Water Resources Research

RESEARCH ARTICLE
10.1029/2020WR028544

**Key Points:**

- Annual time-varying sensitivity analysis revealed unique patterns of parameter importance across 21 proximal study watersheds
- Low elevation parameter importance to Kling-Gupta Efficiency varied with precipitation, while shifts at high elevations varied with elevation
- Parameter sensitivity to select hydrological signatures was generally static through time, despite annual variations in observed values

**Supporting Information:**

- Supporting Information S1

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**Citation:**
Basijokaite, R., & Kelleher, C. (2021). Time-varying sensitivity analysis reveals relationships between watershed climate and variations in annual parameter importance in regions with strong interannual variability. *Water Resources Research*, *57*, e2020WR028544. https://doi.org/10.1029/2020WR028544

Received 4 AUG 2020
Accepted 12 DEC 2020



# Time-Varying Sensitivity Analysis Reveals Relationships Between Watershed Climate and Variations in Annual Parameter Importance in Regions With Strong Interannual Variability

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**Abstract** Climate change impacts on hydroclimatology are becoming increasingly apparent around the world. It is unknown how annual variations in precipitation and air temperature alter the model-inferred importance of hydrological processes and how this varies across watersheds. To examine this, we used parsimonious rainfall-runoff model and applied time-varying sensitivity analysis across 30 Californian watersheds for a 33-year period (1981–2014). We calculated annual total order sensitivity indices for five performance metrics: Kling-Gupta Efficiency (KGE) and model error in simulating hydrologic signatures (runoff ratio, slope of flow duration curve, baseflow index, and timing of streamflow centroid). Sensitivity of hydrological signatures to the parameters differed by signature, while parameter importance with respect to KGE was much more spatially and temporally variable. Variations in parameter sensitivity with respect to KGE were either correlated with air temperature (snow-dominated sites in the Sierra Nevada) or precipitation (lower elevation sites < 1,300 m). Across error metrics and signatures, parameter sensitivity strongly differed between wet and dry years for a subset of our study sites. While parameter importance varied through time, parameter sensitivity variations across watersheds were much more pronounced. This suggests that parameter controls on model performance are much more a reflection of watershed properties as opposed to being dominantly shaped by shifts in precipitation and air temperature. These findings emphasize the importance of understanding simulated watershed responses to fluctuating annual conditions, as this conceptual knowledge is necessary to anticipate similarities and differences in response across even relatively proximal watersheds in the face of growing extreme conditions.

**Plain Language Summary** Computer models are useful tools that can be used to analyze what inputs matter most to ensuring that model output is similar to observed conditions. In order to understand how very wet years versus very dry years impact which model inputs (called parameters) are most important to matching good predictions, we simulated streamflow using a simple mathematical model many thousands of times. We used these outputs to determine how variations in predictions of streamflow (output from the model) are related to variations in model parameters, to identify which parameters are most important for ensuring reasonable model predictions. We focused on watersheds that are close together, but that may experience different average conditions and interannual variability. We found that which parameters are important varied across different watersheds and also varied with total annual precipitation and watershed elevation. In addition, we found that drought impacted the importance of processes in the model, especially in mountainous watersheds. Our results emphasize the importance of understanding how watersheds respond to varying annual conditions, as this type of knowledge is essential to anticipate the future of streamflow availability and inform the management style that needs to be implemented to predict water availability in these systems.

## 1. Introduction

As weather and climate extremes continue to set new records (WMO, 2017), it is becoming increasingly important to study the effects of these extremes on hydrologic cycles (Bates et al., 2008) as well as our ability to simulate these changes within hydrologic models (Nijssen et al., 2001; Xu, 1999). In the United States, California has experienced strong fluctuations between extreme wet and dry years, oscillating between receiving abundant precipitation, often falling as snow in mountain regions, and experiencing extreme droughts, including a recent major drought that lasted from 2012 to 2016 (USGS). This strong seasonality provides a unique test case to evaluate the impacts of regional-scale climate variability within the context of hydrologic modeling. Recent studies in California predict decreases in mean annual streamflow, reduced snowpack, and more rapid snowmelt runoff in the future (Knowles et al., 2002; Medellín-Azuara et al., 2008; Miller et al., 2003; Vicuna et al., 2008). As hydrologic models can provide a coherent picture of hydrological system behavior under past, present, and future conditions (Schewe et al., 2014), learning from the past to understand present catchment processes and using this knowledge to predict future behavior is a major goal of hydrological research.

Linking changes in climate to changes in hydrology is often performed via the use of hydrological models, which simulate the responses of hydrologic processes to average as well as extreme conditions, and identify what characteristics of a watershed system may influence hydrologic behavior (Guse et al., 2016; Zhan et al., 2013). At the watershed scale, hydrological simulations can provide valuable insights regarding system behavior, relevant processes, and how processes vary across different sites (Euser et al., 2013; Hrachowitz et al., 2014), especially when historical observations are available. While watershed models representing a range of complexity exist (Clark et al., 2008; Song et al., 2015), numerous studies have leveraged conceptual models to study watersheds across various hydro-climatologic conditions (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; Pianosi et al., 2015; Sarrazin et al., 2016; Shafii et al., 2015).

By simplifying relationships between model parameters and simulated watershed processes, conceptual models enable straightforward evaluation that can be exploited to advance our understanding of controls on model performance. In particular, diagnostic methods applied to conceptual watershed models can aid in evaluating model behavior with respect to the physical system (Gupta et al., 2008; Wagener et al., 2009). The parsimony of conceptual models further enables rapid simulations that facilitate diagnostic evaluations capable of spanning multidecadal periods and numerous watersheds. These diagnostic evaluations are often performance-based, evaluating the suitability of a model for a specific application by comparing the observed and simulated streamflow values (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; Pianosi et al., 2016; van Werkhoven et al., 2008). Sensitivity Analysis (SA) is one type of performance-based diagnostic analysis that continues to be used for model calibration, diagnostic evaluation, dominant control analysis, and even robust decision-making. It can also be used to evaluate the consistency of model behavior with expected system behavior, even when output observations are not available (Hartmann et al., 2015; Oreskes et al., 1994; Wegener & Pianosi, 2019). Generally, SA methods have been used to interpret model behavior in the context of the system being modeled and to identify which parameter inputs to a given model are most important to model performance (Ghasemizade et al., 2017; Pianosi et al., 2016).

The hydrologic community has applied SA toward numerous objectives. Time-varying SA, in which variance-based methods are applied to different time steps, can be used to determine parameter impact on the model performance through time (Garambois et al., 2013; Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; Pianosi et al., 2016; Wagener et al., 2003, 2001). To date, many studies have applied time-varying SA across numerous periods and time-step lengths (Garambois et al., 2013; Ghasemizade et al., 2017; Pianosi et al., 2016). When these approaches have been applied to multiple watersheds, studies have revealed that parameter sensitivity varies across hydro-climatic gradients (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; van Werkhoven et al., 2008). However, these studies have primarily focused on large, relatively distant watersheds where parameter controls are likely to be quite different. Also, many of these time-varying analyses focus on shorter periods (e.g., 10 years) and do not take into account how parameter importance varies during very wet periods or periods of drought. Thus, it is unclear if parameter importance varies linearly with fluctuating annual conditions or exhibits threshold behavior during annual extremes. Finally, few studies have combined these two approaches, leveraging a long-term period with extreme annual conditions and multiple proximal watersheds of varying sizes, to examine how parameter controls on model performance vary through time and across watersheds.

This study leverages time-varying, variance-based sensitivity analysis to evaluate a lumped watershed model framework applied to simulate streamflow in 21 watersheds located across California. Californian watersheds represent an ideal place to implement time-varying SA to assess the impact of annual variability on

