On the sensitivity of meteorological forcing resolution on hydrologic metrics

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Abstract

Projecting the spatio-temporal changes to water resources under a no-analog future climate requires physically-based integrated hydrologic models, which simulate the transfer of water and energy across the earth’s surface. These models show promise in the context of unprecedented climate extremes given their reliance on the underlying physics of the system as opposed to empirical relationships. However, these techniques are plagued by several sources of uncertainty, including the inaccuracy of input datasets such as meteorological forcing. These datasets, usually derived from climate models or satellite-based products, typically have a resolution of several kilometers, while hydrologic metrics of interest (e.g. discharge, groundwater levels) require a resolution at much smaller scales. In this work, a high-resolution watershed model is forced with various resolutions (0.5 to 40.5 km) of meteorological forcing generated by a dynamical downscaling analysis based on a regional climate model (WRF) to assess how the uncertainties associated with the spatial resolution of meteorological forcing affect the simulated hydrology.

The Cosumnes watershed, which spans the Sierra Nevada and Central Valley interface of California (USA), exhibits semi-natural flow conditions due to its rare un-dammed river basin and is used here as a testbed to illustrate potential impacts on snow accumulation and snowmelt, surface runoff, infiltration, evapotranspiration, and groundwater levels. Results show that localized biases in groundwater levels can be as large as 5-10 m and that other metric biases (e.g. ET and snowpack dynamics) are seasonally and spatially-dependent, but can have serious implications for model calibration and ultimately water management decisions.
1. Introduction

Understanding water and energy fluxes across the Earth and the atmosphere is important to assess the impacts of climate change on water resources. Integrated hydrologic models, solving water-energy interactions and transfers, across the lower-atmosphere, the land surface, and the subsurface, constitute a unique way to analyze water resources in both time and space and to project into no-analog future where empirical models are no longer valid. With the advancement of computing power, these models (e.g. MIKE-SHE (Abbott et al., 1986), HydroGeoSphere (Panday and Huyakorn, 2004), and ParFlow-CLM (Maxwell and Miller, 2005)) are becoming widely used with high-fidelity and high-resolution. However, they are plagued by several sources of uncertainty. Accuracy and precision, as well as uncertainty reduction of hydrologic models, are extensively discussed in the literature. However, more attention is given to the physical representation of the phenomena occurring in the hydrological systems (Beven, 1993; Beven and Binley, 1992; Liu and Gupta, 2007), the reduction of uncertainties related to the hydrodynamic parameters (Gilbert et al., 2016; Janetti et al., 2019; Maina and Guadagnini, 2018; Srivastava et al., 2014), and the numerical resolution of the mathematical equations governing the physics of the environment (Belfort et al., 2009; Bergamaschi and Putti, n.d.; Fahs et al., 2009; Hassane Maina and Ackerer, 2017; Miller et al., 1998; Tocci et al., 1997). Nevertheless, integrated hydrologic models, in essence, require multiple sources of input data such as hydrodynamic parameters, initial and boundary conditions, meteorological forcing data, etc.

Meteorological forcing is essential to inform integrated hydrologic models about the atmospheric dynamics and therefore constitute one of the main drivers of the simulated
hydrologic processes. Like the hydrodynamic parameters or the initial and boundary conditions, these data are impacted by several sources of uncertainty, including the fidelity of the physics of the atmospheric model as well as, the representativity of the spatial resolution at which they occur. Meteorological forcing data are often obtained from field measurements, satellite-based data-assimilation products (Cosgrove et al., 2003), or climate models (Hurrell et al., 2013; Skamarock et al., 2001). Because, the recent integrated hydrologic models require many meteorological variables (i.e., precipitation, temperature, wind speed, solar radiation, air pressure and relative humidity) to better simulate the interactions between the atmosphere and the subsurface environment (i.e. the aquifers), climate models and satellite-based products are the most used due to the scarcity of measurements. Moreover, in the context of climate change, only climate models can provide a spatial distribution of future meteorological conditions. Also, integrated hydrologic models require high resolution forcing to ensure fidelity and accuracy and meteorological variables such as precipitation, one of the most important data and key control of hydrological models, are very heterogeneous especially in mountainous areas (Olsson et al., 2014; Prein et al., 2013).

Impact of the spatial resolution of meteorological forcing notably precipitation on runoff and streamflow is widely documented in the literature with studies relying on (i) empirical hydrologic models with precipitation data coming from measurements (Arnaud et al., 2002; Berne et al., 2004; Loblicheois et al., 2014; Nicótina et al., 2008; Schilling, 1991; Shrestha et al., 2006; Tobin et al., 2011), satellite-based products (Koren et al., 1999; Ochoa-Rodriguez et al., 2015; Vergara et al., 2013) and climate models outputs (Dankers et al., 2007; Kleinn et al., 2005) and (ii) physics-based hydrologic models with precipitation data coming from measurements (Elsner et al., 2014; Fu et al., 2011), satellite-based products (Eum et al., 2014; Haddeland et al.,
and climate models outputs (Mendoza et al., 2016; Rasmussen et al., 2011). Also, Rasmussen et al., (2011) study the impact of meteorological forcing on snow dynamics. Nevertheless, previous studies were mostly focused on runoff and streamflow analysis, lacking a complete analysis of all the hydrodynamic processes occurring at the watershed scale. Moreover, the resolutions of the meteorological data (~km) used remain relatively coarse compared to the scale of resolution of the hydrological models (~m). Hence, the objective of this study is to investigate the impact of the spatial resolution of the meteorological forcing from ~km to ~m on the hydrologic processes occurring at the watershed scale using a physics-based integrated hydrologic model. In other words, we seek to understand how the uncertainties associated with the coarse spatial resolution of meteorological forcing propagate into the high-resolution integrated hydrologic models and affect the output of interest.

