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RESEARCH

Spatial Patterns of Water Supply and Use in California

John J. Helly [1, 2], Daniel Cayan [1], Jennifer Stricklin [3], Laurel Dehaan [1]

ABSTRACT

Spatial and temporal patterns of water supply and consumptive water use were analyzed from 475 Detailed Analysis Units by County (DAUCOs) spatial units across California during 2002 through 2016 to evaluate spatial and temporal variability and how it might associate with precipitation variability and other factors. Many, but not all, DAUCOs have relatively low total water supply variability compared to that of state-wide precipitation. Such low variability, in DAUCOs having sufficient diversity of water supply sources, is the result of switching between sources as needed to maintain a reliable total water supply. We used multiple approaches to explore these variations which involved four categories of water supply (local, groundwater, imported, and other) and two categories of water use (agricultural and urban). First, a cluster analysis of the volumetric water balance data identified a small set of clusters having similar magnitudes and proportions of water supply sources and water use—some of them composed of only a few DAUCOs but accounting for a disproportionate amount of the state's water use. Second, a principal components analysis identified leading modes of anomalous water supply and water use among the 475 DAUCOs, capturing most of the time variation during 2002 to 2016. The most prominent mode exhibits a multi-year trend, most strongly involving increasing groundwater supply and agricultural water use, and decreasing urban water use and imported water supply. Over the study period, trends in both supply and use were pronounced, but differed considerably across California DAUCOs. One predominant subset of DAUCOs grew their agricultural water use with increased groundwater supply; in contrast to a widespread group of DAUCOs which reduced their urban water use. An important result for planners is our finding that variation in precipitation—itself important—is amplified by the human response to water supply availability and regulatory policy.

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KEY WORDS

California, water supply, water use, infrastructure, data, cluster analysis, principal components analysis, hydrology, sustainability

INTRODUCTION

The California Water Plan is the principal strategy document on water supply and use in the state (CDWR 1957, 1994, 2013, 2019a, 2019b). It has been published since 1957 by the California Department of Water Resources (CDWR). Since 1993, it has been updated every 5 years, and guides state agencies in implementing California's Water Resilience Portfolio (WRP). The WRP addresses maintenance and diversification of water supplies, protection and enhancement of natural systems, improvements in physical infrastructure, and water resource management using science, data, and technology (CDWR 2020). These documents are based on a unique dataset called the Water Plan Water Balance Data (CDWR 2023b) now published by the CDWR as annual water-year updates, although the data are typically 2 to 3 years behind the current year for reasons described later in this paper. The CDWR is working to reduce this delay to 2 years: the shortest, practicable delay given current land-use data sources required to produce the annual water balance data.

The water balance data are the finest-grained, state-wide data available. Temporally, these are annual estimates of water supply and use across six major categories (i.e., Agriculture, Urban, Managed Wetlands, Wild and Scenic Rivers, Required Delta Outflow, Instream Flow Requirements) and 172 detail categories with volumetric estimates in units of thousand-acre feet (1.2 × 106 m^3, 0.3 × 10^6 gals). Spatially, the data are defined by polygons at the sub-county scale and referred to as Detailed Analysis Units by County (DAUCOs). Records from 475 DAUCOs employed in this study cover most of the state, ranging from 0.2 acres (0.001 km^2) to 1.9 million acres (7,689 km^2). The mean size is 258,823 acres (1047 km^2), and 50% are less than 165,091 acres (668 km^2). They generally correspond to the National Watershed Boundary Dataset spatial partitioning of HUC8 (USGS and USDA 2013; Seaber et al. 1987). WBD contains eight levels of progressive hydrologic units identified by unique 2- to 16-digit codes. The dataset is complete for the United States to the 12-digit hydrologic unit. The 8-digit level unit is often referred to as HUC8 and is a commonly used reference framework for planning and environmental assessment.

Water balance refers to an approximate relationship between the water supply and water use, based on the assumption that all water supplied by purpose-built infrastructure (i.e., the developed water supply) is used (Figure 1). Developed water supply includes surface water deliveries and groundwater extraction. The balance between developed water supply (DWS) and water use is approximate, because volumetric estimates of water-supply variables are generally developed separately from the water-use variables. Exceptions occur in some instances where estimates can only be made by inferring water-supply-variable estimates from water-use-variable estimates or vice-versa. Groundwater supply for rural residential use—a part of urban water use—is an example of this type of inference.

A detailed discussion of how water balance estimates are developed is provided in Helly et al. 2021, which is the first detailed description of the water balance data. That paper characterized the temporal patterns of water use in California from 2002 to 2016 using the Bay–Delta hydrologic region as a case study, with an extended analysis to the nine other hydrologic regions across the state to examine the generality of the Bay–Delta results. Across those, we found that agricultural water use varied little but correlated inversely with annual precipitation. In contrast, urban water use exhibited relatively higher variability and essentially zero correlation with precipitation.

In broad view, California's developed water is a system that is fed by highly variable precipitation (e.g., Dettinger 2011), and manipulated by a complex mixture of infrastructure and management to provide users a steady water supply. Figure 1 illustrates the concept of a water balance as a system that responds to that

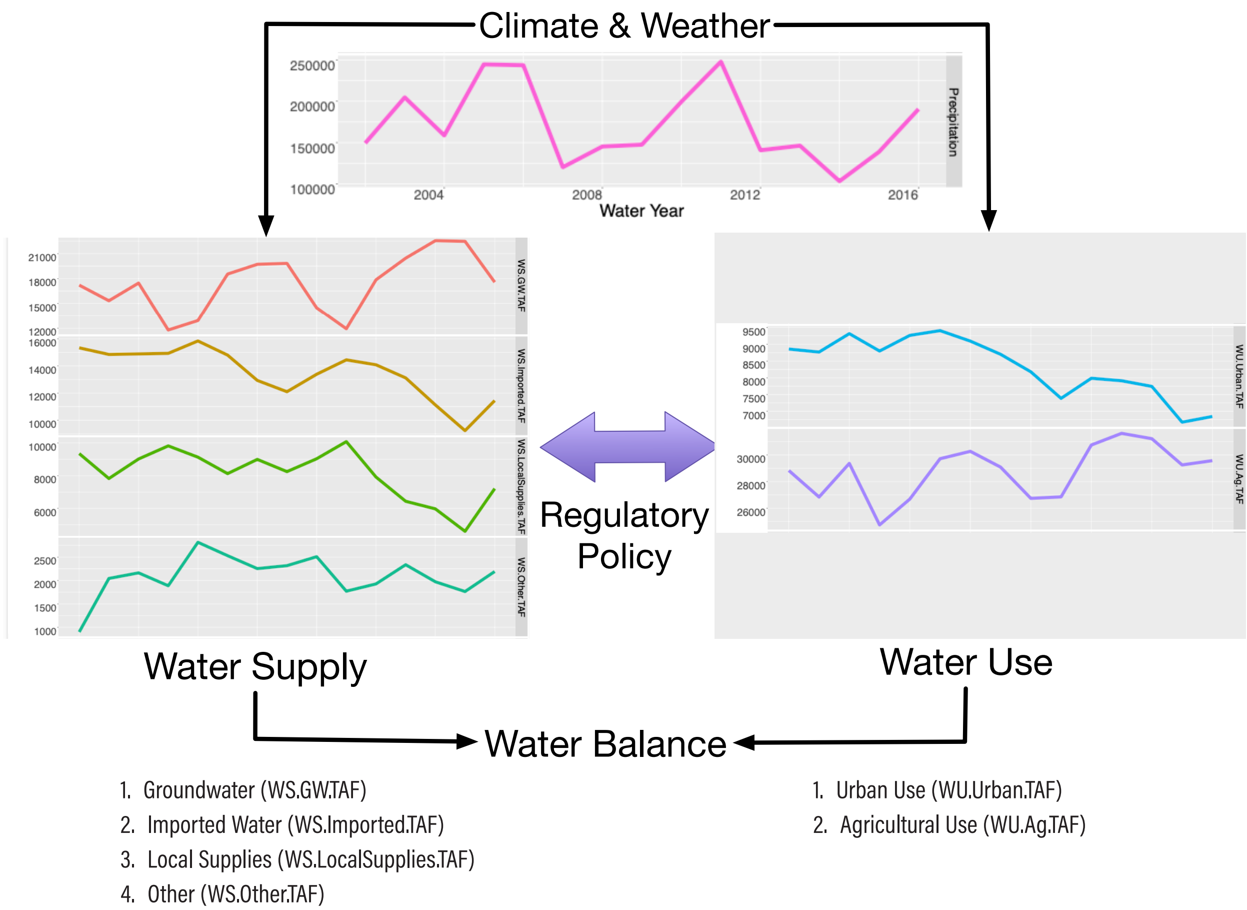

Figure 1 Conceptual diagram of water balance as a system of supply and use driven by climate and weather, via precipitation, and constrained by regulatory policy; including land use. Water balance is described by the six (6) water balance variables listed: four (4) water supply (*left side*) and two (2) water use (*right side*). The time-series depict actual data described in full below. Estimates of supply and use are developed separately but should be approximately equal within the uncertainties described in (Helly et al. 2021). The six water balance variables are listed along with the name of the corresponding variable used in this study.

variability. Precipitation affects the supply and use sides of the water balance simultaneously, as do other environmental variables such as temperature, soil moisture, and humidity. On the use side, urban and agricultural water use also reflect human land-uses decisions that extract water from the atmosphere and lithosphere and transform it into biomass, wastewater, surface runoff, and groundwater recharge. Return flows to the atmosphere as gas and ocean and lithosphere as liquid closes the system in a hydrologic cycle. Regulatory policy constrains infrastructure development, as well as how and how much water is used, and where it is used. All these factors contribute to the spatial and temporal variability we see in the water balance data.

In this study, we examine the patterns of variability across the state's 475 DAUCOs from 2002 to 2016 using an approach we introduce here called water-balance profiles. We find this to be a succinct and effective method to describe and analyze the components of water balance variability and their spatial distribution across DAUCOs. Water balance profiles contain six water-balance variables. On the supply side, these are groundwater, imported, local, and other. On the use side, 172 detailed categories are summarized into agricultural and urban water

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use. Environmental water use is excluded to focus on consumptive water use.

Using these water-balance variables, we develop analyses and maps to represent the spatial and temporal variability in the water balance data, and to characterize DAUCOs into groups with similar and different patterns of water supply and use. We also examine the state-wide response of the water balance variables to fluctuations of water year precipitation over California.

METHODS

The prior study of hydrologic region-scale water balance data by (Helly et al. 2021) used univariate statistics and time-series to analyze the magnitude and variability of water supply and use variables at the hydrologic region scale. Here, we use 475 DAUCOs—as compared to the earlier 10 hydrologic regions—to provide higher spatial resolution for mapping and statistics. Furthermore, this work employs multivariate methods to characterize individual DAUCOs and groups of DAUCOs with similar—and different—water balance profiles. The motivation behind the profile idea is that each spatial unit—at whatever spatial scale—can be characterized by a multivariate, time-series matrix, such as that shown in Table 1. In this study, each DAUCO has a water balance profile. The profiles are analyzed individually and as groups of DAUCOs using the six water-balance variables just mentioned: four supply variables and two use variables, as indicated in Figure 1.

We used cluster analysis (Kassambara 2017) to group DAUCOs with similar water-balance profiles into subsets (i.e., clusters) with similar patterns of water supply and use. Separately, we used principal components analysis (PCA) (Jolliffe and Cadima 2016) to analyze the data to obtain a set of orthogonal variables, called principal components (PCs), that capture a large portion of the overall variability across the DAUCOs as a function of time and space. The PCA provides a method of determining: (1) what time-varying signals are present across all DAUCOs, (2) how the signals correlate with precipitation and water-balance variables by DAUCO, and (3) if there are spatial patterns in those correlations across the state.

We performed a trend analysis, based on linear regressions by DAUCO, for each of the six water-

Table 1 Water-balance profile example for DAUCO 00125: Lost River, Modoc County, Upper Klamath Hydrologic Region. Water-supply variables are prefixed WS.* and water-use variables are prefixed WU.*. TAF is a suffix for volumetric units. Variables based on percentages have a PCT suffix.

	Variable					
	WS.GW.TAF	WS.Imported.TAF	WS.LocalSupplies.TAF	WS.Other.TAF	WU.Urban.TAF	WU.Ag.TAF
2002	8.7	82.5	15.3	18.4	0.3	107.8
2003	6.1	62.7	15.3	10.0	0.3	79.6
2004	6.5	91.8	7.6	1.8	0.3	86.4
2005	5.9	70.0	11.4	1.3	0.3	74.2
2006	8.2	68.3	15.3	30.3	0.2	106.3
2007	9.3	86.5	11.4	21.2	0.2	110.6
2008	8.0	90.0	7.6	21.2	0.3	109.5
2009	8.2	95.7	11.4	17.9	0.2	115.0
2010	8.3	48.3	15.3	42.1	0.2	99.9
2011	12.9	67.8	0.7	34.9	0.2	96.7
2012	19.6	74.8	0.7	36.0	0.2	111.5
2013	13.6	58.5	0.7	30.8	0.2	88.8
2014	13.6	54.1	1.2	24.7	0.1	79.6
2015	12.5	52.8	1.2	23.4	0.2	76.3
2016	15.8	88.8	1.2	0.0	0.1	90.1

balance variables. The purpose of this analysis was to look for linear trends within each DAUCO and across DAUCOs. Maps were developed to evaluate the results by cluster and by DAUCO, within-cluster.

Water Balance Data

The water balance data used here are the same as those described in (Helly et al. 2021), including a description of how the data are developed and the associated uncertainties. The complete, detailed dataset can be obtained from the URL in this citation (CDWR 2023b), along with the Standard Operating Procedure (SOP) that describes how the data are processed for publication.

The six water-balance variables were aggregated, by summation, into supply and use categories as shown in Figure 1. The four water-supply variables are aggregated into: Groundwater (WS.GW.TAF), Imported (WS.Imported.TAF), Local Supplies (WS.LocalSupplies.TAF), and Other (WS.Other.TAF). The two water-use variables are aggregated using the same categories found in the detailed data and as used by CDWR: Agriculture (WU.Ag.TAF) and Urban (WU.Urban.TAF). (Water-supply variables are indicated by the WS prefix, and water-use variables by WU.) These variables are summed from the 172 categories of detailed water-balance estimates for each DAUCO by year using only data for urban and agricultural land uses. Environmental flows have been excluded.

The Imported water variable includes Colorado River Deliveries, State Water Project Deliveries, Central Valley Project Deliveries, Imported Local Deliveries (e.g., Hetch Hetchy), and those described in the full water balance dataset as Other Federal Deliveries. Local Supplies are those obtained from within the DAUCO, including any captured and stored precipitation. The category called Other includes desalination, inter-basin transfers, return flows from outside the DAUCO, interannual carry-over storage, and water from refineries.

Using the aggregated variables, we can describe the organization of the data for our analyses by Equation 1. The parentheses enclose the water-balance variables of interest on the supply and use sides, respectively.

$$\text{Supply(Groundwater, Imported Water, Local Supplies, Other)} \approx \text{Applied Water use(Urban, Agriculture)} \qquad \textbf{Eq 1}$$

Two parameters define applied water use in the water balance dataset (Helly et al. 2021).

$$\text{Applied Water Use (AWU)} = \text{Net Water Use (NW2)} + \text{Reuse} \qquad \textbf{Eq 2}$$

Here, we use Net Water Use (NW2; Equation 2) for agricultural water use, and Applied Water Use (AWU) for urban water use. NW2 is not defined for sub-categories of urban water use (e.g., commercial, residential, energy) to be aggregated, so AWU is used instead for the urban data. We therefore re-state the water balance relationship in the form used throughout this study (Equation 3):

$$\text{Supply(Groundwater, Imported Water, Local Supplies, Other)} \approx \text{AWU(Urban)} + \text{NW2(Agricultural)} \qquad \textbf{Eq 3}$$

That is, urban water reuse is included, and agricultural water reuse is excluded.

Effect of Using Applied Water to Estimate Urban Water Use

As described in Equation 3, applied water use (AWU)—as opposed to net water use (NW2)—was used to estimate urban water use because of data limitations. The consequence of this is to increase the estimate of annual urban water use over 2002 to 2016 by 19% ± 0.3%, relative to the corresponding net water use. This estimate is based on a zero-intercept, simple linear regression of urban applied water use vs. net water use for each combination of DAUCO and water year ($p < 0.001$, $r^2 = 0.96$, $n = 7125$).

