Bias Correction of Hydrologic Projections Strongly Impacts Inferred Climate Vulnerabilities in Institutionally Complex Water Systems

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Abstract

Water-resources planners use regional water management models (WMMs) to identify vulnerabilities to climate change. Frequently, dynamically downscaled climate inputs are used in conjunction with land surface models (LSMs) to provide hydrologic streamflow projections, which serve as critical inputs for WMMs. Here, we show how even modest projection errors can strongly affect assessments of water availability and financial stability for irrigation districts in California. Specifically, our results highlight that LSM errors in projections of flood and drought extremes are highly interactive across timescales, path-dependent, and can be amplified when modeling infrastructure systems (e.g., misrepresenting banked groundwater). Common strategies for reducing errors in deterministic LSM hydrologic projections (e.g., bias correction) can themselves strongly distort projected climate vulnerabilities and misrepresent their inferred financial consequences. Overall, our results indicate a need to move beyond standard deterministic climate projection and error management frameworks that are dependent on single simulated climate change scenario outcomes.

Introduction

The planning and management of water resources depend heavily on projections of water supply and demand (Loucks and van Beek 2017; Wurbs 1995), strongly shaping water infrastructures and institutions (Malek et al. 2018; Trindade et al. 2019; Yoder et al. 2017). The challenge of infrastructure investment for climate adaptation represents a balance between financial stability and the capacity to meet system demands (Baum et al. 2018; Trindade et al. 2019). Moreover, governments often confront high economic costs, political contention, and social conflicts (Gizelis and Wooden 2010; Petersen-Perlman et al. 2017) as they seek to change water related infrastructures or institutions. These factors promote institutional inertia that favors reactive, post-event responses. Ignoring projections can lead to mal-adaptive and myopic actions that ultimately reduce our ability to respond to changes and reduce the vulnerability of water-dependent sectors to stressors (Lamontagne et al. 2019). Projections of future water resource availability can also shape the perceptions of farmers, irrigation district managers, and water and power utilities about their individual vulnerabilities to climate change, therefore influencing local investment and water-stress hedging decisions (Mase et al. 2017; Mills et al. 2016; Udmale et al. 2014).

Typical model-driven projections of water supply vulnerabilities to climate change consists of: (i) dynamically downscaling climate projections to inform simulation of unregulated streamflow that enters river systems (Clark et al. 2011; Overgaard et al. 2006) using hydrologic land surface models (LSMs) and (ii) the use of the resulting streamflow projections to simulate the allocative water balance dynamics across water-dependent sectors (Wurbs 1995) using water management models (WMMs) (Brown et al. 2015). Unregulated streamflow simulations require forcing data from observed meteorological inputs or a combination of global circulation models and regional atmospheric models. Streamflow projections contain errors due to biases in meteorological and soil data as well as model calibration, scale, and limits in process representations (Beven 1993, 2016; Gaganis 2009). A large body of literature has explored how these errors are generated and how they can be categorized (Gupta and Govindaraju 2019; Gupta et al. 2008; Nearing et al. 2016; Refsgaard et al. 2006; Vogel 2017; Wagener et al. 2010). However, it is poorly understood how LSM errors propagate into WMMs, which are themselves subject to errors, and combine to yield biases in our end-point decision-relevant measures of climate vulnerability (e.g., reduced crop yields, water shortages, or financial risks). Recent studies have begun to formally analyze the propagation of uncertainty of inflow water regimes within water management models (e.g., Hassanzadeh et al. 2016; Marton and Paseka 2017; Nazemi and Wheater 2014; Sordo-Ward et al. 2016). These efforts mainly focus on internal variability or uncertainty that results from ensemble simulations based on synthetically generated streamflow time series. Although understanding the effects of observation record limits and internal variability is important, it is fundamentally different than the error perturbation analyses contributed here. The implications of errors within the broadly used top-down GCM- and LSM-based deterministic simulated streamflow projection products is not well understood in terms of its effects on water management models. It is worth mentioning here that, synthetic generation of streamflow time series is commonly used as an alternative bottom up way of exploring streamflow changes and uncertainty (Borgomeo et al. 2015; Herman et al. 2016; Kirsch et al. 2013; Quinn et al. 2018, 2020; Steinschneider et al. 2015). These methods often employ statistical techniques to construct streamflow timeseries that are non-stationary and more diverse, while, they still maintain a reasonable level of statistical consistency with the past observations. Overall, streamflow scenarios have been used to make up for the lack of long-term streamflow observations. These scenarios also allow us to investigate cases that have not been occurred during the observation periods such as low frequency extreme wet and dry events, and multi-year droughts.

Here, we focus on climate-driven vulnerabilities in the California water supply system, which represents one of the most institutionally complex water infrastructure systems in the world. The system (Figure 1) includes thousands of kilometers of conveyance canals and dozens of dams that are operated to satisfy a broad spectrum of objectives, including two state-wide water delivery projects—the State Water Project (SWP) and the Central Valley Project (CVP). California's water supply is highly dependent on the surface water inflows from the Sierra Nevada mountains into its northern reservoirs. While the state has experienced substantial flood and drought events in the past (Howitt et al. 2014; Mann and Gleick 2015), climate change is expected to worsen the situation (Mann and Gleick 2015; Mote et al. 2005; Tanaka et al. 2006). This vulnerability is motivating a myriad of propositions to improve California's water infrastructures and institutions (Forsythe et al. 2017; Nishikawa 2016; Sandoval-Solis 2020). Groundwater resources and water banks are among the most crucial and vulnerable parts of the water supply in California (Kiparsky et al. 2017; Nishikawa 2016), particularly for the agricultural sector, and are the subject of emerging regulations (Forsythe et al. 2017). A significant portion of California's annual precipitation is generated through atmospheric rivers during the winter and early spring (Dettinger et al. 2011), which must be stored to meet summer agricultural demands (Christian-Smith 2013; Kocis and Dahlke 2017). Therefore, water stakeholders in California recharge their groundwater resources during these short-lived extreme events, to use it later when surface water is not sufficient to meet the demand (Ghasemizade et al. 2019; Scanlon et al. 2016). This management regime potentially increases the sensitivity of irrigation focused drought projections to short-term (daily) errors in simulated flood events. To date, the implications of this issue have not been explored in detail.

In this study, we show how errors from a well-established coupled atmosphere-land modeling system (WRF-NoahMP; Cai et al. 2014; Skamarock et al. 2005, 2008; Figures S1- S2) propagate into a California-specific WMM (i.e., CALFEWS; Zeff et al. 2021) and impact the simulation of system-wide water supply, groundwater extraction, and annual revenue of irrigation districts in the Central Valley.

