Anonymous Referee #2

In this work, the authors present global climatic and hydrologic models to simulate the extremes and their impacts on the water-energy balance over California. The paper is well written and with high relevance to the hess journal. Please see some suggestions I kindly ask the authors to address:

We thank the reviewer for their positive comments and feedback and for acknowledging the quality and the significance of our work.

1) The title of the paper is "Projecting the impacts of end of century climate extremes on the hydrology in California.". The title of the paper is a bit strong since it recommends that the whole hydrological-cycle has been modeled for the State of California and also for a time-window reaching the end of the century. Many authors struggle to simulate only one part of the hydrological-cycle of California (e.g., rainfall-runoff model, as for example in Yin et al., 2021; while many similar studies exist in literature). For such a promising title, a strong literature review should be performed to include similar studies for all hydrological-cycle variables and to show how the proposed model is more advanced.

We acknowledge that the title could be misleading since we are only simulating a watershed in California although the watershed is representative of the state's hydrology.
We propose to change the title to "Projecting end of century climate extremes and their impacts on the hydrology of a representative California watershed"
While we didn't simulate the hydrology through the end of the century, we selected particular years of interest by analyzing the end of century hydroclimate (from 2070 to 2100).
In the revised manuscript we will add the listed references although these studies are different from ours as they simulated the hydrology using rainfall-runoff and machine learning models, therefore, targeting single/individual components of the water cycle and/or not accounting for the physical characteristics of the area. To better understand how the hydrology will evolve in response to climate change it is important to represent the transfer of water and energy from the bedrock to the canopy especially in California where the subsurface hydrology downstream (i.e., groundwater dynamics) strongly depends on the land surface processes occurring upstream (i.e., snowmelt). To capture such behaviors, ParFlow-CLM is adequate.
Below is a table with the most used hydrologic models and their advantages and limitations when simulating the hydrology of California, highlighting the strong advantages of ParFlow-CLM. Only Hydrogeosphere and ATS have similar advantages as ParFlow-CLM and are suitable to model the Californian hydrology. Because the equations and the coupling approaches used by these models are similar, we expect their results to be the same.

Hydrologic Model	**Land Surface**	**Surface**	**Subsurface**	**Limitations when simulating Californian hydrology**
MODFLOW (Harbaugh, 2005)/FELFOW	No	No	Yes (diffusivity equation)	These models do not integrate land surface processes (such as snow dynamics) and their

(Trefry and Muffels, 2007)				interactions with the subsurface critical to the Californian hydrology.
SWAT (Soil and Water Assessment Tool) (Neitsch et al., 2000)	Yes	Yes	Yes	The model is based on HRU (hydrologic response units). The model isn't physics-based, therefore, it doesn't account for the two-way interaction between the land surface and the subsurface processes.
SAC-MA (Sacramento Soil Moisture Accounting Model)	No	Yes (Rainfall-Runoff)	Yes (Water Budget)	The model doesn't simulate snow dynamics and evapotranspiration. A water budget equation is used to simulate the groundwater dynamics which doesn't account for the lateral flow and unsaturated zone flow.
Noah-MP (Niu et al., 2011)	Yes (water and energy balance)	Yes (a routing scheme can be used to derive surface flow)	Yes (percolation)	Although this model physically solves the land surface processes including evapotranspiration and snow dynamics, it doesn't account for the two-way interaction between the land surface processes and the subsurface. Lateral and unsaturated zone flows are not represented.
VIC (Variable Infiltration Capacity Model Macroscale Hydrologic Model) (Liang et al., 1994)	Yes	Yes (Rainfall-Runoff)	Yes (percolation and water budget)	Although this model physically solves the land surface processes including evapotranspiration and snow dynamics, it doesn't account for the two-way interaction between the land surface processes and the subsurface. Lateral and unsaturated zone flows are not represented.
Hydrogeosphere (Aquanty, 2015)	Yes (water and energy balance)	Yes (2D diffusive wave equation)	Yes (3D Richards equation)	This model has similar advantages as ParFlow-CLM and could be used to model the hydrology of California.

CATHY (Catchment Hydrology) (Bixio et al., 2002)	Yes (there is a version coupled to Noah-MP)	Yes (1D Saint Venant Equation)	Yes (Mass balance equation)	The mass balance equation is not as robust as the Richards equation for describing the variably saturated flow in the subsurface and recharge processes. In addition, the original model doesn't solve land surface processes.
MIKE-SHE (Abbott et al., 1986)	No	Yes (diffusivity equation)	Yes (Darcy equation and a 1D Richards equation)	The main limitation of this model is the lack of land surface processes and the Darcy equation used to describe subsurface flow doesn't account for the unsaturated flow.
ATS (Advanced Terrestrial Simulator) (Coon et al., 2016)	Yes (water and energy balance)	Yes (2D diffusivity equation)	Yes (3D Richards equation)	This model has similar advantages as ParFlow-CLM and could be used to model the hydrology of California.
ParFlow-CLM (Kollet and Maxwell, 2006)	Yes (water and energy balance)	Yes (2D diffusivity equation)	Yes (3D Richards equation)	