Measurement Units

We used volumetric units, percentages (%), and standardized variables (z values) in our analyses. We discuss later that z values are not the same as z scores. The volumetric units are expressed in

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units of thousand-acre feet (TAF), as published by CDWR. We calculated the percentages for each water-balance variable within each DAUCO based on total water supply and total water use, accordingly. The variance of each water-balance variable is affected by which units are used, and this is important to bear in mind throughout.

The use of percentages normalizes the volumetric units in such a way that the various amounts of water supplied and used are related to their respective totals within a DAUCO. For example, although agricultural water use (WU.Ag.TAF) in adjacent DAUCOs may differ by hundreds of thousands of acre-feet, the DAUCOs may appear to be similar in percentage terms. This is because the percentages are based on total water use, which includes both urban (WU.Urban.TAF) and agricultural water use. The water-supply percentages exhibit similar behavior since their totals are based on four variables. We discuss the effects of the different units in greater detail in the "Results."

Missing Values

Some DAUCOs have been excluded from individual analyses as a result of missing or constant values, including constant zeroes. In cases where variability is zero, some statistics cannot be calculated. Where the statistics are percentages and the denominator—a total, for example—is zero, the percentage is undefined. For these cases, the percentage was set to zero to avoid the propagation of missing values in computations based on percentages. In other cases, if the variance is zero, the correlation coefficients cannot be computed. Some DAUCOs are missing a year of data, so a PCA cannot be computed without removing those DAUCOs from the analysis. Of the 486 DAUCOs in the water balance data, 475 had complete data records and were used in our analyses. We have also excluded the Channel Islands and other land-masses classified as islands throughout the state, as was done in Helly et al. 2021.

Statistical Significance

When there is a meaningful statistical hypothesis test to be made, we apply the conventional criterion of citing a p-value as supporting evidence against the null hypothesis. However, the 15-year water-balance time-series is relatively short, and strict reliance on p-values in evaluating the importance of patterns in the water balance data could be misleading (Wasserstein and Lazar 2016; Hardwicke et al. 2023). We use the coefficient of determination, r^2, as a measure of goodness-of-fit in some of our analyses to detect features (Chambers and Hastie 1992). We then validate the features detected by inspecting the corresponding plots (NIST 2012).

State-Wide Precipitation

We extracted monthly precipitation for the state of California from gridded monthly PRISM 4-km data (PRISM 2019; DiLuzio et al. 2008) and we partitioned it into subsets by DAUCO using CDWR-maintained polygons (CDWR 2018). We then converted the data to units of thousand acre-feet (TAF)—referred to as volumetric units—and water years to correspond to the water balance data conventions. A water year is the 12 months, October through September, that is labeled as the calendar year beginning the following January (e.g., calendar year October 2023 becomes October, water year 2024). Some of the analyses use state-wide annual totals obtained by summing over the DAUCOs. The state-wide results were verified against the California Climate Tracker dataset maintained by the Desert Research Institute (McEvoy 2022).

Spatial and Temporal Analyses

We used standard statistics and methods including mean, standard deviation, coefficient of variation, Pearson correlation, simple linear regression, orthogonal polynomial regression, and the non-parametric Wilcoxon and median tests (Chambers and Hastie 1992). We derived a set of variables including volumetric totals and differences referred to as anomalies. Additionally, we defined z values that are different than z scores and described below.

The formulation of the linear regressions used in trend analysis is shown in Equations 4 and 5.

$$WB_{ij} = k_i\left(WY_{ij}\right) + Intercept_i \qquad \text{Eq 4}$$

$$\text{Standardized Slope}_i = 15 \times \frac{k_i}{|\bar{x}_i|} \quad \textbf{Eq 5}$$

where:
$j = 1{,}15$: j^{th} Water Year (WY_j)
$i = 1{,}6$: i^{th} Water Balance Variable (WB_i)

The k_i are the slopes of the linear regression of each water-balance variable vs. water year. The parameter $|\bar{x}_i|$ is the mean for the i^{th} water-balance variable.

Standardized Water Balance Variables (Z Values)

Volumetric values of the water-balance components range across the DAUCOs by more than six orders of magnitude, so it is useful to standardize them to reduce their biasing effects in the PCA. We therefore standardized the yearly anomalies within each DAUCO across all six water- balance variables. The procedure to transform the yearly anomalies of each water balance variable to z values is defined by Equations 6 through 8.

$$z_{ijk} \equiv \frac{\Delta x_{ijk}}{s_i} \quad \textbf{Eq 6}$$

$$\Delta x_{ijk} = \left(x_{jk} - \bar{x}_j\right)_i \quad \textbf{Eq 7}$$

$$s_i^2 = \frac{1}{(JK-1)} \sum_{j=1}^{J} \sum_{k=1}^{K} \left(\Delta x_{jk} - \overline{\Delta x}_j\right)_i^2 \quad \textbf{Eq 8}$$

where:
Δx_{ijk} : anomaly of the k^{th} observation of the j^{th} variable within the i^{th} DAUCO
s_i : standard deviation of all variable anomalies within the i^{th} DAUCO
$i = 1..I$: 475 DAUCOs
$j = 1..J$: 6 water-balance variables
$k = 1..K$: 15 water years

This transformation centers each variable on its respective mean and scales the anomalies of each variable (Equation 7) by the standard deviation of anomalies of all of the water-balance variables within a DAUCO (Equation 8). We refer to the transformed variables as z values; used as input to PCAs.

Cluster Analysis

We use cluster analysis to identify groups (clusters) of DAUCOs, each having distinct water-balance profiles. We conducted two separate analyses—one using volumetric units (TAF), and one using percentages (PCT)—to classify the 15-year water-balance profile of each DAUCO into clusters of DAUCOs with similar profiles. Each DAUCO is assigned to only one cluster in each analysis.

The clusters are determined using the “kmeans” function of the R statistical software system (R Core Team 2019). Clustering “kmeans” using requires a subjective decision on the meaningful number of clusters to construct. Analytic tools employed in making this judgement are described in (Kassambara 2017). The decision is based on the incremental amount of additional variance explained by each successive cluster—from one to some maximum number—specified as a parameter in the “kmeans” function call.

Orthogonal Polynomial Regression

The purpose of using orthogonal polynomial regression, in this work, is to provide an objective, quantitative method to detect and classify features in the time-series (Gensler et al. 2015). We are not attempting to fit a particular model, but to quantify trends (linear features) and high-order (non-linear) time-dependent features in the water-balance variables that may be related to changes in precipitation, regulatory policy, and land use. The clustered time-series were subjected to orthogonal polynomial regression for each combination of cluster and water-balance variables. This method extracts uncorrelated sources of variability (i.e., orthogonal) in the time-series data, wherein a series of polynomial time functions are fit to the time series of each water balance variable. The sources are quantified by the coefficients of a tenth order polynomial to identify linear trends and higher-order, non-linear fluctuations (Chambers and Hastie 1992). The order of the polynomial is chosen based only on its suitability to provide a useful curve-fit: one with a high coefficient of determination (r^2). The linear model function, “lm(poly(,10))” in R, was used. This resulted in 7

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clusters times 6 variables equalling 42 regressions for each of the volumetric and percentage-based time-series, for a total of 84 regressions.

Principal Components Analysis

We performed PCA (Jolliffe and Cadima 2016) using the R "prcomp" function to transform input variables into a new set of orthogonal variables called principal components (PCs). The PCs are uncorrelated and are also commonly referred to as modes. Each of the 475 DAUCOs has a PC time-series with an associated set of spatial weights; also called loadings.

The modes provide an efficient representation of temporal and spatial variation in the multivariate water-balance time-series. Here, they were correlated with the (1) DAUCO-specific water-balance variables, and (2) state-wide precipitation, seeking spatial patterns of correlation across the state. The correlation patterns illustrate the spatial expression, at the DAUCO-level, of (a) the respective PCA time-varying modes and (b) their association with state-wide precipitation for each of the water-supply and water-use variables. The patterns provide information about how the state-wide, time-series modes resonate across the state locally and regionally at the DAUCO-level. Skewness in the frequency histograms of Pearson correlations was tested using D'Agostino's test (D'Agostino 1970) as implemented in R. The PCA time-varying modes were also lag-correlated against state-wide water-year precipitation, and against their initial annual time-series, to expose multi-year associations within the water-balance components, and to see if they have predictive potential.

The PCA used the standardized anomalies (z values) of the water-balance variables (PCA.Z) according to Equations 6 through 8. Furthermore, the input data were prepared according to a method commonly used in earth science where PCA is referred to as EOF (empirical orthogonal function) analysis (e.g., Davis [1976]). In this approach, as applied here, each DAUCO is represented by the six variables of Equation 1. This results in 475 × 6 = 2,850 variables for each of the 15 years, where each year of data represents an observation of the 2,850 variables. We can think of this as 15 realizations of the state (i.e., condition) of the California water balance. The DAUCO count was reduced in this analysis from 486 to 475 in the manner described in "Missing Values."

Trend Analysis by DAUCO

Trends refer to linear increases or decreases in a water-balance component time-series which may have other features superimposed. A trend analysis was performed by computing a simple linear regression over time for each of the six (6) water-balance variables, and, in addition, total water supply, and total water use for each DAUCO. The regressions are based on Equation 4, and the slopes of those regressions were standardized for mapping using Equation 5, which converts each volumetric trend to a dimensionless, variable-specific measure of change from 2002 to 2016.

RESULTS

We carried out a series of analyses to investigate the water balance across California, including water-supply and water-use profiles, spatial and temporal variation interrelationships, and relationship to state-wide precipitation. Results are organized along the lines of the conceptual diagram of Figure 1, by aggregation level—state-wide or DAUCOs—and by analysis method.

We first consider state-wide aggregates, investigating the temporal variability of precipitation and water-balance components and their associations. Then we consider finer spatial variability provided by the DAUCOs, investigating associations of precipitation with water-balance variables. The results are presented in this order: (1) state-wide variability of precipitation and water supply, (2) state-wide water-balance variability, (3) precipitation and water-balance variability across the DAUCOs, (4) cluster analyses, (5) principal component analysis, and (6) trend analyses.

Variability of Precipitation and Water Balance

The 2002–2016 time-series for state-wide total annual volume of precipitation and water-balance variables are shown in Figure 2 and relevant statistical measures are provided in Table 2. The figure shows that each of these state-wide measures has undergone various degrees of fluctuations and some degree of longer-period trends over the analysis period. Notably, the precipitation record and—to differing degrees, the water-balance components—contain fluctuations that reflect individual wet years and the multi-year 2007–2009 and 2012–2016 droughts (CDWR 2021). Importantly, while there is no clear trend in precipitation, some of the water-balance components exhibit trends that are superimposed on the interannual fluctuations.

Precipitation and the Developed Water Supply

Total precipitation in California for 1895 to 2020 averaged 186188.4 ± 49746.1 TAF. For 2002 to 2016, 172033.8 ± 46663.2 TAF. Although means are not statistically different between the periods ($p = 0.29$, Wilcoxon test), the 2002–2016 mean is nearly 7% less than that for the longer period, indicative of the intermittent dryness that occurred during the study period (Gershunov et al. 2019).

The statistics in Table 2 include the proportion of each water-balance variable relative to the corresponding total: water supply (WS.*.TAF) or water use (WU.*.TAF). The water supply is also referred to as the developed water supply since it is based on purpose-built infrastructure. Groundwater (WS.GW.TAF, 42%) and imported water (WS.Imported.TAF, 32%) make up 75% of the total DWS. Local supplies (WS.Local Supplies. TAF, 20%) and other supplies (WS.Other.TAF, 5%) make up 25% of the DWS. Agricultural water use (WU.Ag.TAF) is 78% and urban water use is 22% of the total state-wide water use. Overall, summing the mean values of the four components, the mean state-wide DWS totals to 41,048 TAF, amounting to 23% of the mean state-wide precipitation over 2002 to 2016. The mean state-wide total water use is 37,097 TAF, about 90% of the mean state-wide total DWS. The residual 10% is accounted for as recharge to groundwater and reuse of urban applied water credited to the supply side of the water balance (see "Water Balance Data").

Figure 3 maps the long-term (1895–2020) and recent (2002–2016) variability in precipitation using the coefficient of variation (CV). There is a north–south gradient in variability in each of Figure 3A and Figure 3B but they are not the same. Figure 3B has high variability that extends farther northward with DAUCOs of high CV values that are not found in Figure 3A. The central tendency of the CV for 1895–2020 is mean = 36% and median = 34%. For 2002–2016, the comparable statistics are mean = 42%, median = 39%.

Coefficients of variation of the state-wide-aggregated water-supply and water-use variables (Table 2) range from 7% to 21%, which are smaller than the CV of state-wide precipitation (0.27) . In contrast, Figure 3C shows the corresponding map for the total of the DWS (i.e., WS.GW. TAF, WS.LocalSupplies.TAF, WS.Imported.TAF, and WS.Other.TAF). This map differs from the precipitation maps in its general tendency toward lower values, and relative uniformity across California. The measures of central tendency are mean = 36% and median = 20%. As reflected in the spread between the median and the mean, the water supply CV distribution contains extreme high values that exceed those of precipitation. The mean is biased high by the few extreme values in these data. More generally, the state-wide statistics diminish much of the variability present in the finer-grained DAUCO-level data, as shown below.

In contrast to the state-wide statistics, frequency distributions of the CVs for all DAUCOs—from the maps of Figure 3—are presented in Figure 4. The CV distributions are pairwise statistically different ($p < 0.001$, R *mediantest*). This result indicates that the DWS variability is different from that of precipitation in either period, and that the precipitation time-series are different from each other. This latter result contradicts the earlier Wilcoxon test of the means further emphasizing the disparity between the means and medians. A closer examination of the distributions details these results.

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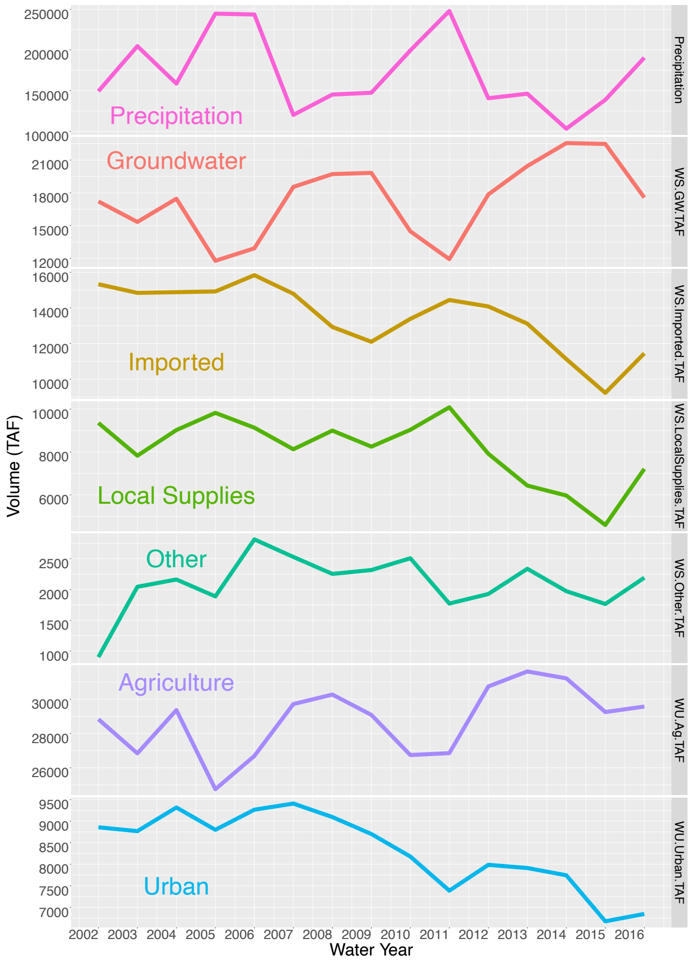

Figure 2 Interannual variability of state-wide water balance variables and precipitation (2002–2016). The units of measurement are thousand acre-feet (TAF). The ordinates are scaled to the range of each variable rather than a common scale to emphasize the patterns in the time-series. Trends and periodicities are prominently exhibited in time series of all variables, although precipitation has negligible trend.

Figure 4 (bottom panel), showing the distribution of DWS CVs, exhibits a long upper tail of extreme values: 42 DAUCOs with a CV > 0.79, 26 with a CV > 1.0, and 8 with a CV > 2.0. The median CV for the DWS is 20%. The median CV for precipitation from 2002 to 2016 is 38%. For the DWS, the CVs range from 0% to 387%; for precipitation, CVs range from 21% to 79%. While DWS CVs have a lower median, they exhibit a much broader range than those for precipitation. The precipitation CVs exhibit a higher median but a narrower range, with a higher minimum and lower maximum and at least two distinct modes: the median and another in the upper tail. The wider range of DWS CVs contains extreme outliers in its upper tail, but it is flatter throughout its range without well-defined modes.