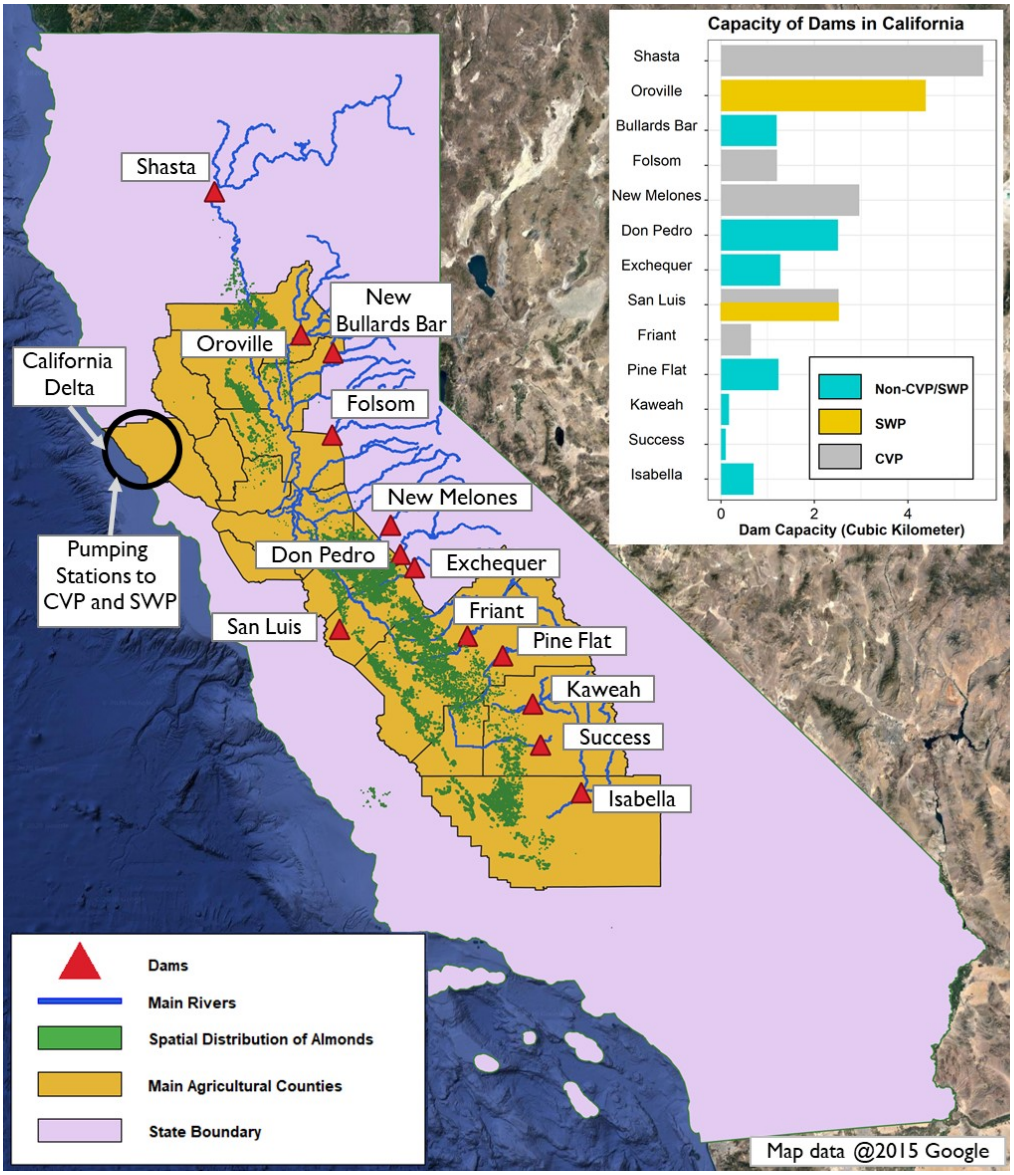

Figure 1. Study area of this study (State of California). The map indicates the locations of various dams and reservoirs in California, the state's main agricultural areas, and the spatial distribution of almond, one of the most important crops in California. The figure also shows the capacity of the dams of the two main water delivery projects in California and the San Luis dam that is shared between the two projects.

We trace how errors in a single dynamically downscaled deterministic streamflow scenario for a recent historically observed period can strongly bias the important water balance dynamics for key actors and infrastructure systems. This work highlights the strong interdependence between errors in flood and drought extremes, which are shown to be nonlinear, path-dependent, and amplified in modeled operations of conveyance and storage infrastructures. In other words, the simulation of various system stakeholders depends on the history of exposure of the stakeholder to streamflow errors as well as their flow paths through other system components. Moreover, we show that standard methods for managing and reducing these hydrologic errors exacerbate these water balance distortions as well as associated inferences of climate vulnerabilities for the region.

Methods

In this study, we explore how errors in dynamically downscaled projections of surface hydrology impact important California water management systems using the California Food-Energy-Water Systems Model (CALFEWS; Zeff et al. 2021). The model adaptively allocates water across scales and sectors using a detailed representation of the state's infrastructure and institutions. Our analysis compare CALFEWS simulations of critical components of the California water distribution system under four sources of streamflow inputs: i) observed streamflow from the California Department of Water Resources' Data Exchange Center (CDEC); ii) raw WRF-NoahMP streamflow outputs (no groundwater correction; NGW); iii) WRF Noah-MP streamflow outputs with an expert-driven manual removal of groundwater biases (groundwater corrected; CGW); and iv) WRF Noah-MP streamflow data that reduced errors via an automatic bias correction method using quantile mapping (bias-corrected; BC). In this section, we describe the computational framework that was used to conduct the simulation-based analyses that underlie this study (Figure S1 in Supplemental Materials). To that effect, we first introduce the regional atmospheric land-surface model (WRF-Noah-MP) that generated our dynamically downscaled streamflow datasets. We then summarize the water management model used in this study (CALFEWS; Zeff et al. 2021). Finally, we then describe the methods used here to produce our bias-corrected datasets.

WRF-Noah-MP Streamflow Projections:

The input streamflow data to our WMM was generated using the Weather Research and Forecast (WRF) regional climate model (Skamarock et al. 2005, 2008; Tang and Dennis 2014). The version of WRF used to generate the streamflow inputs to CALFEWS is integrated with the Noah-MP land surface model (LSM; Barlage et al. 2015) a mechanistic hydrologic LSM that simulates key surface water and energy fluxes and states required by WRF as a surface boundary condition. Noah-MP also simulates surface runoff and sub-flow, cold season processes, vegetation dynamics, soil water movement, frozen soil, and infiltration processes (Cai et al. 2014; Ingwersen and Streck 2011; Liu et al. 2016).

In this study, we compare four sources of streamflow inputs for CALFEWS. The first one is our observed streamflow baseline from the California Department of Water Resources' Data Exchange Center (CDEC). We also considered three variants of WRF-Noah-MP-simulated streamflow scenarios: 1) Raw WRF-Noah-MP (NGW); 2) Groundwater-corrected flow (CGW); and 3) Bias-corrected flow (BC). The first two simulated streamflow scenarios (CGW and NGW) were developed by Holtzman et al. (2020) while the BC scenario was developed in this study (Supplementary Notes S3). To develop NGW and CGW, Holtzman et al. (2020) used two different parameterizations of WRF-Noah-MP. Their baseline WRF setup and parameterization were consistent with Wrzesien et al. (2015), with a spatial resolution of 9 kilometers (27-km outer domain). However, Holtzman et al. (2020) showed that the default WRF parameterizations can lead to biased streamflow simulations in California. Therefore, they published a series of modifications to improve the simulated streamflow. The NGW is a direct output of WRF-Noah-MP after improvement of its internal parameterizations. The CGW, on the other hand, was developed by ex-post statistical correction of NGW-simulated streamflow to make up for the lack of a groundwater representation in the original WRF-Noah-MP setup.

