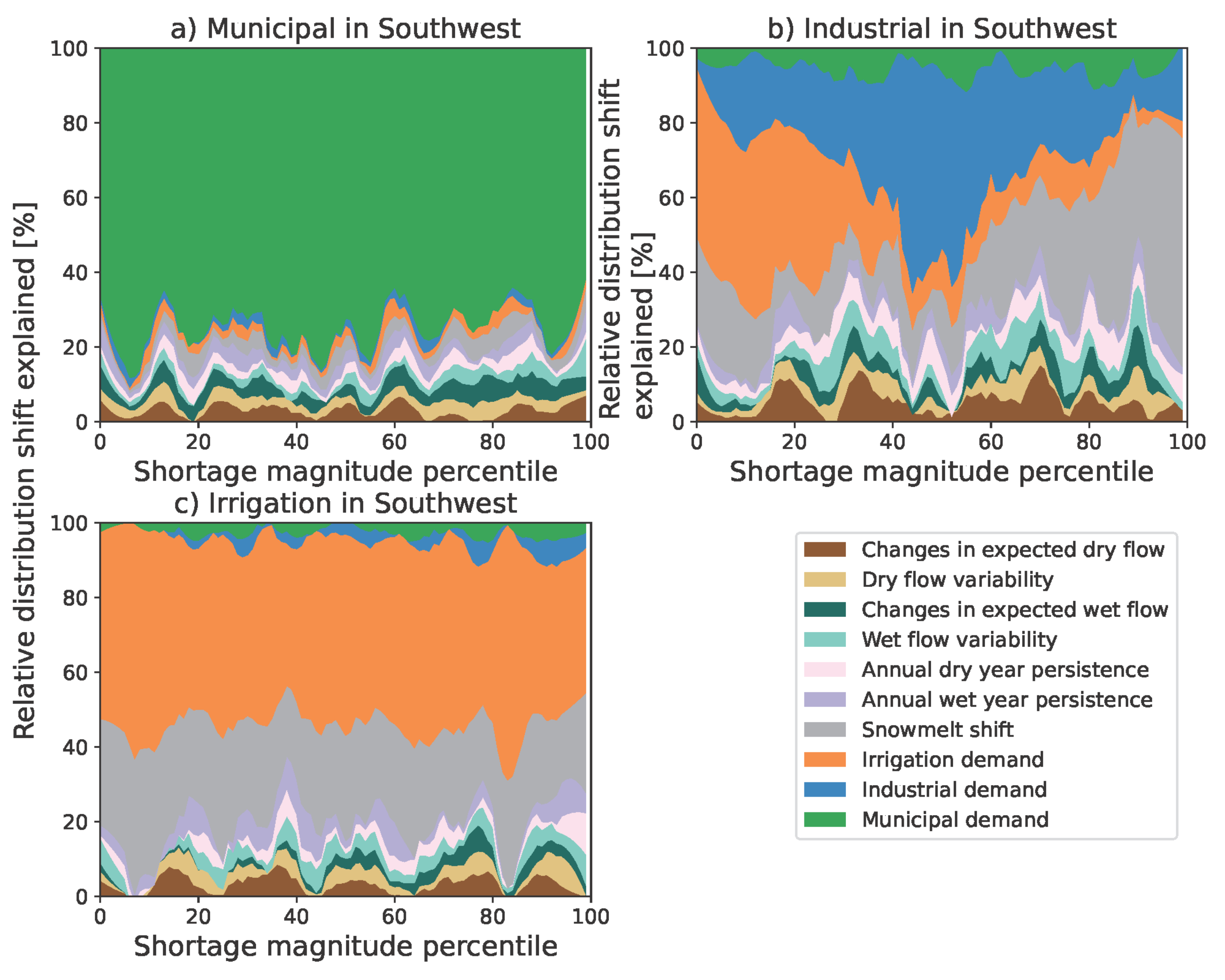
a)
Upper Colorado
b)
Gunnison
c)
White
d)
Yampa
e)
Southwest
Relative distribution shift explained [%]
Shortage magnitude percentile
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation demand
Industrial demand
Municipal demand

**Figure 8.**



Low median rights
High median rights
a)District 36 in UpperColorado
b)District 72 in UpperColorado
c)District 41 in Gunnison
d)District 42 in Gunnison
e)District 57 in Yampa
f)District 56 in Yampa
g)District 77 in Southwest
h)District 63 in Southwest
Relative distribution shift explained [%]
Shortage magnitude percentile
0
20
40
60
80
100
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation demand
Industrial demand
Municipal demand

**Figure 9.**


a) Municipal in Southwest
b) Industrial in Southwest
c) Irrigation in Southwest
Relative distribution shift explained [%]
Shortage magnitude percentile
0
20
40
60
80
100
Changes in expected dry flow
Dry flow variability
Changes in expected wet flow
Wet flow variability
Annual dry year persistence
Annual wet year persistence
Snowmelt shift
Irrigation demand
Industrial demand
Municipal demand

# Supporting Information for "Unraveling the Drivers of Water Shortage across Spatial Scales and Sectors in Colorado's West Slope River Basins"

Sai Veena Sunkara[1], David Gold[2], Patrick Reed[1]

[1]School of Civil and Environmental Engineering, Cornell University, Ithaca, NY, USA

[2]Department of Physical Geography, Utrecht University, Utrecht, The Netherlands

## Contents of this file

1. Text S1 to S3
2. Figures S1 to S10
3. Tables S1 to S2

## Text S1. Quantile sampling selection technique using drought index

As discussed in Section 3.2, for each uncertain factor combination, 1000 streamflow realizations are generated sampling the internal variability. Out of 1000, 20 realizations are selected based on quantile technique of drought index for the analysis. The drought index used is the severity-based metric defined in Gold et al. (2025). This index is defined using a moving-window threshold method identifying periods when n-year rolling mean log annual flow drops 0.5 times standard deviation below the mean flow of the historical record.