Water Balance State-wide

Normalized trends, shown in the bottom of Table 2 and defined by Equation 5, are dimensionless indicators of the direction and relative magnitude of change in each variable over the 2002–2016 period. These trends show a decrease in imported (−0.37) and local (−0.42) water supply, as well as a decrease in urban water use (-0.30). In contrast, they show increases in groundwater supply (0.31), other supply (WS.Other.TAF) and agricultural water use (0.11) during this period. Converting these trends to volumetric changes by multiplying

Table 2 Summary of statistics describing aggregated state-wide water-balance variables and state-wide precipitation. WS.* prefixes water-supply variables and WU.* prefixes water-use variables. TAF is suffix for volumetric units of thousands of acre-feet. Mean and standard deviation are in TAF units. Proportion, coefficient of variation, correlation, trend and r^2 are dimensionless. Proportion is fraction of total water supply or total water use, respectively. Total water supply is the sum of groundwater, imported, local, and other supply components and total water use is the sum of agricultural and urban use. Trend is the standardized slope (Equation 5) of the variable's time-series.

Statistic	WS.GW.TAF	WS.Imported.TAF	WS.LocalSupplies.TAF	WS.Other.TAF	WU.Ag.TAF	WU.Urban.TAF	WS.Total.TAF	WU.Total.TAF	PPT.TAF
Proportion	0.42	0.33	0.20	0.05	0.78	0.22	1.00	1.00	—
Mean	17339.75	13499.70	8116.82	2091.83	28768.24	8329.26	41048.09	37097.50	172033.8
Standard deviation	3474.70	1851.69	1525.65	443.2	1972.67	883.23	2158.12	1991.08	46663.2
Coefficient of variation	0.20	0.14	0.19	0.21	0.07	0.11	0.05	0.05	0.27
Correlation with precipitation	-0.92	0.47	0.59	0.12	-0.87	0.03	-0.63	-0.84	1.0
Correlation (*p*-value)	0.00	0.08	0.02	0.66	0.00	0.91	0.01	0.00	0
Trend	0.31	-0.37	-0.42	0.11	0.11	-0.30	-0.06	0.02	-0.24
Trend (r^2)	0.22	0.64	0.43	0.02	0.23	0.72	0.13	0.01	0.07

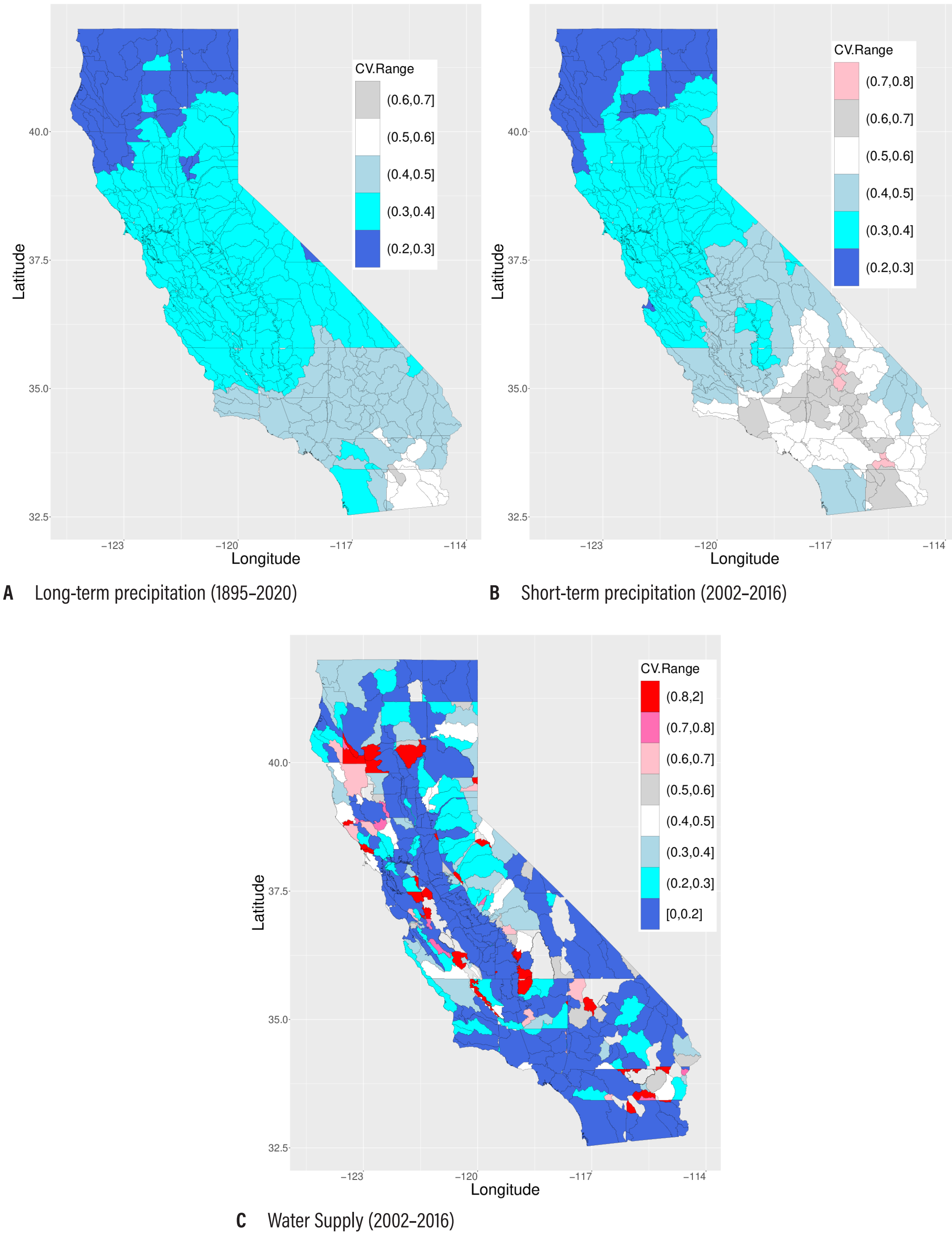

Figure 3 Coefficient of variation (CV) of DAUCO water-year variability of (**A**) long-term (1895–2020) and (**B**) short-term (2002–2020) precipitation and (**C**) developed water supply (2002–2016). These maps correspond to the histograms shown in Figure 4.

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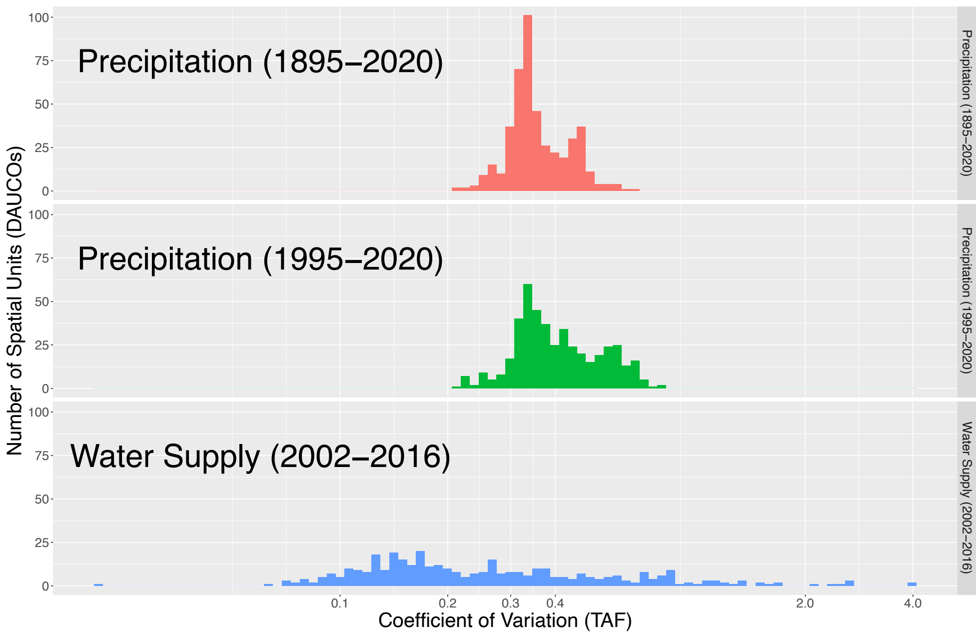

Figure 4 Distributions of CVs of DAUCO precipitation (1895–2020 and 1995–2020) and of total water supply (2002–2016). See corresponding maps in Figure 3.

the standardized values of Equation 5 by the mean values of each water balance component yields quite substantial amounts. For example, the changes in agricultural and urban water use amounts to +3.16 million acre-feet (MAF) and −2.49 MAF, respectively, over the 2002–2016 period. From a relative perspective, however, the CVs of state-wide water balance components are quite low (ranging from 7% to 21%). But as will be shown next, these state-wide aggregate statistics mask the much greater variability of the water balance components at the finer-grained DAUCO level.

State-Wide Correlation of Precipitation and Water Balance

From a state-wide perspective, results from (Helly et al. 2021) and new results presented here demonstrate how interannual fluctuations in regional precipitation influence the temporal variability of the water balance. Large swings of precipitation—the cause of high coefficients of variation described above—featured anomalously wet water years in 2005, 2006, and 2011, and persistent dry water years in 2007 through 2009 and 2012 through 2015. Table 3 (upper rows) show correlations of state-wide-aggregated water-balance variables lagging state-wide precipitation by 0 to 2 years.

The largest current-year (LAG.0) associations include strongly negative correlations with groundwater supply ($r = -0.92$, $p < 0.001$) and agricultural water use ($r = -0.8$, $p < 0.01$). These negative correlations indicate that groundwater extraction and agricultural water use in some DAUCOs increases in years with decreased precipitation, and the converse. In contrast, positive LAG.0 correlations with state-wide precipitation are found with imported ($r = 0.47$) and local ($r = 0.59$) water supplies. There is no correlation at LAG.0 with urban water use ($r = 0.03$).

As noted in previous studies (Goodrich et al. 2020; Helly et al. 2021), the developed water system in California harbors multi-year correlations; notably tying water-balance variations to the fluctuations in annual precipitation. Besides year-to-year carry-overs in annual wetness or dryness, these lags probably reflect water-management actions such as water storage and release in reservoirs, and regulatory and land-use practices with multi-year planning horizons.

Lagging water-balance variables relative to state-wide precipitation by 1-year lag (LAG.1) show a negative correlation with groundwater ($r = -0.40$) and positive correlations with local and

Table 3 Correlation of lagged individual water year state-wide precipitation (above) and multi-year, current and antecedent summands of prior-through-present water years state-wide precipitation. Correlations of individual water years were calculated at 0-year (PPT0), 1-year (PPT1) and 2-year (PPT2) lags. Summands are sums of water year precipitation that include the current year plus n years prior.. The numeral n in each summand name is the number of antecedent years included (e.g. Psum1 includes precipitation of the current year plus that of the previous year; Psum7 includes precipitation of the current year plus that of the previous 7 years). Correlation coefficients highlighted in bold face reach or exceed the 95% confidence level.

	Variable					
Individual current or antecedent precipitation	**WS.GW.TAF**	**WS.Imported.TAF**	**WS.LocalSupplies.TAF**	**WS.Other.TAF**	**WU.Ag.TAF**	**WU.Urban.TAF**
PPT0	**– 0.92**	0.47	**0.59**	0.12	**–0.87**	**0.03**
PPT1	– 0.40	**0.63**	0.38	0.21	–0.09	– 0.40
PPt2	0.10	0.30	0.11	0.77	0.26	0.40
Summand current and antecedent precipitation						
Psum1	**– 0.86**	**0.71**	**0.64**	0.30	**– 0.62**	0.29
Psum2	**– 0.68**	**0.78**	**0.61**	0.31	– 0.39	0.47
Psum3	– 0.46	**0.70**	**0.54**	0.37	– 0.19	**0.60**
Psum4	– 0.27	**0.67**	0.50	0.14	– 0.16	**0.76**
Psum5	– 0.51	**0.70**	**0.64**	– 0.08	– 0.49	**0.63**
Psum6	**– 0.64**	**0.80**	**0.78**	– 0.22	**– 0.53**	**0.60**
Psum7	**– 0.65**	**0.86**	**0.75**	– 0.35	**– 0.53**	**0.59**

other water supply ($r = 0.38$). LAG.1 correlations also increase positively for imported water ($r = 0.63, p = 0.01$) over the current year (LAG.0). There is a weak positive correlation with urban water use ($r = 0.40$). At a 2-year lag (LAG.2), some positive correlations remain with imported water supply ($r = 0.30$) and urban water use ($r = 0.40$)—albeit with lackluster statistical significance.

We also considered effects of multi-year precipitation upon water-balance variability using a series of aggregated precipitation, accumulated from 1 to 7 years during and before the current year (Psum0-Psum7). Correlations of these antecedent summands of precipitation vs. the current-year, state-wide, water-balance time-series are shown in Table 3 (lower 7 rows). Reinforcing previously noted individual year associations, groundwater supply and agricultural use exhibit strong negative 1- and 2-year (i.e., Psum1, Psum2) correlations. In contrast, imported supply, local supply, and urban water use exhibit significant positive correlations with cumulative state-side precipitation. Interestingly, these positive associations indicate there may be influences of dry or wet anomalies that operate over several years, as shown by peak imported and local supply correlations for Psum7 and Psum6, respectively, and peak urban water correlation for Psum4.

Water Balance Among DAUCOs

Figure 5 shows the CV of individual water-supply and water-use variables at the DAUCO-level. The maps of the water-supply variables are more mosaicked than are those for the water-use variables. This contrast illustrates how diversity in water-supply sources is integrated to provide a relatively steady total DWS at many of the DAUCOs. This is clear in the uniform low variability in the maps of the water-use variables. Overall, the CVs for the four water supply variables exceed 200% in 15% to 81% of the DAUCOs. In contrast, 75% of the water-use variable CVs are ≤120%.

There are distinct regional features in Figure 5. From left to right and top to bottom, we can see that groundwater supply is ubiquitous and highly variable (CV >200%). Imported water supply is highly variable and relatively extreme in the western and southern parts of the state (CV >400%). Local supplies are relatively stable in DAUCOs where they occur (CV <200%). Other