To develop the NGW streamflow scenario, Holtzman et al. (2020) made the following major modifications: i) The rain-snow partitioning formulation was changed from a function of air temperature to a more-sophisticated WRF microphysics scheme. This allows the model to accumulate more accurate amounts of snow during the winter months. ii) They updated the depth of subsurface runoff generation because WRF's default runoff generation depth was between 1 and 2 meters in all locations. This ignores the fact that, in higher elevations, soil is generally shallower, and assumption of runoff generation from assumed deeper soil layers can potentially lead to unreasonable baseflow generation and biased streamflow timing. To respond to this problem, Holtzman et al. (2020) assumed runoff generation from a shallower layer (10 to 30 cm). iii) Slope to calculate subsurface flow was another parameter that Holtzman et al. (2020) changed to improve the simulation of subsurface flow. The default value of WRF-Noah-MP was 0.1, but they changed this to 0.5. The higher subsurface flow slope was able to improve the simulation of the streamflow amount. iv) Holtzman et al. (2020) also changed the "sand" and "ice" soil types to "sandy loam" to decrease the occurrence of unrealistically large transient soil moisture changes at the beginning of the simulation. v) Soil porosity of "sandy-loam" soil was modified from a default value of 0.434 to 0.52. The reason was that their initial simulations indicated that the water-holding capacity of the default modeled soils was not high enough, which led to earlier streamflow peaks. vi) Finally, they used a constant value for snow capacitance (0.2) of Thompson microphysics scheme (Thompson et al. 2008) to ensure a more reasonable simulation of snowflake shape in WRF-Noah-MP.

In regions with significant surface water-groundwater interactions (Criss and Davisson 1996; Shaw et al. 2014) such as the Sierra-Nevada watersheds, the lack of groundwater representations can lead to biases in simulation of magnitude and timing of runoff and river flow. Because WRF-Noah-MP's NGW setup did not include a mechanistic simulation of groundwater dynamics (Barlage et al. 2015), a post-processing groundwater correction module was utilized in the development of the CGW streamflow scenario. The GW correction was performed using an offline statistical relationship that was utilized to improve the NGW streamflow. The corrected streamflow on a given day was obtained as a weighted sum of three quantities: i) the original NGW daily streamflow, ii) the average NGW streamflow over the past 365 days, and iii) an intercept term which was set so that the correction did not change the overall mean NGW streamflow over the entire simulation period. The weights were constant in time over the simulation period but were allowed to vary between spatial locations. Conceptually, the 365-day running average term represents releases from medium-term groundwater storage, and the intercept represents baseflow due to long-term groundwater storage that is released over a time scale of many years. Including both these terms helped model spatial variation in the residence time of groundwater.

Values of the correction weights were obtained separately for each streamflow location using the following procedure: first, both NGW and observed full natural flows (i.e. gauged flows with corrections for upstream human activities) were normalized by dividing by their overall mean value; then, linear regression was used to obtain the weight values that minimized the mean square error between the corrected normalized NGW and the normalized observations. The correction coefficients were fit on normalized flows instead of raw flows because the primary goal of the correction was to remedy errors in the NGW seasonality pattern, not to correct any overall bias. Results presented by Holtzman et al. (2020) suggest that this model substantially improves on the uncorrected Noah-MP results (i.e., the NGW scenario) using a soil-only modeling system. Note that Noah-MP does include an optional groundwater model, but it is often impractical to use because it takes many simulation years to spin up (Niu et al. 2007).

Note that, there are other approaches that past studies have utilized to improve the representation of groundwater dynamics in their streamflow simulations. For example, past studies have developed and incorporated simple groundwater modules (Niu et al. 2007; Yang and Xie 2003) or dynamically integrated their land surface hydrologic models into well-established groundwater models (Faunt et al. 2009; Kim et al. 2008; Molina-Navarro et al. 2019; Xu et al. 2012). A few other studies have used statistical bias correction approaches to match the overall statistical moments of their simulated streamflow with observations which implicitly takes into account groundwater dynamics (Hamlet and

Lettenmaier 1999; Tiwari et al. 2021). Finally, there are other methods such as Bayesian filtering methods (Ait-El-Fquih et al. 2016; Panzeri et al. 2014; Rajabi et al. 2018) or offline post-processing procedures (Holtzman et al. 2020; Trabucchi et al. 2021) that implicitly improve the representation of groundwater dynamics and overall quality of streamflow simulations.

California Food-Energy-Water Systems Model (CALFEWS)

We use a Water Management Model (Figure S1) that has been developed to simulate north-central California agro-hydrologic systems. The California Food-Energy-Water Systems model (CALFEWS) model (Zeff et al. 2021) abstracts critical institutional and infrastructure elements (>1000) that capture the complex dynamics for how north-central California's water balance is managed given the region's extreme streamflow variability. CALFEWS simulates the daily timescale operation of dams, water conveyance systems, groundwater banks, and water allocation decisions.

CALFEWS exploits state-aware rules that allow it to abstract the highly dynamic and adaptive operational behaviors of the system while complying with the institutional constraints that shape the storage and conveyance of water. More specifically, CALFEWS includes the operation of 12 major reservoirs in north-central California (Figure 1). However, most of the water is conveyed from northern dams such as Shasta and Oroville to central California's agricultural areas. The model mimics the operation of these dams in terms of water storage, flood prevention, and water release for agricultural and environmental services. The dams provide water to a complex transfer system that conveys water to the agricultural and urban areas of California, which are mainly located in the central and southern parts of the state (Figure 1). The conveyance systems are based on two state-wide water transfer projects: the State Water Project (SWP) and the Central Valley Project (CVP). Both projects own the storage and conveyance water infrastructures that are included in the CALFEWS model. CALFEWS also takes into account all the major river water rights holders in the Tulare Basin (e.g., Kings, Kaweah, Tule, Kern).

The CALFEWS model takes several environmental constraints into account. The model simulates delta-related environmental concerns such as saltwater intrusion, minimum outflow from the delta, and constraints in the old and middle river flow. It also captures other minimum flow regulations in California rivers and their reaches. There are also non-environmental constraints that are enforced in the model, such as pumping limitations, canal capacity limitations, and water rights constraints. The model includes over thirty irrigation districts, ten distinct imported water contract and storage allocations, and nine major water banks in the system. Additionally, the model simulates the water redistribution system in the agricultural areas. For example, it captures direct groundwater banking partnerships and in-lieu exchanges.

CALFEWS does not have a physically-based groundwater model that can mechanistically simulate groundwater dynamics, but it does have a water balance accounting model that distributes water to individual irrigation districts and groundwater banks based on surface water allocations, carry-over storage reservations in surface water reservoirs, and the ownership of individual aquifer recharge and recover assets. The model also simulates claims to excess flood water flows based on access and conveyance constraints. The detailed operational rules used within CALFEWS enabling estimation of the annual revenue and financial stability at the irrigation district scale.

Although capturing the diverse range of institutional and infrastructure operational considerations that shape water allocation decisions is non-trivial and CALFEWS is subject to representational limits, the model does reasonably capture the complex dynamics of the infrastructure systems and their operations (see more details on the CFEWS-HIS baselines for major storages and Sacramento-San Joaquin Delta exports in Note S1, Figure S3-S4, and Table S1-S4 in Supplemental Materials, and Figure 2). Also, more details and baseline capabilities of CALFEWS are available in Zeff et al. (2021).