$$drought_t = True \qquad if \qquad \mu_n^t < \mu_{hist} - 0.5\sigma_{hist}; False \qquad otherwise \tag{1}$$

$\mu_{hist}$ is the mean flow of the 105-year historical record, and $\sigma_{hist}$ is the standard deviation of flow in the 105-year historical record. Multiple temporal definitions of drought are explored using equation 1 by varying from 6 years (multi-year drought) to 25 years (multi-decadal drought). For a given drought event, we define the drought severity as the sum of the normalized difference between the annual flow during each year of the drought period and the mean annual flow of the historical record shown an cumulative deficit in equation S2.

$$CumulativeDeficit = \int_{start}^{end} \frac{\mu_{hist} - Y_t}{\sigma_{hist}} dt \tag{2}$$

We compute the drought index for 1,000 realizations corresponding to each uncertain factors sample. The realizations are then sorted in decreasing order, and every 5th quantile is selected, yielding a set of 20 representative samples that capture a broad range of drought conditions across the full ensemble.

**Text S2. Deriving Streamflow Variations from Global Climate Model projections**

In this study, we represent drier and wetter futures by altering the HMM parameters as described in Section3.2. This adjustment resulted in a mean annual real-space streamflow reduction (across all basins) in the range of -30% to 20% compared to a baseline period from 1980-2010. This ranges reflects the climate change impacts on streamflow in the Upper Colorado River Basin as evaluated in previous studies (Hoerling et al., 2024; Hegewisch et al., 2023). Figure S2(a) presents the projected distribution of mid-century streamflow variations at Lees Ferry based on 220 samples from large ensemble simulations (LENS) conducted by Hoerling et al. (2024), which incorporate climate projections from CMIP6. A precipitation sensitivity of 1.9, estimated from historical observations, was applied along with three plausible temperature sensitivity scenarios (three different histograms in Figure S2(a)) to characterize the range of streamflow responses.

The analysis conducted by Hoerling et al. (2024) employs a baseline period of 2000–2020, which does not exactly overlap with the range used in this study and therefore prevents a direct comparison. Nevertheless, CMIP6 LENS simulations for that period indicate warmer conditions with precipitation patterns similar to those of the 20th century. As a result, the 2000–2020 baseline reflects comparatively optimistic streamflow outcomes relative to the 1980–2010 reference period used in Figure S2(b), since higher temperatures typically correspond to lower streamflows. In this context, the range of 30% reduction to 20% increase in streamflow from the HMM ensemble in this study aligns well with climate change scenarios as represented in the CMIP6 LENS projections.

**Text S3. Sectoral sensitivity to uncertain factors across basins**

While Figure 9 highlights the Southwest basin, similar patterns of sectoral sensitivity to uncertain factors are observed across other basins, with notable differences outlined as follows. (Supplementary Figures S7-S10). Under both drier and wetter future scenarios, the industrial sector in the Gunnison Basin experiences zero shortages (Figure S5 b), likely due to the smaller number of users and the absence of significant projected growth in the region. The municipal sectors in the White and Yampa basins (Figure S6 and S7) also exhibit distinct behavior compared to other basins. For the municipal water users in the White basins, shortages are not observed at certain shortage magnitude percentiles. In the Yampa basin, this is further complicated by water availability challenges, where shortages are largely driven by hydrological factors such as snowmelt timing and variability.