Table R1c: Advantages and limitations of the most used hydrological models

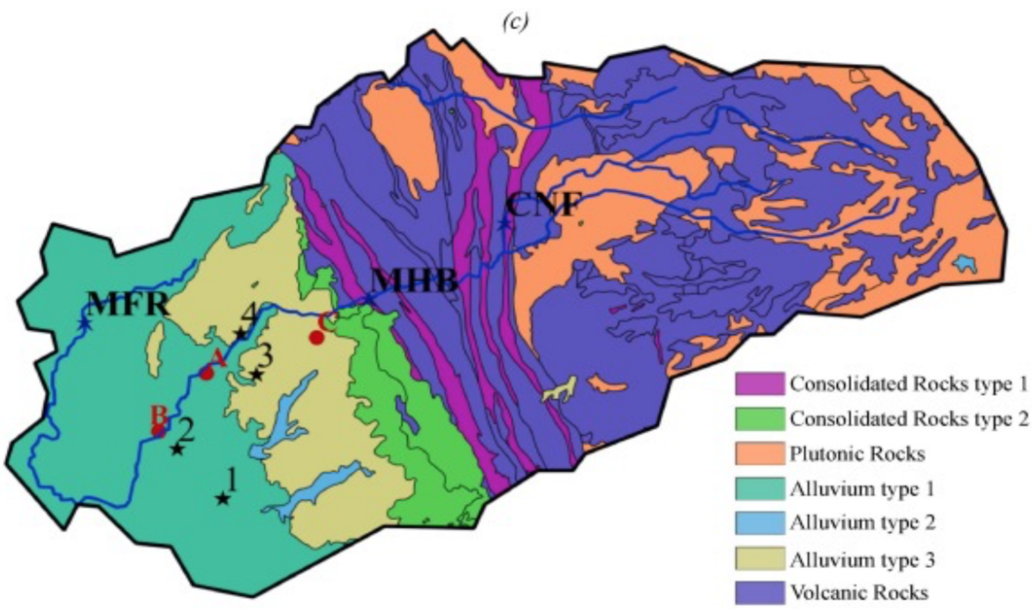
2) There is a lack of calibration, validation, and verification of the proposed model. When a forecast is performed, one should use a part of the timeseries to calibratevalidate-verify their model, and then perform a forecast for the near future. I suggest the authors see/discuss this procedure concerning their own model.

We didn't employ a time-series based comparison for the climate model due to the uncertainties of the model to capture individual events throughout the year. VR-CESM is simulated under AMIP-protocols (bounded by monthly observed sea-surface temperatures and sea-ice extents), and therefore we do not expect VR-CESM to exactly recreate past historical WYs. However, we do expect that our 30-year simulation can reasonably recreate the range of WY types over California and the Cosumnes, which is why we utilize the broader range of PRISM WYs that are available. The VR-CESM simulations are not forecasts or predictions, but rather projections. There is a subtle but important difference in a prediction, which aims to exactly recreate an event or time period, versus a projection, which aims to encapsulate the envelope of plausible future scenarios given socioeconomic development/greenhouse gas emissions, etc. The end-century projections performed with VR-CESM allow the atmosphere and land-surface model to interact under assumptions of the "upper end" emissions scenario (RCP8.5), land-surface cover changes, and increases in sea-surface temperatures and decreases in sea-ice. Therefore, the 30-year period (2070-2100) encapsulated by these VR-CESM projections should be thought of as "what might happen to the middle and end member years (i.e., driest and wettest) if the world warms by +4 - 5∘C?"

We calibrated and validated the hydrologic model using remotely sensed and ground measurements of streamflow, groundwater levels, snow water equivalent, soil moisture, and evapotranspiration.
Below are the details of the comparisons which have been published in a previous paper and will be added to the appendix of the revised manuscript.

Model validation procedure (also added to the response to reviewer 1)

We compared temporal variations of streamflow at 3 stations located in the Sierra (uplands), the intersection between the Sierra and the Central Valley, and the outskirts of Sacramento (see Figure R1). Four wells in the watershed (see Figure R1a) have reasonable, publicly-available records of groundwater levels and were used to check the ability of the model to reproduce water table depth variations.



Download : Download high-res image (403KB)
Download : Download full-size image

Figure R1a: The Cosumnes watershed geology and the locations of the 3 streamflow gauges (CNF, MHB, and MFR) and 4 groundwater wells (stars).

Figure R1b depicts the comparisons between simulated and measured river stages at the 3 stations indicated in figure R1a. Absolute errors (L1) in m and relative errors (L2) are shown in Table

R1a. Differences between simulated and measured streamflow vary between 0.4 and 0.8 m (Table R1a) indicating that the model is able to reproduce the river dynamics.

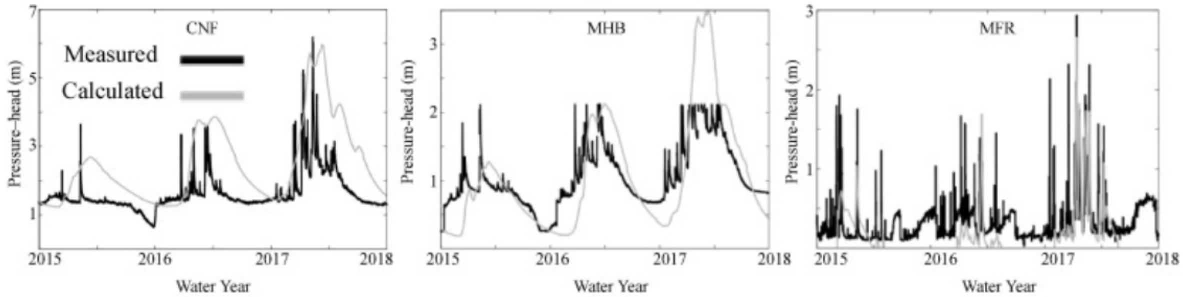


Figure R1b: Comparisons between measured and calculated river stages (i.e., pressure-heads simulated by ParFlow-CLM). Measurements locations are indicated in Figure R1a.