Quantile Mapping-Based Bias Correction

In this study, we used the frequently employed statistical bias-correction technique called quantile mapping (Cannon, Sobie, and Murdock 2015) to remove systematic biases of raw WRF-Noah-MP streamflow data. To do this, we developed and used an R package called “biascorrection” (Supplementary

Notes 3) that follows the methodology described by (Hamlet and Lettenmaier 1999). In short, the bias correction module uses the historical observed streamflow to create the monthly flow quantiles of each individual month. After that, it uses the simulated streamflow data to create simulated monthly flow quantiles. Afterwards, the bias correction module creates the monthly bias-corrected flow by swapping each month of the simulated flow with the same quantile from the observed streamflow. Since hydrologic models can simulate the average annual flow reasonably well, after constructing the monthly bias-corrected flow, we adjust them to make sure that their average annual flow is consistent with what the WRF-Noah-MP model has simulated. Finally, we disaggregate the monthly bias-corrected flow to daily by multiplying the raw daily simulated flow of each month by the simulated bias-corrected ratio of that month.

Results and Discussions

Diagnosing Streamflow Errors across Timescales

The Shasta reservoir represents a key storage project for the CVP as well as flood control in northern California. As a means of distinguishing floods, seasonal transitions, and drought periods for the Shasta reservoir system, our error analysis is formulated across daily, monthly, and annual timescales (Figure 2 and Figure S5-S12 in Supplemental Materials). We show that the raw streamflow output of the WRF-Noah-MP model (NGW scenario) systematically underestimates streamflow during low flow periods (Figure 2 – Panel a). Previous literature has attributed these biases mainly to the significant computational and conceptual constraints associated with representing groundwater processes in Noah-MP (Cai et al. 2014; Holtzman et al. 2020). Our results (Figure 2 – Panel a) demonstrate that the groundwater corrected stream flows (CGW) reduce errors during low-flow periods. However, the expert-based CGW calibration (Figure 2 – Panels a and e) yields a consistent underestimation during high-flow periods. More broadly, the distributions of the observed and the simulated streamflow scenarios at the daily time-step (Figure 2 – Panels c, d, e, and f) show that the CGW scenario significantly reduces the range of variability in streamflow and extremes. The water added during the low-flow periods is drawn from the high-flow periods – more specifically, from extreme flood events such as atmospheric rivers. Atmospheric rivers (and other extreme flow events) are a crucial component of water availability in California, and the presence or absence of them is what distinguishes a drought year from a wet year (Diffenbaugh et al. 2015). We also show that the quantile mapping-based bias correction scenario (BC) enhances aggregated monthly and annual model performance in a manner comparable to the CGW, improving the representation of streamflow during dry periods (e.g., Figure 2).

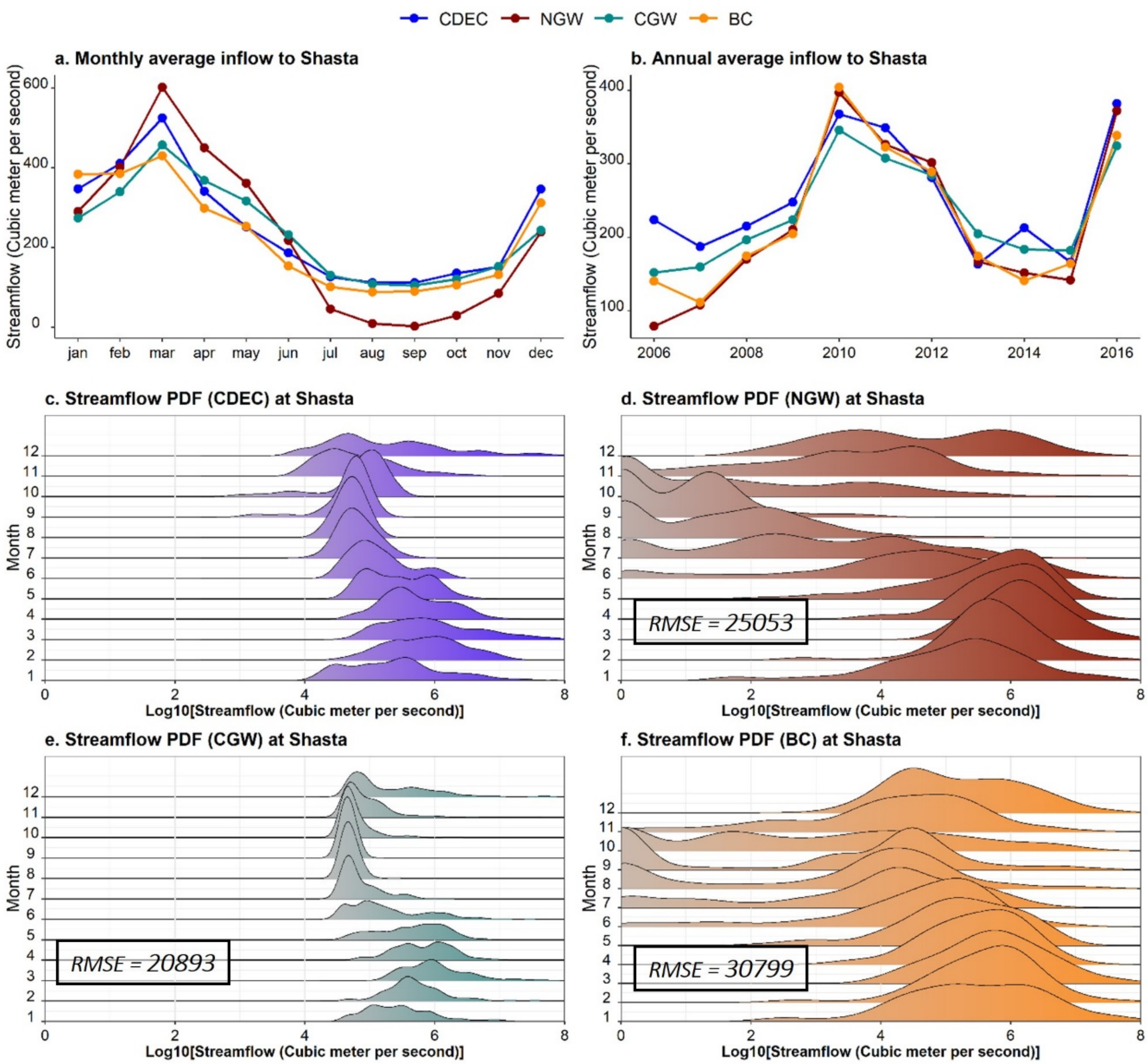

Figure 2. Comparison between the observed (CDEC) and simulated streamflow scenarios at Shasta Dam. The simulated streamflow scenarios include raw WRF-Noah-MP flow (NGW), WRF Noah-MP groundwater-corrected

flow (CGW), and bias-corrected flow (BC). Panel a. and b. demonstrate the average monthly and average annual streamflow, respectively. Panel c., d., e., and f. show the monthly separated probability density function of daily streamflow for our four flow scenarios (observed, no groundwater correction, groundwater corrected, and bias-corrected).

However, similar to the CGW scenario, statistical bias correction deteriorates the representation of streamflow during high-flow periods, which dampens inter-seasonal variability. The streamflow error management methods (i.e., BC and CGW) do not improve the entire distribution of flows critical to north-central California. A key concern that emerges from these results is how these streamflow biases could create path-dependent and persistent errors that propagate into the other components of the California water system and affect our perception of downstream, multi-sector climate vulnerabilities. While, we only explain the results for Shasta Dam here, our analysis demonstrate that the simulated inflow time series into other California reservoirs (e.g., Oroville, Folsom, Pine Flat, New Melones, Millerton, Isabella, Don Pedro, and Yuba Dam) are predominantly in agreement with the Shasta dam (Figures S5-S12 in the Supplemental Materials).