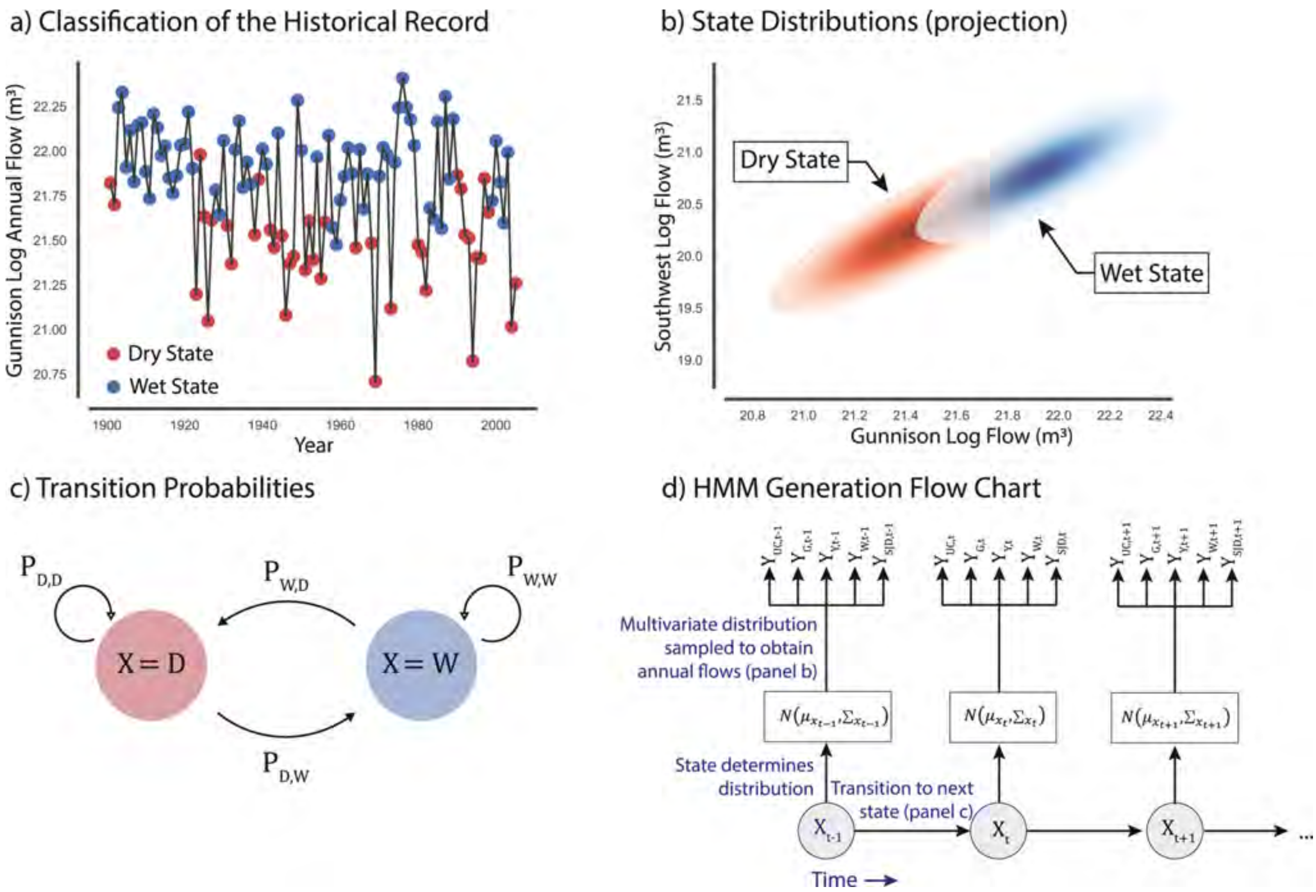



**Figure S1.** Figure S1. (a) Dry and wet state classification of the historical record in the Gunnison River basin. (b) 2-dimensional projections of the 5-dimensional Gaussian distributions of streamflows of the Gunnison and Southwest Basins based on its dry and wet state. (c) Figure to show transition probabilities from each state. (d) Multi-basin Hidden Markov Model overview used to generate synthetic streamflow records for the West Slope Basins. Figure adopted from Gold et al. (2024).

**Table S1.** Table S1. Percentage change in streamflows for the 20000 sampled scenarios relative to the historical baseline (1990-2010) and the number of scenarios under each category of percentage change.

| Percent change | Number of scenarios | Percentage of scenarios |
|---|---|---|
| $> 20\%$ | 34 | 0.17% |
| 15% to 20% | 253 | 1.2% |
| 10% to 15% | 932 | 4.66% |
| 5% to 10% | 1777 | 8.88% |
| 0% to 5% | 2548 | 12.74% |
| 0% to -10% | 6649 | 33.2% |
| -10% to -20% | 6206 | 31.03% |
| $< -20\%$ | 1601 | 8% |

**Table S2.** Table S2. F-test as a statistical measure to assess the significance of differences in responses due to individual parameters and their interactions. The p-value for the F-statistic, represents the probability of observing the calculated F-statistic or a more extreme one if the null hypothesis were true.

| **West Slope basin** | **F-statistic** | **P-value** |
|---|---|---|
| Upper Colorado | $9.4 \times 10^{32}$ | 0.0 |
| Gunnison | $6.9 \times 10^{32}$ | 0.0 |
| Yampa | $3.4 \times 10^{32}$ | 0.0 |
| White | $0.26 \times 10^{32}$ | 0.0 |
| Southwest | $30.6 \times 10^{32}$ | 0.0 |

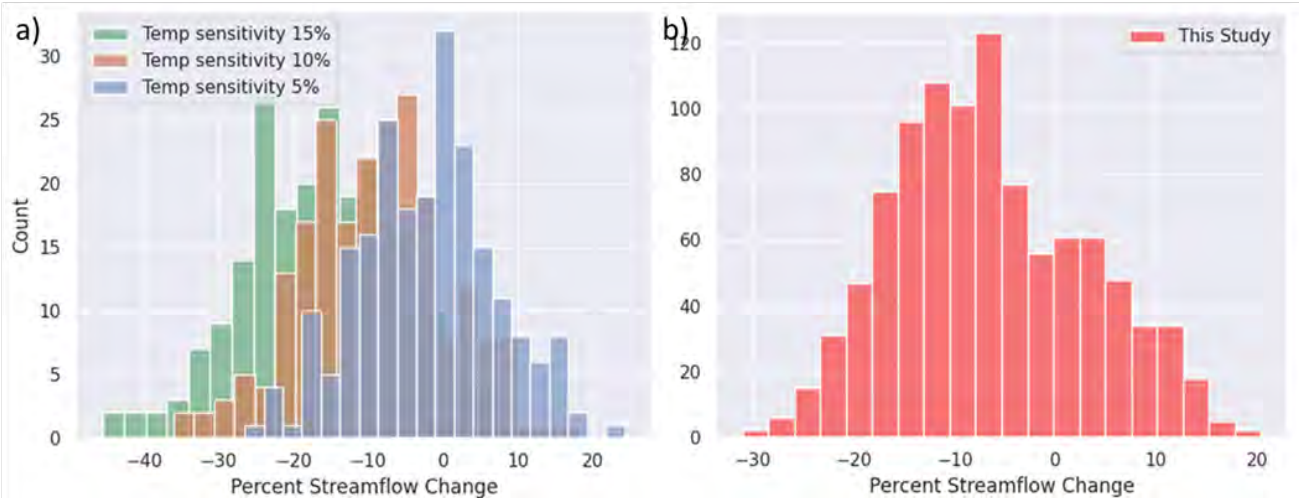



**Figure S2.** (a) Streamflow changes resulting from large ensemble simulations of mid-century projections evaluated by Hoerling et al. (2024). (b) Streamflow changes sampled in this study to reflect similar ranges from (a) used to evaluate vulnerability measures for the West Slope basins.