Measurements		
	L_1(m)	L_2
River stages (CNF)	0.8	0.5
River stages (MHB)	0.4	0.36
River stages (MFR)	0.57	1.09
Groundwater Levels (Well 1)	3.73	0.0553
Groundwater Levels (Well 2)	1.63	0.025
Groundwater Levels (Well 3)	0.476	0.0077
Groundwater Levels (Well 4)	1.08	0.016

Table R1a: Differences between measured and calculated surface and groundwater levels. L1 is the absolute error and R2 the relative error.

Comparisons between simulated and calculated groundwater levels (here referred to as the pressure-heads at the bottom of the domain) shown in figure R1c indicate that the model has reasonable agreements with measurements. As shown in table R1a, the error varies between 0.47 to 3.73 m depending on the station. Mismatches between simulated and observed groundwater levels at wells 1 and 2 are likely due to an inaccurate estimation of pumping in these areas. The temporal variations of the groundwater levels show an impact of withdrawals but because these withdrawals are hard to estimate the model isn't correctly reproducing these trends.

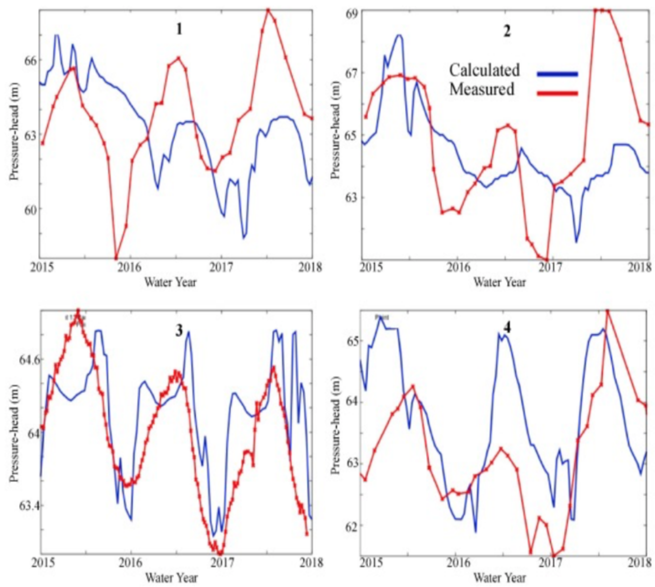


Figure R1c: Comparisons between measured and calculated pressure-heads at the bottom of the domain. Measurements locations are indicated in <u>*Fig.*</u> *R1.*

ParFlow-CLM also solves the key land surface processes governing the transfer of water and energy at the land-atmosphere-soil interface: evapotranspiration, snow dynamics, and soil moisture. In Maina et al., (2020a), rigorous comparisons between the ParFlow-CLM simulated land surface processes and remotely sensed estimates of these variables was conducted. Table R1b shows the correlation coefficient between ParFlow-CLM results and the various datasets compared.