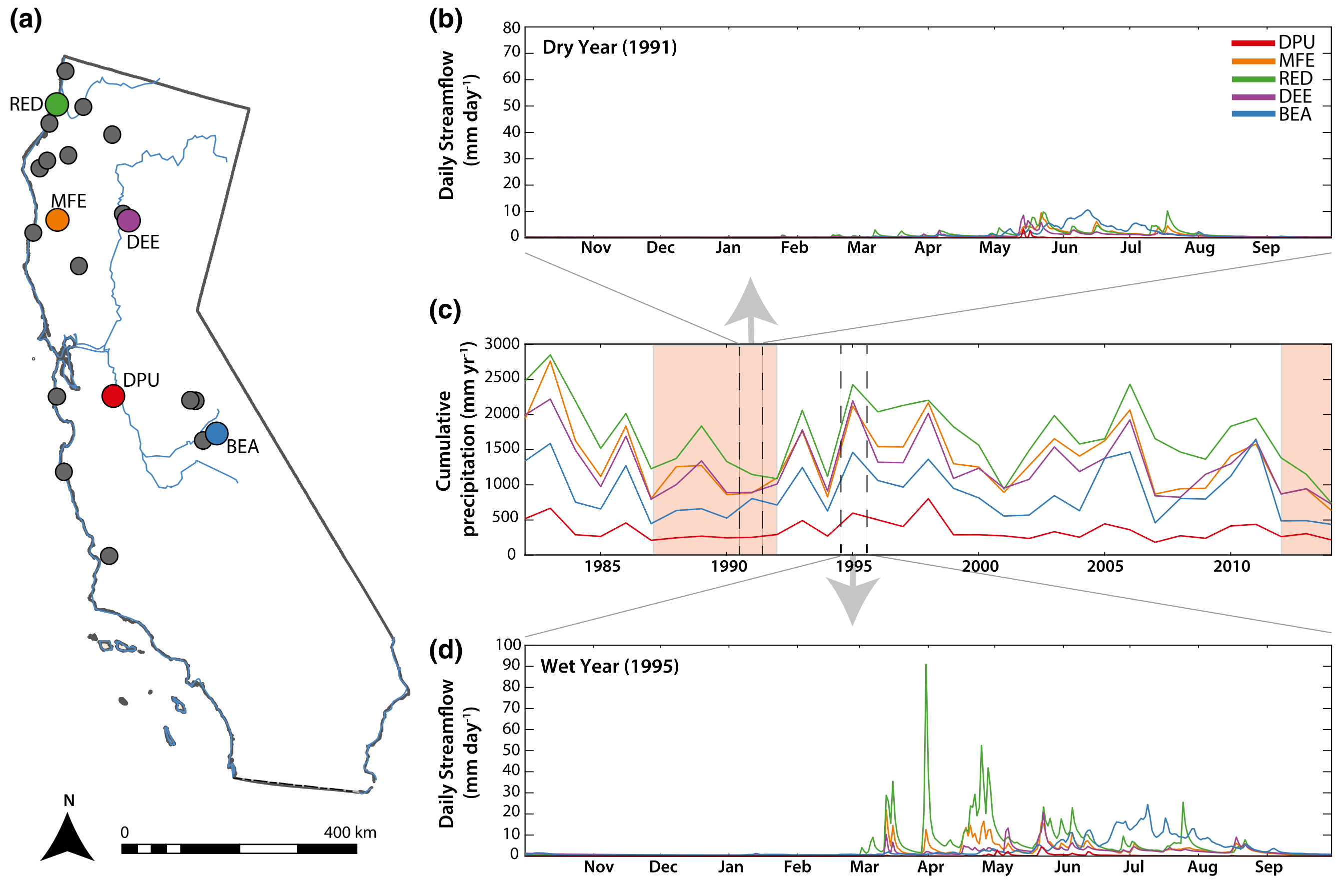


**Figure 1.** (a) Location of study watersheds and (c) annual differences in cumulative precipitation across five random study sites. Colored circles indicate sites represented in time series plots. Drought periods are highlighted in time series plots in red. Hydrographs are scaled to highlight the differences in streamflow during dry and wet years. During 1995, water year streamflow in some of the watersheds was almost 10 times higher (d) compared to the dry year (b). Timing of the hydrograph varies since watersheds are located at different elevation. For example, BEA has a mean elevation of 3,245 m, which results in delayed peak streamflow.

hydrologic dynamics given large variations in annual air temperature and precipitation as well as intense droughts these regions have experienced. Our analysis includes sites in three different regions across the state: watersheds located in the Sierra Nevada Mountains (snowmelt driven), watersheds located in northern California (high rainfall), and watersheds located in the Central Valley (low rainfall) (Figure 1). As precipitation availability across California watersheds may vary by an order of magnitude from year to year, identifying how controls on model performance vary at an annual scale and across watersheds is essential for determining how our approaches to calibration may need to change based on the period being simulated and to quantify environmental impacts on hydrologic systems. We first use a data-driven approach to quantify hydrologic signatures across these watersheds and to what extent these signatures vary from year to year. Next, we implemented model-based assessment of annual parameter sensitivity calculated with respect to metric of model performance (Kling-Gupta Efficiency, KGE) and the difference between observed and simulated hydrologic signatures, used to quantify different aspects of hydrologic functioning. In this analysis, our primary goal was to determine whether or not parameter sensitivities with respect to model error and model signatures across regionally distributed watersheds varied through time and space and to what extent this could be organized by watershed climate and topography. We hypothesized that parameter importance would vary from year to year, as strong annual weather shifts likely play an important role in parameter sensitivity. Since drought has been shown to have a profound effect on watershed function, we also expected parameter importance to shift during drought periods to parameters that are insensitive during average or wet periods. To our knowledge, this type of rigorous temporal parameter sensitivity comparison has not been published to date and thus is significant for filling the existing knowledge gap in this field.

Alongside field observation, this type of approach has the potential to identify important watershed processes and how they vary during shifting weather conditions, which could be used to improve our understanding of model-inferred dominant hydrologic processes and how these processes may vary over multidecadal periods and across relatively proximal watersheds.

## 2. Materials and Methods

### 2.1. Study Area

To analyze the time-varying nature of hydrologic systems in relatively proximal watersheds, our study focuses on 30 watersheds that vary in size, elevation, location, and climate (Figure 1). All selected watersheds are minimally impacted by human activity, to allow us to analyze how hydrological processes respond solely to weather shifts. Most study watersheds experience a Mediterranean climate with hot, dry summers and mild, rainy winters. At higher altitudes, the weather reflects a four-season cycle with snowy winters followed by snowmelt in spring. Prior studies have shown that watersheds in the Sierra Nevada receive annual snowfall during an exceptionally short time period compared to other mountain ranges in the western United States (Lundquist et al., 2015; Serreze et al., 2001). In California, streamflow is dominated by snowmelt at high elevations and by winter rainfall at lower elevations where temperatures are too warm to accumulate snow (Knowles et al., 2006; Luce et al., 2014). Information about average climate conditions, mean watershed elevation, drainage area, and other site characteristics can be found in Table S1. Throughout this study, the watersheds will be identified using three-letter abbreviations of the site name.

Our analysis spanned a 33-year period from October 1, 1980 to September 30, 2014. Daily streamflow across this period was extracted for all sites from the United States Geological Survey (USGS) gage network. During this period, annual cumulative precipitation at study sites varied by an order of magnitude (Figure 1). The region also experienced two major droughts, one from 1987 to 1992 and one from 2012 to 2016 (USGS). Drought periods were classified as extreme years in this study.

### 2.2. Rainfall-Runoff Modeling

The selection of a hydrological model framework should depend on the application, available data, and knowledge of the system being studied (Clark et al., 2011; Kadane et al., 2004; Nilsen, 2015; Wagener et al., 2005). For this analysis, we used a conceptual lumped rainfall-runoff model, Hymod. Hymod is a parsimonious daily step watershed model based on the Probability Distributed Model (Moore, 2007). This model is widely applied in practice and is useful for representing simplified hydrologic systems (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; Pianosi et al., 2015; Sarrazin et al., 2016; Shafii et al., 2015). As multiple versions of Hymod exist, we include schematic representation for the model framework used in our analysis (Figure 2).

We used a version of Hymod with 10 parameters; parameter ranges are reported in Table S2. Our warm-up period extends from October 1, 1980 to September 30, 1981, and our simulation period runs from October 1, 1981 through September 30, 2014. In this model, two input variables (average temperature, precipitation) are used to simulate streamflow, which is controlled by soil storage, quick flow parameters, and slow flow parameters (Figure 2). Time series of daily meteorological inputs for the study sites were obtained from the Catchment Attributes and Meteorology for Large-sample Studies (CAMELS) data set (Addor et al., 2017; Newman, Clark, Craig, et al., 2015; Newman, Clark, Sampson, et al., 2015). Streamflow was obtained from USGS streamflow data. Potential evapotranspiration (PET) was computed following:

$$\mathrm{PET} = \frac{R_e}{\lambda\rho}\frac{T_a + 5}{100} \quad \text{if } T_a + 5 > 0 \tag{1a}$$

$$\mathrm{PET} = 0 \quad \text{otherwise} \tag{1b}$$

where PET is the rate of potential evapotranspiration (mm day$^{-1}$), Re is extraterrestrial radiation (MJ m$^{-2}$ day$^{-1}$), $\lambda$ is the latent heat flux (MJ kg$^{-1}$), $\rho$ is the density of water (kg m$^{-3}$), and $T_a$ is mean daily air temperature (°C) (Oudin et al., 2005). This approach was selected as it has been shown to outperform other

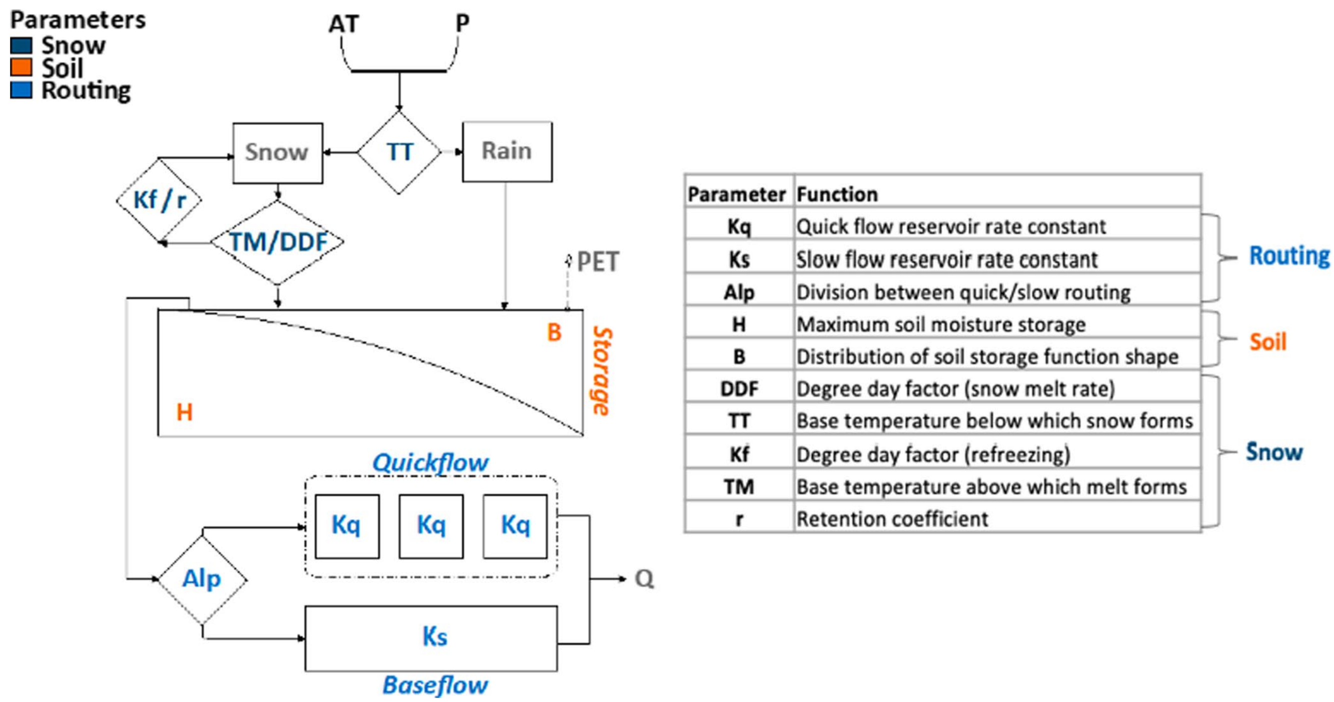


**Figure 2.** Model Framework: Hymod model with snow routine that incorporates refreezing capability. The model has two inputs (average daily temperature [AT] in °C and daily precipitation [P] in mm day$^{-1}$), 10 parameters (described in the figure) and one output (streamflow [Q] in mm day$^{-1}$). Potential evapotranspiration (PET) is calculated within the model to account for water loses occurring in the real world.

estimation approaches in a rainfall-runoff modeling across multiple watersheds (Oudin et al., 2005). As several sites used in this study are located at high elevations, we combined the Hymod framework with a parsimonious snow accumulation and melt model that incorporates the refreezing capability of snowpack (Kokkonen et al., 2006). Since our study sites span variety of elevations and available precipitation levels, it was important to use a model that not only accurately captures evapotranspiration, but can also simulate snow accumulation and melt processes. Altogether, the model framework includes three model parameters related to streamflow routing, two model parameters related to soil processes, and five model parameters related to snow routine. These groupings are used throughout the rest of the manuscript.