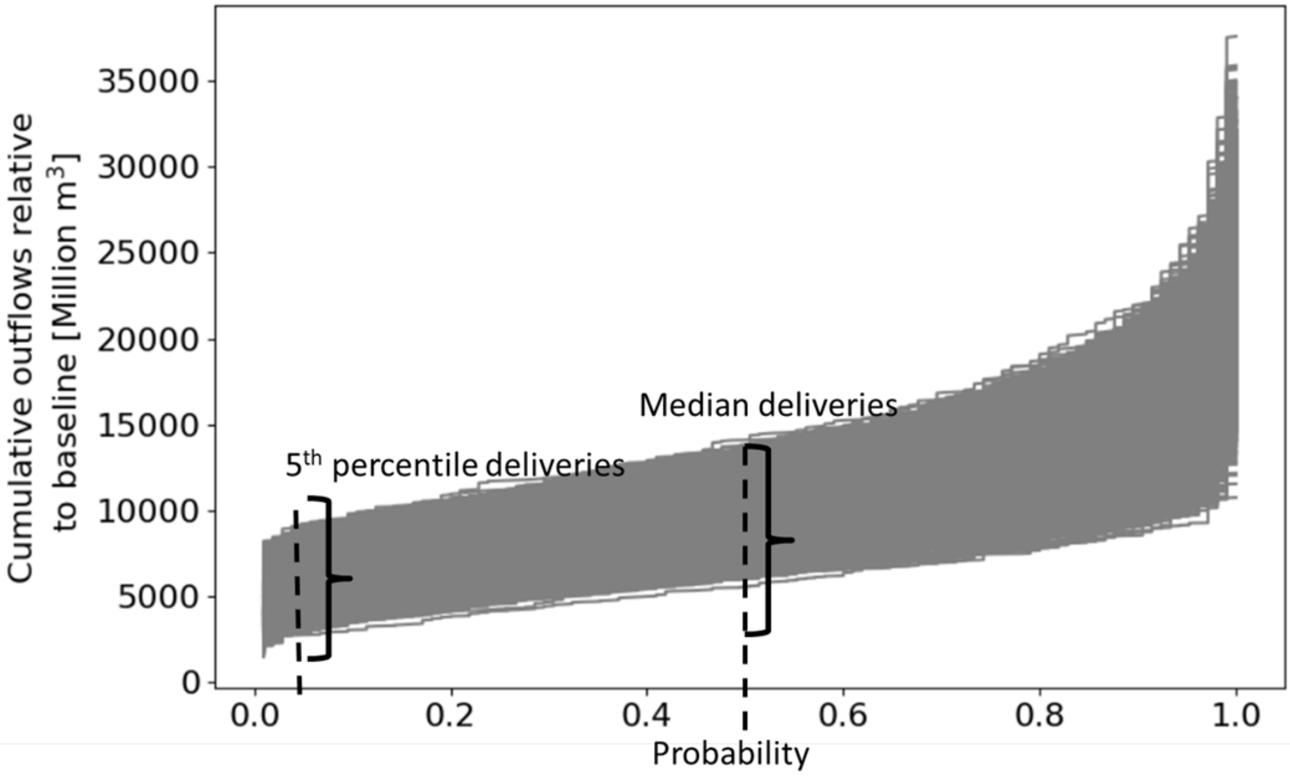



**Figure S3.** Distribution of cumulative annual outflows (in million $m^3$) from the West Slope basins under all scenarios relative to historical baseline.

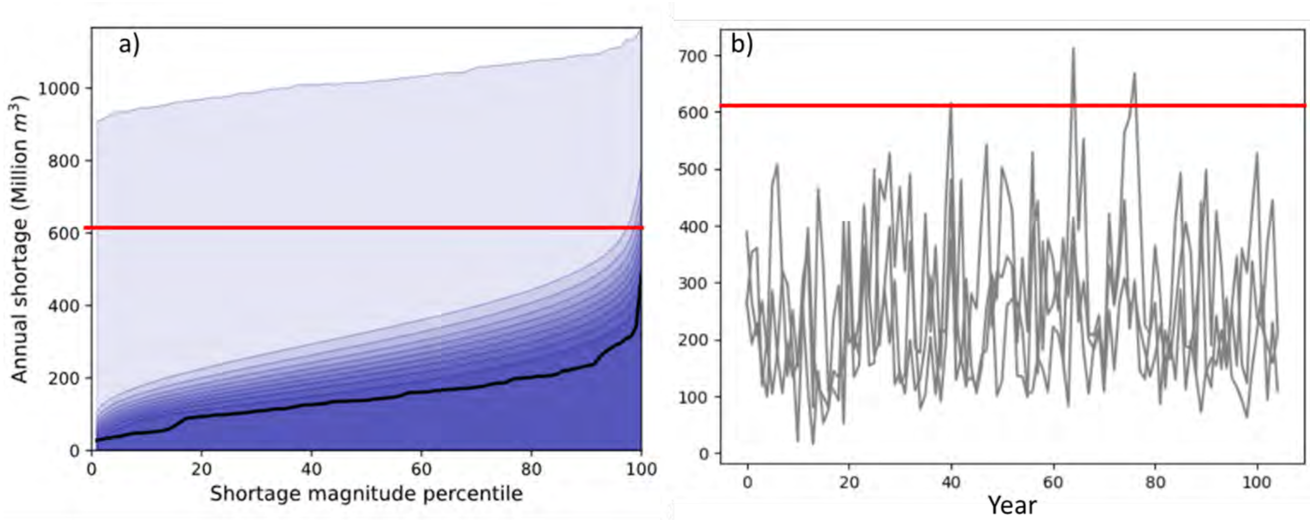



**Figure S4.** (a) Percentile-varying impacts on cumulative annual shortage magnitude and frequency for the Southwest basin (same as the Figure 6e) (b) Annual shortage magnitude for three randomly selected scenarios in the 105-year timeseries. Redline represents the shortage magnitude of 610 million m3