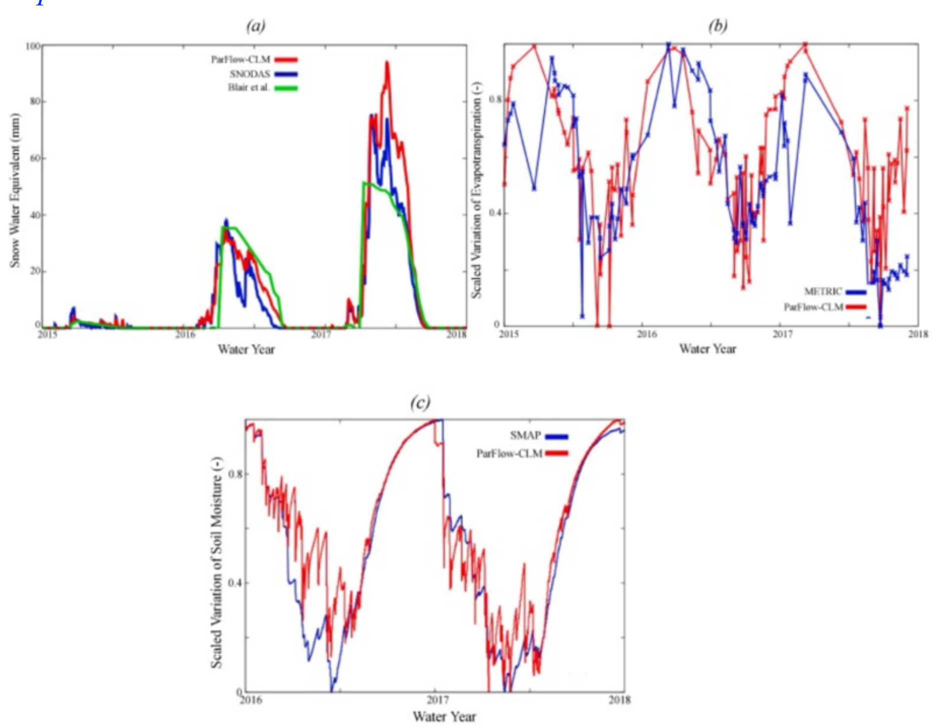


Figure R1d: (a) Comparisons between domain-averaged total snow water equivalent obtained with ParFlow-CLM, SNODAS and Bair et al., reconstruction, (b) Comparisons between actual evapotranspiration obtained with ParFlow-CLM and METRIC (c) Relative variation of soil moisture obtained with ParFlow-CLM and SMAP. Note that the x-axis of (c) is shorter because of the availability of SMAP data

Satellites-based products

	L_1	L_2	Pearson correlation coefficient
SNODAS (mm)	3.09	3.77	0.97
Bair et al., 2016 (mm)	3.80	2.69	0.84
SMAP (-)	0.217	3.07	0.94
METRIC (mm/s)	0.0367	1.40	0.6

Table R1b: differences between measured and remotely sensed evapotranspiration (METRIC), soil moisture (SMAP), and snow water equivalent (SNODAS and Bair et al., 2016)

Also, the End of Century (EoC) forecast for such a large area is very optimistic in my opinion. Since climate dynamics is highly complex, I imagine that a forecast of only a few steps ahead is possible. If one is studying, for example, runoff on an annual scale, then after a couple of years, the variability of the forecast would be very wide, thus, reducing the credibility of the result (e.g., see Han et al., 2021). Also, the credibility of the outcome should depend on the available length of records. Here, the authors perform a forecast of 80 years ahead, which is double the length of records the authors use to construct the climatic and hydrologic model. I suggest to test/discuss how the variability/probability of the forecasts change as we move away from the present/historic data.

The study mentioned by the reviewer (Han et al., 2021) uses a deep learning approach which is different from the type of model we employed in this study which is based on physics. Although physics-based models depend on the initial conditions, the impact of the initial conditions decreases with time (Maina et al, 2017), because these models simulate the hydrology based on the physical characteristics of the watershed such as the geology and the land cover. While the geology dictating the hydrodynamic parameters such as hydraulic conductivity, porosity, and specific storage could change with time, this change follows geological scales and timing (thousands or millions of years). As acknowledged in the manuscript, the land cover may change by the end of the century, nevertheless, this change is uncertain and difficult to predict hence we didn't incorporate them in this study.

We specifically used the physics-based integrated hydrologic models because these models do not strongly rely on the historical/initial conditions rather on the physical characteristics of the area. Likewise, because the climate model is based on physics, it doesn't rely on historical and past observations. Moreover, the memory of physics-based climate models is shorter than that of the integrated hydrologic models. The uncertainties that could arise from the long forecast is the

trajectory of CO_2 emissions that could potentially change by the end of the century, nevertheless, the predictions as documented in the literature (i.e., RCP 8.5). We also perform long-term simulations because we are not trying to forecast the exact conditions in various years. We are trying to assess the envelope of possibilities if warming occurs and the interactions between alterations in atmospheric dynamics and thermodynamics that shape the water cycle in the Cosumnes watershed.
We will discuss these impacts and the advantages of using physics-based models in the revised manuscript.

3) It is shown that due to long-range dependence effect to key hydrological-cycle processes (e.g., Dimitriadis et al., 2021) such as the ones the authors use, the variability of each climatic process would be even higher than, for example, under the assumption of zero auto- and cross- correlation (i.e., white noise). Please show/discuss whether the proposed model assumes a correlation function for the input variables. I also suggest the authors see/discuss whether their model forecasts also capture (and verify) the stochastic characteristics of the historical timeseries including the effects from climate change (such as marginal distribution function, autocorrelation function, etc.).

As mentioned in the previous answer, we used a physics-based model not a machine learning model that is based on the previous observations to perform prediction and is strongly dependent on the previous conditions and the period used to do the training and make the predictions. We will clarify these differences between physics-based models and trained models in the revised manuscript.
Also, because these models are based on physics there is no need to account for a longer historical period that captures the statistical distribution of the event. Nonetheless, we validate our model by testing its ability to simulate dry and wet years in California. The comparisons have shown that the developed model captures such extremes.

4) There are many equations in the text. Please consider creating a Table with all the inputs variables, output variables, boundary conditions, model assumptions, model limitations, simulation times, discretization method, etc., in order to help the readers identify the complexity/strength of the proposed model.

We will add the following section to the Appendix.