Errors in the Main North-to-South Surface Water Transfers

The two major pumping stations at the Sacramento – San Joaquin River Delta play a crucial role in California's north-to-south water transfer projects. Pumping rates from these stations to the SWP and CVP are among the most important indicators of the system-wide water availability in California, particularly for users in the water-scarce San Joaquin Valley as well as Southern California. Here, we compare CALFEWS simulated pumping rates using the different sources of streamflow inputs with the actual observed historical pumping rates as recorded in CDEC. Our results (Figure 3 – Panels a and b, Figure S13 in Supplemental Materials) show that, in general, the LSM-based streamflow results (CGW, NGW, and BC) introduce significant errors compared to the CFEWS-HIS simulation (CALFEWS simulations under observed streamflow inputs). While, at least in some cases, the baseline (CFEWS-HIS) results do show non-negligible deviations from the observed pumping rates (Figure 3 – Panels a and b), the error distribution is relatively consistent during wet and dry years (Figure 3 – Panel c). It should be noted that capturing the diverse range of institutional and infrastructure operational considerations that shape pumping from the Sacramento – San Joaquin River Delta is non-trivial. As noted above, CALFEWS itself is subject to representational limits. Nonetheless, the CFEWS-HIS results largely capture key trends and dynamics. In the case of the NGW results (raw WRF-Noah-MP streamflow outputs), the underestimation of reservoir inflow during the summer causes a systematic underestimation of the pumping rate to the CVP during that season (Figure 2 – Panels a and d). These errors, which overlap in timing with peak irrigation demand, create consequential biases for projections of agricultural productivity and groundwater extraction.

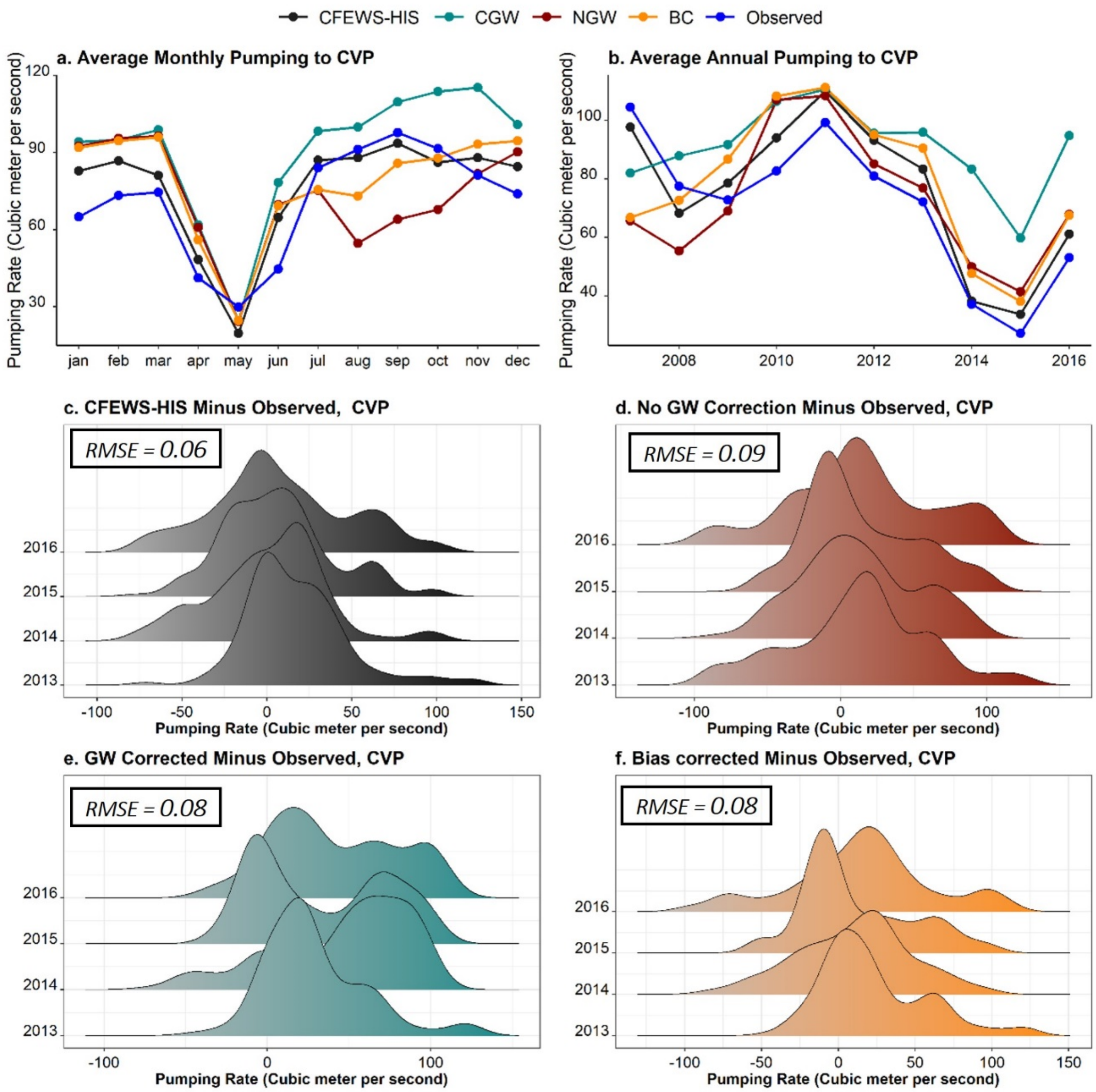

Figure 3. Pumping rate to Central Valley Project (CVP). This figure compares the "observed" pumping to CVP with simulations of CALFEWS under different streamflow scenarios (i.e., CDEC [CFEWS-HIS], raw WRF-Noah-MP output [NGW], groundwater corrected [CGW], and bias-corrected [BC]) across monthly (Panel a), annual (Panel b), and daily time scales (Panels c-f). In this figure, the unit of Root Mean Square Error (RMSE) is cubic meter per second.

Efforts to address these biases in the CGW (groundwater corrected) and BC (bias-corrected) results do partially address the pumping underestimation issue, at least in some instances (Figure 2 – Panels e and f).

However, these scenarios also produce higher pumping biases when estimating the pumping rates to the CVP and SWP (see SWP pumping rate errors in Figure S13 in the Supplemental Materials). These overestimation biases become more pronounced in key CA drought years (e.g., 2014 and 2015). Put simply, the groundwater correction and quantile-mapped bias correction falsely overestimate delta water deliveries in the evaluated drought years.

The overestimation issue appears more frequently in the CGW case, primarily during high-flow periods in the winter and early spring. This effect is most pronounced in drier years (Figure 3 – Panel e) because the manual deterministic improvements in the representation of dry months can eliminate many low flow days that naturally exist in the observed record (Figure 2 – Panel c. and e.). Also, as the system transitions from the 2013-2015 drought to a wetter year in 2016, the CGW's bias leads to an overly optimistic inference of drought recovery. The BC scenario more closely follows the distribution of the raw simulated results (Figure 3 – Panel f), however, it also amplifies some of the extreme flood events, leading to overestimated project pumping for several periods. Moreover, as discussed before, both the BC and CGW streamflow scenarios tend to underestimate flow during the high-flow periods, which can significantly affect the magnitude and timing of dam storage in the spring and winter. The biases in the delta-to-project deliveries also imply that LSM streamflow errors can significantly influence projections of energy supply and demand in California.