### 2.3. Sensitivity Analysis

Sensitivity analysis is a diagnostic method used to attribute variation in model output (e.g., error metric) to variations in model inputs (e.g., parameters) (Saltelli, 2008; Saltelli et al., 2010). If the model is assumed to accurately conceptualize watershed behavior and functioning, these sensitivity results may also be interpreted to indicate the importance of watershed characteristics or functions, represented by parameters (Wagener & Pianosi, 2019). Time-varying SA, a particular type of SA, is often used to determine whether parameter importance varies through time (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; O'Loughlin et al., 2012; Reusser et al., 2011; van Werkhoven et al., 2008; Wagener et al., 2003, 2001, 2009), more specifically for our case, potentially in response to oscillating wet and dry conditions. We applied the global Sobol' method (Sobol', 2001) pointwise in time to decompose the variance of model performance into total-order contributions per model parameter. Though this method yields an assessment of first and total order sensitivity, for brevity, we analyzed the total sensitivity index as it represents the sum of individual parameter contributions as well as the interactions of one parameter with other parameters for each water year. It is defined according to:

$$S_{T_i} = 1 - \frac{D_{\sim i}}{D} \tag{2}$$

where $D_{\sim i}$ is the variance contributed by all parameters except $i$. Parameters that produced total-order sensitivity values greater than 0.3 were interpreted as sensitive. This threshold is somewhat arbitrary, and therefore we also display total sensitivity indices throughout our results, such that the magnitude of sensitivity can also be interpreted. Annual values of total order sensitivity were computed for all 10 parameters per error metric and signature, per watershed, and per year.

Sampling of the parameter space was performed using near-random Latin Hypercube sampling (McKay et al., 1979) to achieve uniform distribution of sampling across the parameter space. For this study, we used a total of 60,000 parameter sets per watershed. In addition, we performed the same analysis method using 72,000 parameter sets to verify that model results do not depend on the selected sample size (Nossent et al., 2011; Sarrazin et al., 2016; Yang, 2011). Comparison between runs with different number of parameter sets is shown in Figure S1.

An assumption made in the interpretation of sensitivity analysis is that a given model is a good representation for the system—in this case, observed streamflow at our study watersheds. Given the equifinality inherent to all hydrological models, we do not use an optimization approach to calibrate. Instead, we report the top 1% of total order sensitivity index values obtained for the 33-year simulation period per watershed, per metric, and per year (Table S3), and use this to determine for which watersheds the model yields a reasonable approximation of observed streamflow.

### 2.3.1. Metrics of Model Performance

Objective function selection is a key step in the sensitivity analysis workflow. The choice of output metric has been found to substantially impact measurements of model behavior and thus assessment of parameter sensitivities (Diskin et al., 1977; Gupta et al., 1998, 2008). We used an annual, multicriteria approach to evaluate model performance, parameter sensitivity, and modeled hydrologic system behavior, incorporating both an error metric and hydrologic signatures. We selected the Kling-Gupta Efficiency (KGE) coefficient to evaluate agreement between simulated and observed streamflow. We chose this error metric as previous work has suggested it may be superior to the widely used Nash Sutcliffe Efficiency (NSE) when assessing rainfall-runoff models (Gupta et al., 2009). This is because KGE accounts for different aspects of the model performance, while NSE tends to focus on the performance for high flows only. KGE was calculated according to:

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \tag{3a}$$

$$\alpha = \frac{\sigma_s}{\sigma_o} \tag{3b}$$

$$\beta = \frac{\mu_s}{\mu_0} \tag{3c}$$

where $r$ can be interpreted as the linear (Pearson) correlation coefficient between simulated and observed streamflow, $\alpha$ is a measure of relative variability in the simulated ($\sigma_s$) and observed ($\sigma_o$) standard deviation values (taken as a representation of time-step analyzed), and $\beta$ is the ratio between the mean simulated ($\mu_s$) and mean observed daily streamflow values ($\mu_0$), which represents bias. Total order sensitivity indices were calculated with respect to annual KGE.

### 2.3.2. Hydrologic Signatures

Hydrologic signatures are metrics that quantify various aspects of streamflow response that are derived from series of hydrological data such as precipitation, soil moisture, or streamflow. They are designed to extract relevant information about hydrological behavior of the system as each metric is designed to quantify underlying process that is linked with a particular hydrologic signature. Due to this ability to capture and quantify hydrologic behavior (McMillan, 2019), hydrologic signatures have many applications. Here, we applied signatures to evaluate whether simulations accurately represent watershed behavior and to link dominant model parameters with hydrologic signatures using sensitivity analysis. To explore variability in hydrologic signatures across watersheds and through time, we reported annual values for four hydrologic signatures: the runoff ratio (RR), the slope of flow duration curve (SFDC), the baseflow index (BFI), and the timing of streamflow centroid (CT). The runoff ratio is used to estimate overall water balance and its loss to groundwater, which was calculated using the following formula:

$$\mathrm{RR} = \frac{\sum_{i=1}^{N} Q_i}{P} \quad (4)$$

where $Q$ is $i$th daily streamflow (mm day$^{-1}$) and $P$ is cumulative annual precipitation (mm year$^{-1}$), $N$ is number of days in a year. BFI captures what proportion of streamflow is contributed by baseflow and was calculated based on previous study proposed by Lyne and Hollick (1979) and corroborated by Eckhardt (2004, 2008) using one-parameter single-pass digital filter method:

$$\mathrm{BFI} = \frac{\sum_{i=2}^{N} \left( c \times b_{i-1} + \left( \frac{1-c}{2} \right) \times \left( Q_i + Q_{i-1} \right) \right)}{\sum_{i=1}^{N} Q_i} \quad (5)$$

where $b_i$ is baseflow at time-step $i$ (mm day$^{-1}$), $Q_i$ is the total flow at time-step $i$ and $c$ is streamflow filter value of 0.925 recommended by Nathan and McMahon (1990). Equation 5 is subject to $b_i \leq Q_i$. SFDC was calculated between 33rd and 66th percentile flows, since this represents a relatively flat part of FDC at a semi-log scale (Yadav et al., 2007; Zhang et al., 2008):

$$\mathrm{SFDC} = \frac{\ln\left(Q_{66}\right) - \ln\left(Q_{33}\right)}{0.33 - 0.66} \quad (6)$$

where $Q_{66}$ is streamflow (mm day$^{-1}$) at the 66th percentile and $Q_{33}$ is streamflow (mm day$^{-1}$) at the 33rd percentile. Discharge seasonality was examined by calculating timing of streamflow centroid (Stewart et al., 2005):

$$\mathrm{CT} = \frac{\sum_{i=1}^{M} t_i \times Q_{c_i}}{\sum_{i=1}^{M} Q_{c_i}} \quad (7)$$

where $t_i$ is time (on scale 0–1) from the beginning of the water year, $Q_{ci}$ is streamflow corresponding with the centroid of streamflow, and $M$ is the number of days it takes to reach the streamflow centroid.

We assessed parameter sensitivity to hydrologic signatures in terms of a percent error, calculated as the absolute value of the difference between the observed and simulated signature values, normalized by the observed signature value, per year and per watershed. As the study sites chosen are located in a region with prominent drought periods, comparing the values of these signatures (as well as testing parameter sensitivity with respect to these annual signatures) across a range of conditions is important in order to form an empirical basis for inferring similarities and differences in parameter importance across watersheds.

### 2.4. Parameter Sensitivity and Annual Conditions

To examine relationships between annual conditions and parameter sensitivity, we compared annual total order sensitivity indices with average air temperature and total annual precipitation within each watershed. Due to the form of these relationships, we presented these comparisons as linear regressions between annual air temperature or precipitation and total order sensitivity indices. We reported Pearson correlation coefficient ($R$) to evaluate the strength of these relationships.