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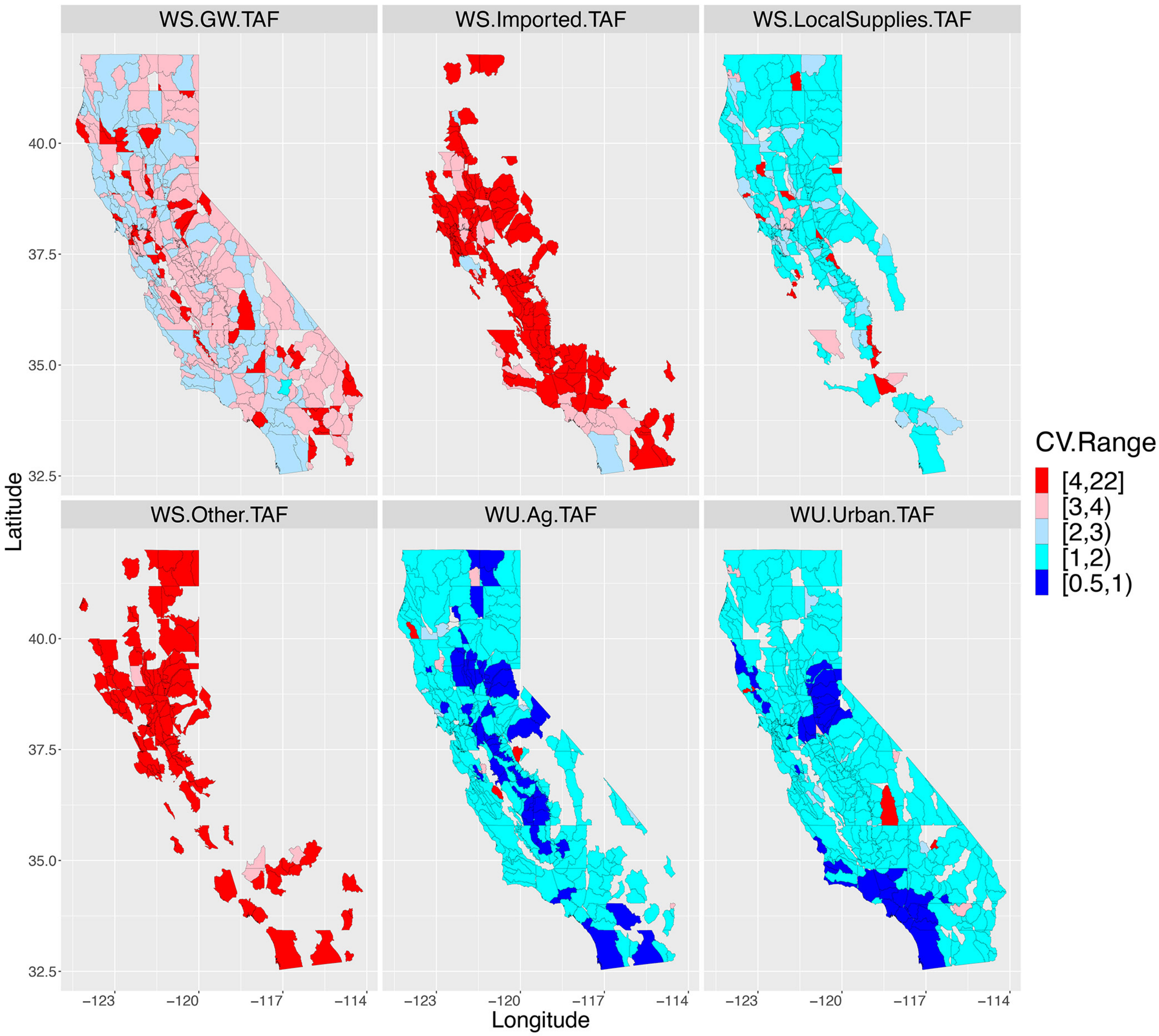
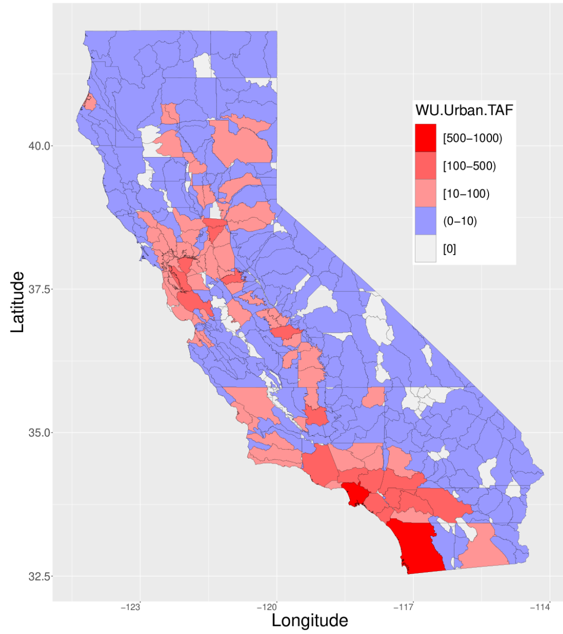


Figure 5 CVs of water balance variables mapped over California. Water-supply variables are indicated by the WS prefix, and water-use variables by WU. Ranges are chosen according to break points apparent in the data.

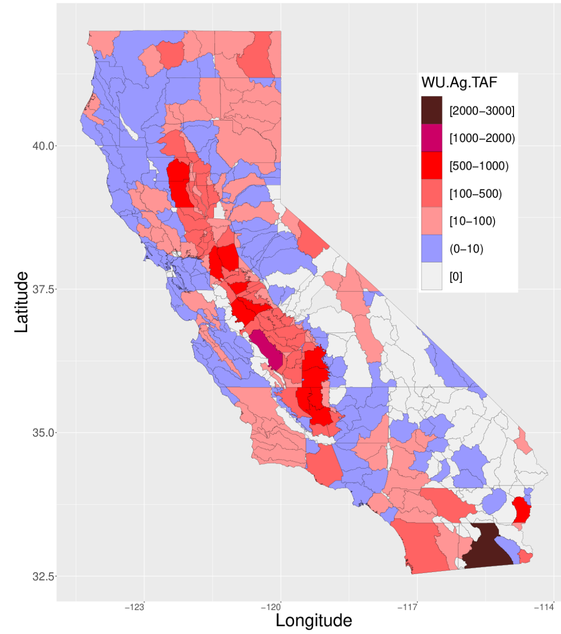
sources of water (WS.Other.TAF) are regionalized in northern California but also scattered through southern California and highly variable (CV >300%). Water use, on the other hand is relatively stable, with variability generally low (CV <200%) and in some DAUCO CVs as low as 50% to 100%.

Water Use as a Reflection of Land Use

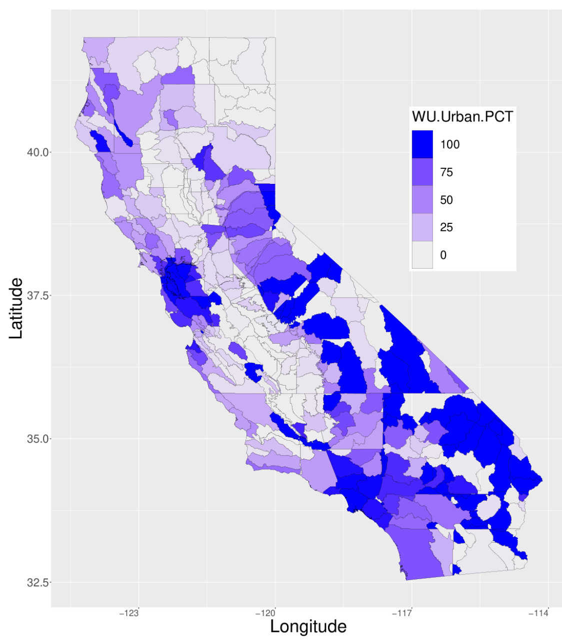
Figure 6 maps the distribution of land use through agricultural and urban water use. The same data are shown in volumes (Figures 6A, 6B) and in percentages (Figures 6D, 6D). The urban volumetric maps show that most of the state uses relatively little water, and that urban land use is concentrated in two regions: (1) the San Francisco Bay area with extensions into the northeast and Central Valley, and (2) southern California with extensions into the desert to the east, and north to San Luis Obispo. In contrast, agricultural land use is primarily concentrated in the Central Valley and the northeast of California. However,



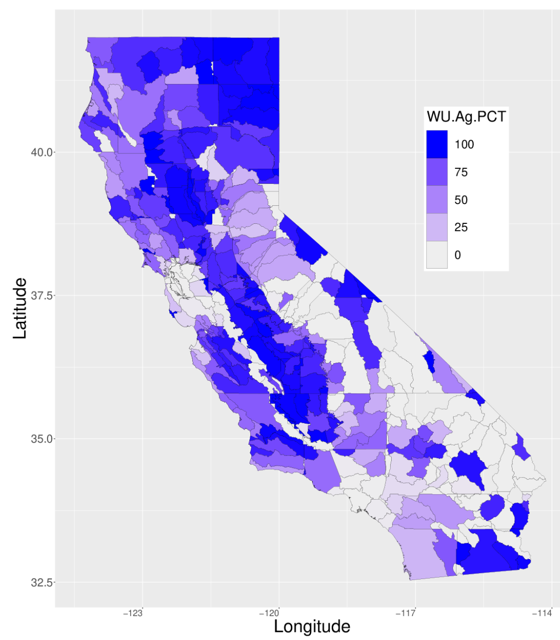
A Mean annual urban water use volume (WU.Urban.TAF)



B Mean annual agricultural water use volume (WU.Ag.TAF)



C Mean annual percentage urban water use volume (WU.Urban.PCT)



D Mean annual percentage agricultural water use volume (WU.Ag.PCT)

Figure 6 Comparison of DAUCO-specific, mean annual urban (**A** and **C**) and agricultural (**B** and **D**) water use during 2002–2016 using volumetric units (**A** and **B**; TAF) versus percentage units (**C** and **D**; PCT). *Upper figures* (**A** and **B**) emphasize intensity of water use by quantity: whether for urban use or agricultural use. *Lower panels* (**C** and **D**) emphasize they relative (i.e., percentage) water use: whether urban or agriculture. The *lower figures* are uniquely complementary of each other, emphasizing the strong separation between urban and agriculture land use, although there are DAUCOs with both types.

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it also occurs in urbanized DAUCOs in southern California. A notable exception is Imperial DAUCO, which is in the southeast corner of the state, and is dominated by agricultural land use.

The percentage-based data help refine this view in relative terms. We can see that urban land use is extensive throughout California, except in the Central Valley and the northeastern part of the state. DAUCOs that have both agricultural and urban land use are predominantly one or the other. The maps are nearly complementary based on land use.

Cluster Analysis of Water-Balance Variables

Figure 7 presents the time-series average over all DAUCOs in each cluster by water-balance variable for the volumetric clusters (T-clusters) and the percentage-based clusters (P-clusters), respectively. The time-series are input to an orthogonal polynomial regression to examine the linear and higher-order features in the time-series, and to compare them across clusters and variables. Tables 4 and 5 summarize the T- and P-clusters by their mean water-balance profiles. Figure 8 shows how the T-clusters rank in terms of the proportion of water used throughout the state. These results are expanded below.

Volumes (T-Clusters) and Percentages (P-Clusters)

Figure 8 shows the cumulative proportion of the state water use by DAUCO within each T-cluster. Additionally, Table 4 and Figure 9A show the number of DAUCOs in each cluster, and Table A3

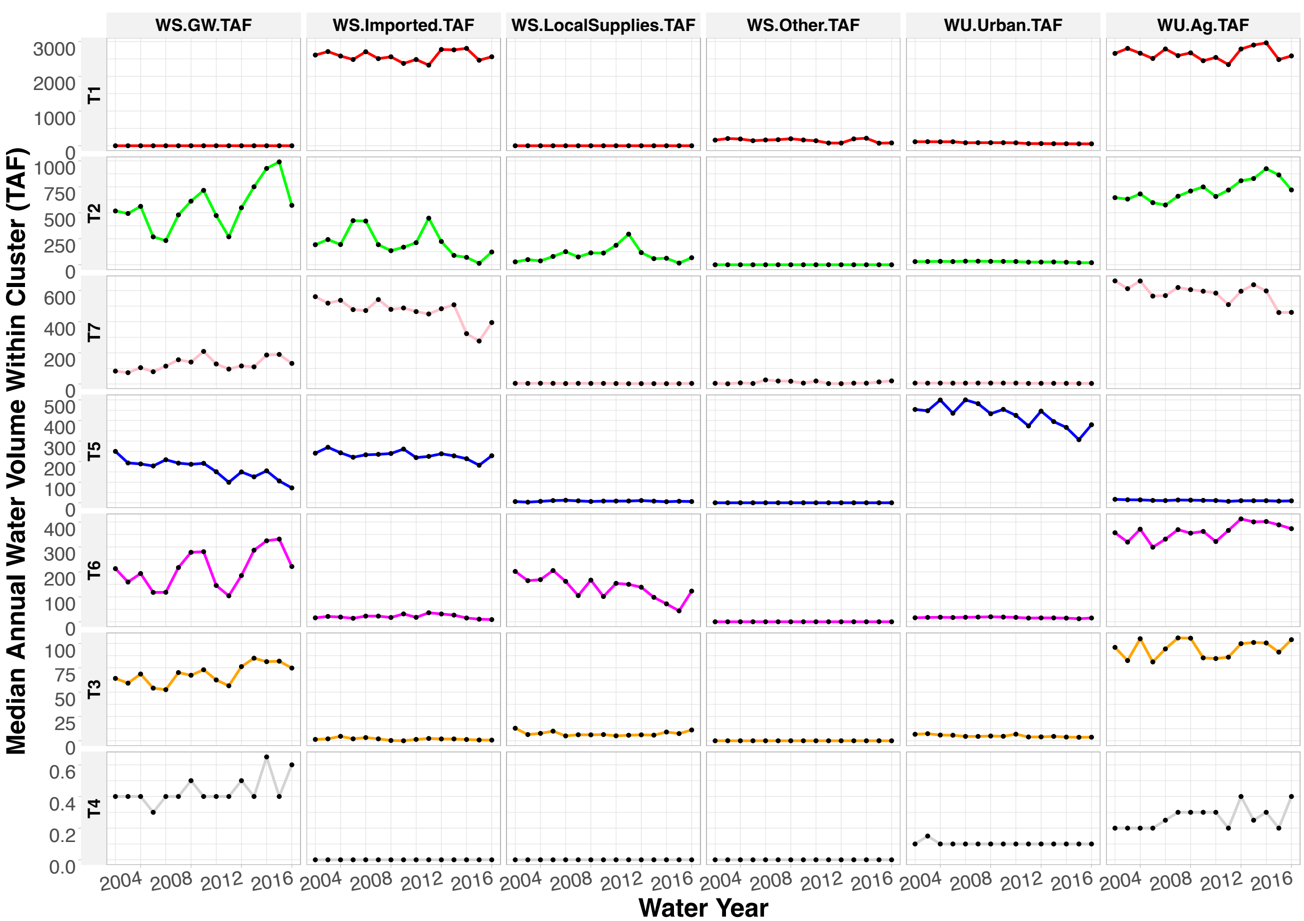

Figure 7 Median annual volume of water balance variables based on volumetric units (TAF) by cluster. Note that the vertical ordering of clusters is based on their respective maximum values, with the greatest volumes in the *top row* and the least in the *bottom*. The superimposed trends (*linear features*) and fluctuations (*non-linear features*) are quantified using orthogonal polynomial regression (Table 7).

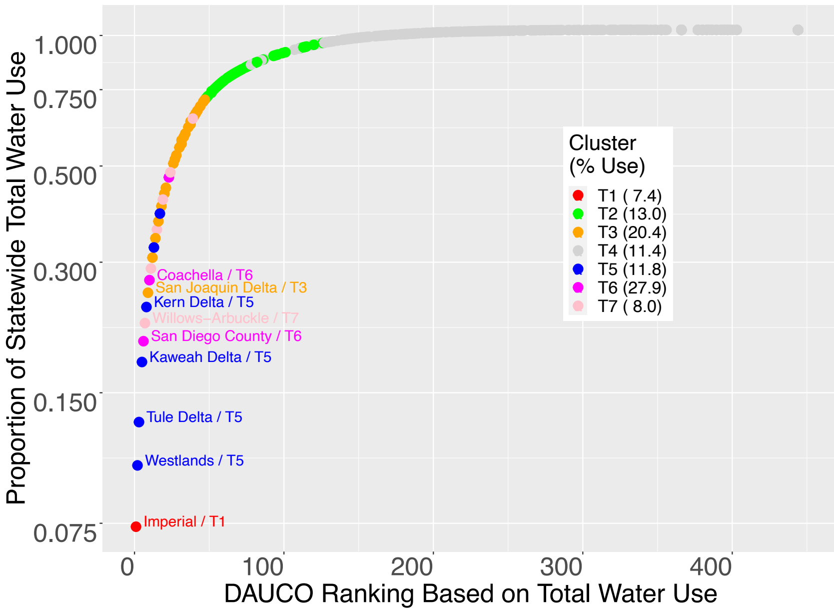

Figure 8 Cumulative proportion of total water use (2002–2016) by DAUCO in rank order of highest to lowest.

Legend indicates cluster membership by *color* and its corresponding percentage of state-wide total water use (Table A18). Cluster T4 contains 79% of all DAUCOs in California but accounts for a small proportion of water use (11%). A few DAUCOs—principally T1 (Imperial) and members of clusters T5 and T6—account for nearly 30% of state-wide water use.

Table 4 Summary of DAUCO membership in each volumetric cluster (TAF) with profiles summarized by water supply and use patterns. Integers in columns are the number of DAUCOs in each T-cluster (T1-T7). Water Use and Water Supply columns contain brief descriptions of the mean characteristics of the corresponding T-cluster.

T1	T2	T3	T4	T5	T6	T7	Water Use	Water Supply
1							Imperial DAUCO only. Agriculture (97%), Urban (3%)	Imported water (94%)
	6						Mostly agricultural (94%).	Mixed (GW 60%)
		56					Mostly agriculture (84%).	Mixed (GW 50%)
			375				Split between urban (45%) and agricultural (55%)	Mixed (GW 44%)
				8			Mostly urban (83%)	Mixed (Imported 50%)
					24		Mostly agriculture (91%)	Mixed (GW 47%)
						5	Mostly agriculture (99%)	Mostly imported (73%)

provides a summary of the data by T-cluster. Clusters T1, T2, and T7 comprise only 12 DAUCOs but consume, on average, 79% of the total water used state-wide (Table A1). Cluster T1 is first in rank-order of water use and consists of a single DAUCO—Imperial—supplied almost entirely by imported water (94% of total supply) for agricultural water use (97% of total use). T3 is the second-largest cluster with 56 members. Cluster T4 is the largest cluster by number, comprising 375 of 476 total DAUCOs (79%) in California, but because these are low-water supply and use DAUCOs, T4 is by far the smallest cluster by volume (e.g., Figure 7). The DAUCOs in cluster T4 cover much of the state with a mix of agricultural (45%) and urban (55%) water use predominantly supplied use groundwater (44%), with lesser fractions of imported and local supply (Table A2). The urban clusters (T2,T5)—14 DAUCOs—account for 25% of the state's total combined agricultural and urban water use. Cluster T5 has eight DAUCOs, supplied considerably by imported water (50%). Clusters T2, T3, T6, and T7 have predominantly agricultural water use (84% to 99%), with substantial supply from groundwater (47% to 73%), and the balance from imported and local water sources.