Groundwater Banks

Groundwater banks (GWBs) are critical components of California's water system. In California, GWBs are used as additional sources of storage that help capture excess water during flood events to hedge against droughts (Ghasemizade et al. 2019). For example, from 2012 to 2017, GWBs provided the system with more than 40 km^3 of drought relief water (Xiao et al. 2017), playing a key role in California agricultural systems seeking to avoid yield losses and in some cases complete bankruptcy (Diffenbaugh et al. 2015; Sarhadi et al. 2018).

Our results indicate that upstream streamflow errors propagate into GWB simulations and significantly degrade the simulated banked storages (Figure 4 – Panels a and b, and Supplemental Materials Table S5), recharge to GWBs (Figure 4 – Panels c and d), and extraction from GWBs (Figure 4 – Panels e and f). For example, the simulated streamflow scenarios (NGW, CGW, and BC) all lead to systematic overestimations of water storage in two groundwater banks of California: Kern Water Bank (Kern) and Berrenda Mesa Project (Berrenda ; Figure 4 – Panels a and b). There are two main factors influencing this overestimation. First, groundwater banks have slower turnover times relative to the other components of the system, allowing water to stay in them for longer periods of time (i.e., higher residence times). This implies that if streamflow inputs have systematic errors in overestimating available water, the errors will not dissipate immediately, and the GWBs can substantially accumulate long-lasting erroneous storage contributions. For example, during the Spring of 2010, our simulated streamflow scenarios (NGW, CGW, and BC) consistently overestimated inflow to upstream reservoirs (Figure S14 in Supplemental Materials). Our results (Figure 4 – Panels c and d) clearly show how a portion of the overestimated water ended up recharging the groundwater system. This erroneous recharge causes a spike in groundwater storage as compared to the CFEWS-HIS baseline (Figure 4 – Panel a and b), and this gap remained to the end of our simulation period six-years later. The second major factor influencing the overestimation of available storages in GWBs within the NGW, BC, and CGW projections is their overestimation of the average annual pumping to the CVP (Figure 2 – Panel b). These overestimation errors ultimately contribute to higher groundwater recharge and lower water deficits and, thus, lower groundwater extraction. Our results emphasize that when evaluating water management options and vulnerabilities in California, drought years and flood years are tightly coupled. This implies that, if a modeling framework struggles to capture floods and wet periods well, it would not be able to capture the dynamic impacts of droughts. These consequential, long-lasting and path-dependent errors also highlight that extra attention should be paid to statistical and deterministic bias correction methods (e.g., BC and CGW) that inadvertently shift the dynamic water balances associated with highly consequential extreme events (Figure 2 – Panels e and f). The overestimation of groundwater bank storage can be also attributed to the fact that the recharge capacities in the groundwater banks are significantly higher than groundwater extraction capacities. This difference increases the residence time of error in groundwater systems, and further demonstrate the contrasting sensitivity of the system to errors during wet and dry periods.

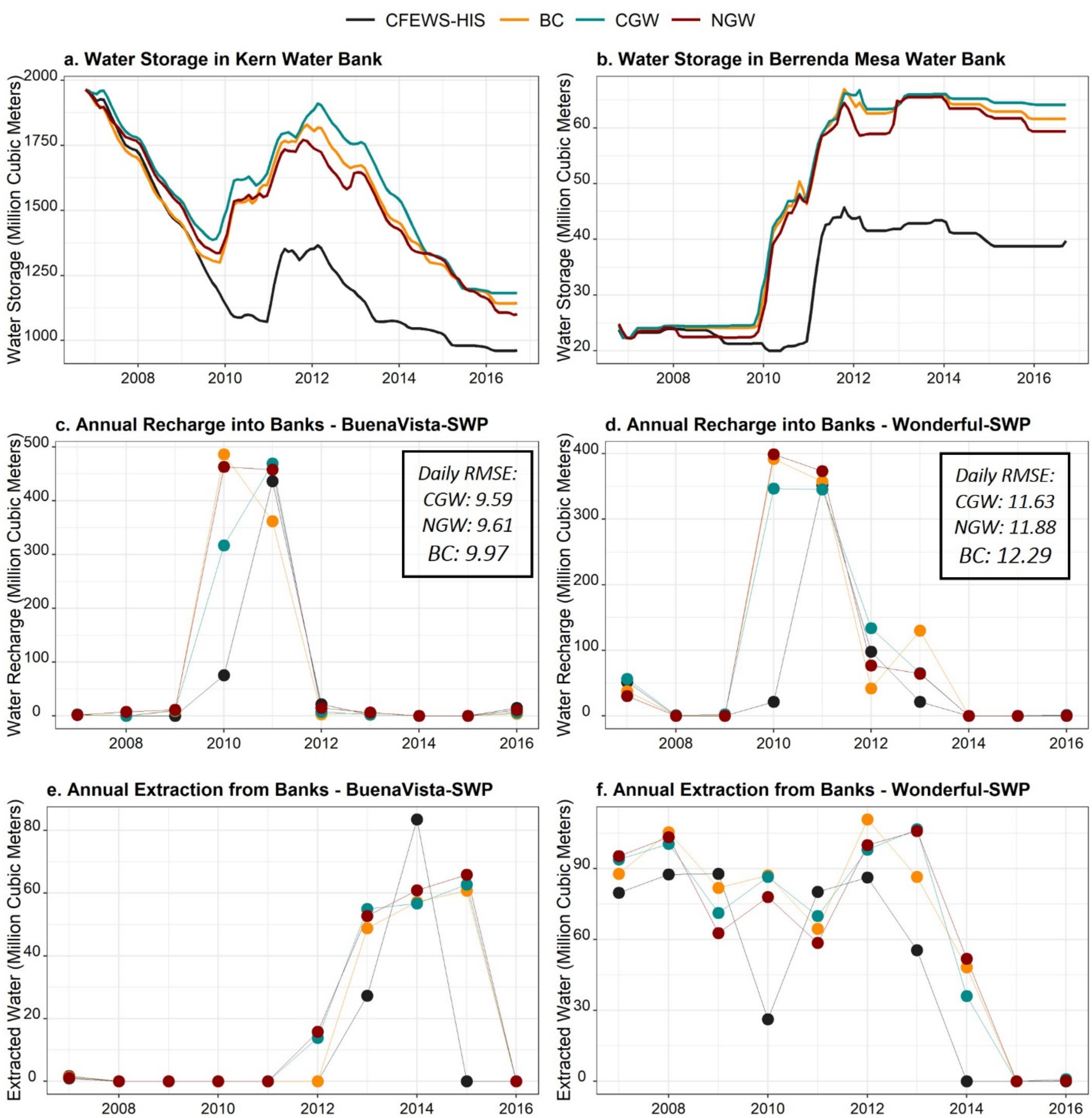

Figure 4. Groundwater storage, recharge, and extraction. This figure shows how different streamflow scenarios (i.e., observed [CFEWS-HIS], raw WRF-Noah-MP output [NGW], groundwater corrected [CGW], and bias-corrected

[BC]) affect CALFEWS simulation of groundwater banks of the Central Valley. In this figure, the unit of Root Mean Square Error (RMSE) is million cubic meters.