We use ParFlow-CLM (Kollet and Maxwell, 2006; Maxwell, 2013; Maxwell and Miller, 2005) forced with the Weather Research and Forecasting (WRF) model (Skamarock et al., 2008a; Skamarock and Klemp, 2008). ParFlow-CLM simulates subsurface and surface flows as well as their interactions by solving the mixed form of the Richards equation (Richards, 1931) and the kinematic wave equation respectively as well as the processes driving the transfer of water and energy from the ground surface to the atmosphere using a community land model (Dai et al., 2003). Therefore, the model allows to analyze in both time and space, all the hydrological components of interest such as the distribution of pressure head which encompasses the information on the water level in the river and the groundwater levels, the groundwater and surface water storages, the evapotranspiration, the infiltration, and the snow dynamics. ParFlow-CLM is widely used by the scientific community as it physically solves several hydrologic processes and can run in a high-performance computing framework. WRF, on the other hand,
solves the physics governing the atmospheric dynamics using a nested domain configuration to
provide meteorological forcing data at different spatial resolutions for ParFlow-CLM.

Our study focuses on Cosumnes, a unique watershed located in Northern California, USA. This region, one of the largest in the United States, has unfortunately begun to experience the effects of climate change. These effects are characterized by a fluctuation between extreme drought causing unprecedented wildfires and periods of intense precipitation mainly caused by atmospheric rivers. These rivers, a filament of concentrated moisture in the atmosphere, generate storms with intensity much higher than the average and sometimes very localized. It is, therefore, urgent to better understand how the water resources of this region evolve in response to these uncommon conditions. Understanding water resources evolution is crucial to sustaining California’s agriculture ranked among the highest in the World. Assessing California’s hydrodynamics requires models that not only take into account the strong variations in topography and land cover and land use, but also the snow dynamics. Indeed, the majority of the water resources in this region originates from snowmelt. Also, because complex physics governs the hydrology of the state such as sharp variation of wetting front accurate and high-resolution models are necessary. As the region is characterized by both strong variations of weather and complex hydrodynamics, it is, therefore, a good candidate to study how the spatial resolution of meteorological forcing impact the hydrologic processes. The Cosumnes, a rare large-scale watershed as it hosts one the last river without a dam in the state offering the opportunity to study natural flow. Interestingly, the watershed is also capturing all the complex hydrologic processes occurring in a typical Californian watershed including snow melting, groundwater, and overland flow as well as, their interactions, bedrock hydrodynamics, strong spatial variation of land use and land cover and topography. We study the water year 2017, the wettest water year on
California record characterized by several atmospheric rivers. The developed integrated hydrologic model has a spatial resolution of 200 m and we use five different spatial resolutions (40.5, 13.5, 4.5, 1.5 and 0.5 km) of meteorological forcing derived from the WRF dynamical downscaling approach. Our study aims to answer the following questions:

- What is the effect of the spatial resolution of meteorological forcing on the simulated snow accumulation and melt, evapotranspiration, infiltration and pressure head and/or water table depth? In broader terms, how meteorological uncertainties propagate into the resolved hydrodynamics and which processes require high-resolution meteorological forcing?

- At which spatial resolution should the climate models be solved to accurately describe the strong variations in meteorological conditions induced by atmospheric rivers and their effect on the hydrology and therefore water supply?

The section 2 of this manuscript describes the study area, section 3 is dedicated to the mathematical models used (ParFlow-CLM and WRF), and section 4 describes the results and the discussion of these findings.

2. The Cosumnes watershed model

a. Study area

Located in Northern California, USA, the Cosumnes watershed is approximately 7,000 km² in size (Figure 1a) and hosts one of the last rivers in the region without a major dam. Thus, it offers a rare opportunity to study the natural flow conditions. The geologic composition consists of materials ranging from nearly impermeable formations (volcanic and plutonic rocks located mainly in the Sierra Nevada Mountains) to highly porous and permeable aquifers in the Central
Valley. The study area shows complex topographic patterns with elevations comprised between the 2000 m and the sea level and strong variations of land use and land cover. The agricultural region of Central Valley located in the southwest of the watershed consists of various crop types, including alfalfa, pasture lands, and vineyards. These agricultural regions are subject to seasonal pumping and irrigation while the Sierra Nevada Mountains are covered by predominately evergreen forest. Spatial patterns of precipitation are highly heterogeneous across the watershed. On average, the Sierra Nevada Mountains receive three times more precipitation (1500 mm) than the Central Valley (Cosgrove et al., 2003), primarily in the form of snow. The regional climate is considered Mediterranean, with wet and cold winters (with a watershed average temperature equal to 0 °C) and hot and dry summers (with watershed average temperature reaching 30 °C) (Cosgrove et al., 2003).
Figure 1: (a) Land-use and land-cover (Homer et al., 2015) and (b) geology (Jennings et al., 1977) and topography (USGS) of the Cosumnes Watershed

3. Numerical Modeling Methods

In this section, we briefly describe the two numerical models that we used in this study:

(1) ParFlow-CLM, which simulates interactions as well as the transfer of water and energy between the lower atmosphere, the land surface, and the subsurface, and (2) Weather Research
Forecast (WRF), which simulates mesoscale numerical weather prediction, and is used here to drive the meteorological conditions of the ParFlow-CLM simulations.