To assess whether periods of drought impact parameter importance and lead to shifts in dominant processes, we compared distributions of total order parameter indices between drought years and nondrought years. Statistical significance was determined using the Kolmogorov-Smirnov (K-S) test (at 5% significance level), which evaluates sample probability distributions and statistically quantifies a distance between the empirical distribution functions of two samples. We report P-values to evaluate if total order sensitivity

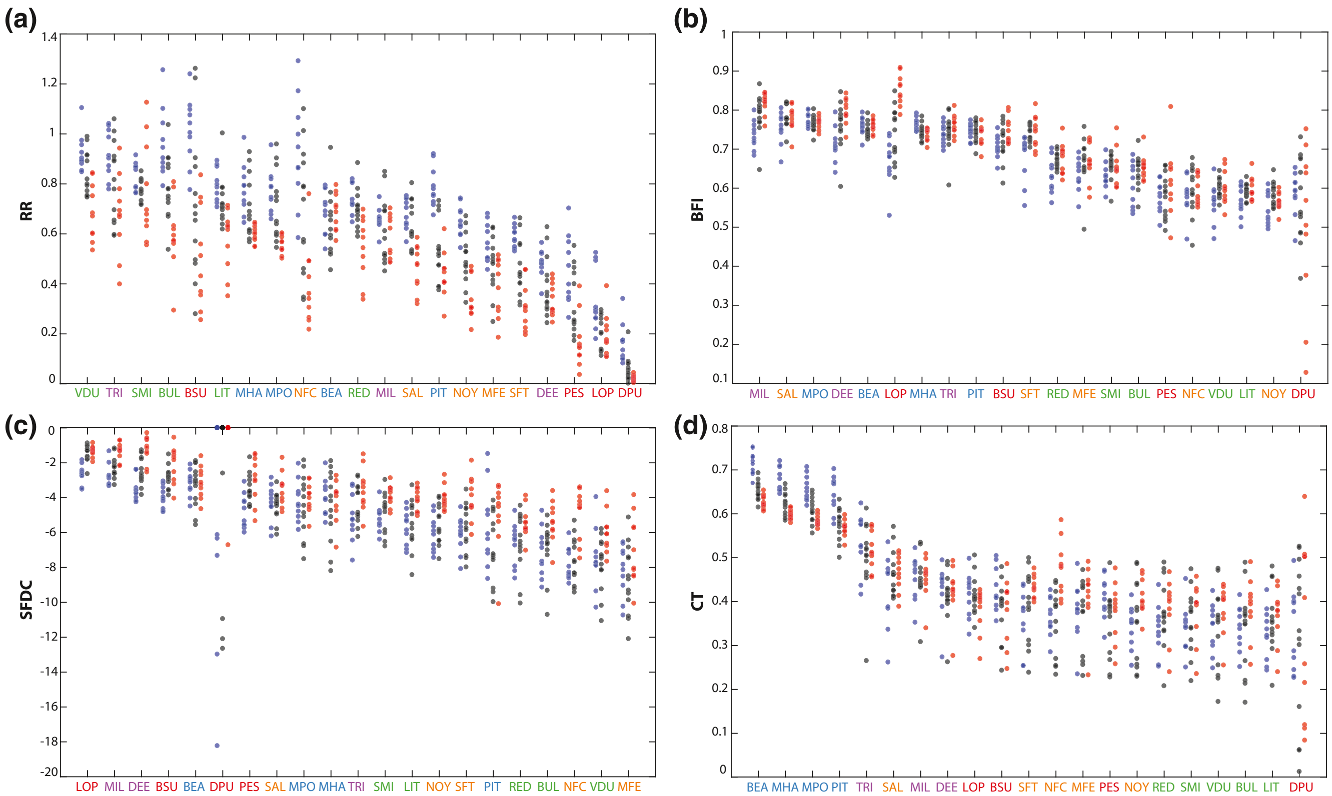


**Figure 3.** Hydrologic signature values during dry (red), moderate (black), and wet (blue) years for (a) RR, (b) BFI, (c) SFDC, and (d) CT. Watersheds were organized by average hydrologic signature value. While RR and SFDC responses were consistently influenced by precipitation in most watersheds, BFI and CT values during dry and wet years differed only for a subset of watersheds. RR values were typically lower during dry years, while SFDC values were higher during low precipitations years indicating a flatter flow duration curve. BFI, baseflow index; CT, centroid; RR, runoff ratio; SFDC, slope of flow duration curve.

index during drought and nondrought years are significantly different ($P$-value<0.05) for KGE and hydrologic signatures.

## 3. Results

### 3.1. Hydrologic Signatures

Annual hydrologic signatures calculated across study watersheds are illustrated in Figure 3. These signatures had varying magnitudes between watersheds and years. While most watersheds exhibited minimal changes in signature values throughout the years, our driest site (DPU) recorded the greatest variability across the 33-year period most often. BFI, SFDC, and CT signature values in DPU were noticeably more variable compared to other study sites (Figure 3).

In Figure 3, signature values were colored by annual precipitation rank, to discern whether signatures shifted in response to total annual precipitation. 10 years with the lowest amount of precipitation were classified as dry years, 10 years with the highest amount of precipitation were classified as wet years, and remaining years were classified as moderate years. Watershed responses were consistent for RR and SFDC. RR, for instance, was typically lower during low precipitation years and higher during high precipitation years across all watersheds (Figure 3a). SFDC was closer to zero (flatter slope) during drier years, and more negative (steeper slope) during wetter years (Figure 3c). In contrast, CT and BFI during wet versus dry years only differed for a subset of watersheds. For BFI (Figure 3b), it was difficult to discern any pattern relating signature values and wet versus dry years; some watersheds exhibited higher BFI during drier periods (e.g., LOP) while others showed the opposite (MHA), and others showed no difference. CT values were influenced by total precipitation only in snowmelt dominated regimes; in these watersheds, CT values were larger than for other watersheds. Wetter years corresponded to later flow centroid timing (Figure 3d). Flow timing was not discernably organized by total annual precipitation for rain-dominated watersheds. Overall, these hydrologic signatures span a wide range. Given the regional scale of this investigation, the large differences across relatively proximal watersheds are impressive and notable.

### 3.2. Model Performance

Prior to analyzing sensitivity results, we verified that streamflow simulated within the Hymod framework could reasonably match observations. Summary statistics for the top 1% and overall KGE values are reported in Tables S3 and S4. In addition to assessing error metric statistics for the best performing simulations, we also analyzed statistics associated with the most poorly performing simulations and confirmed that no simulations exhibited abnormally low values that could potentially impact sensitivity results.

Annual parameter sensitivity values for KGE were compared to values generated from the whole study period in Figure S2. For the majority of our study watersheds, the achieved KGE values indicated that the model produced reasonably accurate simulations that reflected observed streamflow across a relatively long period (33 years). For 21 of 30 study watersheds, average KGE values ranged from 0.52 to 0.82. However, nine watersheds averaged KGE values below 0.5 (Table S3). To eliminate any uncertainty in streamflow behavior and therefore key watershed functions due to inaccurate model simulations, we eliminated these watersheds from further analysis. Model runs that were not able to surpass a 33-year average KGE value of 0.5 were interpreted to indicate that the chosen model framework did not accurately simulate streamflow behavior in these systems. All eliminated watersheds except one received limited precipitation, with annual averages ranging from 294 to 963 mm year$^{-1}$.

### 3.3. Annual Sensitivity Indices Across Metrics

Sobol' total order sensitivity indices were computed for all study sites at an annual timescale with respect to KGE and four hydrologic signatures (RR, SFDC, BFI, and CT). Figures 4 and 5 contain average and the standard deviation of parameter sensitivities for KGE and hydrologic metrics summarizing 33 years of total order values across all sites. Prior to examining annual differences, we first evaluated the standard deviations and averages of all sensitivity indices, to summarize how the magnitude of parameter sensitivity varied across the 33-year record. Higher magnitude standard deviation values were interpreted to indicate that parameters varied through time more often. Parameter sensitivities with respect to KGE revealed that average total order indices varied from site to site as well as in time; the importance of routing, soil, or snow parameters varied by watershed. Similarly, parameter sensitivity values for CT indicated high spatial and temporal variability, while parameter sensitivities calculated with respect to the other three hydrologic signatures exhibited less variability by comparison (Figures 4 and 5).

Figures 4 and 5 also show that the number and type of sensitive parameters differed between error metrics. Across our 33-year study period, the number of parameters as well as the magnitude of parameter sensitivity varied among sites. Average total order sensitivity indices suggested that as few as one and as many as five parameters were sensitive to KGE (Figure 4a). This is noteworthy, as these watersheds are all relatively proximal. However, only one parameter ($K_s$) was sensitive to SFDC across all 21 watersheds (average total order sensitivities for $K_s$, slow flow reservoir rate constant, exceeded 0.3). Predictions of BFI were most sensitive to the three parameters associated with routing ($K_s$, $K_q$, Alp), while RR was most sensitive to parameters associated with soils (H, B). CT was most sensitive to $K_s$, but also registered extensive temporal variability, as indicated by large standard deviations for multiple parameters.

### 3.4. Spatial Patterns in Time-Varying Sensitivity Indices

Though a few hydrologic signature metrics displayed analogous patterns in parameter sensitivities across watersheds (Figure 5), patterns for KGE differed greatly (Figure 4a). These KGE patterns were used to visually group study watersheds into five distinct categories of total order sensitivities based on dominant parameters (Figure 6). Figure 6 illustrates watershed groupings, precipitation differences, and locations of these sites. The first three groups are located along the coast and spans a gradient of precipitation from low (Group 1), to intermediate (Group 2), to high (Group 3). Group 4 and Group 5 watersheds are located