1. Input Variables

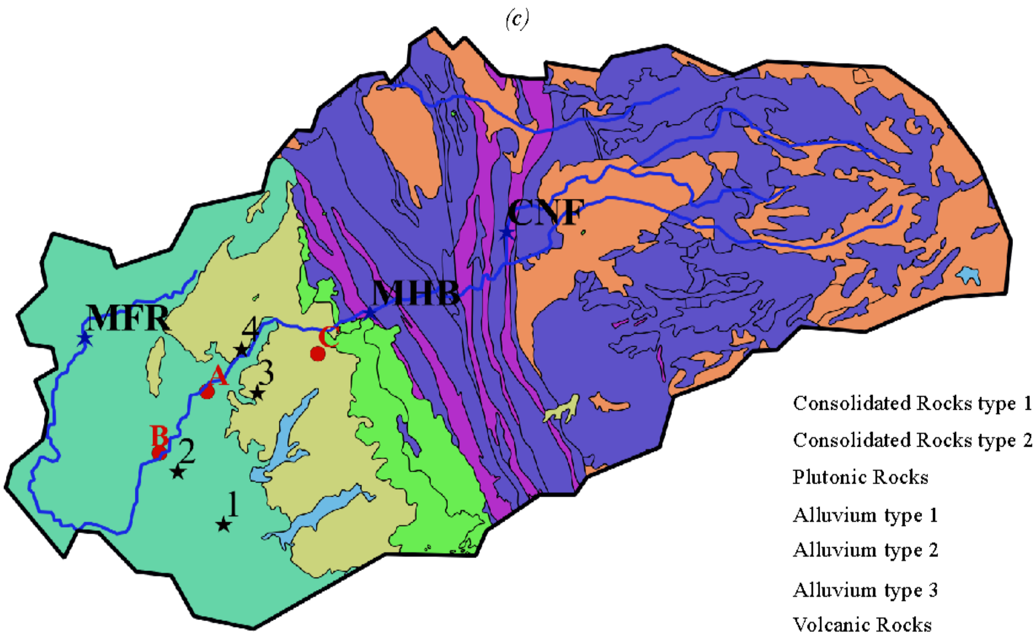


Figure R2a: Geological map of the Cosumnes watershed (source: USGS, Jennings et al., 1977)

Hydrodynamic properties based on the geology				
Geological Formation	Porosity (-)	Specific Storage (m-1)	Van Genuchten α (m-1)	Van Genuchten n (-)
Bedrock (Consolidated, Plutonic and Volcanic Rocks)	0.02	10-6	3.0	3.0
Alluvial aquifers	0.2	10-4	3.0	3.0

Table R2b: Assigned values of hydrodynamic parameters (porosity, specific storage and Van Genuchten parameters). Values are based on literature review (Faunt et al., 2010; Faunt and Geological Survey (U.S.), 2009; Flint et al., 2013; Gilbert and Maxwell, 2017; Welch and Allen, 2014).

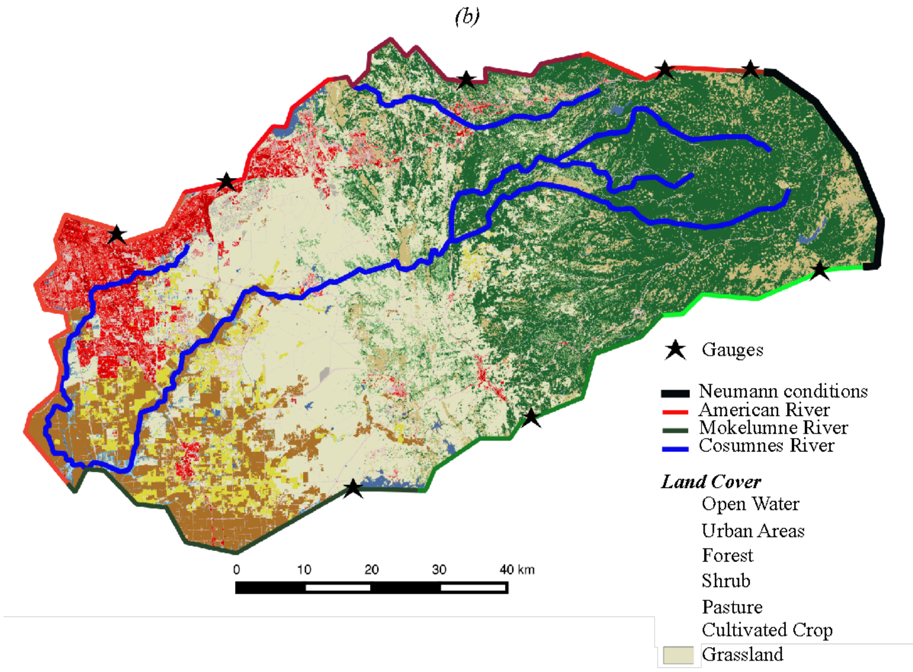


Figure R2b: Cosumnes watershed characteristics: land use and land cover (source: Homer et al., 2015), and model boundaries.