Water-balance clusters based on percentages (PCT) have more evenly distributed DAUCO

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Table 5 Summary of DAUCO membership in each percentage cluster (PCT) with profiles summarized by water supply and use patterns. Integers in *columns* are the number of DAUCOs in each P-cluster (P1 to P7). Columns for water use and water supply contain brief descriptions of the mean characteristics of the corresponding P-cluster.

P1	P2	P3	P4	P5	P6	P7	Water use	Water supply
127							Mostly agriculture (81%)	Mostly groundwater (83%)
	83						Mostly urban (88%)	Mostly groundwater (87%)
		63					Mostly agriculture (93%)	Mixed (local supplies 68%).
			96				Split urban (2%) and agriculture (2%).	Local supplies (1%) and groundwater (3%).
				37			Mostly urban (87%)	Mixed (imported 67%)
					34		Mostly agricultural (95%)	Mixed (imported 61%)
						35	Split agricultural (45%) and urban (53%).	Mixed (local supplies 58%)

Table 6 Summary of 10th-order polynomial coefficients ($p \leq 0.05$) of regressions of variable *x* water year for volumetric variables (TAF) state-wide. *Columns* are arranged by the value of the coefficient of determination (r^2) as an indication of goodness-of-fit. The non-linear polynomial terms (2-10 order) have been grouped for simplicity. The full tabulation is given in Table ??.

		r^2			
Term	**Variable**	**0.7**	**0.8**	**0.9**	**1**
Intercept	Precipitation	177836.3	—	—	—
	WS.GW.TAF	—	—	—	17339.7
	WS.Imported.TAF	—	—	—	13499.7
	WS.LocalSupplies.TAF	—	—	8116.8	—
	WS.Other.TAF	—	2091.8	—	—
	WU.Ag.TAF	—	—	—	28768.2
	WU.Urban.TAF	—	—	—	8329.3
Linear	WS.GW.TAF	—	—	—	6087.2
	WS.Imported.TAF	—	—	—	−5521.6
	WS.LocalSupplies.TAF	—	—	−3758.9	—
	WU.Ag.TAF	—	—	—	3543.5
	WU.Urban.TAF	—	—	—	−2800.7
Non-linear	Precipitation	−141523.7	—	—	—
	WS.GW.TAF	—	—	—	−4816.0
	WS.Imported.TAF	—	—	—	815.3
	WS.LocalSupplies.TAF	—	—	−119.0	—
	WU.Ag.TAF	—	—	—	−23.7
	WU.Urban.TAF	—	—	—	−183.2

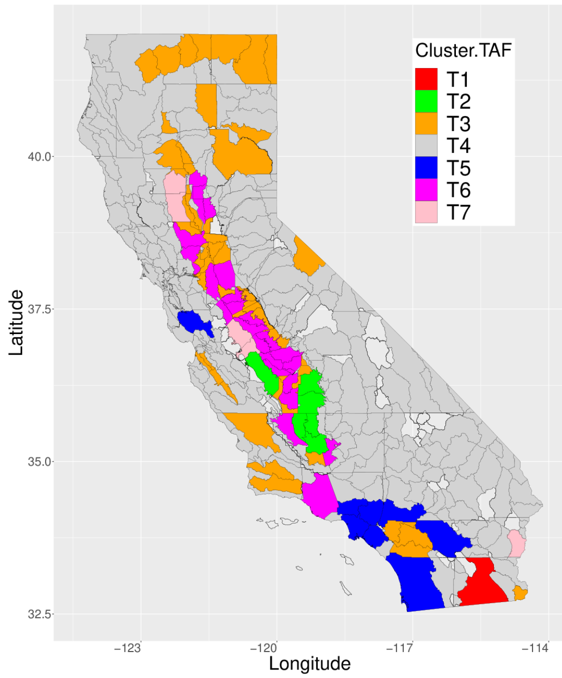
membership (Table 5 and Figure 9B). Clusters P1, P3 and P6 consist of 224 DAUCOs (47% of DAUCOs) whose water is predominantly used for agriculture (81% to 95%), supplied mostly by groundwater (83% to 87%) and imported water (61%). Clusters P2 and P5 are dominated by urban water use (87% to 88%), accounting for 18% of the state's total use and 76% of urban use, supplied by groundwater (87%) and imported (67%) sources, respectively. Clusters P4 and P7 have mixed agricultural (2% to 45%) and urban (2% to 54%) water use, supplied by groundwater (3%) and local sources.

Table 5 summarizes the P-cluster characteristics based on the percentages of water supply and water use within a DAUCO as a relative basis for clustering. The P-clusters reflect similar land use and sources within a cluster, rather than similar volumes and sources. Figure 9B helps with interpreting the percentage-based results. This figure shows that the DAUCOs with similar water-balance profiles are more widely distributed geographically, albeit with distinct agricultural and urban centers.

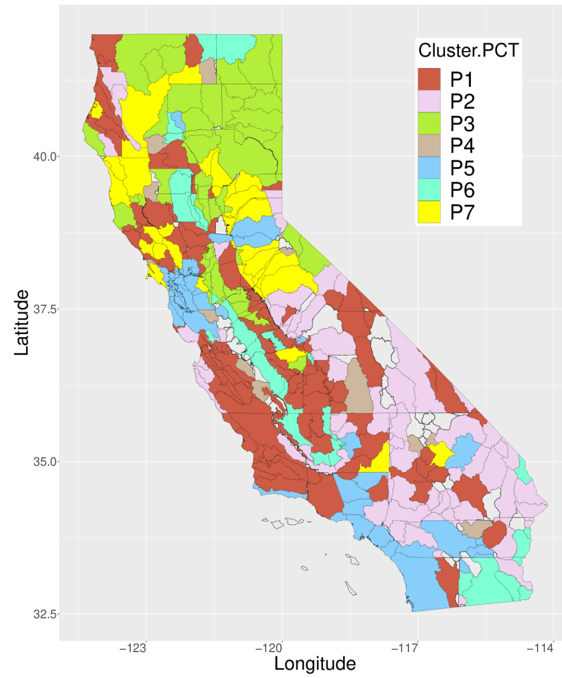
A tabulation of the P-clusters, identified by land use—as done above with T-clusters—is shown in Table A4. There we see that agricultural land-use in P1, P3, and P6 accounts for a median agricultural water use of ≥93% in 224 DAUCOs. P2 and P5 account for a median urban water use of ≥98% in 120 DAUCOs. P7 is evenly split between 47% agricultural and 50% median urban water use across 35 DAUCOs.

Water Use by Volumetric Cluster

Figure 10 compares agricultural and urban water use by cluster across 2002 to 2016. The ordinate



(**A**) Volumetric units (TAF)



(**B**) Percentages of volumetric units (%, PCT)

Figure 9 Comparison of the spatial distribution of clusters derived from (**A**) volumetric units versus those from (**B**) percentages. The T-clusters in (**A**) are strongly regionalized based on amount of water used and supplied, as well as the type of supply. The clusters in (**B**) are also organized by land use, but these P-clusters incorporate a wider mixture of land use between urban and agriculture. Blank polygons (NA) denote DAUCOs with only zero values for total water supply.

is scaled to the range of each variable uniquely to emphasize the similarity and difference in patterns. The row-order of the plots is arranged with the highest agricultural-water-use cluster at the top.

The plots show that urban water use was in nearly continuous decline, on average within cluster, over 2002 to 2016 everywhere in the state. Agricultural water use from the volumetric clusters exhibits a very different time trajectory. Across the clusters, agricultural water use has considerable short period fluctuations, but perhaps its strongest signal is the positive linear trends in T2, T6, T3, and T4. Agricultural water use in T1 shows a decline from 2002 to 2011, followed by a spiking increase from 2011 to 2015. Agricultural water use in T1, T2, T3, and T4 all show the same increase post-2011. Agricultural water use in all clusters, except T1 and T5, show similar periodic features: minima in 2005, and in 2010 through 2012, and maxima in 2007–2008 and in 2013–2014.

Orthogonal Polynomial Regression

The coefficients of the regressions weight each polynomial term in the overall fit to the data, shown here for the volumetric cluster time series. An example of the efficacy of the method is provided in Figure A1. This curve-fitting is simply a mechanism to identify objective features in these particular time-series for descriptive purposes; there is no intent to suggest that these fits have any predictive value. The features discussed below can be graphically verified by examining Figures 2 and 7.

For each variable, the features of interest are the mean volume (intercept), trend (linear), and fluctuations (non-linear). The linear and non-linear features represent sources of variability including precipitation, regulation, and land-use changes. The linear features are further

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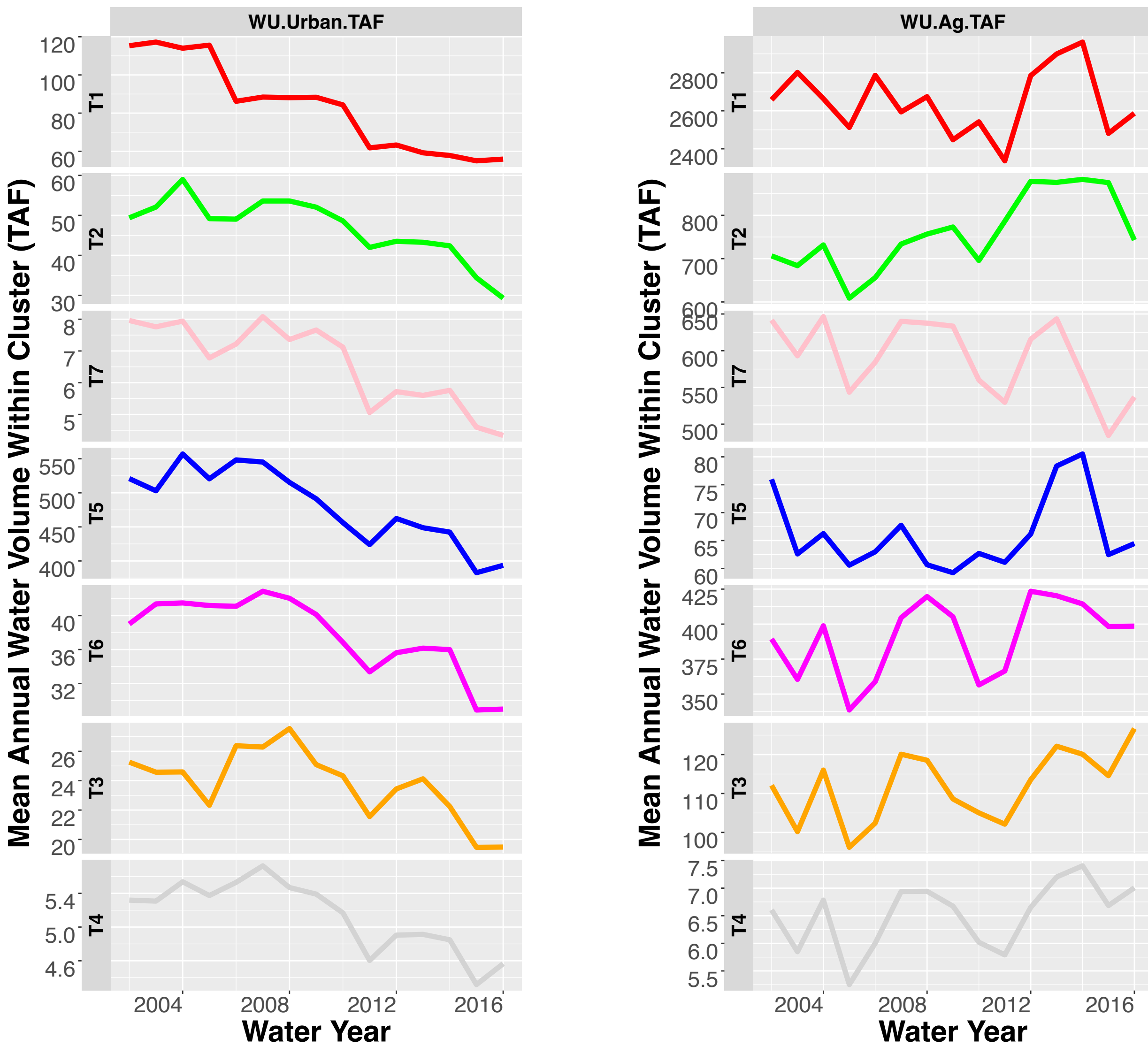

A Urban water use

B Agricultural water use

Figure 10 Volumetric water use time-series by cluster broken into urban (*left*) and agricultural *(right)* water use. Note that the *vertical order* of the clusters is based on the maximum of the corresponding WU.Ag.TAF scale (*y*-axis) and that the scales vary by cluster. The features—in (**A**) urban or (**B**) agricultural water use only—show superimposed trends (*linear features*) and fluctuations (*non-linear features*), reflecting the combined effects of land use, regulatory policy, and fluctuations in precipitation.

described later in the linear trends discussion in "Water Balance Trend Analysis." Tables 6 and A5 provide a condensed and full set of coefficients derived from the orthogonal polynomial regression. Table 7 summarizes the results for the state-wide time-series of Figure 2. For example, precipitation has the largest intercept: the mean volume of precipitation. This is the same value as is seen in Table 2. Comparing this to the intercept for the other variables provides a perspective on their relative magnitudes. WU.Ag.TAF is the closest and it is 16% of total precipitation.

Precipitation exhibited considerable variation but no significant trend: that is, no linear term ($p < 0.05$, $r^2 \geq 0.7$). Table A6 shows that the only polynomial term with $p < 0.05$—other than the intercept—is a non-linear term of 10th order. The

Table 7 Summary of results of the orthogonal polynomial regression within each T-cluster for each of the six water-balance variables. All regressions have $p \leq 0.05$. The mean volumes characterize the dominant types of water supply and water use. The *linear terms* indicate the direction of the 15-year trend for corresponding variables (↑ positive, ↓ negative). The entries for *non-linear terms* are ones whose coefficients meet the significance criteria. Full tabulation of coefficients orthogonal polynomial regressions for T-clusters is provided in Table A5.

Cluster	Mean volume (Intercept)	Trend (Linear)	Fluctuation (Non-linear)	Comments
T1	Imported water is used for agriculture. Little other supply (WS.Other.TAF) or urban water use (WU.Urban.TAF)	↓WS.Other.TAF ↓WU.Urban.TAF	WS.Other.TAF	Contains only Imperial DAUCO.
T2	Uses groundwater, imported and local water for agriculture and a small amount of urban land use	↑WS.GW.TAF ↑WU.Ag.TAF ↓WS.Imported.TAF ↓WU.Urban.TAF	WS.GW.TAF WU.Ag.TAF	
T3	Uses groundwater and local supply for agriculture	↓WS.Imported.TAF ↓WS.LocalSupplies.TAF	WS.GW.TAF WS.Imported.TAF WS.LocalSupplies.TAF	
T4	Does not use much water although supplies from all sources	↓WS.GW.TAF ↓WS.Imported.TAF	WU.Ag.TAF WU.Urban.TAF WS.Other.TAF	Largest number of DAUCOs
T5	Predominantly urban land use supplied by groundwater and imported water	↓WS.GW.TAF ↓WS.Imported.TAF ↓WU.Urban.TAF	WS.GW.TAF WS.Imported.TAF WS.LocalSupplies.TAF WS.Other.TAF WU.Ag.TAF WU.Urban.TAF	
T6	Mixed land-use with mixed water supply dominated by groundwater supply and agricultural water use.	↑WS.GW.TAF ↑WU.Ag.TAF ↓WS.Imported.TAF ↓WS.LocalSupplies.TAF ↓WU.Urban.TAF	None	
T7	Strongly agricultural land use using mostly imported water.	↑↑WS.Imported.TAF ↑↑WU.Ag.TAF ↑WS.GW.TAF ↓WS.LocalSupplies.TAF ↓WU.Urban.TAF	WS.GW.TAF WS.LocalSupplies.TAF WU.Ag.TAF	

other terms have coefficients that contribute to the fit but do not meet the $p < 0.05$ criterion. Nonetheless, they contribute to the overall regression outcome and predicted values. The overall fit of the polynomial is reflected in the coefficient of determination ($r^2 \geq 0.7$). Figure A1 illustrates the goodness-of-fit.