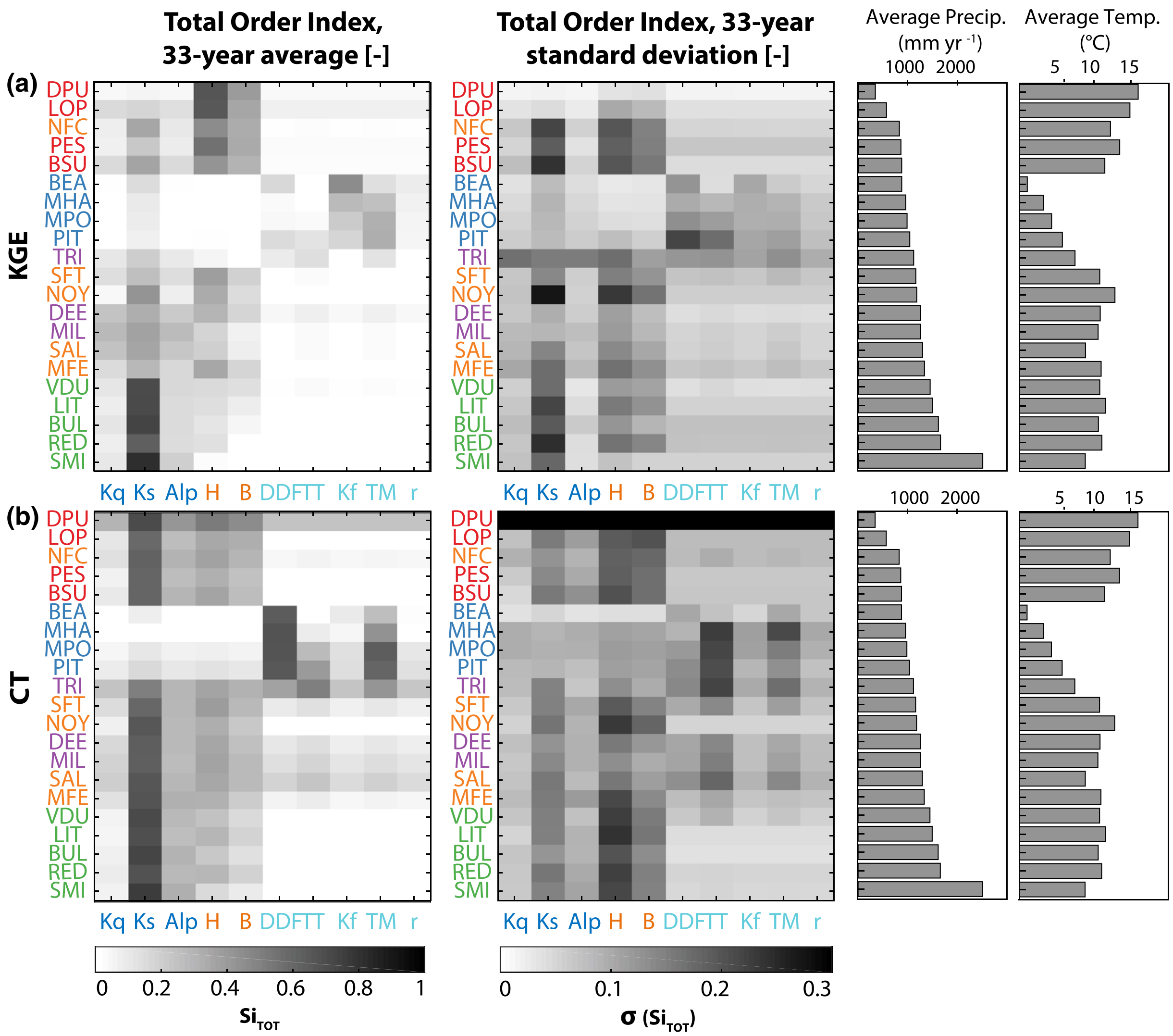


**Figure 4.** Average and standard deviation of annual total order sensitivity index values (33 years) for (a) KGE and (b) CT reveal how parameter sensitivity differs between sites. Average values (left) highlight sensitive parameters, while standard deviations (right) illustrate how parameter sensitivity varies from year to year. Average annual cumulative precipitation and temperature values emphasize the differences between study sites. CT, centroid; KGE, Kling-Gupta Efficiency.

further from the coast and at higher elevations. Parameter sensitivities to hydrologic signatures are also generalized within Figure 6. These patterns revealed differences in parameter sensitivity between signatures and across sites. For most watersheds, SFDC and BFI are dominated by sensitivity to routing parameters, while RR is sensitive to soil parameters. CT is dominated by a combination of routing and soil parameters. Watersheds with hydrologic responses dominated by snow (Group 5) exhibited distinct patterns of parameter sensitivity as compared to rain-dominated watersheds.

Annual total order indices are shown for one characteristic watershed within each group in Figure 7 and Figure S3. These results demonstrate that different combinations of parameters dominate in different watersheds. Dominant parameters within each group reflect differences in watershed location and climate, underscoring the importance of hydroclimatology to ensuring accurate streamflow predictions. In some cases, these patterns displayed discrete differences. For example, watersheds located at high elevations in the Sierra Nevada Mountains were dominated by snow parameters (expected of a snowmelt dominated system), while watersheds around the Central Valley were dominated by parameters conceptualizing soil water processes. In other cases, these patterns revealed how gradients of sensitivity vary in kind with watershed average precipitation totals. For instance, $K_s$ was insensitive to KGE (Figure 7) in drier watersheds (Group

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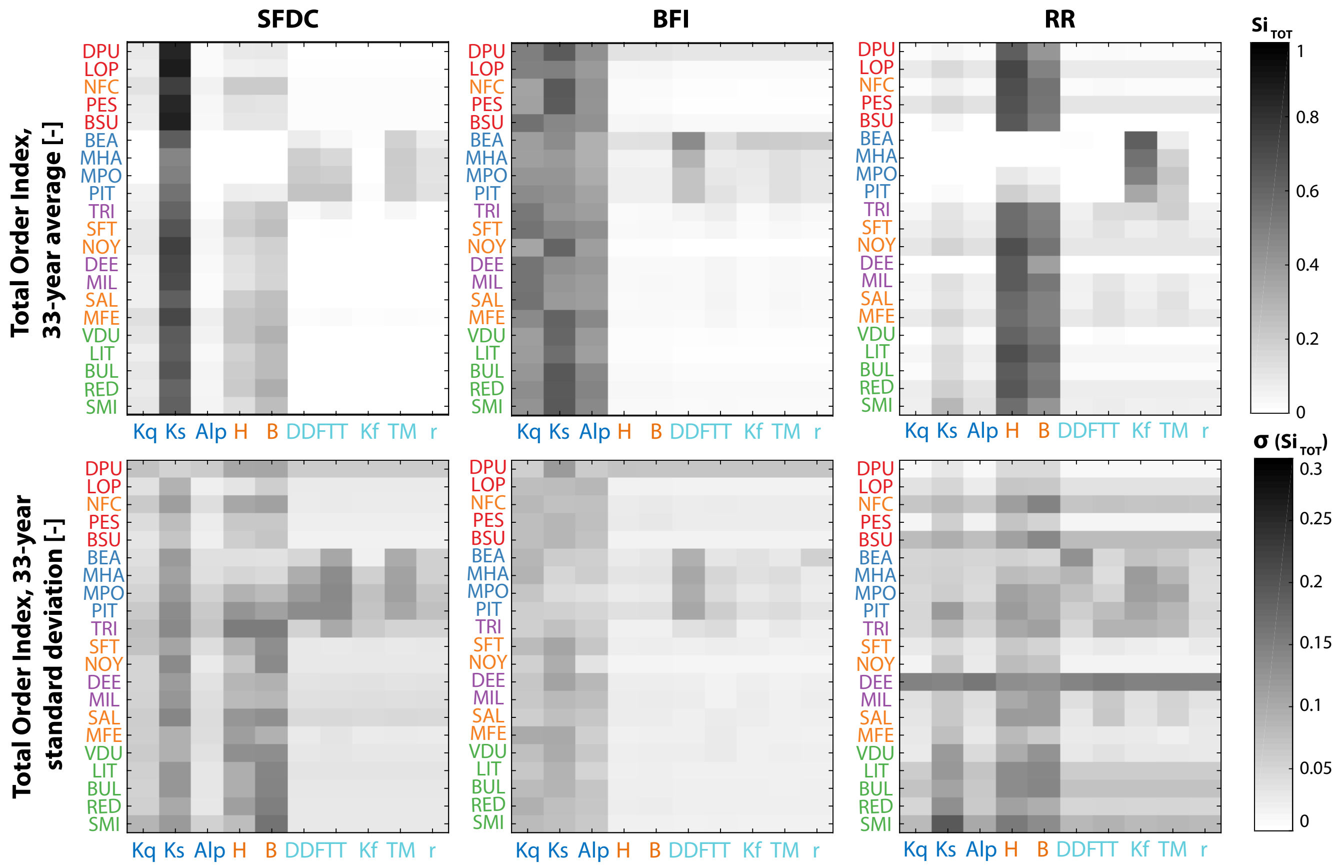


**Figure 5.** Average and standard deviation of annual total order indices for SFDC, BFI, and RR. Watersheds were organized by average annual cumulative precipitation values like in Figure 4. Parameter sensitivities with respect to SFDC, BFI, and RR revealed that average total order indices varied much less in time as well as among sites compared to KGE and CT. BFI, baseflow index; CT, centroid; KGE, Kling-Gupta Efficiency; RR, runoff ratio; SFDC, slope of flow duration curve.

1), more sensitive as average annual precipitation totals increased (Groups 2, 4, 5), and dominant for the wettest watersheds (Group 3).

Two periods of drought are highlighted in Figure 7: 1987–1992 and 2012–2016. Total order sensitivity indices calculated with respect to KGE displayed significant ($p$-value < 0.05) differences as compared to indices during nondrought water years (Figure S4). In contrast, sensitivity indices calculated with respect to hydrologic signatures were significantly different between drought and nondrought years only for certain sites (Figure S5).

### 3.5. What Influences Dominant Parameters?

SA results with respect to KGE were further analyzed to assess potential relationships between sensitivity indices and site characteristics. The goal of this analysis was to determine if annual air temperature and precipitation could be empirically linked to annual magnitudes of sensitivity indices. Total annual precipitation across the analysis period varied drastically among our study watersheds (Figure 6). The average annual precipitation across study sites varied from as little as 352 mm (DPU) to as much as 2,571 mm (SMI). Annual precipitation totals also varied extensively from year to year. In DPU, the driest watershed among our study sites, cumulative annual precipitation during our study period ranged from 183 to 804 mm, a fourfold increase.