	Surface roughness based on land use			
Land Use		**Manning Coefficient (h.m-1/3)**		
Forest		5x10-2		
Shrub land and agricultural area		5x10-3		
Urban areas		5x10-5		
	Crop properties			
	Crop Type and Reference	**Height (m)**	**Maximum Leaf Area Index (-)**	**Minimum Leaf Area Index (-)**
	Alfalfa (Evett et al., 2000; Orloff, 1995; Robison et al., 1969)	0.6	6.0	2.0
	Pasture (Buermann et al., 2002; King et al., 1986; Rahman and Lamb, 2017)	0.12	6.0	1.0
	Vineyards (Johnson and Pierce, 2004; Vanino et al., 2015)	0.9	3.0	0.6

Table R2b: Manning coefficients and crop properties

Boundary conditions	**Value**
Mokelumne and American river	Weekly-varying Dirchlet boundary conditions. These values are based on the measured river stages.
Sierra Nevada limit	No flow Neumann boundary condition

Bottom of the model	No flow Neumann boundary condition

Table R2c: boundary conditions

2. Numerical model set-up

Domain size	~7000 km2
Spatial discretization	200 m horizontal from 0.1 m to 30 m in the vertical direction Vertical Resolution Layer: 1, 2, 3, 4, 5, 6, 7, 8 Δz (m): 0.1, 0.3, 0.6, 1.0, 8.0, 15.0, 25.0, 30.0
Simulation time	Model validation (from water year 2012 to water year 2017), then water years 1998, 2004, 2007, 2076, 2078, and 2084.
Temporal discretization	hourly

Vertical Resolution								
Layer	1	2	3	4	5	6	7	8
Δz (m)	0.1	0.3	0.6	1.0	8.0	15.0	25.0	30.0

Table R2d: Numerical model discretization

3. Output variables

Selected output variables	**Temporal scale**	**Spatial scale**
Snow Water Equivalent	Yearly, monthly, and hourly	Domain-average and point scale
Evapotranspiration	Yearly, monthly, and hourly	Domain-average and point scale
Soil Moisture	Yearly, monthly, and hourly	Domain-average and point scale
River Stages (also surface water storages)	Yearly, monthly, and hourly	Domain-average and point scale
Groundwater levels variations (also subsurface storages)	Yearly, monthly, and hourly	Domain-average and point scale

Table R2e: Selected output variables

5) Please include more details on the water-energy balance equation and show whether is preserved in historical and forecasts. Also, have the authors included in the mass-energy balance analysis groundwater depletion in California (e.g., Badiuzzaman et al., 2017) and effects from sea level rise and ocean dynamics (e.g., Katsman et al., 2008)?

Mass balance is preserved when solving the mixed form of the Richards equation shown in equation (1) (Celia, et al., 1990). ParFlow-CLM numerically solves this equation by using the New-Krylow linearization scheme, this scheme iteratively solves the equation at each time step until the mass balance criteria set (equal to 10^{-3}) is satisfied. Any large errors in the mass balance will automatically stop the resolution of the equation.

The Richards equation as shown in (1) accounts for groundwater depletion which is included in the term qs. While groundwater depletion plays an important role in the hydrodynamics of California we didn't account for this effect in this study because the current pumping rates are difficult to estimate and their prediction by the end of the century is highly uncertain as it depends on many factors including policy and management.

Discussion on the potential impacts of groundwater depletion on hydrologic projection in California

Because pumping rates may substantially change in the future due to new demands, policies/ regulations, and changes in land cover and land use, a model which includes a projection (or an envelope of these projections) is a work in itself. Therefore, we did not include them in this work, although the ParFlow-CLM model of this basin was developed to account for an approximation of the pumping and irrigation practices (to date) in the Central Valley. In the simulations originally shown here, we chose to simulate the natural system, given the constraints and uncertainty around the aforementioned projections in water and land management practices. However, we have taken the reviewer's comment very seriously, and we have performed additional simulations since receiving their comments, which now compare the EoC simulations with pumping and irrigation as a type of "numerical experiment". Specifically, we performed two additional simulations for both historical and EoC median water years with pumping and irrigation. The two simulations are as follow:

- *Baseline without any pumping and irrigation*
- *Pumping and irrigation, around 700 pumping wells operating from April to November have been placed in the Central Valley aquifers. The number of wells, timing, and rates of pumping were determined by discussion with stakeholders in the areas and an estimation technique, which accounts for the water required by each crop for its optimal growth. More details about the estimation technique can be found in Maina et al., (2020a).*

Figure R6 illustrates the temporal variations of surface water and groundwater storages obtained with the four simulations. As expected, the pumping scenarios have lower storages than the baselines. We notice that both pumping and baseline EoC scenarios are characterized by an earlier and higher increase in groundwater and surface water storage compared to the historical conditions (similar to the main conclusions of our study). These storages decrease by the end of the water year to become nearly equal to the historical baseflow conditions. In the baseline scenarios, the EoC groundwater storage is lower than the historical groundwater storage into August, though the historical baseline storage dips below the EoC baseline in September. In contrast, in the historical pumping scenario the groundwater storage remains lower throughout the summer, showing distinct behavior in the pumping scenarios. We attribute this difference to reduced evapotranspiration in the pumping scenarios because of the deep water tables.