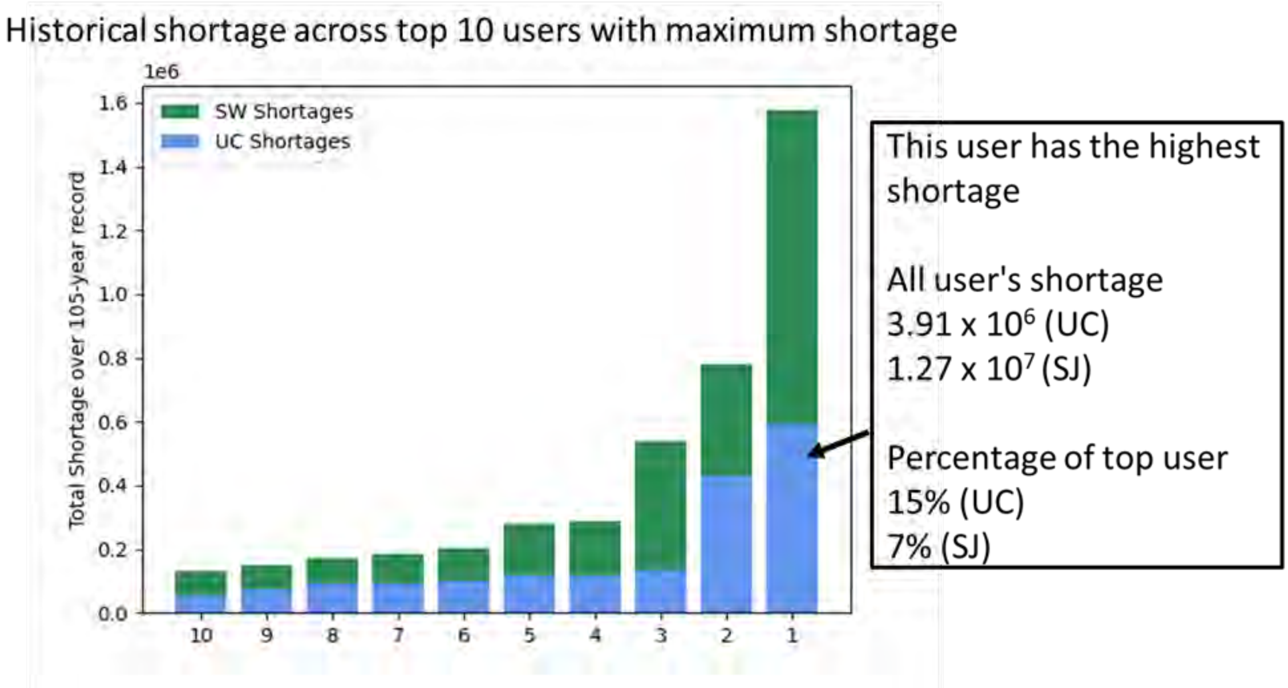



**Figure S5.** Historical shortage comparisons for top 10 Upper Colorado and Southwest users that contribute the most to total shortage in their respective basins.

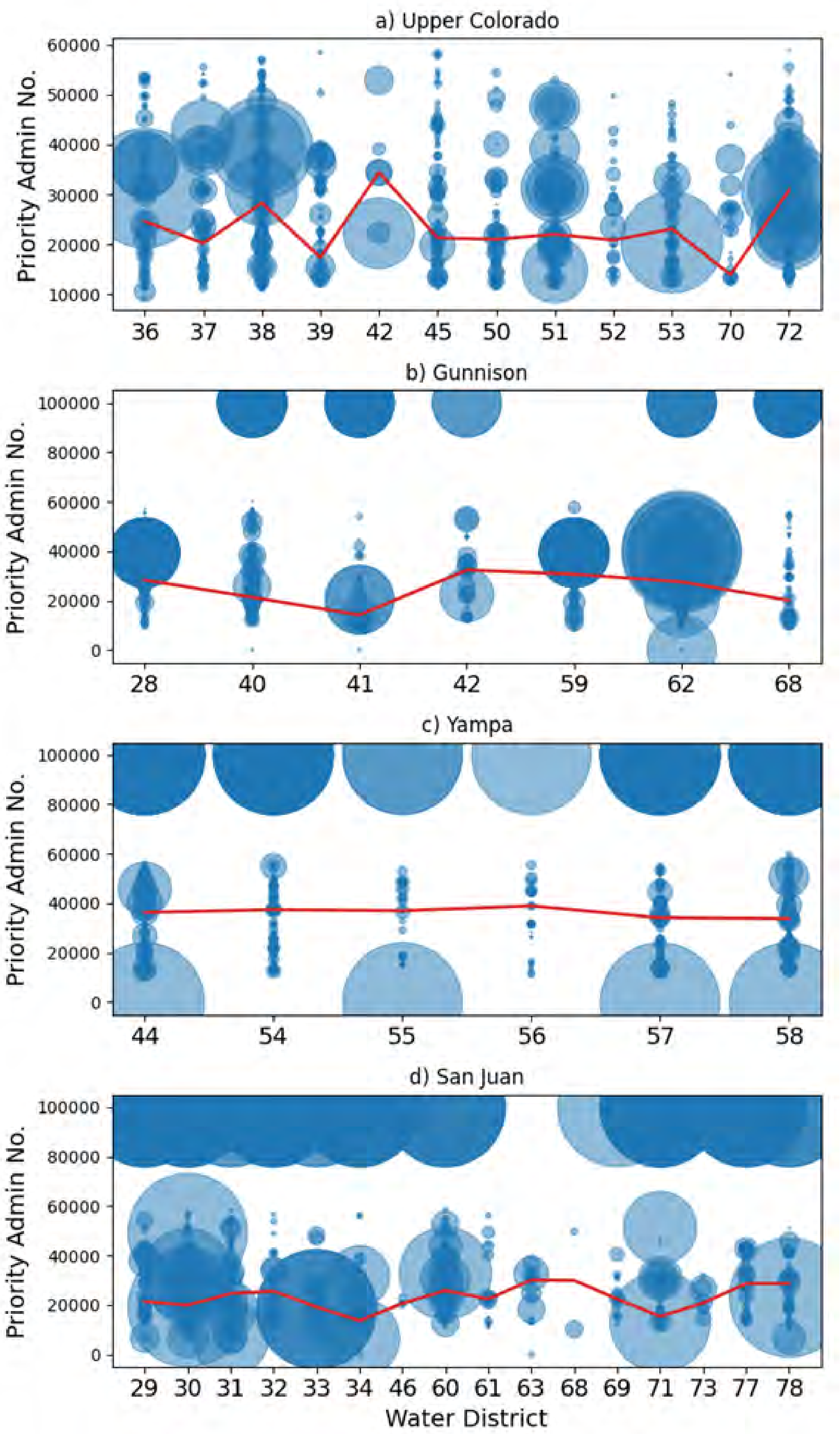



**Figure S6.** Priority admin number that represents water rights for each users in a water district are shown with bubble size indicating water allocation for the West Slope basins a) Upper Colorado b) Gunnison c) Yampa and d) Southwest. The X-axis represents water districts and y-axis priority admin number. Lower priority admin number is defined for higher right seniority users. Larger bubble size indicates larger decree volumes of users. Red line shows median priority admin numbers across all users within the district.