As total annual precipitation and average air temperature varied widely among sites as well as from year to year, we analyzed whether these annualized conditions were related to the magnitude of time-varying sensitivity indices across individual watersheds and groups of watersheds. Relationships between select KGE

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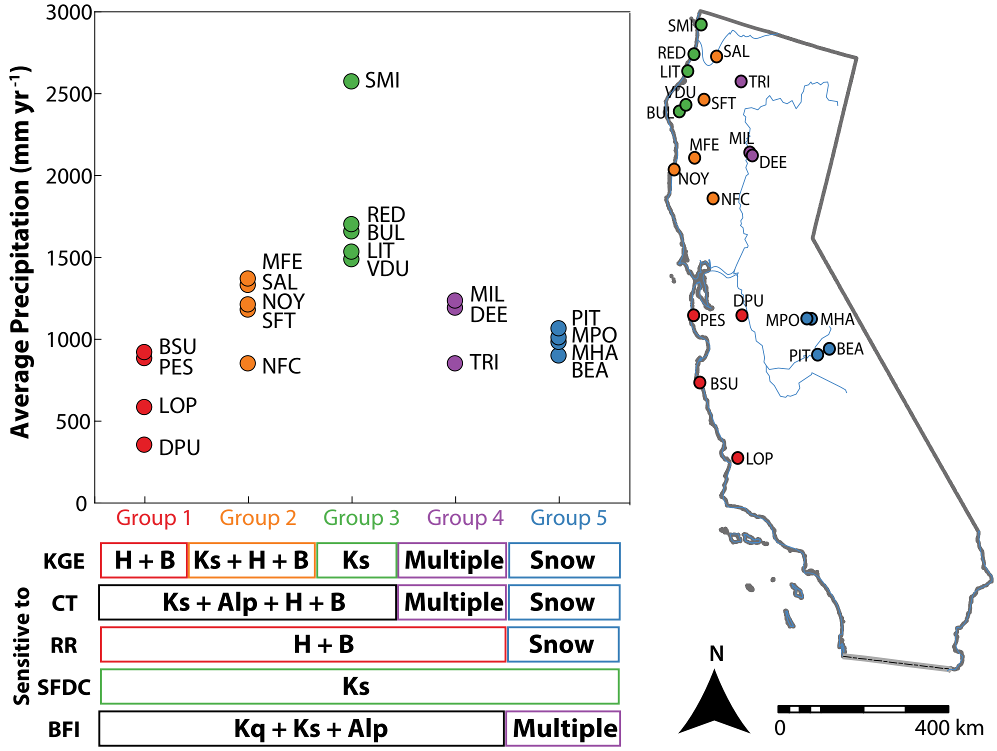


**Figure 6.** Watersheds were grouped based on their dominantly sensitive parameters to KGE. These groupings are geographically explicit (right) and correspond to different hydroclimates (shown in terms of average annual precipitation, left). Watersheds located at high elevations (Group 5) were dominated by snow parameters, sites located in dry regions like the central valley (Group 1) were sensitive to soil processes, while watersheds located in the northern CA wet regions (Group 3) were dominated by *Ks*. Occasional deviations from these patterns occur during certain years. Parameters sensitive to hydrologic signatures were less variable among sites. KGE, Kling-Gupta Efficiency.

total order sensitivities and total annual precipitation were strong. Years with greater annual precipitation displayed greater sensitivity to $K_s$ (Figure 8). Annual precipitation was also inversely related to soil parameter total sensitivities ($H$, maximum soil moisture storage, and $B$, distribution of soil storage function shape; Groups 1, 2, 3). Fitted trend lines and correlation coefficient ($R$) values demonstrate that despite varying sensitivity index magnitudes, parameter responses to shifting precipitation levels were relatively consistent across sites in each group.

For sites dominated by the importance of snow parameters (Group 5), total order indices for snow parameters did not correlate with annual precipitation. Instead, annual variations in total order indices were correlated with average annual air temperature (Figure 9). These four watersheds span an elevation gradient, which also appeared to organize the range of total order indices. Total order indices for $K_f$ (refreezing) were larger for sites at greater elevations; total order indices for TM (base temperature above which melt occurs), were larger for sites at lower elevations. Notably, while correlations between total order indices for $K_f$ and air temperature were all positive, correlations between total order indices for TM and average air temperature were positive for three watersheds and negative for the watershed at the lowest elevation (PIT). This suggests that the importance of TM is elevation dependent.

## 4. Discussion

### 4.1. Parameter Importance Varies Through Time

In this analysis, one of our primary goals was to determine whether or not parameter sensitivities across regionally distributed watersheds varied through time, and to what extent this was organized by annual precipitation and air temperature. Although one potential criticism of the Sobol' method is that it relies

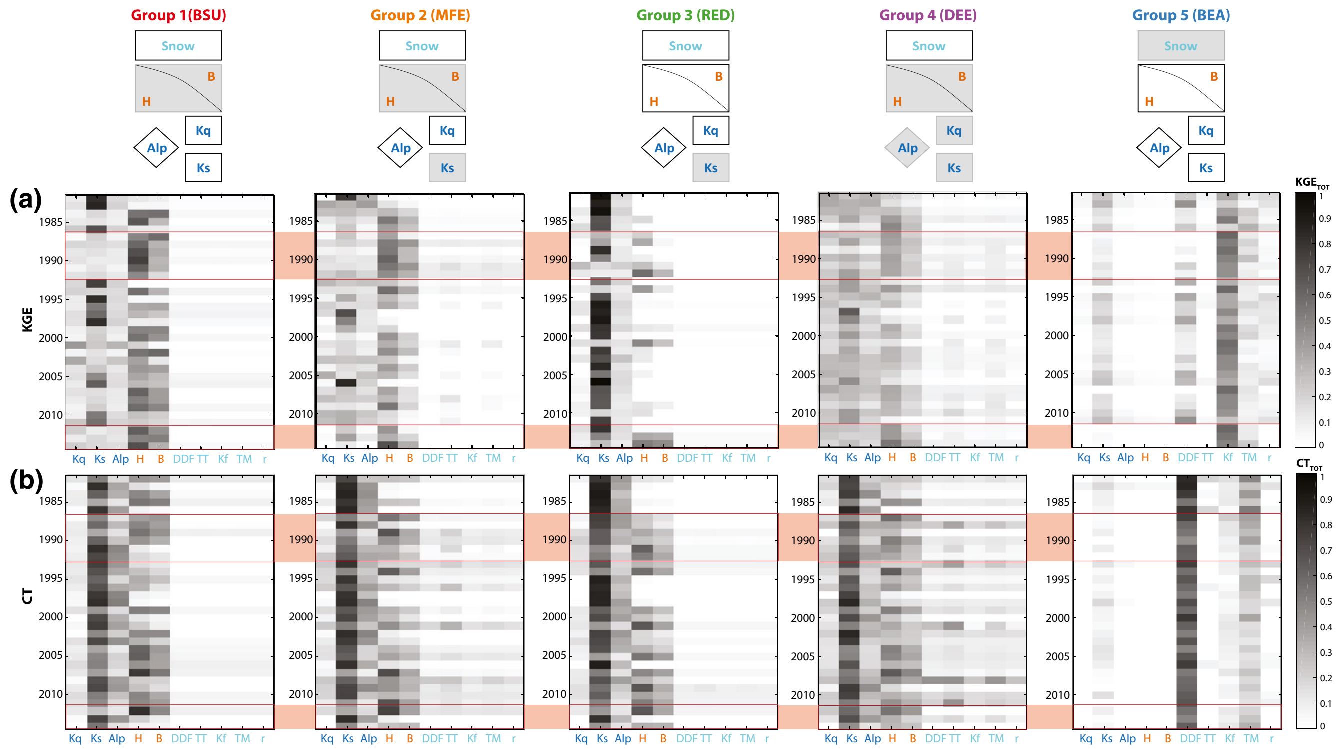


**Figure 7.** (a) Heat maps reflect the magnitude of annual parameter sensitivity indices for $KGE_{TOT}$, shown for one site characteristic of each watershed grouping. Group 1 watersheds were sensitive to soil parameters *H* and *B*. Group 2 watersheds were sensitive to a combination of $K_s$ and soil parameters, where magnitude and type of parameter sensitivity varied annually. Group 3 watersheds were dominated by $K_s$, with importance of *H* and *B* varying through time. Group 4 watersheds were sensitive to routing and soil parameters. Lastly, Group 5 watersheds were generally sensitive to snow parameters $K_f$, DDF, and TM. (b) Annual parameter sensitivity indices for $CT_{TOT}$ followed similar dominant parameter distribution, although differences for Groups 1–3 were less visible. KGE, Kling-Gupta Efficiency.

on output variance (Borgonovo et al., 2011; Dell'Oca et al., 2017), this approach was efficient in identifying changes in dominant parameters over time. Similarly, we employed a potentially subjective threshold to identify sensitive parameters, though we note that other approaches offer improvements on this assessment (Huo et al., 2019; Sheikholeslami et al., 2019). Across 33 years of data, we found that nearly all watersheds contained parameters that displayed time-varying sensitivity (Figures 4 and 5).

Although many studies have analyzed the effects of climate change on California's watersheds (Bales et al., 2006; Null et al., 2010; Thorne et al., 2015), research regarding SA in this region is limited. Other time-varying SA work has focused primarily on smaller time steps, showing that parameter importance changes during wet and dry periods (Ghasemizade et al., 2017; Herman, Reed, et al., 2013) or demonstrating relationships between parameter dominance and climate variables (van Werkhoven et al., 2008). This study represents one of the first to use time-varying SA to examine relationships between parameters and model performance metrics under oscillating annual extremes for period of 33 years. While annualized parameter importance did not change for some metrics (RR, BFI, SFDC; Figure S3), parameter importance exhibited exceptional temporal variability for simulating other metrics (KGE, CT; Figure 7). Dominant model parameters with respect to KGE shifted in response to varying annual conditions (Figures 8 and 9). Total order sensitivity indices across catchments varied from 0 (insensitive) to 0.8 (very sensitive), which illustrates the extent of time-varying parameter dominance we found across study watersheds. Other time-varying studies have found similar parameter sensitivity ranges while analyzing at national scales (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; van Werkhoven et al., 2008). However, changes in parameter sensitivity magnitudes are not well explored at regional and subregional scales.