3.1. Integrated Hydrologic Model: ParFlow-CLM

ParFlow-CLM (Kollet and Maxwell, 2006; Maxwell, 2013; Maxwell and Miller, 2005) describes the movement of water in the subsurface by solving the three-dimensional mixed form of Richards equation (Richards, 1931), given by:

\[ S_S S_W (\psi_p) \frac{\partial \psi_p}{\partial t} + \phi \frac{\partial S_W (\psi_p)}{\partial t} = \nabla \cdot [k(x) k_r (\psi_p) \nabla (\psi_p - z)] + q_s \]  

(1)

Where \( S_S \) is the specific storage (L\(^{-1}\)), \( S_W (\psi_p) \) is the degree of saturation (-) associated with the subsurface pressure head \( \psi_p \) (L), \( t \) is the time, \( \phi \) is the porosity (-), \( k_r \) is the relative permeability (-), \( z \) is the depth (L), \( q_s \) is the source/sink term (T\(^{-1}\)), and \( k(x) \) is the saturated hydraulic conductivity (L T\(^{-1}\)). The interdependence of variables (i.e. relationships between saturation and pressure head and between relative permeability and pressure head) is described by the Van Genuchten model (van Genuchten, 1980). Overland flow is described by the two-dimensional form of the kinematic wave equation given by:

\[ -k(x) k_r (\psi_0) \nabla (\psi_0 - z) = \frac{\partial \| \psi_0 \|}{\partial t} - \nabla \cdot \tilde{u} \| \psi_0 \| - q_r (x) \]  

(2)

Where \( \| \psi_0 \| \) indicates the greater term between \( \psi_0 \) the surface pressure-head and 0, \( \tilde{u} \) is the depth averaged velocity vector of surface runoff (L T\(^{-1}\)), \( q_r \) represents rainfall and evaporative fluxes (L T\(^{-1}\)). The depth of the ponding water at the surface in x direction (\( u_x \)) and y direction (\( u_y \)) is calculated by:

\[ u_x = \frac{\sqrt{S_{f_x}}}{n} \psi_0^{2/3} \quad \text{and} \quad u_y = \frac{\sqrt{S_{f_y}}}{n} \psi_0^{2/3} \]  

(3)

Where \( S_{f_x} \) and \( S_{f_y} \) are the friction slopes in the x and y directions (respectively), and \( n \) is the manning coefficient.
Resolutions of the Richards and kinematic wave equations require the terms $q_s$ and $q_r(x)$ respectively. These terms include all the land surface processes simulated by CLM such as evapotranspiration, infiltration, and snow dynamics. To compute these processes CLM uses the soil moisture calculated by ParFlow, the vegetation characteristics (the type of land cover as well as the physical properties of the plants) and the meteorological forcing calculated by WRF.

The Cosumnes ParFlow-CLM model is horizontally resolved at 200 m and varies in vertical from 10 cm at the land surface to 30 m at the bottom of the domain. The total thickness of the domain is 80 m. An analysis of variations in measured groundwater levels showed that this thickness is sufficient to capture water table depth fluctuations and that in general, beyond 50 m below the ground surface, the aquifer remains fully saturated. Simulations utilize parallel high-performance computing to accommodate the large number of cells (approximately 1.4 million) that constitute the high-resolution model.

The Cosumnes watershed is bounded by the American and Mokelumne rivers and is constrained in the model with the use of weekly-varying values of Dirichlet boundary conditions along these borders. A no-flow (i.e. Neumann) boundary condition is imposed at the eastern, headwater side of the watershed. Hydrodynamic properties (including hydraulic conductivity, specific storage, porosity, Van Genuchten parameters) are derived from a regional geological map (Geologic Map of California, 2015; Jennings et al., 1977) and previous studies (Faunt et al., 2010; Faunt and Geological Survey (U.S.), 2009; Flint et al., 2013; Gilbert and Maxwell, 2017; Welch and Allen, 2014).

The 2011 National Land Cover (NLCD) map (Homer et al., 2015) is used in CLM to define land use and land cover. Agricultural maps provided by the National Agricultural Statistics Service (NASS) of the US Department of Agriculture’s (USDA) Cropland Data Layer
(CDL) (Boryan et al., 2011) are further used to delineate specific croplands in the Central Valley. Vegetation parameters are defined by the International Geosphere-Biosphere Programme (IGBP) database (IGBP, 2018). Pumping and irrigation rates are estimated in the model because a comprehensive dataset of such rates in the Central Valley does not exist. Water demand is calculated based on the average parcel size, the crop type, and the country. Irrigated water is internally sourced from either nearby groundwater pumping wells or, if adjacent to a river, surface water diversions. This allows for the mass conservation of water within the model.

Fractions of water use between groundwater pumping and river diversions have been determined by the California Department of Water Resources (DWR) (California Department of Water Resources, 2010) and the United States Geological Survey (USGS) (USGS, 2018) databases, and are used here. A seasonal pumping and irrigation cycle is assumed to be from April to November based on the regional climate and discussions with local stakeholders.

A full water year is simulated to demonstrate how different scales of meteorological forcing impact both wet and dry seasons of the year. The water year 2017 (i.e. October 1st, 2016-September 30th, 2017), a particularly wet year, is selected to conservatively demonstrate how forcing scales may impact hydrologic results in a wide range of weather conditions. Initial conditions of pressure head are derived from a longer simulation 2012-2017 performed with a calibrated and spun-up model.

3.2. Meteorological Model: WRF

WRF (Skamarock et al., 2008b; Skamarock and Klemp, 2008) is a state-of-the-art, fully compressible, non-hydrostatic, mesoscale numerical weather prediction model. The parametrizations that represent physical processes in the configuration of WRF used here include
the Dudhia scheme (Dudhia, 1988) for shortwave radiation, the Rapid Radiative Transfer Model (Mlawer et al., 1997) for longwave radiation, the Morrison double-moment scheme (Morrison et al., 2009) for microphysics, University of Washington (TKE) Boundary Layer Scheme (Bretherton and Park, 2009) for the planetary boundary layer, and the Eta Similarity scheme (Monin and Obukhov, 1954) for the model surface layer. The Grell-Freitas scheme (Grell and Freitas, 2014) is used for cumulus parameterization in two outer-most domains only (d01 and d02). For domain d03 and d04, the higher-resolutions allow for convection to be resolved explicitly. Mass balance validation results are shown in Appendix A. The described configuration of WRF has been extensively validated against ground observation of meteorological conditions in the California region in previous work (Vahmani et al., 2019; Vahmani and Jones, 2017).