Moreover, our results indicate that the water extractions and recharge of various irrigation districts show distinctly different responses to streamflow scenarios. This is due to their unique institutional contexts as defined by their level of water right seniority, contracts, water supply projects (CVP vs. SWP), and geographical location in California (Table S6 in Supplemental Materials). The persistence and path dependence of errors in downscaled hydrologic projections strongly depends on the institutionally complex infrastructure systems of the north-central California water system. Infrastructure elements or users with the most secure water rights, or most advantageous positions within the water distribution network, receive their total water demand more frequently; therefore, an over- or underestimation errors for available inflow to the system are themselves institutionally allocated across the complex network of other water right holders.

The Financial Dynamics of Irrigation Districts

Errors in streamflow projections and the current standard approaches for managing them also strongly shape our ability to infer the financial stability of irrigation districts. Irrigation districts are cooperative water management institutions that facilitate the delivery and storage of water. They are also responsible for the maintenance of water storage and delivery infrastructure. These operational activities are the primary source of irrigation districts' income. Generally, a lower amount of system-wide water supply reduces the total volume of water that they are able to convey and sell to their retail customers leading to lower overall revenues that can cause potential financial instability, higher borrowing costs, lower investment in infrastructure maintenance, and an inability to retain trained staff, all of which have detrimental consequences for the wellbeing of the region's agriculture.

Our results show that streamflow errors significantly influence our ability to infer the revenue vulnerabilities of irrigation districts (Figure 5 – Panel a). To estimate these revenues, given the unfortunate dearth of transparently recorded water price data, we explore here 100 plausible water price scenarios that represent five plausible trajectories of water price change during drought years (Note S4 and Figure S15 Supplemental Materials). More specifically, the five baseline trajectories that have been used to generate our 100 synthetic water price scenarios represent -20%, 0%, +20%, +50%, and +80% change in water price during drought years. The biases in revenue vulnerability results stem from different operational activities such as surface water delivery, aquifer recharge and groundwater pumping. Consequently, all of the previously discussed surface- and ground- water sources of errors contribute to the resulting errors for irrigation districts' financial dynamics. We estimate that the combined annual expected costs of the errors among the 26 simulated irrigation districts totals to about $114-million, $91-million, and $81-million US dollars under the CGW, NGW, and BC scenarios, respectively.

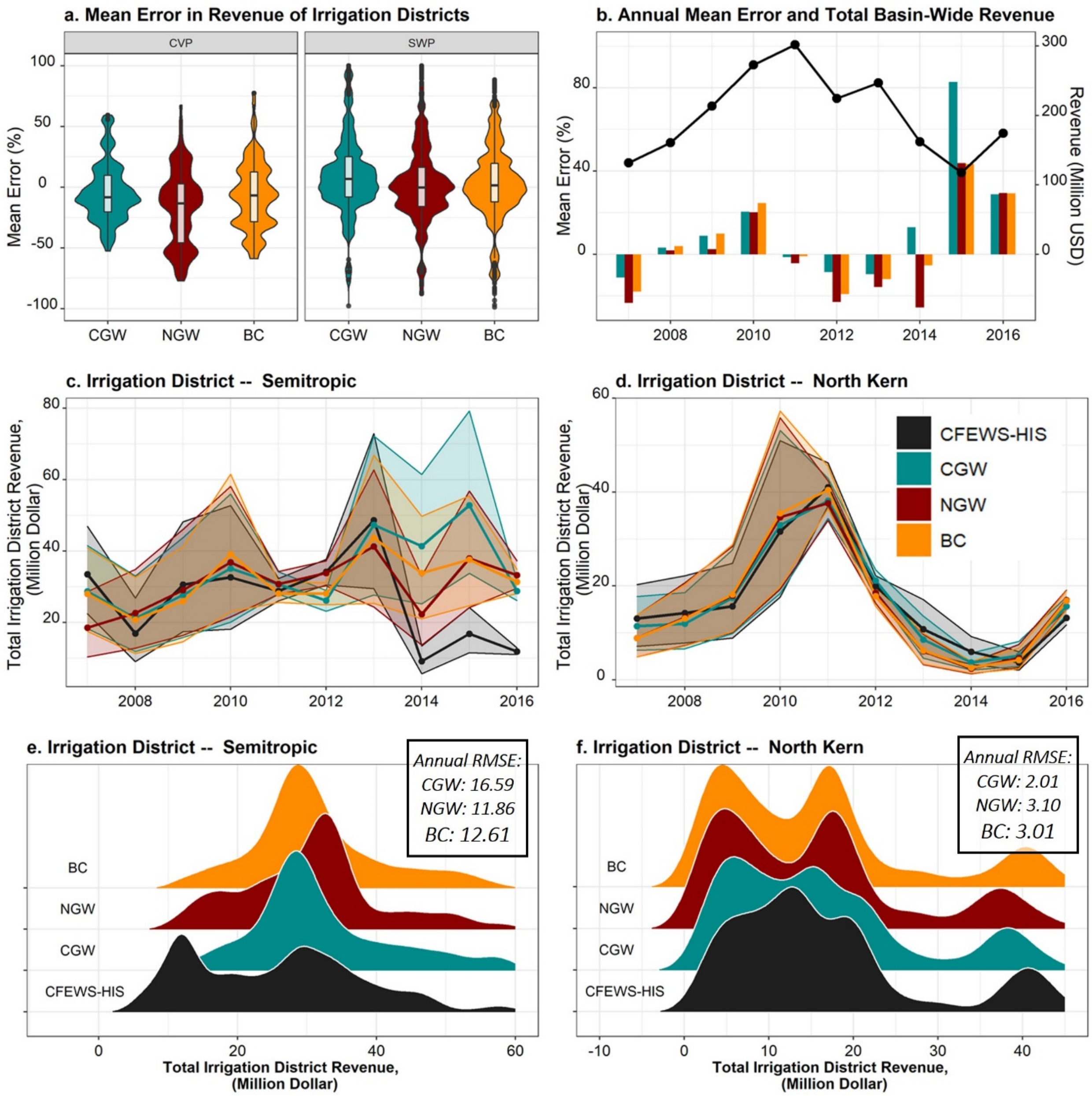

Figure 5. Financial stability of irrigation districts. This figure shows how different streamflow scenarios (i.e., baseline [CFEWS-HIS], raw WRF-Noah-MP output [NGW], and groundwater corrected WRF-Noah-MP output [CGW], and bias-corrected WRF-Noah-MP [BC]) affect the simulation of financial stability for the Central Valley's irrigation districts. In Panel a, c and d, the distributions and uncertainty bounds are generated from our 100 water price realizations and the solid lines demonstrates the average of all those water price scenarios. Panels e. and f. show the probability density function of average yearly revenue across different irrigation districts and under the

observed, NGW, CGW, BC conditions. In this figure, the unit of Root Mean Square Error (RMSE) is million dollars.