Results of this study indicate that model performance, as well as dominant watershed controls, changed noticeably across much smaller spatial scales than previously thought. Most previous analyses have demonstrated that parameter sensitivity varies with hydroclimate at broad spatial scales (Herman, Kollat,

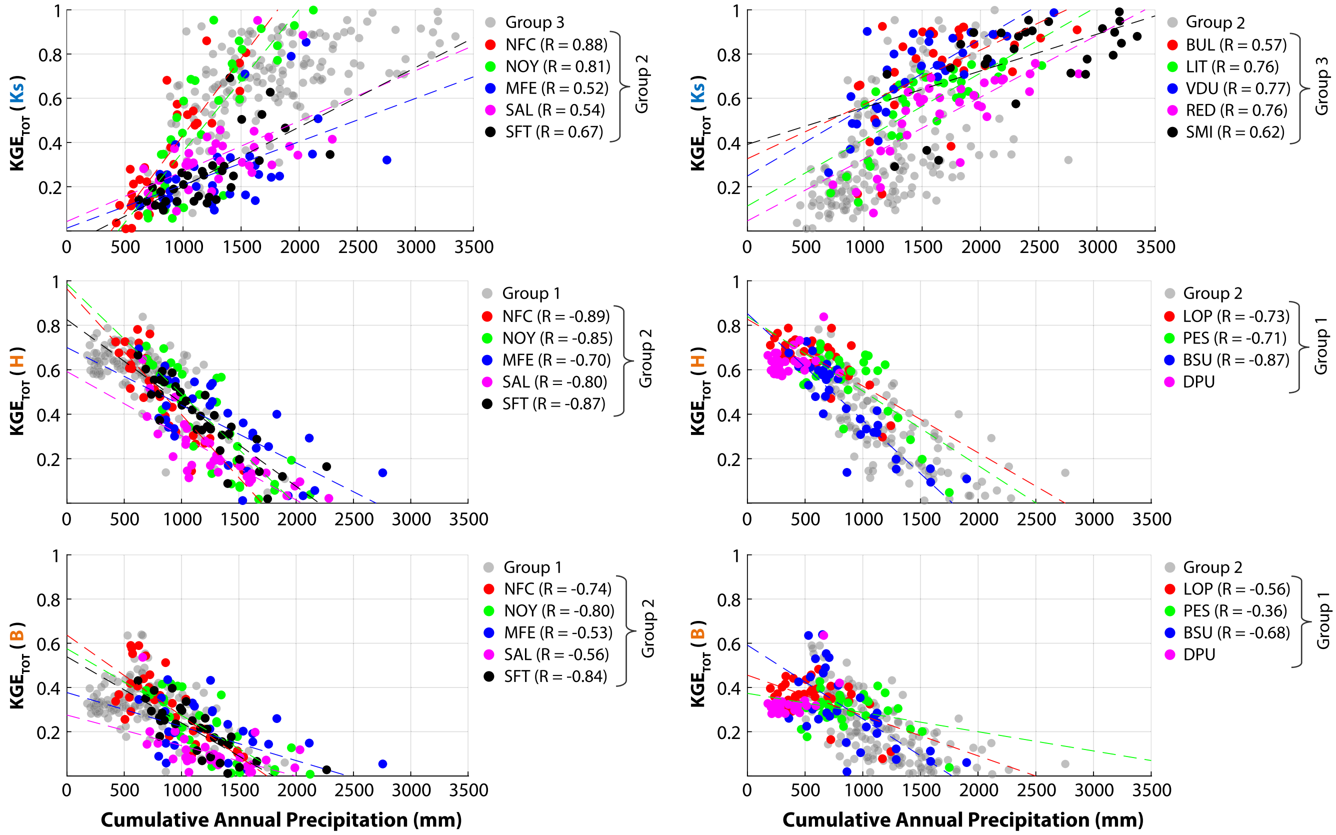


**Figure 8.** Cumulative annual precipitation (mm year $^{-1}$) effect on parameter sensitivity indices evaluated with respect to KGE. Each graph relates total order sensitivity and annual precipitation, with each point corresponding to a different year, and color corresponding to different sites. Results are shown for $K_s$ (top), $H$ (middle), and $B$ (bottom). Only one group is represented in color per graph. We report the correlation coefficient ($R$) of the strength of each linear relationship and display the trend line for each watershed. Visually, $K_s$ was more sensitive when precipitation levels were higher, whereas parameters $H$ and $B$ were more sensitive during drier conditions. KGE, Kling-Gupta Efficiency.

et al., 2013; Herman, Reed, et al., 2013; van Werkhoven et al., 2008). As we show, watersheds located within a few 100 km are characterized by unique patterns of parameter sensitivity (Figures 6 and 7). This distinction implies that changes in streamflow regimes differ between rainfall-dominated and snowfall-dominated regions (Figures S6 and S7). This is in some ways surprising, as watersheds in California experience similar extreme interannual weather shifts, representing a wide range of hydrologic conditions. However, it demonstrates that dominant model controls on hydrology can vary even within subregional spatial scales and that watershed location and proximity largely determine the importance and type of key hydrological processes. Given that patterns of parameter importance can vary for relatively proximal watersheds (Figure 6), proximity alone may not be able to dictate which model parameters may need to be calibrated to match longer-term observations. Our analysis focuses on one model framework, though we expect similar patterns could emerge for other model applications to this region.

As shown in previous national-scale work, we also found that time-varying shifts in parameter dominance differed between error metrics. The type and magnitude of parameter sensitivity to KGE and CT varied greatly from watershed to watershed, while only the magnitude of parameter sensitivity varied with respect to SFDC, RR, and BFI for all watersheds except those influenced by snowmelt (Group 5). Though other studies have shown that parameter sensitivity does differ between model error metrics and hydrologic signatures (Gupta et al., 1998, 2008), our finding of such strong dominance and convergence of single parameter importance for predicting low flows is unique. In addition, we found that patterns of sensitive parameters with respect to hydrologic signatures were largely consistent through time (Figures 4 and 5). This is in some ways surprising, given the wide variability in signature values observed across our study sites (Figure 3), which span the range of values observed even at national scales (Addor et al., 2017). Together,

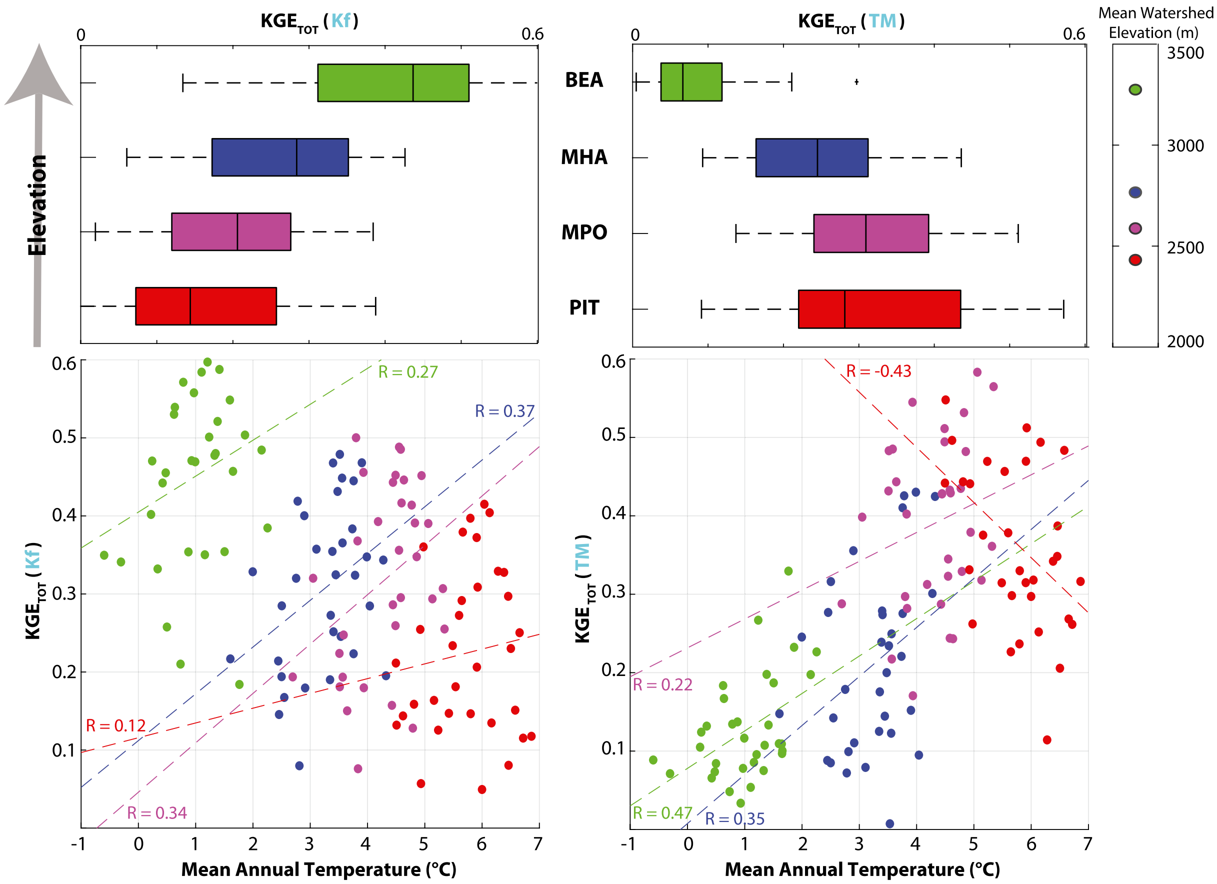


**Figure 9.** Group 5 total order sensitivity indices for two snow parameters ($K_f$, TM) arranged by average watershed elevation (top) and by average annual air temperature (bottom). Generally, watersheds at higher elevations displayed greater sensitivity to $K_f$, while those at lower elevations were more sensitive to TM. Correlations between total order indices for TM and average air temperature were negative for the watershed at the lowest elevation (PIT) suggesting that the importance of TM is elevation dependent.

these findings suggest strong convergence in terms of the parameters key to predicting hydrologic signatures, but divergent parameters for ensuring high values of KGE.

Differences in SA results between error metrics suggest that some objective functions used to evaluate model parameter sensitivity are better suited to capture the time-varying nature of shifting parameter dominance. Our results reveal that modeler's choice of objective function can impact the conclusions of time-varying system analysis, since the hydrologic signatures that we selected did not reveal shifting parameter sensitivity to varying interannual air temperature and precipitation. As we show, differences in the time-varying importance of model parameters were especially pronounced between error metrics and hydrologic signatures. No thorough analysis has been done to identify which error metric is best suited for time-varying analysis to date and how this would vary for different temporal scales (e.g., daily, weekly, monthly, decadal).

Generally, our results are consistent with previous research that has shown, unsurprisingly, that soil parameter sensitivity is high in arid regions (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; Lidén et al., 2000; van Werkhoven et al., 2008). For watersheds at lower elevations, parameter importance shifted largely in response to total annual precipitation. However, the direction of this shift was somewhat counterintuitive. While we had expected to observe baseflow importance to be inversely proportional to precipitation, we instead found that the process importance of baseflow ($K_s$) increased for years with greater than average precipitation. In contrast, several other studies have found that the parameter governing quick flow routing was dominant during high flow conditions for analyses that were performed at subannual scales (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; Wagener et al., 2003; Yang et al., 2011). For watersheds at higher elevations, shifts in parameter importance were correlated to annual air temperature.