As shown in Figure 2, we configure WRF version 3.6.1 over four two-way nested domains with a horizontal resolution of 13.5 km (domain 1), 4.5 km (domain 2), 1.5 km (domain 3), and 0.5 km (domain 4). Each domain is composed of 30 vertical atmospheric levels. Land cover in WRF matches the one used in ParFlow-CLM. Post-spin-up soil moisture from ParFlow-CLM is used to initialize the WRF model at the beginning of the simulation. Other WRF initial conditions, as well as boundary conditions, are based on the NLDAS-2 forcing data set. Using the nested domain configuration of WRF described above, we design a series of simulations to dynamically downscale across the four spatial resolutions. The coarsest scale of forcing at 40.5 km resolution is generated by statistically up-scaling the coarsest of the WRF simulations (13.5 km). WRF simulations are conducted from September 1st, 2016 to September 30th, 2017, covering the entire water year 2017 plus one month of spin-up. Spatial distributions of
precipitation and temperature at selected times obtained with the five spatial resolutions of forcing are shown in Appendix A.

Figure 2: Land cover map (Homer et al., 2015) and geographical representation of four WRF nested domains with 13.5, 4.5, 1.5, and 0.5 km spatial resolutions for d01, d02, d03, and d04, respectively.

3.3. Hydrologic metrics

Results from the 5 spatial resolutions are compared for key land surface and subsurface
processes. We consider the results obtained with the finest spatial resolution of meteorological forcing (0.5 km, closest to that of the hydrologic model) as the exact resolution, and evaluate the differences relative to that of the 4 remaining resolutions (1.5, 4.5, 13.5 and 40.5 km). Comparisons are shown as an absolute error ($AE$) and/or percent error ($PE$) relative to the 0.5 km results via:

$$AE_{i,t} = X_{0.5i,t} - X_{Ri,t}$$

and

$$PE_{i,t} = \frac{X_{0.5i,t} - X_{Ri,t}}{X_{0.5i,t}} \times 100$$

where $X$ is the model output ($ET$, Infiltration $I$, SWE, or pressure head, $\psi$) at a given point in space ($i$) at a time ($t$), and $R$ is the spatial resolution of the forcing (1.5, 4.5, 13.5 or 40.5 km). Snap-shots in time of these errors highlight the sensitivity of each scale of forcing in space. Global (i.e. domain-wide) differences are also calculated for select parameters of interest and shown as a function of time by taking a domain average of each cell-based value of $AE_{i,t}$ or $PE_{i,t}$ within the watershed.

Because large-scale changes in storage are of interest from a water management perspective, total surface water (SW) storage is calculated via:

$$Storage_{SW} = \sum_{t=1}^{n_{SW}} \Delta x_i \times \Delta y_i \times \psi_i$$

where $n_{SW}$ is the total number of river cells (-), $\Delta x_i$ and $\Delta y_i$ are cell discretizations along the x and y directions (L), and $i$ indicates the cell. Note that because ParFlow-CLM is an integrated hydrologic model, only surface cells whose pressure head is greater than zero are taken into account in the above summation. Similarly, total groundwater (GW) storage is calculated via:
\[ S_{\text{Storage}} = \sum_{i=1}^{n_{GW}} \Delta x_i \times \Delta y_i \times \Delta z_i \times \psi_i \times \left( S_{i} / \phi_i \right) \]  

where \( n_{GW} \) is the total number of subsurface saturated cells (-) and \( \Delta z_i \) is the discretization along the vertical direction the cell (L).

4. Results and discussions

4.1. Snow Water Equivalent, SWE

In this watershed characterized by strong topographic variations and a large amount of precipitation falling in the form of snow in the upper part of the watershed, it is crucial to analyze how the different spatial resolutions of forcing data affect snow dynamics, a key control of the hydrodynamics in the Central Valley aquifers. First, we compare the total SWE at the watershed scale obtained with the 5 resolutions (see Figure 3). Our results indicate that all the four resolutions overestimate the SWE when compared to the results obtained with 0.5 km forcing and that there is a large difference in SWE spatial resolution depending on the scale of the forcing used. We note that the accumulation of SWE starts at the same time for all resolutions while the time of snowmelt varies considerably from one resolution to another. The coarser a resolution is, the more the snowmelt timing is delayed. For example, SWE results obtained with the 40.5 km resolution forcing exhibits low global error for the first half of the water year during snow accumulation, however during ablation the differences are very large both in terms of magnitude (\( PE = 90 \% \)) and timing (which is delayed by around 40 days). Due to the complexity of the snow dynamics, in addition to the strong variations in the topography of our study area, the results show that SWE is very sensitive to the spatial resolution of the meteorological data, and that an accurate representation of SWE requires forcing data that is of similar resolution to that of the hydrologic model. These conclusions are somewhat different from those drawn by
(Rasmussen et al., 2011), who found that the representation of SWE in mountainous systems can be accurate for spatial resolutions of forcing lower than 6 km. A possible explanation for this difference is the resolution of the physics-based model used in this study compared to that of Rasmussen and co-authors and potentially to the varied complexity of the two simulated watersheds and models.

Figure 3: Temporal variations of the total Snow Water Equivalent (SWE) obtained with meteorological forcing at spatial resolutions of 0.5, 1.5, 4.5, 13.5, and 40.5 km.