Such a costly misperception (ranging from underestimation -81% to an overestimation of +111% of average annual revenues among individual districts) of irrigation districts' revenues could lead to infrastructure investment and financial decisions that would likely harm them as well as the broader water dependent north-central California systems. We also highlight that susceptibility of different irrigation districts to streamflow errors depends on the details of their specific institutional contexts (Figure 5 – Panels c and d). For example, our analysis suggests that SWP irrigation districts are more sensitive to streamflow errors (Figure 5 – Panel a), mainly because they tend to rely closely on error-prone water balance dynamics. In addition, various other institutional factors such as water right seniority level of districts, degree of their dependence on ground- versus surface- water systems, and the geographical location of districts contribute to their susceptibility or immunity to headwater streamflow errors.

Our analysis indicates that, on average, the expert-based and automatic error management methods (CGW and BC) tend to systematically overestimate irrigation districts' annual revenues (Figure 5 – Panel a and b). The reason is that, under these scenarios, surface water delivery during summertime is generally higher, and higher supply increases the income of irrigation districts. However, as discussed earlier, these errors also compounded with groundwater errors that can stem from failures in capturing key flood events. Given that these groundwater biases have longer residence times, they adversely impact irrigation districts' revenue estimates over the longer term. It is concerning that these biases are very pronounced and more clearly emerge during extreme drought years. For example, the relative error is significantly higher during 2015, which was the most significant drought year in our study period (Figure 5 – Panel c). Furthermore, as the tail of the revenue probability density functions suggest, simulated streamflow scenarios perform exceptionally poorly during extreme low-revenue periods (Figure 5 – Panels e and f, also see Figure S16-S21 in Supplemental Materials). Again, this result is of significant concern because these extreme drought years can trigger major investments or inform planned institutional changes.

Finally, our analysis (Figure S22 in Supplemental Materials) suggests that our broad envelope of water pricing scenarios do not substantially modify the core insights from the revenue impacts shown in Figure 5. However, water pricing strongly depends on projections of state-wide availability of water (Medellín-Azuara et al. 2012), and is a factor that should be studied closely for its interactions with streamflow error propagation. While fully exploring these dependencies is beyond the scope of this study, future work that employs hydro-economic models that capture the interactions between water supply availability estimates and water rates would provide more comprehensive understanding of the compound dynamics of human-natural system under uncertainty.

Do Streamflow Corrections Increase the Error in Modeled Impacts?

Our results suggest that, at least in some cases, the expert-based manual groundwater bias correction and quantile mapping-based bias correction increase the bias and deteriorate the quality of the CALFEWS simulations. This is slightly counterintuitive, considering the fact that there are severe and well-known biases in the NGW streamflow simulation results from WRF-NoahMP, especially during low-flow periods (Figure 4 – Panels c and e), and the standard aggregated accuracy model performance metrics (e.g., NSE) are higher for the CGW and BC. One reason for the increases in error is that, among the many features of a streamflow time series (including average annual magnitude, average flow magnitude in different seasons, and seasonality), any specific bias correction method will optimize error in terms of only some of those features, while errors in other features may even be increased. Also, capturing the properties of extreme events is very important, as the severity and persistence of streamflow during low- and high-flow periods affect the operation of many components of the north-central California water infrastructure and institutional systems (Hanak et al. 2018; Scanlon et al. 2016). As such, we recommend that future studies claiming to improve simulated representation of hydrologic systems for the purpose of informing water resource decision-making move beyond typical bulk hydrograph metrics (e.g. RMSE, NSE, Kling-Gupta Efficiency) because they do not capture important nonlinear water balance dynamics that shape water resources management. Although these metrics are easy to calculate, our results suggest that they can provide a misleading sense of improvement.

Additionally, there is a close relationship between floods and droughts in California's water system. Floodwater is often either stored in surface reservoirs or controlled and diverted toward recharge basins, feeding groundwater banks. Later, the banked/stored water is used by irrigation districts (Dettinger et al. 2011; Xiao et al. 2017). Therefore, error generated during high-flow periods will propagate into low-flow years and affect the simulation of system-wide water availability, groundwater extraction, and irrigation district revenue during water shortage periods, when the north-central Californian water system is more vulnerable. In other words, errors across time and space pool, transfer and reside in the institutionally complex infrastructure systems. We use our north-central California example to argue that, in each region, one or more characteristics of flow might be more important to capture, and the interaction of these properties (high- and low- flow periods) must be known in order for a reasonable understanding of the system to be gained. Finally, we warn that the complex institutional and infrastructure contexts of the errors in simulated streamflow projections, are critical to understanding the consequences of any error management strategies. Deterministic bias correction that are commonly used in climate scenario modeling exacerbate this issue, as they ignore the water resources system context in which they are employed. Our results highlight that the impact of changing hydrology on water resources in climate projections cannot be treated as being dominantly a natural systems modeling problem.

Conclusions

In this study, we explore how our management of the well-known errors and biases in coupled land-atmosphere modeling systems (e.g., WRF-NoahMP) used to simulate current hydrology (as in this study) and increasingly to project regional climate change impacts (Huang et al. 2018; Musselman et al. 2018;

Schwartz et al. 2017; Wrzesien and Pavelsky 2020) can strongly distort our perceptions of vulnerabilities in institutionally complex major global water resources systems such as the north-central California case analyzed in this study. We show how streamflow errors from an atmospheric and land-surface hydrologic model, WRF-Noah-MP, propagate into a water management model, CALFEWS, and affect perceptions of system-wide water supplies, groundwater banking, and the annual revenue of irrigation districts. We show that the north-central California water management infrastructures serve their intended purpose, highly coupling the water balance dynamics of floods and droughts. The infrastructures likewise shape the residence times and conveyance of water balance errors across extreme events. We show that these errors have long, multi-year residence times and become more consequential during severe drought periods. This is concerning because the inferences we draw from simulating extreme drought years are more likely than other years to shape perceptions and trigger institutional and infrastructural changes. We also show that errors and their effects can be unique and path-dependent as illustrated in the north-central California system's dependencies on different major water delivery projects (CVP vs. SWP), the network of water rights, and the complex water portfolios for each irrigation district. We show that ex-post corrections of raw WRF-Noah-MP outputs do not necessarily reduce biases in the simulation of key processes and, in some cases, can strongly degrade system simulations.

Finally, our results indicate that the need for future research to more fully engage with how institutional and infrastructure context shapes the efficacy of bias-correction choices in our climate vulnerability assessments for complex water resources systems. We show that they can strongly distort our inferences of climate-driven vulnerabilities given the highly interdependent nature of the human and natural processes that WMMs simulate. The results of this study also highlight the necessity of considering alternative paradigms of water resources vulnerability assessments, such as exploratory modeling (e.g., (Hadjimichael et al. 2020), which can more fully incorporate and address the key errors and uncertainties that shape projections of climate change vulnerabilities.

Data Availability Statement

All datasets and scripts used in this study are available in the GitHub repository of the paper. The CALFEWS model is an open-source software and its latest version can be obtained from its doi repository (https://doi.org/10.31224/osf.io/sqr7e). Also, the *biascorrection* R package can be found here (https://github.com/keyvan-malek/biascorrection).

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Author Contribution Statement

Keyvan Malek conducted simulations and wrote the first draft of the manuscript. Patrick Reed supervised the project. Keyvan Malek, Patrick Reed, Harrison Zeff, Andrew Hamilton, Melissa Wrzesien, Natan Holtzman, Scott Steinschneider, Jonathan Herman, and Tamlin Pavelsky participated in development of the paper's central ideas, its study design, and the final version of the manuscript.

Conflict of Interest

The authors declare no conflicts of interests.

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