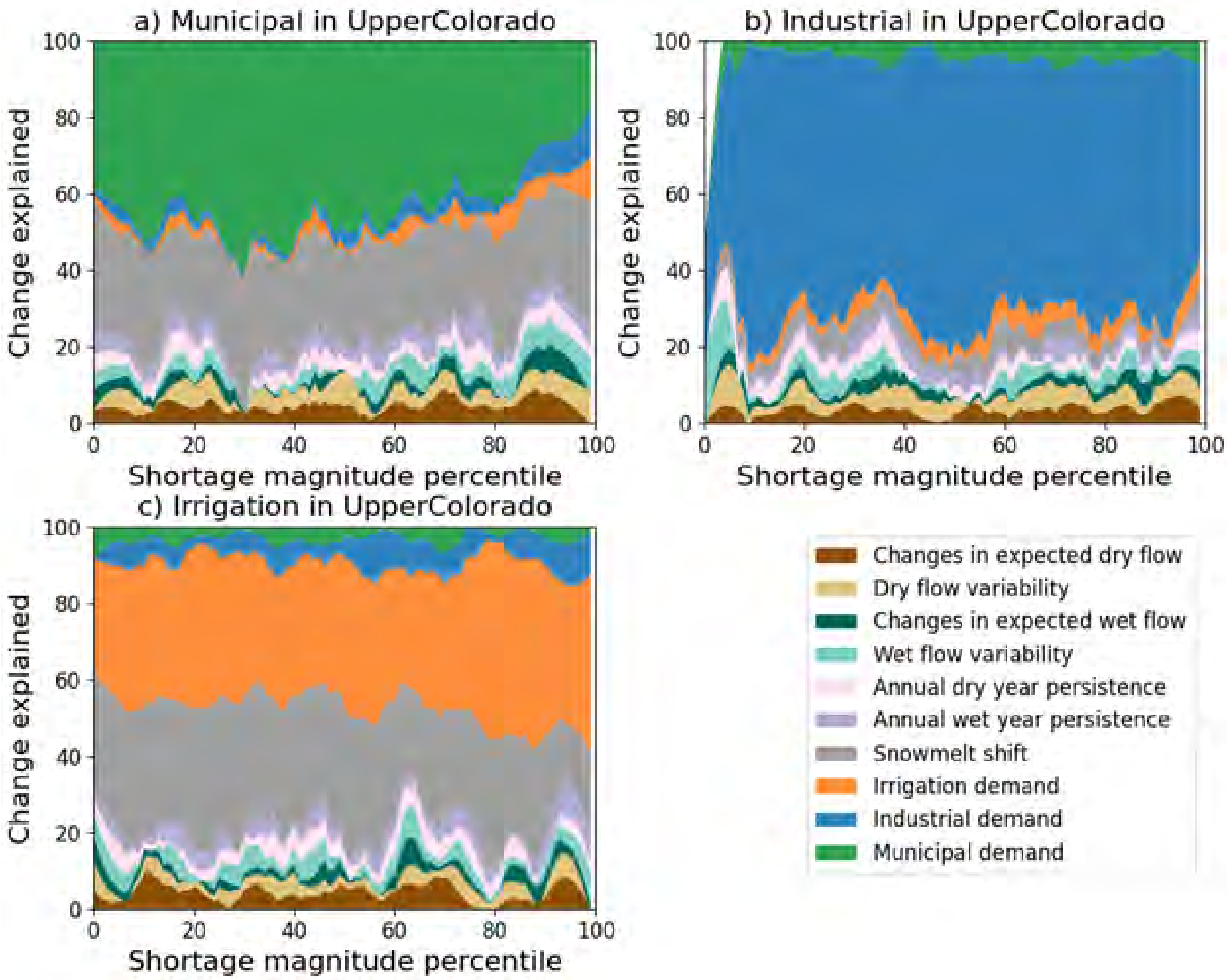



**Figure S7.** Percentile-varying sensitivity indices of shortage magnitude across different sectors in Upper Colorado basin. X-axis represents the shortage magnitude percentile with increasing in shortage magnitude from 0 to 100. Y-axis represents the percentage of contribution by each uncertain factor. Each panel presents the magnitude-varying sensitivity indices attributed to each factor, for the shortages experienced by (a) Municipal, (b) Industrial and, (c) Irrigation sector. The colors in the legend are listed in the order that they are plotted, from bottom, up.