Cluster T1 contains only Imperial DAUCO. It is an agricultural DAUCO with almost complete reliance on imported Colorado River water for supply. In Table A5. reading the column from top to bottom, we see the following profile characteristics. Based on the intercept, there is no groundwater supply. All of the imported water is used for agriculture. There is comparatively little other supply (WS.Other.TAF) and little urban water use (WU.Urban.TAF). There is a negative linear trend in each of these, suggesting conservation. There are non-linearities apparent, but these are median values of all high-order terms, summarized here for simplicity. We have to consult Table A5 to see that the 97.23 non-linear value is the median of two terms for WS.Other.TAF. As mentioned above, these features can also be clearly seen in Figure 7. Brief, but similar, summaries are provided for each T-cluster in Table 7.

The outliers in variability—measured by CV (Figure 4, bottom panel)—warranted a further analysis. We examined the T-clusters by volume class (Table 12) and found that cluster T4—with

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Table 8 Median values of the coefficient of determination (r^2) for each combination of PC1.Z-PC3.Z and water-balance variable for all DAUCOs for ($r^2 \geq 0.30$). Fifty percent (50%) are above and below these values. The *columns* are arranged by PCx.Z and then by the sign of the slope (±) indicating the direction of the linear trend.

Variable	PC1.Z		PC2.Z		PC3.Z	
	-	+	-	+	-	+
WS.GW.TAF	0.64	0.57	0.43	0.39	0.45	0.49
WS.Imported.TAF	0.48	0.50	0.51	0.37	0.44	0.51
WS.LocalSupplies.TAF	0.56	0.59	0.52	0.49	0.52	0.43
WS.Other.TAF	0.68	0.59	0.55	0.40	—	0.34
WU.Ag.TAF	0.61	0.68	0.44	0.42	—	0.46
WU.Urban.TAF	0.69	0.56	0.49	0.45	0.42	0.42

the largest state-wide membership (Table 4)—also contained the most DAUCOs with the lowest volumes of water supply. Then we examined the variability of those supplies by the availability of conjunctive-use alternatives. Among the DAUCOs that are more than 90% dependent on a single source (e.g., groundwater), we found that there is a distinct trend in variability based on the volume class of the DAUCO, such that variability diminishes as the volume of available water supply increases (Figure 15). These DAUCOS depend mostly on groundwater (143 of 175 total); a few (32) depend on surface or imported water supplies (Table A10). Of the 143 groundwater-dependent DAUCOs, 131 are members of cluster T4.

Principal Components Analysis

As noted earlier under "Principal Components Analysis" in the "Methods," we applied a PCA to the standardized water-balance anomalies (z values). Table A9 compares the proportion of variance accounted for by PC1.Z-PC5.Z. Since PC1.Z-PC3.Z contain 66% of the variance in the water balance data, we selected these three PCs for further correlation analyses.

Weighting of Water-Balance Variables by Principal Components

The time-series of each PC1.Z-PC3.Z is shown in Figure 11. These are the time-series used for the correlations (i.e., weights) by DAUCO and water-balance variable mapped in Figure 12. As is characteristic of PCAs, because of their numerical implementation, the sign of the correlation for a given PCx.Z and water-balance variable for a given DAUCO is its polarity with respect to other DAUCOs within a variable or across variables in the same PCA.

Table 8 summarizes the median correlation (i.e., the median of the spatial loadings) of PC1.Z–PC3.Z with the water-balance variables in terms of the coefficient of determination (r^2) for those correlations with ($r^2 > 0.3$). The maps of Figure 12 provide a graphical version of these results. Fifty percent (50%) of the DAUCOs have coefficients as great or greater than those in the table. Most of the correlations indicate a good fit to the data ($r^2 > 0.4$) with a few exceptions. PC3.Z is only correlated positively with other supply (WS.Other.TAF) or agricultural water use (WU.Ag.TAF).

PC1.Z exhibits the strongest correlations of all PCs. For groundwater, the preponderance of positive correlations, together with the rising PC1.Z timeseries, indicates the increased reliance upon groundwater (WS.GW.Z) supplies at many (but not all) DAUCOs throughout the state. The map for agricultural water use (WU.Ag.TAF) looks similar to that for groundwater, with mostly positive correlations. Urban water use (WU.Urban.TAF) shows a nearly uniform opposite (negative correlation) pattern to each of those. Imported water (WU.Imported.TAF) shows moderate to strong negative correlations in the central and western part of the state, reflecting a broad scale decline over the study period. Local supplies (WS. LocalSupplies.TAF) have strong negative

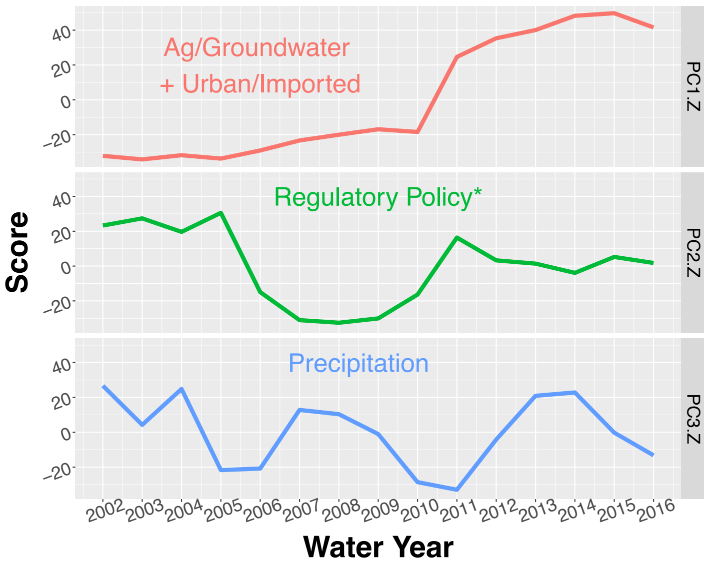

Figure 11 Time-series of principal components PC.Z.1-3 used in the correlations shown in Figure 12. PC1.Z reflects the increases in groundwater supply, local supplies, agricultural water use, and decreases in urban water use. Hypothetically, PC2.Z reflects the two prominent events caused by regulation of the Delta outflow (see "Weighting of Water Balance Variables by Principal Components"). It is starred (*) because of its conjectural status. PC3.Z has little trend and exhibits a strong inverse correlation with the fluctuations in precipitation.

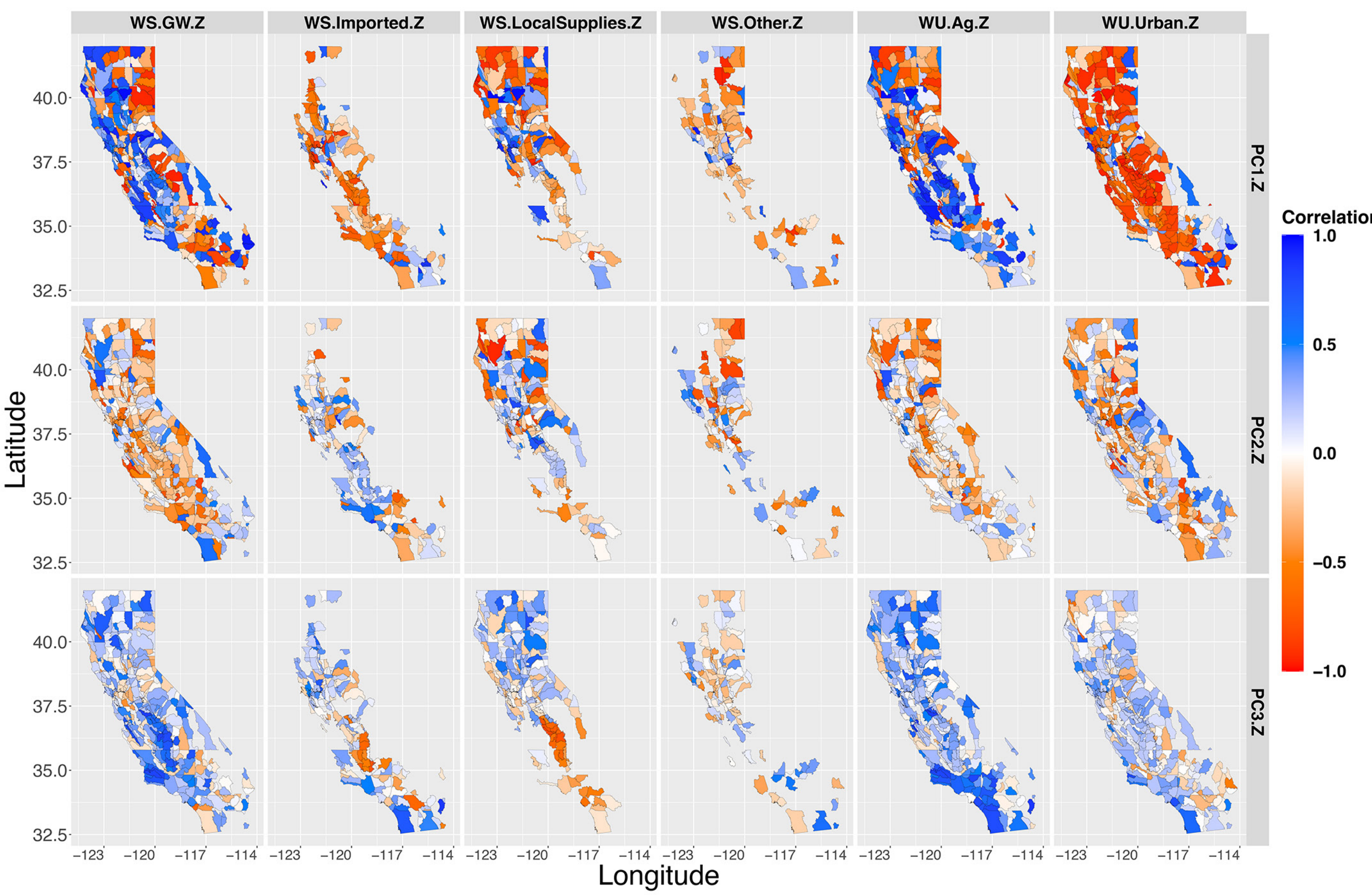

Figure 12 Weights of PC1.Z-PC3.Z formed from correlations of PC.Z time-series vs. time-series of water-balance variables at each DAUCO. *Blank polygons* denote DAUCOs with only zero values for the indicated variable.

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correlations in the north, mixed in central, and mostly low correlations in southern California. The pattern for other supplies (WS.Other.TAF) has large negative correlations in northeastern California and is otherwise mixed and relatively insignificant.

PC2.Z accounts for 14% (Table A9) of the normalized water-balance anomaly variance. The major attribute of PC2.Z is a strong convex deflection that spans 2005 to 2011, which is not a primary feature of any of the major, state-wide, water-supply or water-use time-series (Figures 7 and 2). However, it has correlation weights—in varying strength and direction, positive or negative—with the four supply and use components at many DAUCOs. Correlations of PC2.Z with groundwater and other supplies are negative across a California-wide array of DAUCOS, indicating that groundwater and other supplies increased during 2005–2011 deflection period. In contrast, most correlations with imported supplies are positive, indicating that imported water supplies declined during 2005 to 2011, with the exception of a few negative correlations in the Central Valley and inland southern California. Significant correlations with local supplies are confined to northern California, with negative correlations with DAUCOs along the north coast, the San Francisco Bay region, and the Sacramento Valley; and positive correlations with DAUCOs within the San Francisco Bay region extending northward into inner coastal valleys. Correlations with urban and agricultural water use were both negative and positive, indicating both increased and decreased water use, depending on DAUCO, during the 2005–2011 period.

PC.Z.3 captures 13% of the water-balance variance and is characterized by interannual variations, but negligivle trend. PC.Z.3 exhibited a strong, negative correlation ($r = -0.79$) with state-wide precipitation reflecting wet years in 2005, 2006 and 2011 and dry years in 2002, 2007, 2008, 2009, 2012, 2013, 2014, and 2015. As shown in Figure 12, PC.Z.3 featured out-of-phase variation with imported water supplies in a collection of DAUCOs and local water supplies from some DAUCOs.

PC.Z3 has in-phase variation of groundwater supplies at numerous DAUCOs across California. Notably PC.Z.3 associations with urban water use were generally weak. This indicates that urban water use did not respond immediately to precipitation variability but, as discussed below, urban use exhibited significant correlations at lags of 4 to 7 years with state-wide precipitation (Table 3). PC3.Z is predominately positive across [missing words?] (WS.GW.TAF, WU.Ag.TAF, and WU.Urban.TAF), while there are strong negative correlations apparent in the south Central Valley extending more moderately into southern California.

Correlation of Principal Components with State-wide Precipitation

The state-wide water balance and precipitation-lagged correlations (see "State-Wide Correlation of Precipitation and Water Balance") are supported by lagged correlations between state-wide precipitation and principal component time-series (Table 11). The strongest correlation with precipitation is is an inverse correlation with PC3.Z for LAG.0 ($r = -0.79$, $p < 0.001$). The time-series for PC3.Z is characterized by interannual fluctuations and overall trend (Figure 11). The PC3.Z result reflects the correlation of precipitation with state-wide water balance variables shown in Table 3 and described in "State-Wide Correlation of Precipitation and Water Balance."

Robustness of PCA Results

In deciphering the results from the PCA.Z, we had concern that the abrupt increase in PC1.Z from 2010 to 2011 (Figure 11, top panel) may have reflected a methodological change or some other spurious effect in the water balance data collection. We therefore performed a sensitivity analysis of the PCA.Z using perturbed water-balance variables individually and in combinations to examine the relative influence of each water-balance variable on the results.

We found that the results are relatively insensitive to the inclusion or exclusion of any individual variable and even combinations of variables. Furthermore, we varied WU.Ag.TAF and

WU.Urban.TAF to evaluate the sensitivity to the choice of crop coefficients used in model-based estimates of the water-use variables. The results were unaffected even when post-2010 agricultural water use (WU.Ag.Z) was reduced by 50%. This leads us to infer that the variability accounted for by the PC1.Z time-series is widely distributed across the state in the water-balance variables as illustrated in Figure 12. This variability is reflected by opposite correlations between agricultural water use (WU.Ag.TAF) and urban water use (WU.Urban.TAF). The pattern of PC1.Z correlations with agricultural water use (WU. Ag.TAF) resembles that of PC1.Z correlations with groundwater supply (WS.GW.TAF).

Water-Balance Trend Analysis

We performed simple linear regressions for each of the six water-balance variables as well as total water supply (WS.Total.TAF) and total water use (WU.Total.TAF). The results are summarized in Table 9 and Figure 13.

Table 9 tabulates the number of DAUCOs according to the slope of the regressions to evaluate trends in water supply and use over 2002–2016. The table is divided into columns according to the value of the coefficient of determination (r^2) of each regression, and further sub-divided according to slope direction: positive, negative or zero (insignificant). The coefficient of determination is a measure of goodness-of-fit and is the proportion of the variance in the data accounted for by the regression model (Chambers and Hastie 1992). Notably, as gaged by trends in Table 9 whose r^2 values are statistically significant, the trends of other supply and urban water use are predominantly negative (decreasing over 2002-2016), while those of ground water supply and agricultural water use are predominantely positive (increasing).

Figure 14 maps the distribution of these trends using the same regression results but with slopes standardized according to Equation 5. The trend analysis shows that urban water use is declining broadly throughout the state while agricultural water use is generally increasing, except in the northeast of California where it is declining, and in southern California where it is unchanging or declining. Imported water use is unchanging or declining almost everywhere. The spatial make-up of the trends of total water supply and total water use has imprints from each of the variables, reflecting those with greatest volumes and fractions.

DISCUSSION

Our findings (see "Results") underscore the following questions:

First, how are we to make sense of the differences in variability in water supply and use at the state and DAUCO levels of aggregation?

Table 9 Number of DAUCOs with positive, negative or zero trend from simple linear regressions within each DAUCO by water-balance variable plus anomaly (WB.Anomaly.TAF), use total (WU.Total.TAF), and supply total (WS.Total.TAF). r^2 is undefined for zero-slope regressions.