Figure 4a shows that the spatial distribution of SWE is more accurate for high-resolution meteorological data and that the Cosumnes watershed forcing resolutions at and above 13.5 km
the extent of the watershed covered by snow is not well estimated. Figure 4b shows that while
the errors in SWE distribution certainly decrease with increasing the resolution of the forcing
data, errors remain relatively high (on the order of $AE = 100$ mm). However, the partition
between the areas of over and under-estimation appears to be uniform, for the SWE, we notice
that these zones also depend on the topography. This is because the snow processes depend not
only on the meteorological conditions but also on the slope and aspect. Depending on the
elevation, the orientation of the cell (north and south facing), the energy fluxes are different
resulting in very different snow dynamics. This strengthens the conclusions drawn previously
stating that the meteorological data should be at the resolution of the input data as well as the
physics-based model to ensure a good precision and accuracy in the representativity of the snow
dynamics.
Figure 4 Spatial distributions of (a) the SWE obtained with the five spatial resolutions of meteorological forcing and (b) absolute error (AE) of ET with respect to the highest spatial resolution of meteorological forcing (0.5 km). Results are shown at WY days 125 and 166.
4.2. Evapotranspiration, ET

ET, as shown here, is a combination of evaporation from the ground, canopy surfaces, transpiration by plants, and sublimation. Figure 5 shows the domain-average, temporal variation of the relative difference in the total ET flux as calculated with equation (5). Our results show that differences in spatial resolution on ET flux are mostly weak, and are only high after a storm event. The error generally increases as the resolution of the meteorological forcing increases. It is interesting to note, however, that for some time steps the relative differences obtained with the third coarsest meteorological forcing (13.5 km) are the largest. A possible explanation is the aggregated nature of the domain-average ET. Depending on the time step, the coarser forcing resolutions can lead to either an over or under-estimation of ET. Results do not show a systematic trend with regards to the over- or under-estimation of ET, where even at a single time-step, some resolutions indicate an overestimate of ET, others an underestimate. It is therefore difficult to establish a clear relationship between the spatial resolution and the directionality of ET error at a watershed scale. Note, however, that these errors do not increase over time. This can be related to the fast-changing nature of ET that is strongly linked to short-lived weather patterns and the diurnal cycle.
Figure 5: Temporal of the percent error ($PE$) of $ET$ with respect to the highest spatial resolution of meteorological forcing (0.5 km).

Figure 6a shows the spatial distribution of $ET$ associated with the five resolutions at two selected time steps (summer and winter). The spatial distribution of $ET$ at these time steps is different, and in general, all the five resolutions can distinguish these spatial differences of $ET$ in time. As expected, the most accurate $ET$ distribution is obtained with the highest resolution of the meteorological data, the coarser a resolution of meteorological data is the less accurate the spatial distribution of $ET$. Because the results obtained with the high-resolution forcing is similar to the resolution of the integrated hydrologic model (and thus the resolution of input data such as topography, geology and land use and land cover), it allows us to better understand the
relationships between ET and these high-resolution data layers. Such analyses are difficult to undertake for coarser resolutions.

(a)

(b)
Figure 6: Spatial distributions of (a) the ET obtained with the five spatial resolutions of meteorological forcing and (b) percent error (PE) of ET with respect to the highest spatial resolution of meteorological forcing (0.5 km). Results are shown at the first day of the simulation (WY day 0) and during the time at which peak differences are observed (WY day 167).

Seasonality and location impact the degree to which forcing scales impact ET. Note that for the spatial distributions of ET associated with the second time step considered (day 167), the results obtained with the five resolutions are very similar in the Central Valley. At this time spatial patterns of ET only differ in the Sierra Nevada Mountains and the intrusion. The geology, as well as, the land cover and the topography are more or less uniform in this valley, whereas these parameters notably topography vary significantly in the Sierra Nevada Mountains. For the first time step, the differences observed in the Central Valley are due to the fact that for very precise resolutions of the forcing, the evolution of the storm is accurate (see Appendix A) and so is the ET. Thus, for relatively homogeneous areas such as the Central Valley, high-resolution forcing data is required only if the storm shows a strong spatial variation within the areas whereas for highly heterogeneities associated with geology, topography, and land-cover, high-resolution forcing data are always required if one is interested in analyzing accurately the spatial distribution of ET.

Figure 6b shows the spatial distributions of percent error of ET relative to the results of the 0.5 km meteorological forcing. Whatever the resolution considered, we note both an over- and under-estimation of ET on the same scale of error (+/- 3000%), but with more localized and less wide-scale differences at the finest scale of meteorological forcing. Also, as previously noted, the error is higher in the Sierra Nevada Mountains than in the Central Valley for all
resolutions, especially later in the water year. This reinforces the conclusions drawn previously, namely that for complex environments a precision in the meteorological data is strongly required.

### 4.3. Infiltration

As shown in Figure 7a, the spatial resolution of forcing data strongly impacts the spatial distribution of infiltration. Indeed, for coarse resolutions (i.e. 40.5 km), it is almost impossible to determine the position of the storm and its impact on infiltration, the results obtained at this scale are strongly dependent on the resolution of the forcing. However, for more precise resolution (i.e. 0.5 km), we can exactly see the location of the storm, this resolution allows distinguishing areas characterized by a very weak infiltration as the upper part of the catchment corresponding to the Sierra Nevada Mountains. Indeed, in this area, due to the accumulation of snow (precipitation is in the form of snow unlike in the Central Valley), the resulting infiltration is zero. The spatial extension of the area subject to the snow accumulation is only accurate for high-resolution meteorological forcing results.
Figure 7: Spatial distributions of (a) infiltration $I$ obtained with the five spatial resolutions of meteorological and the (b) percent error ($PE$) of infiltration $I$ with respect to the highest spatial resolution of meteorological forcing (0.5 km). Results are shown in winter (WY day 83) and summer (WY day 291).