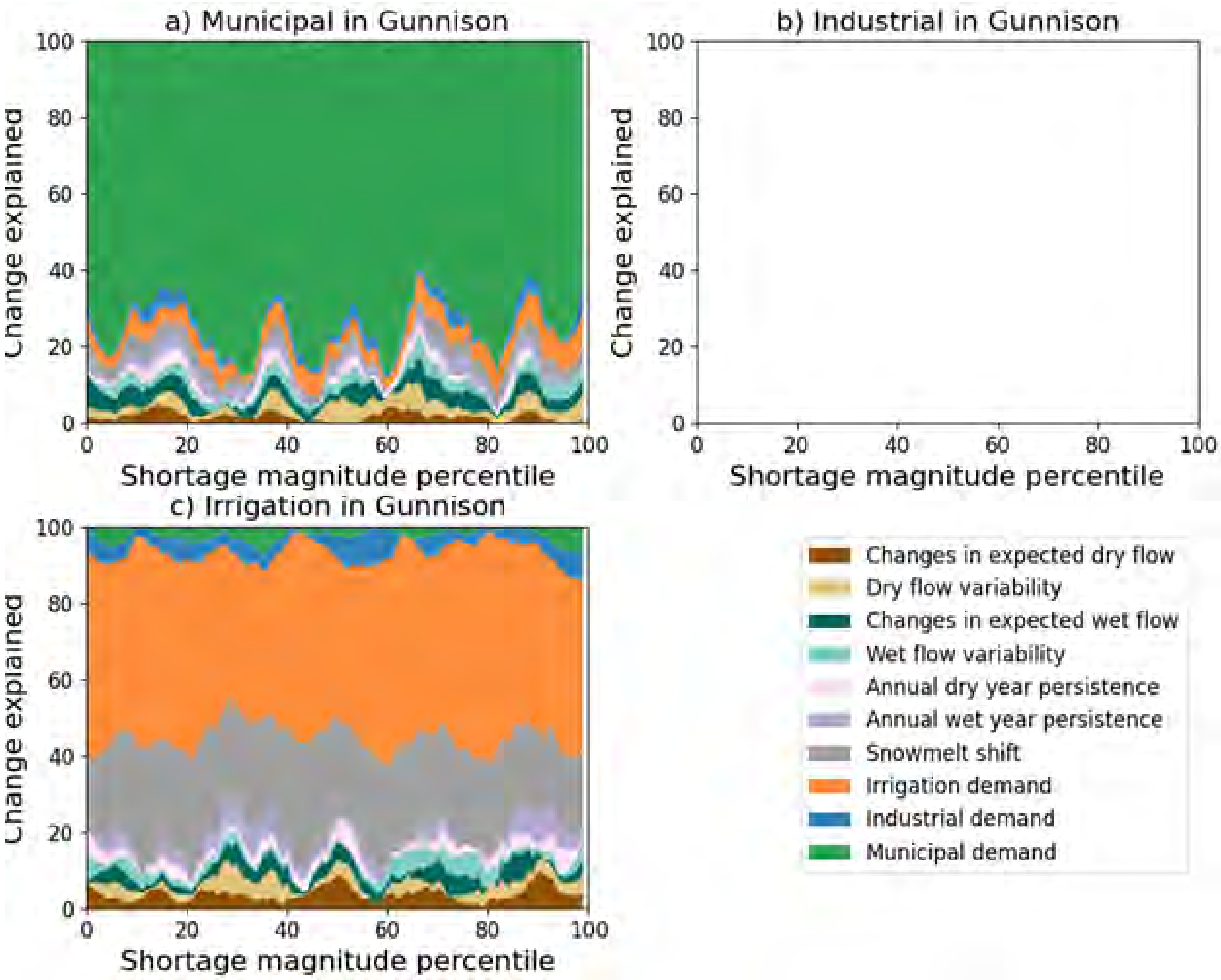



**Figure S8.** Percentile-varying sensitivity indices of shortage magnitude across different sectors in Gunnison basin. X-axis represents the shortage magnitude percentile with increasing in shortage magnitude from 0 to 100. Y-axis represents the percentage of contribution by each uncertain factor. Each panel presents the magnitude-varying sensitivity indices attributed to each factor, for the shortages experienced by (a) Municipal, (b) Industrial and, (c) Irrigation sector. The colors in the legend are listed in the order that they are plotted, from bottom, up.