	$r^2 \geq 0.7$			$0.5 \geq r^2 \geq 0.7$			All			
Variable	-	+	All	-	+	All	-	+	Zero	All
WS.GW.TAF	16	17	33	25	66	91	145	238	92	475
WS.Imported.TAF	14	2	16	20	3	23	128	46	301	475
WS.LocalSupplies.TAF	10	3	13	21	16	37	129	91	255	475
WS.Other.TAF	1	1	2	5	4	9	82	43	350	475
WS.Total.TAF	28	13	41	25	66	91	198	196	81	475
WU.Ag.TAF	7	20	27	21	46	67	120	199	156	475
WU.Total.TAF	29	17	46	26	69	95	178	216	81	475
WU.Urban.TAF	75	6	81	53	44	97	245	122	108	475

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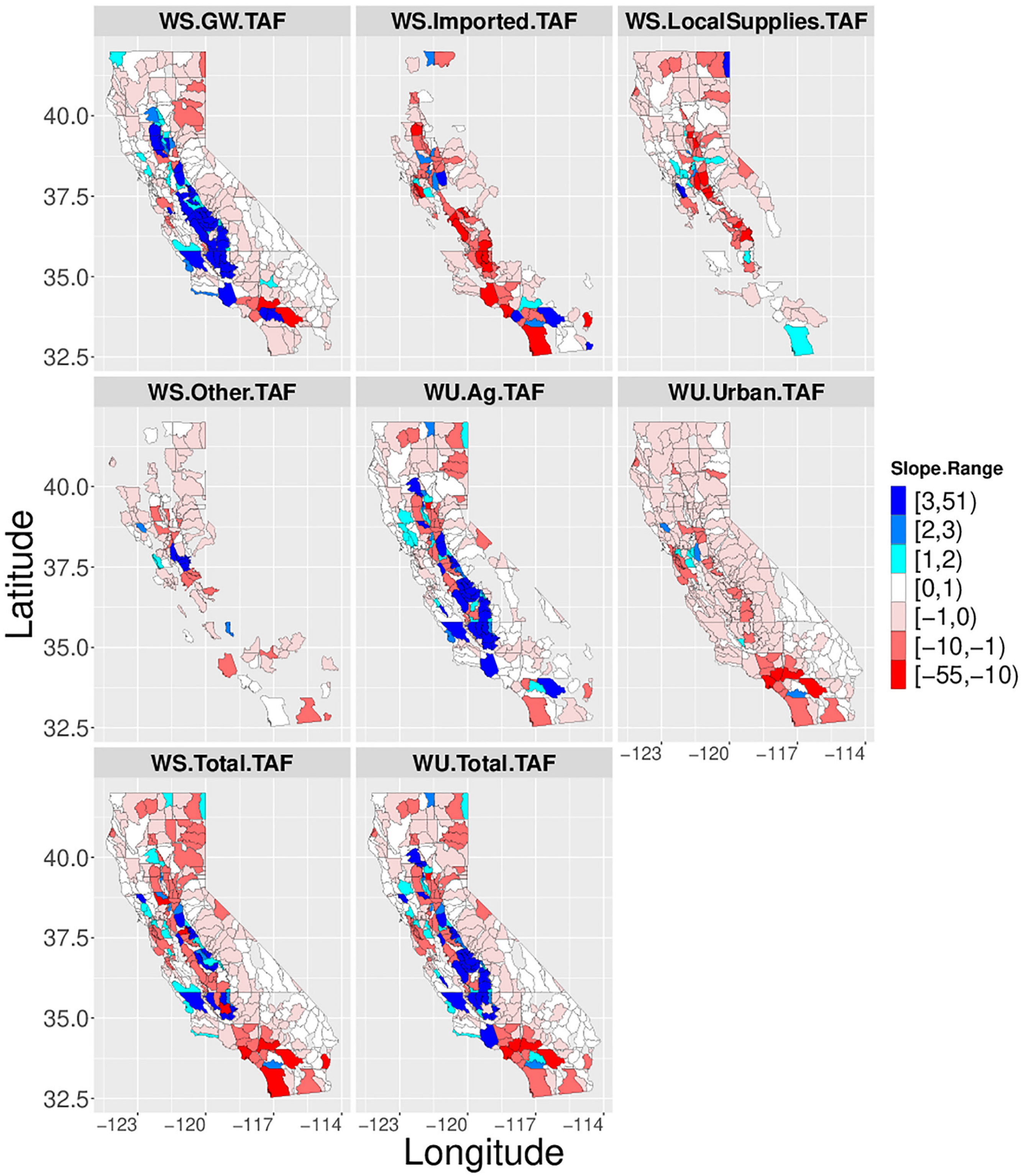

Figure 13 Trends in volumetric water-balance variables and totals measured by the slope of Equation 4. The units of slope are thousand acre-feet per year and highlight DAUCOs with increasing or decreasing water supply or use by water-balance variable. *Blank polygons* denote DAUCOs with only zero values for the indicated variable.

Second, how does the ability to manage conjunctive use of water-supply compensate for variability in precipitation to meet water-use demands?

Third, how do limitations on conjunctive-use supplies expose DAUCOs to water-supply risk?

How Do We Make Sense of California's Diverse Water Supply and Water Use?

Over state-wide and hydrologic region-scales it is useful to think of the California water balance as a system of developed water supply and water use. However, the water balance data exhibit considerable spatial and temporal complexity at the DAUCO level. As mentioned earlier, our evidence (see "Results") demonstrates that multiple approaches are required to describe its many aspects.

One approach aggregates the water-balance variables over the state-wide domain (Table 2), but these aggregations mask the diversity of supply and use across California, which is considerable. Consequently, this aggregated state-wide approach misses important features.

The second approach, which is the main theme of this study, investigates the temporal and spatial structure and linkages between water balance variables. The range of values across the 475 DAUCO profiles requires a balance between summarizing the common features across DAUCOs and discriminating between important features in individual—or small numbers of—DAUCOs. To usefully evaluate California water-resource practice and policy, we employed three separate analyses to identify dominant water-balance patterns across the state.

The first analysis focused on volume, classifying water supply and use according to the observed magnitudes of the water-balance variables. A cluster analysis based upon water-balance volumes yields a very uneven set of DAUCO groupings. For example, cluster T4 (375 DAUCOs) accounts for 11% vs. the remaining 100 DAUCOs in the other clusters that account for 89% of California's water use. The largest DAUCO water consumers are predominantly agricultural or predominantly urban (Figure 8).

The second analysis focused on proportionate water supplies and uses, based upon an alternative cluster analysis of the percentages of total supply and total use at each DAUCO. This proportionate water-balance analysis identifies groups of DAUCOs that are more evenly distributed than in the volumetric clusters. The resultant sets of volumetric and proportionate clusters also demonstrate that a small number of distinct profiles of supply and use occur across the state, based primarily on land use.

The third analysis focused on temporally co-varying supply and use across California using PCA. Amongst the PCA modes are ones that express opposing multi-year variation in groundwater supply and agricultural water use, in contrast to local and imported supplies and urban water use. Importantly, the PCA modes also demonstrate that—in the midst of groups of DAUCOs with temporally co-varying water supply and use—there are contrarians with uncorrelated or even oppositely phased supply and use.

The PCA clearly identifies separate modes of water-balance variation that are driven by changing policy and practice (PC1.Z), and by interannual variation in precipitation (PC3.Z). PC1.Z has a pronounced trend. In contrast, precipitation has no mean trend over 2002 to 2016. Consequently, the trend must be the result of other causes, and the most likely are increases in agricultural water use based on groundwater and urban conservation of water.

Notably, the groups of DAUCOs that were highly weighted in particular PCA modes have little correspondence to the groups of DAUCOs identified by the cluster analyses. Together, these results demonstrate that the different analyses reveal distinct aspects of the California water balance and that a combination of approaches is required to make sense of them.

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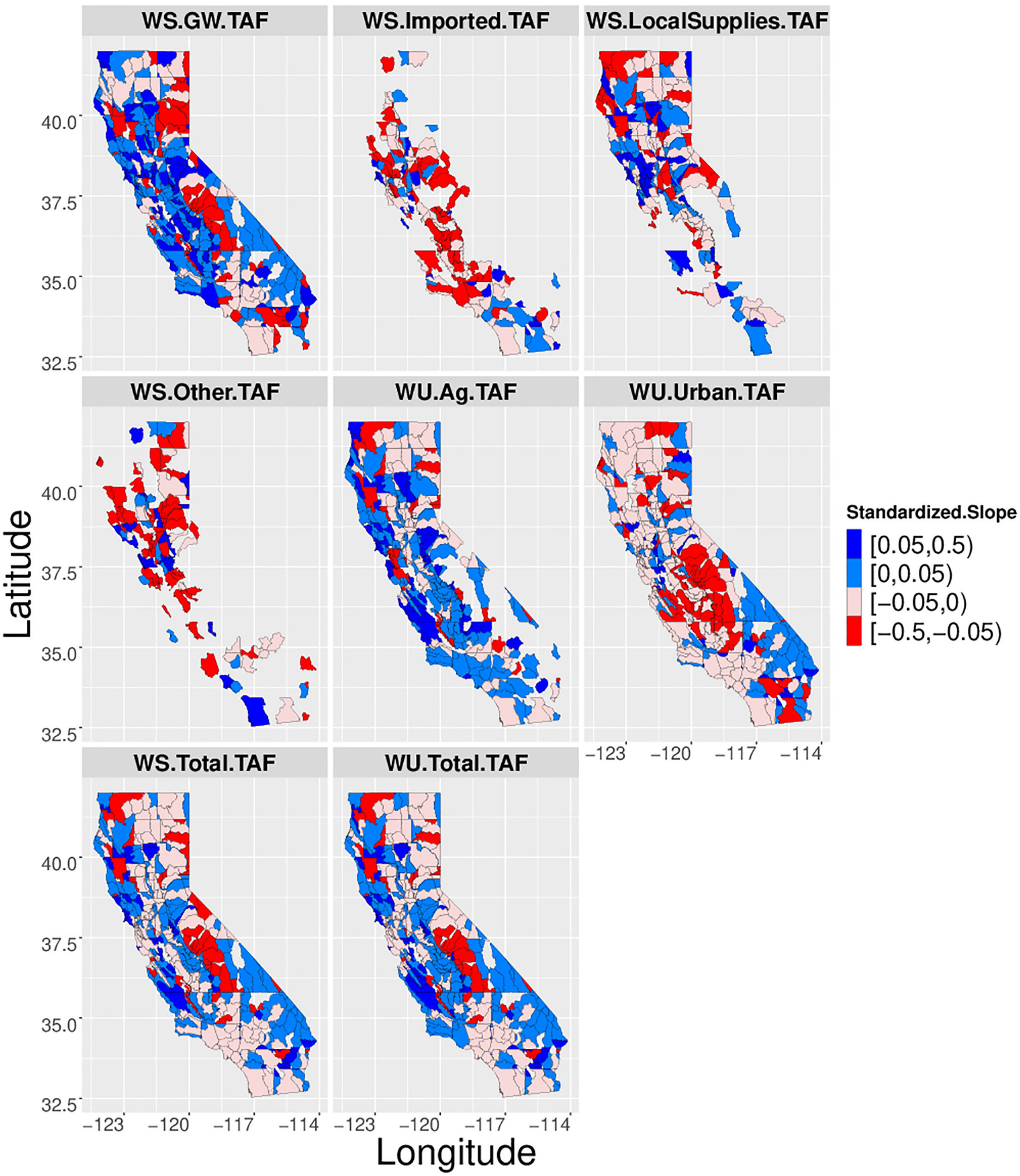

Figure 14 Trends in water-balance variables and totals measured by the standardized slope of Equation 5 as a proportion of the variable mean within a DAUCO then multiplied by 15 years (2002–2016) to reflect the cumulative change. This metric is a dimensionless number that indicates the relative trends by variable across the state. Blank polygons denote DAUCOs with only zero values for the indicated variable.

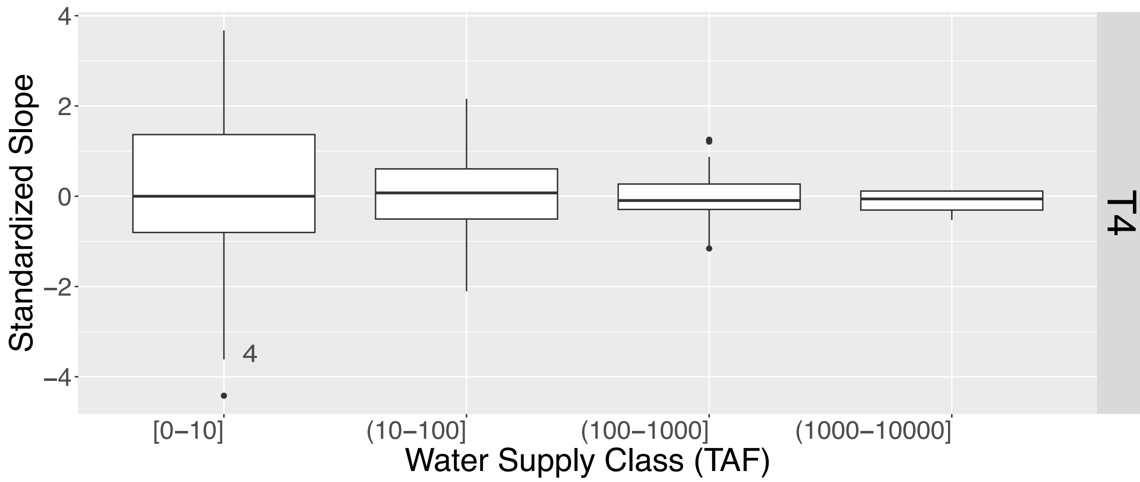

Figure 15 Box plots of water-supply trends, from nearly single water supply source DAUCOs in four sucessively larger classes of total water supply volume (TAF). DAUCOs are members of cluster T4. "Single source" DAUCOs are those whose total supply is >90% from either groundwater, or imported, or local, or other supply category. The *rectangular boxes* enclose the 25% to 75% range (inter-quartile range), with the median shown as a *horizontal line* through the box. The *vertical lines* represent outliers ≤ 1.5 times the inter-quartile range. The *dots* represent the most extreme values.

Possible Effects of Policy and Regulation

PC2.Z accounts for 14% of the normalized water balance anomaly variance, but its time-series is idiosyncratic in its lack of an overall trend and its absence of strongly interannual variability. Its weighting maps are mosaics across components and DAUCOs throughout California. In searching to explain the curious PC2.Z 2005–2011 deflection (Figure 11), Figure A2 shows that most of the deflection coincides with drier-than-normal conditions from 2007 to 2010, suggesting that this feature represents a set of responses to persistent dryness. A relatively strong correlation with local supplies (WS.LocalSupplies.TAF), however, led us to examine that variable more closely.

Time-series of Delta outflow and exports, from Dayflow data that are not part of the water balance data (CDWR 2023a), exhibit peaks in 2005 and 2011, which correspond to the inflection points in PC2.Z (Figure A2). These peaks may be caused by—or amplified by—the San Joaquin River Agreement (SJRA) and Vernalis Adaptive Management Plan (VAMP) experiment. These regulatory actions had goals of increased water deliveries through the Sacramento–San Joaquin Delta water export facilities to provide freshwater flows to protect juvenile Chinook Salmon that migrate from the San Joaquin River through the Delta (San Joaquin River Group Authority 2010). These regulatory actions may have created concomitant reductions in State Water Project and Central Valley Project water deliveries, which would presumably propagate into various supplies and uses across affected DAUCOs that depend on imported water. Reductions in imported water would then stimulate increased demand on groundwater and other conjunctive-use supplies, which would further amplify the signal and be imprinted on the variance in the water balance data. The documentary record we have found only describes the increased flows around 2005 (San Joaquin River Group Authority 2010). However, the permit for the experiment expired in 2012, and it seems likely that the second peak (2011) was related, in purpose, to the first, although we do not have documentary evidence for that.

Thus, our hypothesis is that the dry period from 2006 through 2010—following precipitation peaks in 2005 punctuated by one in 2011—was amplified by a non-linear system response, including the effects of regulatory measures. The PC2.Z weighting maps suggest that these actions resound through the water balance data: affecting all of the other water-balance variables (Figure 2). The variability of Delta outflows, and the compensatory variations in other water-supply variables in conjunctive use, carry a substantial portion of the variance in the water balance data (14%, Table A9).

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Table 10 Number of DAUCOs with positive, negative, or zero trend from simple linear regressions within each DAUCO, partitioned into subsets of small, intermediate, and large total water supply. As in Table 9, the trends are shown by water-balance variable plus water use total (WU.Total.TAF) and water supply total (WS.Total.TAF). The table is organized in *columns* according to the value of the coefficient of determination (r^2). r^2 is undefined for regressions whose slope is statistically insignificant.