As can be seen in Figure 9, the magnitude of sensitivity for two snow parameters ($K_f$ and TM) appeared related to elevation. This is significant because it emphasizes the differences between the sites and implies that watersheds at varying elevations respond to hydroclimatic shifts differently. Correlations between the magnitude of total order indices and elevation have not been previously documented in the literature, with many studies focusing on large watersheds at low elevations.

### 4.2. Drought Alters Parameter Importance

Given the uniqueness of recorded historical droughts in this region, we sought to assess whether parameter sensitivities during drought differed from nondrought conditions. Our annualized discretization of sensitivity indices enabled us to compare model controls across a range of hydrologic conditions for an extended period (33 years) with two recorded droughts. These results show that drought impacts on watershed processes varied between sites (Figures S3 and S4). While we expected to see threshold-based responses to drought periods, mimicking the activation of parameter importance observed during precipitation events at subannual scales found by other time-varying SA studies (e.g., Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013), we instead observed more gradual responses of parameter sensitivity to annual precipitation. These changes were somewhat subtle (Figure 7), but do indicate that different parameters may become sensitive during low precipitation years. This is noteworthy, as it indicates that the parameters that are most important to predicting observed streamflow may differ between wet and dry periods, suggesting that longer-term sensitivity analyses are needed to characterize the time-varying importance of model parameters and how these may shift under annual extremes.

Although drought effects on parameter importance have not been studied extensively, recent field studies were able to quantify the 2012–2016 drought impact on mountain hydrology. Bales et al. (2018) found that increased evaporation rates due to warmer temperatures (1°C warmer than the previous decade) intensified the drought impact on mountain hydrology, reducing the fractional allocation of precipitation to runoff by 30%. These rising temperatures also amplified drought-induced stress on watershed ecology as tree mortality across drought-stricken landscapes was recorded at multiple studies (Goulden et al., 2019; Guardiola-Claramonte et al., 2011; Pile et al., 2019; Young et al., 2017). This is noteworthy, since increasing temperatures also increase plant water demand while soil moisture decreases due to reduced precipitation levels. Postdrought survey studies illustrate that recent drought has short term as well as long-term effects on local vegetation and hydrology. More generally, drought impact studies need to be expanded, particularly in hydrological modeling, as drought effects will need to be considered in future water resources assessment.

As climate change is predicted to increase the length and severity of droughts (Diffenbaugh et al., 2015; Hayhoe et al., 2004), our analysis has important implications for the future. In short, climate change may shift parameter importance to accurately simulating observed streamflow. Considering predicted climate change effects (Hoegh-Guldberg et al.2018), we hypothesize that changing climate may not only shift model-inferred parameters, but may shift dominant hydrologic processes within individual watersheds. Similar suggestions about changing hydrologic processes were made by Peel et al. (2011), noting that understanding hydrologic processes and their response to change could inform future climate change studies.

### 4.3. Conceptualizing Hydrological Processes Using a Parsimonious Model Framework

Our model results show that simple rainfall-runoff models, like Hymod (Figure 2), are flexible enough to represent a wide range of watersheds. In addition, a large number of sites were analyzed to increase understanding about the regional hydrology and changes in dominant processes. The use of a large catchment sample approach to model rainfall-runoff processes was suggested by Gupta et al. (2014) as a way to balance model complexity (depth) with number of sites studied (breadth) to understand hydrologic change. We argue that our study combined these concepts efficiently, in addition to extensive data records, to understand regional hydrologic changes in various sites across California using a parsimonious lumped watershed model.

In addition, using hydrologic signatures alongside sensitivity analysis allows not only to conceptually assess if our model is capable of accurately simulating watershed behavior, but also to examine how each simulated hydrologic process responds to changes in model parameters. We incorporated hydrologic signatures representing very different watershed functions in order to provide more insight on dynamic model behavior under changing weather conditions, further informing model diagnostic analyses. Unlike KGE, used to assess model performance, analysis of hydrologic signatures offers us an insight into the model's ability to reproduce certain aspects of streamflow. In addition to identifying which model parameter is the most important in successfully simulating certain aspects of streamflow (assessed by model error in simulating four different hydrologic signature metrics), we are also able to assess observed flow metrics. Since our study area represents extensive variability in hydroclimatologies, results in Section 3.1 are useful to assess these hydrologic differences among our study watersheds. To best of our knowledge, this is a first study comparing multiple hydrologic signatures in the context of time-varying sensitivity analysis, hence we visually compare observed flow signature values (Figure 3) with sensitivity analysis results (Figures 4, 5, and 7) as a way to add an element of real-word hydrologic watershed assessment to our model-based study.

Model performance (Table S3) across 30 watersheds revealed that our chosen model framework led to poor performance for nine watersheds. The inability of the model framework to reproduce streamflow observations was largely limited to watersheds located around the central coast of California, where precipitation was low and varied between 290 and 960 mm annually. We hypothesize that the model framework adopted in our study was not suitable to capture the nuances of hydrologic system for watersheds with drier climatic conditions (Atkinson et al., 2002; Bai et al., 2015; Sarrazin et al., 2018) like those observed in these nine watersheds. It is likely that model inaccuracy emerges from an oversimplified soil routine, as other studies have shown soil parameters are often sensitive in arid watersheds (van Werkhoven et al., 2008). One alternative approach to identify a robust model in this region would be to employ model intercomparison (Clark et al., 2015, 2008; Kollet et al., 2016; Reed et al., 2004). Many studies have used model intercomparison to examine large-scale differences imposed by varying hydroclimate (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013; van Werkhoven et al., 2008). This type of large-scale analysis is important, but can miss small scale variations like those we observed in our study.

Another alternative to the approach we use in this study is to calculate sensitivity with respect to model outputs, without taking into account observations. We include one example of this type of output in Supporting Information (Figure S8). However, we do not use this approach, because we aim to interpret parameter sensitivity in terms of our ability to replicate streamflow observations. This ties our analysis to observed watershed behavior, instead of using a solely model-based approach.

Broadly, our findings show the challenge of using parsimonious hydrologic models to replicate streamflow in arid areas. This is an important consideration, as changing climate is likely to exacerbate annual shifts in air temperature and precipitation that will contribute to more intense and longer drought periods. Finer-scale model comparisons are needed in this region to identify model framework that would be capable of replicating streamflow behavior during dry conditions as it is likely that hydrologic systems will be moving to new, drier hydrologic regimes.

### 4.4. Time-Varying Sensitivity Analysis May Help Inform Real-World Interpretations

One of the many touted outcomes of sensitivity analyses is that sensitivity results can assist with understanding of process importance within and across watersheds. However, a sensitive parameter does not always identify processes occurring in the actual watershed. Therefore, sensitivity indices should be interpreted as controls on model performance as they identify parameter variations that strongly influence model performance (Herman, Kollat, et al., 2013; Herman, Reed, et al., 2013). SA must be viewed through the filter of the hydrologic model framework used to approximate watershed hydrology. The model we selected is capable of reproducing historical streamflow, which is our only “real” check on whether the model is a good representation of watershed behavior at each of our study sites. However, having additional observational data (e.g., soil moisture, ET) could further constrain internal states and fluxes, improving the realism of the simulations and the controlling processes.

It is important to recognize that sensitive parameters do not always reflect the dominant watershed processes in the real word. While sensitivity analyses are attractive tools, a major challenge is always in interpreting outcomes from sensitivity analyses in terms of field-based observations. This feedback is necessary to incorporate the nuances of a particular region and to use regional model-based outcomes for broad-scale process understanding. In terms of enabling this feedback loop to improve understanding of watershed functioning, we call for more work to connect hydrologic modeling with field-based observations in places that experience oscillating annual conditions.

Following the recent California drought, analyzing the hydrologic responses to climate extremes is becoming increasingly important. As snowmelt from mountains is the main source of many regional water supplies, understanding hydrologic feedbacks in mountainous regions is essential to climate impact assessment and watershed management. Examining relationships between inter- and intraannual conditions and dominant watershed processes can teach us how hydrologic responses may vary through space and time, making it possible to observe relationships between model parameters and predicted responses during a variety of climate conditions. Broader use of this type of analysis could provide insight into multiwatershed, multiscale hydrologic responses that can improve our understanding of watershed functioning and increase our preparedness for the future.

## 5. Conclusions

In this study, we explored how different hydroclimate conditions impact parameter importance, assessed via time-varying sensitivity analysis across 21 California watersheds. We found that variations in parameter importance through time were the most pronounced with respect to KGE and that these variations could be organized into five unique patterns. These groupings are somewhat spatially organized, revealing the role of air temperature and precipitation in shaping parameter importance. As the sensitivities of model parameters varied from year to year and across approximate sites, our work highlights the value of time-varying sensitivity analysis to evaluate the potential consequences of regional climatic variability. In the region where we focused our analysis, drought can have major impacts on streamflow. We show that drought can also lead to differences in parameter importance, especially in wetter or snowmelt driven watersheds.

Overall, we show the importance of diagnostic analysis applied to examine long records and to simulate hydrology in regions that experience hydrologic extremes. Unexpectedly, watersheds experiencing widely varying hydrologic signatures displayed convergent patterns of parameter sensitivity, suggesting that only a few parameters across all watersheds were key to simulating streamflow. In contrast, very different patterns of parameter importance emerged with respect to model error metrics, even for proximal watersheds. These findings are crucial for advancing historical simulations of streamflow and future predictions of streamflow as climate change continues to alter air temperature and precipitation into the future.

## Data Availability Statement

The data used in this study were obtained from the United States Geological Survey (https://waterdata.usgs.gov/nwis/uv/?referred_module=sw) and Catchment Attributes and Meteorology for Large-sample Studies data set (https://ral.ucar.edu/solutions/products/camels). Monte Carlo and uncertainty analysis software are available as the Sensitivity and Uncertainty Analysis for Everyone (SAFE) package (https://www.safetoolbox.info/).

**Acknowledgments**
This material is based upon work supported through the Division of Graduate Education under Grant DGE-1449617. Contributions from R. Basijokaite and C. Kelleher were additionally funded by the Syracuse University CUSE Grant Program, and work would not have been possible without support from Syracuse University Research Computing.

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