To better understand how the quality and precision of the spatial distribution of infiltration deteriorates by decreasing the resolution of the input data, we illustrate in Figure 7b, the spatial distribution of the percent error associated with the four resolutions considered at two selected time steps. These time steps show different dynamics. For the first time step corresponding to the period of snow accumulation, the errors are null in the Sierra Mountains.
which is not the case for the second time step. Whatever the resolution considered, and as previously discussed, we note that depending on the point considered there may be over- and under-estimation of the infiltration and this is because the coarse resolutions represent an average as explained previously. Note that these differences are observed over the entire watershed except in the Sierra Mountains for the first time step, while for the second time step, these errors are only observed along the river and its tributaries as well as in the Sierra Nevada Mountains. This second time step corresponds to the summer, a snowmelt period and without rain. As such, differences of infiltration in the Sierra Nevada Mountains are due to the snow melting. As for the differences observed close to the areas subject to the overland flow, these are due to the exchanges between the surface flow and the subsurface. Because the amount of snow accumulated as well as the spatial extent of the area subject to snow dynamics is different for the five resolutions considered, the resulting snowmelt is different. Thus, the runoff controlled by this snowmelt will also be different and so is the infiltration of the quantities of water coming from the overland flow. This indicates that the effects of the spatial resolution of forcing data can be delayed in time.

4.4. Surface and subsurface flow

4.4.1. Surface water storage and river stage

Figure 8 illustrates the $PE$ between the highest resolution considered as the exact solution and the other coarser resolutions. In general, the percent error is small (inferior to 5%) regardless of the time of the year, and that these differences are almost zero for the results obtained with 1.5 and 4.5 km forcing resolutions for the entire water year. These errors are relatively small given that some regions in the domain over-estimate pressure head and other regions under-estimate
pressure head (see Figure 9). In contrast, while the error is negligible at the beginning of the simulation for results obtained with forcing at 13.5 and 40.5 km, the $PE$ increases over time, eventually reaching a nearly maximum at the end of the water year. This suggests that $PE$ may be cumulative and that longer simulations with overly coarse scales of forcing will compound through time. It’s interesting to also note that while the results obtained with the 13.5 km resolution forcing overestimates the surface water storage at any time, the 40.5 km resolution over-estimates at the beginning of the simulation and under-estimates at the end of the simulation. Moreover, the errors obtained with the 13.5 and 40.5 km resolution are of the same order but opposite signs. This suggests that although the total water budget is nearly equivalent for each scale of forcing considered here (see Appendix A), an inaccurate spatial distribution of forcing can lead to an inaccurate redistribution (and possibly a delay) of water and energy, and hence different signals of surface water storage.
Figure 8: Temporal variations of the percent error (PE) of surface water storage relative to the 0.5 km forcing.

Figure 9 shows the spatial distributions of the absolute error associated with the pressure-head of the first layer at two selected time steps. As mentioned in the preceding paragraphs, this error increases with time, therefore, at the first time step the error is almost null for the spatial resolutions of 1.5 and 4.5 km whereas it is non-zero for the second time step. Although the spatial resolutions of 13.5 and 40.5 km have non-zero errors at the first time step, the error increases considerably as the simulation proceeds. We note that the areas sensitive to the spatial resolution of the meteorological forcing data are approximately the same for all four resolutions.
Indeed, the absolute error is null at the intrusion on contrary to the Central Valley and in the Sierra Nevada Mountains. Interestingly, these two zones have different areas of influence, in the Central Valley, the errors are non-zero everywhere except at the river, which is contrary to the trend observed in the Sierras. This is related to the geological nature of these environments. Due to the very low permeability and roughness of Sierra Nevada Mountains, any water from precipitation will quickly contribute to surface runoff, which is highly sensitive to the spatial resolution of forcing, on contrary to the Central Valley characterized by high permeability and low manning coefficient and therefore low overland flow.

Figure 9: Absolute error ($AE$) of surface pressure-head ($\Psi_s$) with respect to the highest spatial resolution of meteorological forcing (0.5 km). Results are shown in winter (WY day 83) and summer (WY day 333).
Figure 10 shows the spatial distribution of the maximum difference in river water levels between the results obtained with each spatial resolution of forcing and those obtained with the 0.5 km forcing. Maximum river water level differences are shown in absolute values (in units of meters) and can occur at any point of time in the simulated water year. Differences in river water levels at a given time step can reach 3 m. These differences are mainly located in the headwater region of the watershed for results obtained with the finer resolution forcing progressively extend into the Central Valley as the spatial resolution of forcing decreases. Our results suggest that although the impact of spatial resolutions of forcing on the watershed-scale surface water storage is low to insignificant (see Figure 8), at a given point in space and time differences may be considerable. This can be especially problematic especially for calibration and validation purposes because these methods adjust the input parameters of the model to reproduce the measured water levels in the river with the model. In this case, differences between measured and simulated values are not only due to parametric uncertainties but rather the forcing.
Figure 10: Spatial distributions of the maximum of Absolute Error (AE) in absolute values of river height ($\Psi_s$) with respect to the highest spatial resolution of meteorological forcing (0.5 km).

4.4.2. Groundwater storage and water table depth

For the cases considered here, the different spatial resolutions of forcing have very little impact on the total groundwater storage of the watershed (Figure 11).
Figure 11: Temporal variations of the percent error ($PE$) of groundwater storage relative to the 0.5 km forcing.

Except the coarsest scale of forcing resolution towards the end of the simulation, the error in groundwater storage for the different spatial resolutions of forcing yield very similar results. The spatial resolution of 13.5 km overestimates the storage, however, this overestimation remains very low of the order of 1% at certain times. In contrast, the groundwater storage results obtained with the 40.5 km scale forcing are close to the exact solution at the beginning of the simulation, yet reach error up to 10% at the end of the simulation. As stated previously, although the total water budget associated with the meteorological forcing at the watershed scale is the
same for all the resolutions, the different spatial resolutions lead to different processes both in
time and space leading to different groundwater storages. Similar to the other maps of absolute
error, water table depth maps showing the $AE$ relative to the results obtained with the 0.5 km
forcing show both over- and under-estimation of the water table depth as a function of the
forcing resolution (Figure 12a). As with the surface water storage, the groundwater storage error
is low due to the counterbalancing of opposite error signs. Note that we focused on the late time
step because for the first time steps these differences are too small to be used for interpretations.