		$r^2 \geq 0.7$			$0.5 \geq r^2 \geq 0.7$			All			
Class	**Variable**	**-**	**+**	**All**	**-**	**+**	**All**	**-**	**+**	**Zero**	**All**
Default	WS.GW.TAF	6	5	11	11	19	30	65	109	1	175
	WS.Imported.TAF	12	—	12	20	1	21	100	27	48	175
	WS.LocalSupplies.TAF	4	1	5	11	7	18	81	53	41	175
	WS.Other.TAF	.	1	1	4	2	6	56	34	85	175
	WS.Total.TAF	10	3	13	9	11	20	109	66	—	175
	WU.Ag.TAF	3	6	9	7	26	33	71	103	1	175
	WU.Total.TAF	12	5	17	8	20	28	90	85	—	175
	WU.Urban.TAF	45	1	46	35	5	40	138	34	3	175
Median WS Total ≤ 1 TAF	WS.GW.TAF	3	8	11	9	34	43	36	58	87	181
	WS.Imported.TAF	1	2	3	.	2	2	1	7	173	181
	WS.LocalSupplies.TAF	2	2	4	4	2	6	13	9	159	181
	WS.Other.TAF	—	—	—	—	1	1	4	2	175	181
	WS.Total.TAF	5	7	12	11	40	51	35	65	81	181
	WU.Ag.TAF	3	5	8	7	7	14	15	27	139	181
	WU.Total.TAF	5	7	12	10	36	46	35	65	81	181
	WU.Urban.TAF	4	5	9	8	31	39	31	54	96	181
Median WS Total ≤20 TAF	WS.GW.TAF	7	4	11	5	13	18	44	71	4	119
	WS.Imported.TAF	1	—	1	—	—	—	27	12	80	119
	WS.LocalSupplies.TAF	4	—	4	6	7	13	35	29	55	119
	WS.Other.TAF	1	—	1	1	1	2	22	7	90	119
	WS.Total.TAF	13	3	16	5	15	20	54	65	—	119
	WU.Ag.TAF	1	9	10	7	13	20	34	69	16	119
	WU.Total.TAF	12	5	17	8	13	21	53	66	—	119
	WU.Urban.TAF	26	—	26	10	8	18	76	34	9	119

Table 11 Pearson correlations and *p*-values of PC1.Z-PC3.Z and statewide precipitation. LAG.0-LAG.2 are one and two year lags of each variable with respect to precipitation (i.e., LAG.0 = 2016, LAG.1 = 2015, LAG.2 = 2014). For each lag, each principal component is shifted back in time by the LAG amount while precipitation remains fixed in time to examine the correlation with prior-year precipitation. Correlation coefficients highlighted in bold face reach or exceed the 95% confidence level.

	PC1.Z		PC2.Z		PC3.Z	
Lag	**Corr**	***p***	**Corr**	***p***	**Corr**	***p***
LAG.0	− 0.32	0.24	0.38	0.17	**− 0.79**	0.00
LAG.1	− 0.20	0.49	− 0.09	0.75	− 0.18	0.53
LAG.2	− 0.13	0.63	− 0.21	0.44	0.31	0.26

Table 12 Number of DAUCOs within each cluster by cumulative total water supply

Cluster.TAF	Class.TAF)0-10)	(10-100)	(100-1000)	(1000-10000)	(10000-100000)	All
	n	n	n	n	n	n
T1	—	—	—	—	1	1
T2	—	—	—	—	6	6
T3	—	—	—	56	—	56
T4	161	90	106	18	—	375
T5	—	—	—	5	3	8
T6	—	—	—	21	3	24
T7	—	—	—	3	2	5
All	161	90	106	103	15	475

Table 13 Correlation of PC1.Z-PC3.Z with volumetric clusters (T-clusters) and water-balance variables (TAF) for ($p \leq 0.05$)

PC.Z	Variable	Cluster.TAF T1	T2	T3	T4	T5	T6	T7
		Correlation	Correlation	Correlation	Correlation	Correlation	Correlation	Correlation
PC1	WS.GW.TAF	—	.	0.59	.	– 0.80	0.58	—
	WS.Imported.TAF	—	– 0.60	– 0.65	– 0.89	– 0.67	– 0.54	– 0.61
	WS.LocalSupplies.TAF	—	—	– 0.86	—	—	– 0.71	—
	WS.Total.TAF	—	—	—	—	– 0.81	—	– 0.52
	WU.Ag.TAF	—	0.84	—	—	—	0.57	—
	WU.Total.TAF	—	0.80	—	—	– 0.83	—	—
	WU.Urban.TAF	– 0.93	– 0.84	– 0.68	– 0.88	– 0.87	– 0.85	– 0.91
PC2	WS.GW.TAF	—	—	—	– 0.57	—	—	– 0.59
	WS.LocalSupplies.TAF	—	—	—	—	—	—	0.59
	WS.Other.TAF	—	—	– 0.62	—	—	—	—
	WU.Total.TAF	—	—	—	– 0.56	—	—	—
	WU.Urban.TAF	—	—	– 0.54	—	—	—	—
PC3	WS.GW.TAF	—	0.68	0.66	0.63	—	0.63	—
	WS.LocalSupplies.TAF	—	– 0.78	—	—	—	—	—
	WS.Other.TAF	0.60	—	—	—	—	—	—
	WS.Total.TAF	0.58	—	0.71	0.74	—	0.66	0.61
	WU.Ag.TAF	0.56	—	0.59	0.71	0.68	0.64	0.63
	WU.Total.TAF	0.58	—	0.64	0.75	—	0.70	0.62

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Table 14 Correlation of PC1.Z-PC3.Z with percentage clusters (P-clusters) and water-balance variables (PCT) for ($p \leq 0.05$)

		Cluster.PCT				
		P1	P3	P5	P6	P7
PC.Z	Variable	Correlation	Correlation	Correlation	Correlation	Correlation
PC1	WS.GW.PCT	0.52	—	0.59	0.53	0.68
	WS.Imported.PCT	—	—	—	– 0.65	—
	WU.Ag.PCT	0.94	0.66	0.78	0.89	0.96
	WU.Urban.PCT	– 0.89	– 0.74	—	– 0.88	– 0.94
PC2	WS.GW.PCT	– 0.62	—	—	—	—
	WS.LocalSupplies.PCT	—	0.67	—	—	– 0.69
PC3	WS.LocalSupplies.PCT	—	—	– 0.55	—	—
	WU.Urban.PCT	—	—	– 0.65	—	—

Groundwater Supplies as Compensation for Highly Variable Precipitation

Interannual variability of precipitation in California, amongst the greatest in the United States, is projected to grow with climate change (Berg and Hall 2015; Swain et al. 2018; Gershunov et al. 2019). The 2002–2016 study period was emblematic of this highly variable hydroclimate, featuring a few wet years and recurrent drought (2007–2009 and 2012–2016), which resulted in higher variability and lower average total precipitation than that from the longer historical record.

In California water-balance variables, this variability was clearly registered in local and groundwater supplies and agricultural water use. Not surprisingly, precipitation variability is also related to variations in imported water supply and urban water use, but the precipitation signal appears to be substantially shifted to subsequent years and modified, likely as a result of water system infrastructure, regulation, policy, and practice. The variability of all state-wide supply and use variables—especially total water supply and total water use—is damped. This is in keeping with the engineered infrastructure through diversion, storage, pumping, and conveyance from distant watersheds (State of California 1979; Reisner 1993; Dettinger 2011). However, many individual DAUCOs and individual water-balance variables have much higher variation.

An intuitive model of California's water balance might be that overall supply and overall use responds directly to the ups and downs of annual precipitation. For example, supply and use rise in wet years and fall in dry years. However, access to groundwater has inverted that model. Even though state-wide precipitation correlates positively with local and imported supplies, state-wide precipitation correlates negatively with groundwater supply and agricultural water use. And, because the volumes of groundwater supply (42% of total supply) and agricultural water use are larger than the other supply and use variables, the overall correlations of state-wide precipitation with total water supply and total water use are negative (–0.63 and –0.84, respectively; Table 2).

Similarly, at the DAUCO level, most of California exhibits negative correlations between precipitation and total use. Further, this inverse association is also apparent in the linear trends of the total use: while the 15-year trend (2002–2016) of state-wide precipitation was slightly negative, the trend in state-wide total use is slightly positive, although neither meets conventional levels of statistical significance.

Collectively, reductions in urban water use over 2002–2016 occurred in a large majority of DAUCOS across California. On the other hand, also in response to dryness, groundwater supplies increased over the study period, mostly where land use is dominated by agriculture. Can this pattern be sustained? In future years, further substantial reductions in urban use and continued increases in groundwater supplies for agricultural users seems unlikely, given limitations in conservation options and growing signals of aquifer depletion, along with Sustainable Groundwater Management Act (SGMA) regulations (CA-Assembly 2014).

Vulnerability

Many California DAUCOs have a diversity of water supplies, but a significant fraction rely on a single supply: 175 DAUCOs have 90% or more of their total supply drawn solely from either local, groundwater, or imported water sources. Of those, 123 have a relatively small 15-year, 2002–2016 total water supply (<100 TAF), with 71 having even less (<10 TAF). And, many of these mostly-single source DAUCOs registered high amounts of change in supply over the 2002-2016 period, some of which were large declines, suggesting that some of them operate under high risk of severe water shortage during future dry spells. Unsurprisingly, 84 are members of the one volumetric cluster (T4) with the largest membership but the smallest total water supply.

Most of the smallest systems (62 of 71, 87%) use groundwater as their dominant source. A serious problem for these small-total-supply DAUCOs is that their water is at particular risk of running out as droughts intensify, given increasing atmospheric demand for water as climate warms, limited aquifer recharge and little or no alternative water sources.

CONCLUSIONS

Annual water-balance records compiled from 475 DAUCOs in California exhibit highly varied water supply and water use—by volume, and proportion across water-balance variables—and over the 2002–2016 study period.

Precipitation in California is highly variable but with little or no total volume change over decades. The variability appears to be increasing with the intensification of wet and dry periods. In state-wide aggregate, the California water system has been very effective in reducing the effects of interannual variation in precipitation. However, at the DAUCO-level, variability is much higher as a result of the diversity of conjunctive-use alternatives for water supply and the variety of land use. These effects are seen throughout the state in distinctive patterns of water supply and use.

Historically, the water balance data show that many DAUCOs have supplies diverse enough or with enough capacity that they have been able to sustain a steady overall supply, despite intense dry spells and reductions in individual supply sources. However, some DAUCOs have exceeded those historical capacities, leading to shortages, and it appears that others are similarly vulnerable. In particular, some of the smallest water-use DAUCOs were dependent mostly von a single source of supply, most often groundwater, and exhibited extremely high variation in total supply. Thus, it appears there is immediate short-term risk of severe shortage to these relatively low-demand, low-capacity DAUCOs. More generally, it is obvious that there are limits to each type of supply source, regardless of the mix for a given DAUCO. This raises concerns about the reserve capacity of current conjunctive-use DAUCOs in the face of increasing precipitation variability, depletion of aquifer reserves, loss of rechargeable storage, and increasing water use.

Many DAUCOs cut back on water use over the generally dry period of study, especially in the urban sector, which exhibited broad-scale increases in water conservation; members of that sector learned to use about 30% less water by 2016 than they used in 2002. On a state-wide aggregate level, however, water use actually increased slightly over the study period, primarily because of increases of groundwater withdrawal to support agricultural production. Percentage increase in agricultural use was only about 10%, but, being of larger magnitude, this increase amounted to more than 3 MAF addition in 2016 from the beginning of the analysis in 2002. This increase was more than enough to alleviate the nearly 2.5 MAF reduction (2016 vs. 2002) from the urban sector. While trends in agricultural water

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use ranged from negative to positive, a relatively small number of DAUCOs—ranked amongst the highest water consumers in California—drove the overall increase. The increased reliance on groundwater is likely to be unsustainable in the face of aquifer depletion, land subsidence, and tightened regulations under California's SGMA.

Water-balance profiles, covariance analyses, and trend analyses demonstrate different ways to organize and help monitor California's complex network of water supply and use. Results from cluster analyses identify types of water users based on patterns of supply and use, which may have practical application in managing regulation, communication, and infrastructure. Principal components analysis offers a means of identifying, separating, and prioritizing major drivers of change that operate state-wide. Because the PCA includes temporal information explicitly, they may also have predictive value. Trend analysis provides a measure of system responses and may also offer an early-warning metric of risk to those DAUCOs that are near the limits of sustainable water supplies.

More years of data will further illuminate California's developed water system response to continued highly varying precipitation, including anomalous wetness in 2017 and 2019, extreme drought in 2020–2022, and an anomalously wet 2023 water year. To understand and manage both short- and longer-term effects, more rapid updates of the DAUCO water balance data are urgently needed. Careful monitoring of water supplies and use is needed in small systems, many of which have exhibited high variation and a relatively high degree change over the 2002-2016 study period.

Finally, these results have important implications for planners. A great deal of effort is being invested to anticipate the effects of climate change over the globe (e.g., IPCC 2023) and over the California region (Bedsworth et al. 2018; CA-OPR 2022). Components of the regional assessment that are relevant to the present study include the development of climate-change scenarios and a chain of model evaluations of vulnerability and effects such as the response of land-surface hydrology to climate change. Our results indicate that changing precipitation directly affects the variability in California's developed water supply and water use, but any future assessment must also consider effects of possible changes in policy, regulatory, and other human behavioral patterns. Response to drought and anticipation of regulatory change appear to introduce—even amplify—the variability of the water-balance components. A challenge is to realistically insert these socio-economic elements in models to improve our understanding and our ability to predict California water-system responses.

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GLOSSARY

CDWR—California Department of Water Resources. A department of the California Natural Resources Agency.

DAUCO—Detailed Analysis Unit code, determined by CDWR, concatenated with the County code used by the State of California.

MAF—Volumetric unit of one million acre-feet. The volume of water in 1,000,000 acres flooded to a depth of 1 foot.

P1...P7—Clusters computed using percentages.

PCA—Principal Components Analysis.

PCT—Volumetric units of a thousand acre-feet converted to a percentage (PCT, %).

PRISM—Parameter-elevation Relationships on Independent Slopes Model.

T1...T7— Clusters computed using volumes (expressed in units of a thousand acre-feet).

TAF—Volumetric unit of one thousand acre-feet. The volume of water in 1,000 acres flooded to the depth of 1 foot.

WS.GW.PCT— Water supplied from groundwater measured as TAF expressed in PCT.

WS.GW.TAF—Water supplied from groundwater measured in TAF.

WS.GW.Z—Water supplied from groundwater as TAF expressed as z values.

WS.Imported.PCT—Water supplied from outside the DAUCO measured in TAF, expressed in PCT.

WS.Imported.TAF—Water supplied from outside the DAUCO measured in TAF.

WS.Imported.Z - Water supplied from outside the DAUCO as TAF, expressed as z values.

WS.LocalSupplies.PCT—Water supplied from within the DAUCO measured in TAF, expressed in PCT.

WS.LocalSupplies.TAF—Water supplied from within the DAUCO measured in TAF.

WS.LocalSupplies.Z—Water supplied from within the DAUCO as TAF, expressed as z values.

WS.Other.PCT—Water supplied from industrial processes or desalination measured in TAF, expressed in PCT.

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WS.Other.TAF—Water supplied from industrial processes or desalination measured in TAF.

WS.Other.Z—Water supplied from industrial processes or desalination as TAF, expressed as *z* values.

WS.Total.PCT—Sum of all volumetric water-supply variables measured as TAF, expressed as PCT.

WS.Total.TAF—Sum of all volumetric water-supply variables measured in TAF: WS.GW.TAF. WS.Imported.TAF, WS.LocalSupplies.TAF, and WS.Other.TAF.

WS.Total.Z—Sum of all volumetric water supply variables measured as TAF, expressed as *z* values.

WU.Ag.PCT—Water used in agriculture measured as TAF, expressed in PCT.

WU.Ag.TAF—Water used in agriculture measured in TAF.

WU.Ag.Z—Water used in agriculture measured as TAF, converted to *z* values.

WU.Total.PCT—Sum of volumetric water use variables measured as TAF, expressed in PCT.

WU.Total.TAF—Sum of volumetric water use variables measured in TAF: WU.Ag.TAF and WU.Urban.TAF.

WU.Total.Z—Sum of volumetric water use variables measured as TAF, expressed as *z* values.

WU.Urban.PCT—Water used in urban applications measured TAF, expressed in PCT.

WU.Urban.TAF— Water used in urban applications measured in TAF.

WU.Urban.Z—Water used in urban applications measured as TAF, expressed as *z* values.