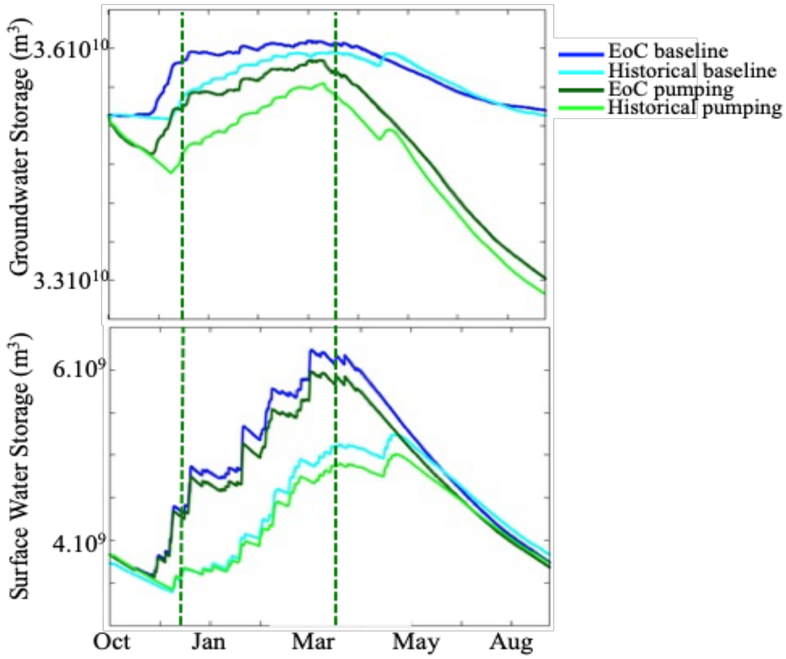


Figure R2c: Temporal variation of groundwater and surface water storages associated with EoC and historical baseline and pumping scenarios. The dashed green lines indicate the beginning and end of the pumping.

An analysis of the spatial differences between the baseline and the pumping differences (not shown here) has shown that these differences are mostly located in areas close to the pumping wells. Figure R7 depicts the temporal variation of water table depth and recharge associated with EoC and historical baseline and pumping scenarios at a selected point (located close to the pumping wells) in the Central Valley.

In the pumping scenarios, the water table decreases in the first two months whereas the water table is constant during this period in the baseline simulations. As the water table becomes deeper, the recharge also decreases. In the EoC, there is an early rise of the water table and an increase in recharge in both pumping and baseline scenarios due to the meteorological conditions (high and early precipitation). The water table rises earlier in the baseline compared to the pumping scenario. This rise is much earlier in the EoC than the historical conditions because the high precipitation of the EoC quickly compensates for the depressions created by pumping and increases the water table and therefore increases the recharge as explained in the schematic figure R8.

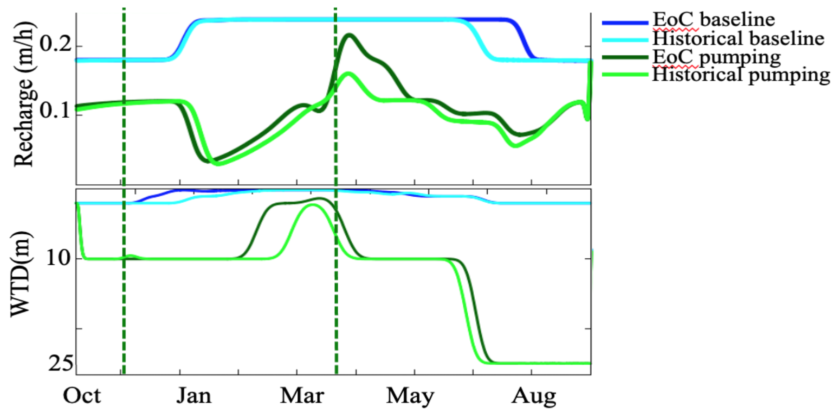


Figure R2d: Temporal variation of water table depth (WTD) and recharge associated with EoC and historical baseline and pumping at a selected point in the Central Valley. The dashed green lines indicate the beginning and end of the pumping.

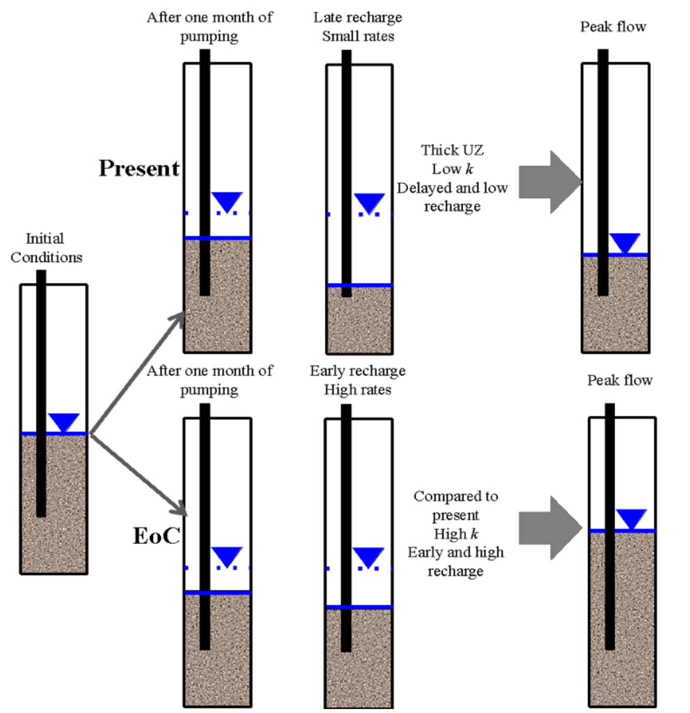


Figure R2e: Schematic representation of the influence (on recharge) of pumping in historical and EoC conditions. At a local point, early and high precipitation of the EoC leads the water table to rise earlier and the recharge to increase because the unsaturated zone (UZ) becomes less thick, and the effective permeability k becomes higher.