For all the spatial resolutions considered, the Sierra Nevada Mountains are the most sensitive
areas to the spatial resolution of meteorological data, while the intrusion remains insensitive with
almost zero relative errors. This is due to the characteristics of the Sierra Nevada Mountains
which include strong variations of topography, snow dynamics, and impermeable rocks. The
intrusive zone is constituted of extremely impermeable materials so it has no groundwater
dynamics, as such the errors are zero. The spatial resolutions of 1.5 and 4.5 km have little impact
on the water table depth field associated with the Central Valley alluvial aquifers, the strong
relative errors are mostly observed for the results obtained with spatial resolutions of 13.5 and
40.5 km. Nevertheless, these errors are not uniform, they are marked along the river and outside
urban areas. As pointed out above, the hydrodynamics of the Central Valley depend on the Sierra
Nevada Mountains, whose snowmelt feeds the rivers and recharges the groundwater. The
absolute errors associated with the river areas are particularly due to the hydrodynamics of the
Sierra Nevada Mountains, in fact, as the snowmelt changes significantly according to the spatial
resolutions of the meteorological forcing considered as discussed in section 4.1, the exchanges
between the river and groundwater will thus be different. Note that these differences are also due
to the difference in evapotranspiration (section 4.2) and infiltration (section 4.3) and we highlight
that these differences accumulate over time as indicated by the errors that increase as the simulation progresses.

(a) $1.5\text{ km}$  $4.5\text{ km}$  $13.5\text{ km}$  $40.5\text{ km}$

(b) $WY$ day $333$

Figure 12: Spatial distributions of (a) the absolute error ($AE$) of the water table depth ($WTD$) with respect to the highest spatial resolution of meteorological forcing (0.5 km) at WY day 333, and (b) the maximum of Absolute Error ($AE$) in absolute values of the water table depth ($WTD$) with respect to the highest spatial resolution of meteorological forcing (0.5 km).
Figure 12b depicts the maximum differences (for all time steps) of the water table depth in absolute value between the results obtained with the exact (highest) spatial resolution and the other four spatial resolutions. As previously stated, due to the almost zero permeability of the intrusion, the latter is insensitive to the spatial resolution of the meteorological data. The water table depth differences are greater than 1 m in several places, particularly in the Sierra Nevada Mountains. In the Central Valley, it should be noted that the strong differences are mainly observed in the areas near the rivers and close to the pumping wells.

Figure 13 shows the temporal variations of the difference of the water table depth between the highest resolution and the four other resolutions at 6 selected points. We selected points located in the Central Valley as this zone hosts an alluvium aquifer (see their location in Figure 1). For all these points, we note that the differences are almost zero for the spatial resolution of 1.5 km indicating that this spatial resolution is sufficient to represent the groundwater dynamics of this region. The spatial resolution of 4.5 km also shows relatively low differences, the latter is indeed zero at three points and only the points 2, 4 and 5 have non-zero differences, but these remain less than 50 cm. The strongest differences are observed for results obtained with forcing spatial resolutions of 13.5 and 40.5 km; note that the coarsest resolution does not necessarily give the highest differences. In fact, at points 4 and 5, the highest differences are obtained with the resolution of 13.5 km, indicative of the complex over- and under-estimation patterns of bias observed at these coarser resolutions of forcing. In general, the use of these large-scale spatial resolutions of forcing can lead to an over- or under-estimation of the pressure-head between 50 cm and 10 m.
Figure 13: Absolute Error (AE) of the water table depth (WTD) with respect to the highest spatial resolution of meteorological forcing (0.5 km) at six selected points.

Thus, while our results indicate that the spatial resolution of meteorological forcing has little impact on the total groundwater storage, at discrete points within the watershed the spatial resolution of forcing is very important, especially for resolutions greater than 4.5 km in this watershed. Again, this is particularly an issue for model calibration purposes given that hydrologic numerical models are typically validated/calibrated by comparing the groundwater measurements with the model outputs. In this case, our results indicate that careful attention must be given to the spatial resolutions of forcing, as some errors are only due to the latter not to any model parameterization.
5. Conclusions

Numerical methods that solve integrated hydrologic models are becoming increasingly precise and of high-resolution. They thus require high-resolution and accurate input data such as meteorological forcing. However, while integrated hydrologic models increase in precision, the meteorological data used are most often of coarse resolution whereas these data are strongly heterogeneous in space. It is, therefore, important to better understand not only how the uncertainties associated with the spatial distribution of meteorological data affect the outputs of hydrologic models, but also the spatial resolution of the meteorological forcing required to minimize these uncertainties. Moreover, thanks to the development of atmospheric models, it is now possible to obtain meteorological data at the same resolutions as the hydrologic models.

In this study, we used in a high-performance computing framework, the integrated hydrological model ParFlow-CLM, to simulate the hydrodynamics of a complex and unique watershed located in Northern California, the Cosumnes Watershed. Five different spatial resolutions of meteorological data were obtained via the dynamical downscaling approach of the Weather Research Forecasting (WRF) model. The Cosumnes watershed is an excellent candidate to better understand how the different spatial resolutions affect the results of an integrated hydrologic model of a watershed characterized by strong variations of topography, geology, land use and land cover leading to highly heterogeneous and complex atmospheric and hydrologic dynamics. The watershed allows also to investigate how the uncertainties related to the spatial resolution of meteorological data affect the following key components of the hydrologic cycle: snow dynamics, evapotranspiration, infiltration, surface and groundwater interactions, etc.