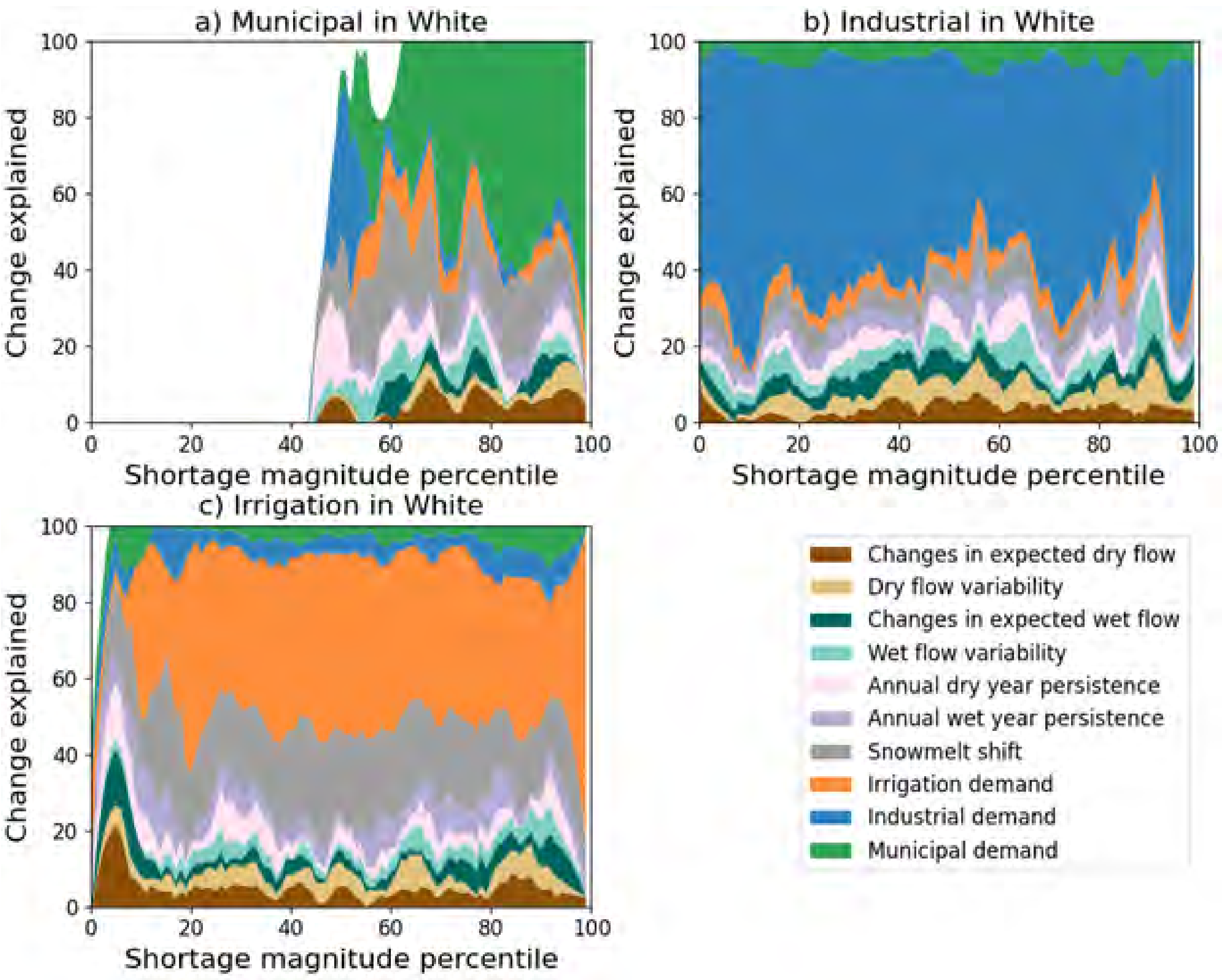



**Figure S9.** Percentile-varying sensitivity indices of shortage magnitude across different sectors in White basin. X-axis represents the shortage magnitude percentile with increasing in shortage magnitude from 0 to 100. Y-axis represents the percentage of contribution by each uncertain factor. Each panel presents the magnitude-varying sensitivity indices attributed to each factor, for the shortages experienced by (a) Municipal, (b) Industrial and, (c) Irrigation sector. The colors in the legend are listed in the order that they are plotted, from bottom, up.

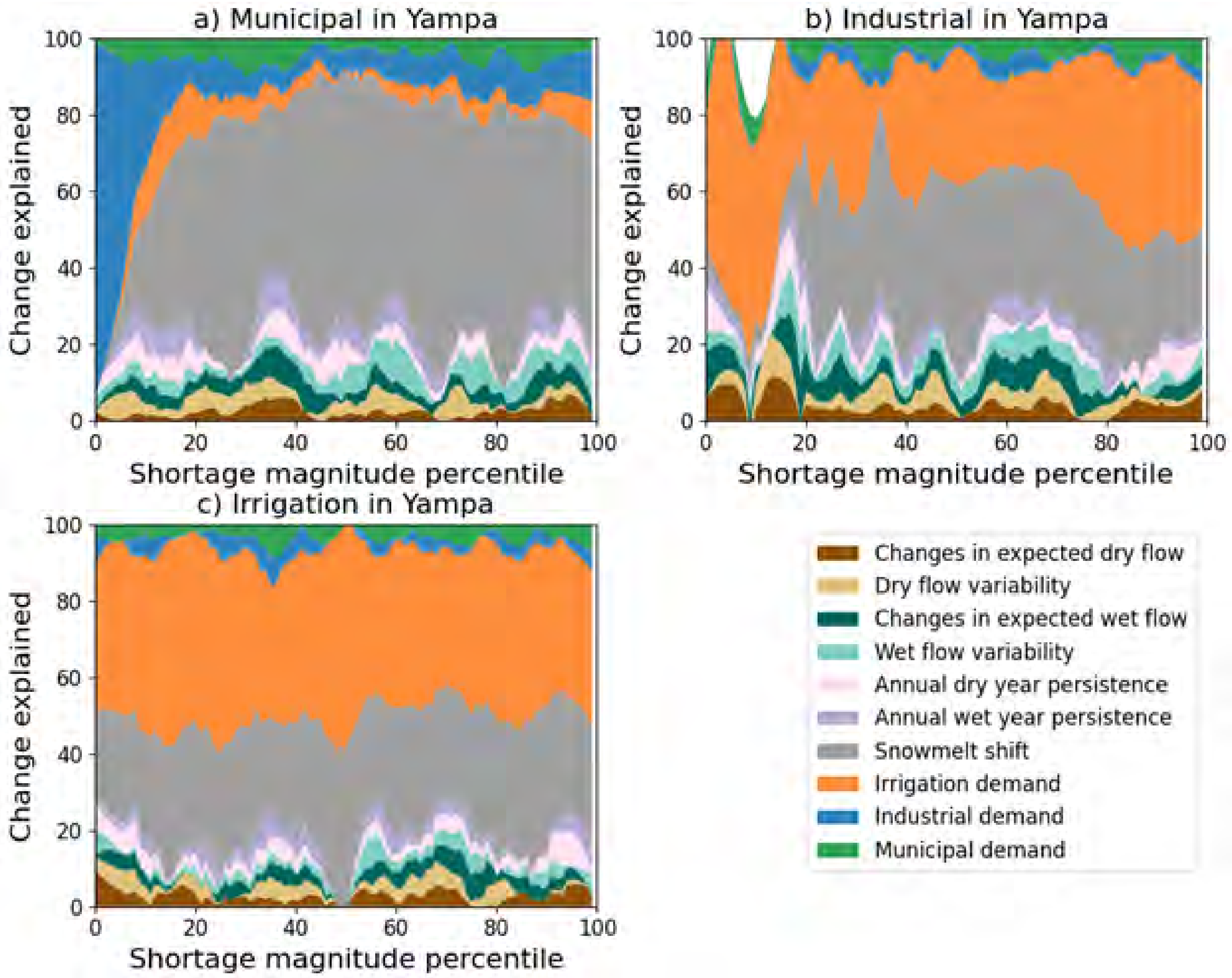



**Figure S10.** Percentile-varying sensitivity indices of shortage magnitude across different sectors in Yampa basin. X-axis represents the shortage magnitude percentile with increasing in shortage magnitude from 0 to 100. Y-axis represents the percentage of contribution by each uncertain factor. Each panel presents the magnitude-varying sensitivity indices attributed to each factor, for the shortages experienced by (a) Municipal, (b) Industrial and, (c) Irrigation sector. The colors in the legend are listed in the order that they are plotted, from bottom, up.