While the pumping simulations have lower storages than the baselines, the mechanisms (early and high increases in storages and depletion in spring and summer) in both EoC and historical conditions remain the same. This is because we applied the same rate of pumping in both EoC and historical conditions and the timing of the pumping is assumed to be the same in both simulations.

However, we note that the simulations without pumping could overestimate the depletion of aquifer by evapotranspiration by 5 to 10%.

The watershed is not located near the coastal region; therefore, the effects of sea level rise are nonexistent.

References

Badiuzzaman, P., E. McLauglin, and D. McCauley, Substituting freshwater: Can ocean desalination and water recycling capacities substitute for groundwater depletion in California?, J. Environ. Manag., 203, 123–135, 2017.
Dimitriadis, P., D. Koutsoyiannis, T. Iliopoulou, and P. Papanicolaou, A global-scale investigation of stochastic similarities in marginal distribution and dependence structure of key hydrological-cycle processes, Hydrology, 8 (2), 59, 2021.
Han, H., C. Choi, J. Jung, and H.S. Kim, Deep learning with long short term memory based sequence-to-sequence model for rainfall-runoff simulation, Water, 13 (4), p. 437, 10.3390/w13040437, 2021.
Katsman, C., W. Hazeleger; S. Drijfhout; G.J. van Oldenborgh, and G. Burgers, Climate scenarios of sea level rise for the northeast atlantic ocean: A study including the effects of ocean dynamics and gravity changes induced by ice melt, Climatic Change, 91, 351–374, 2008.
Yin, H., X. Zhang, F. Wang, Z. Yanning, R. Xia, and J. Jin, Rainfall-runoff modeling using LSTM-based multi-state-vector sequence-to-sequence model, J. Hydrol., 10.1016/j.jhydrol.2021.126378, 2021.

Additional references

Maina, Fadji Z., Siirila-Woodburn, E. R., Newcomer, M., Xu, Z., & Steefel, C. (2020a). Determining the impact of a severe dry to wet transition on watershed hydrodynamics in California, USA with an integrated hydrologic model. Journal of Hydrology, 580, 124358. https://doi.org/10.1016/j.jhydrol.2019.124358
Maina, F. Z., Siirila-Woodburn, E. R., & Vahmani, P. (2020b). Sensitivity of meteorological-forcing resolution on hydrologic variables. Hydrology and Earth System Sciences, 24(7), 3451–3474. https://doi.org/10.5194/hess-24-3451-2020
Maina, Fadji Zaouna, & Siirila-Woodburn, E. R. (2020c). Watersheds dynamics following wildfires: Nonlinear feedbacks and implications on hydrologic responses. Hydrological Processes, 34(1), 33–50. https://doi.org/10.1002/hyp.13568
Harbaugh AW (2005) MODFLOW-2005, The U.S. Geological Survey modular ground-water model: the ground-water flow process. US Geol Surv Tech Methods 6-A16. http://pubs.usgs.gov/tm/2005/tm6A16/.
Trefry, M.G.; Muffels, C. (2007). "FEFLOW: a finite-element ground water flow and transport modeling tool". Ground Water. 45 (5): 525–528. doi:10.1111/j.1745-6584.2007.00358.x.
Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2001). Soil and Water Assessment tool (SWAT) user's manual version 2000. Grassland Soil and Water Research Laboratory. Temple, TX: ARS.

Niu, G.-Y., et al. (2011), The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. J. Geophys. Res., 116, D12109, doi: 10.1029/2010JD015139.
Liang, X., D. P. Lettenmaier, E. F. Wood, and S. J. Burges (1994), A simple hydrologically based model of land surface water and energy fluxes for general circulation models, J. Geophys. Res., 99(D7), 14415–14428, doi:10.1029/94JD00483.
Aquanty, I. (2015), HydroGeoSphere User Manual, 435 pp., Waterloo, Ont.
Bixio, A. C., G. Gambolati, C. Paniconi, M. Putti, V. M. Shestopalov, V. N. Bublias, A. S. Bohuslavsky, N. B. Kasteltseva, and Y. F. Rudenko (2002), Modeling groundwater-surface water interactions including effects of morphogenetic depressions in the Chernobyl exclusion zone, Environ. Geol., 42(2-3) 162-177
Abbott, M. B., J. C. Bathurst, J. A. Cunge, P. E. Oconnell, and J. Rasmussen (1986), An introduction to the european hydrological system: Sys- teme hydrologique Europeen, She .2. Structure of a physically-based, distributed modeling system, J. Hydrol., 87(1–2), 61–77.
Coon, E. T., J. D. Moulton, and S. L. Painter (2016), Managing complexity in simulations of land surface and near-surface processes, Environ. Modell Software, 78, 134-149
Kollet, S. J., & Maxwell, R. M. (2006). Integrated surface–groundwater flow modeling: A free surface overland flow boundary condition in a parallel groundwater flow model. Advances in Water Resources, 29(7), 945–958. https://doi.org/10.1016/j.advwatres.2005.08.006
Maina F. Z., Delay F., Ackerer P. (2017). Estimating initial conditions for groundwater flow modeling using an adaptive inverse method. J. Hydrol. 552, 52–61. doi:10.1016/j.jhydrol.2017.06.041