Our results show that the impact of the spatial resolution of meteorological data depends on the hydrologic component of interest as well as the temporal and spatial scale.
• At the scale of the watershed, the total fluxes of evapotranspiration are more or less insensitive to the spatial resolution of forcing. However, to obtain an accurate distribution of evapotranspiration based on the physical properties of the watershed, a high-resolution forcing is required. Indeed, our results show that it is almost impossible to identify the change in evapotranspiration as a function of land use or geology with low-resolution meteorological data.

• The results obtained with infiltration are quite similar to those of evapotranspiration. Note that for these two processes, the relative errors induced by a coarser resolution obtained are most often marked after a storm, and that these errors automatically become very low as soon as the storm ends.

• In this watershed characterized by strong variations of topography, the errors associated with the spatial resolution of the meteorological data have a considerable impact on snow accumulation and melting, even at the scale of the watershed. The different spatial distributions obtained suggest that meteorological data with the same resolution as the hydrologic model is needed to accurately reproduce the distribution as well as the total volume of snow water equivalent. Unlike evapotranspiration and infiltration, where there is always an over- and under-estimation, for snow water equivalent, the relative errors obtained depend on both the spatial resolution and topography.

• The spatial resolution of the forcing data does not impact the total storage of the surface water at the watershed scale. Indeed, our results have shown that even for the coarsest resolution (i.e. 40.5 km), the error, increasing with time, is around 5%. However, we have emphasized that for the river levels at one point and at a
given time, the differences between the highest spatial resolution of the forcing data and the four other resolutions can exceed 3 m. Our physical model has also allowed us to determine areas such as the Sierra Nevada Mountains where runoff is very sensitive to the spatial resolution of the weather data.

- We also obtained similar total groundwater storages at the watershed scale with the five different spatial resolutions of the meteorological data. However at the local scale, the variations of pressure head in the subsurface obtained with the different resolutions are not the same, the differences can reach 9 m at a given time and location, especially in the Central Valley alluvium aquifers.

Although the total water balance of the five spatial-resolutions of the meteorological forcing is the same, the different spatial resolutions lead to different hydrological processes that change both in time and space. For a good representation of the land surface processes (infiltration, evapotranspiration and snow dynamics), a spatial resolution of the meteorological data which is close to that of the hydrologic model is required due to the instantaneity and complexities of these phenomena. For the surface and subsurface processes, we have demonstrated that for this particular watershed, a spatial resolution of 4.5 km is sufficient to reproduce precisely these mechanisms. As a result, satellite-based products such as NLDAS resolutions may induce errors that may limit the use of these products for spatially accurate studies. Because the coarse spatial resolutions may lead to very different groundwater and streamflow variations compared to the highest resolution, particular attention must be paid to the spatial resolution of meteorological data, especially in the calibration and/or validation processes of numerical models. Indeed, the differences between the measured and simulated outputs are
not only due to the hydrodynamic parameters of the model but may also be related to the parameterization of the meteorological data.

In this study, we have focused on the spatial distribution of meteorological data, future studies will focus on the propagation of uncertainties related to the temporal resolution, and thus determine the main source of uncertainties. Climate Models are also used for future climate projections purposes, it would also be important to determine the ideal spatial-resolution of forcing in this context.

**Code and Data availability**

Simulations inputs, models and data are available from the authors upon request.
Appendix A

A.1 Mass Balance Validation

The physics represented for the four WRF domains are identical, except for cumulus parameterization which is used for domains d01 (resolution of 13.5 km) and d02 (resolution of 13.5 km) and not for domains d03 (resolution of 1.5 km) and d04 (resolution of 0.5 km). The reason behind this is that WRF at resolutions higher than around 4 km (Gilliland and Rowe, 2007) can resolve convection explicitly. To assess the sensitivity of the WRF simulated forcings to this inevitable inconsistency between the domains, we compare watershed-wide daily precipitation and air temperature in figure XX. Our results show that there are minimal differences (RMSE of less than 0.002 m and 0.01 C for precipitation and temperature, respectively) between 4 WRF domains, when averaged over the watershed. This shows that the only difference between the forcings from WRF domains are due to different resolutions and the effects of described difference in physics representations are limited.
Figure A1: Daily variations of WRF simulated precipitation (a) and air temperature (b), averaged over the entire watershed for spatial resolutions of 0.5, 1.5, 4.5, 13.5, and 40.5 km.
A.2 Spatial distributions of precipitation and temperature over the domain d04

<table>
<thead>
<tr>
<th>Precipitation (mm/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
</tr>
<tr>
<td>5.10^{-4}</td>
</tr>
<tr>
<td>10^{-3}</td>
</tr>
<tr>
<td>1.5 10^{-3}</td>
</tr>
<tr>
<td>2 10^{-3}</td>
</tr>
</tbody>
</table>

- **WY day 1**
- **WY day 83**
- **WY day 125**
Figure A2: Spatial distributions of precipitation associated with the five spatial resolutions of meteorological at three selected times
WY day 1  |  WY day 83  |  WY day 125
---|---|---
40.5 km

13.5 km

4.5 km

1.5 km

0.5 km

Temperature (K)

275.0 281.2 287.5 293.8 300
Figure A3: Spatial distributions of temperature associated with the five spatial resolutions of meteorological at three selected times.

Author contribution
The authors contribute equally to this work.

Competing interests
The authors declare that they have no conflict of interest.

Acknowledgements
This work was supported by http://dx.doi.org/10.13039/ 100007000 (LDRD) funding from Berkeley Lab, provided by the Director, Office of Science, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. This research used computing resources from the National Energy Research Scientific Computing Center, a DOE Office of Science User Facility supported by the http:// dx.doi.org/10.13039/100006132 of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

The authors are thankful to Peter-James Dennedy-Frank for his careful reading and constructive suggestions and comments.
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