MODELING THE HYDROLOGY OF CLIMATE CHANGE IN CALIFORNIA’S SIERRA NEVADA FOR SUBWATERSHED SCALE ADAPTATION

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ABSTRACT: The rainfall-runoff model presented in this study represents the hydrology of 15 major watersheds of the Sierra Nevada in California as the backbone of a planning tool for water resources analysis including climate change studies. Our model implementation documents potential changes in hydrologic metrics such as snowpack and the initiation of snowmelt at a finer resolution than previous studies, in accordance with the needs of watershed-level planning decisions. Calibration was performed with a sequence of steps focusing sequentially on parameters of land cover, snow accumulation and melt, and water capacity and hydraulic conductivity of soil horizons. An assessment of the calibrated streamflows using goodness of fit statistics indicate that the model robustly represents major features of weekly average flows of the historical 1980-2001 time series. Runs of the model for climate warming scenarios with fixed increases of 2°C, 4°C, and 6°C for the spatial domain were used to analyze changes in snow accumulation and runoff timing. The results indicated a reduction in snowmelt volume that was largest in the 1,750-2,750 m elevation range. In addition, the runoff center of mass shifted to earlier dates and this shift was non-uniformly distributed throughout the Sierra Nevada. Because the hydrologic model presented here is nested within a water resources planning system, future research can focus on the management and adaptation of the water resources system in the context of climate change.

(KEY TERMS: climate variability/change; watershed management; runoff; planning.)


INTRODUCTION

One of the most robustly described impacts of projected climate warming will be on the water resources of snowmelt-driven hydrologic systems, which provide water for one-sixth of the world’s population (Barnett et al., 2005). The Sierra Nevada of California is a particularly well-studied example, in which climate change will impact the natural and human systems...
that rely on the hydrologic character of the mountain range. Runoff of winter precipitation is delayed until closer to times of peak demand, as mountain snowpack acts in essence as the state’s largest reservoir.

While the general implications of climate warming for California’s hydrology have caught policy maker’s attention, specific adaptive responses have yet to materialize. To explore possible strategies for adaptation and management, an analytical platform is needed that will allow for a better understanding of the climate change impacts within individual river basins and, in turn, to assess how water and land managers may adapt to them (Poff, 2002; Palmer et al., 2008) as it is at this scale where many management decisions will need to be made (Hulme, 2005; Palmer et al., 2008). At the same time it is useful to have the scope of such a tool be the entire Sierra Nevada as climate change impacts are expected to be spatially heterogeneous in terms of elevation and latitude. By being able to see more of the “big picture,” planners can begin prioritizing conservation and management actions.

Although several recent studies report on the potential effects of rising temperatures on snowpack accumulation and the earlier initiation of snowmelt (Cayan et al., 2001; Kim, 2001; Miller et al., 2003; Dettinger et al., 2004; Knowles and Cayan, 2004; Stewart et al., 2004; Knowles et al., 2006; Maurer et al., 2007), to date, less effort has been spent trying to calculate the local impacts of these changes within individual watersheds. Studies in other regions indicate that changes in hydrologic patterns will modify the flow regime, sediment inputs, and water temperature affecting physical habitat (Gibson et al., 2005), and similar impacts are also expected in the Sierra Nevada. For instance reduction in summer flows, coupled with increasing atmospheric temperatures, will increase water temperatures and potentially the suitability of stream reaches as habitat for temperature sensitive aquatic species (Myrick and Cech, 2004). On land, changes in atmospheric temperature and CO$_2$ concentrations may affect the distribution of plant communities as they respond to environmental change (Diffenbaugh et al., 2003; Kueppers et al., 2005; van Mantgem and Stephenson, 2007) which, in turn, will affect the hydrologic characteristics of the watershed. Within the operated water resources system, changes in the timing and volume of snowmelt will affect water supply, hydropower generation, flood control, and recreational flows (Zhu et al., 2005; Vicuna et al., 2007).

Here, we present the first phase of development of a water resources planning system, which in the end will span the continuum from climate change to hydrologic response to management adaptation to impact assessment. The underpinning of this system is the Water Evaluation and Planning System (WEAP21), a spatially based model capable of calculating changes in the hydrologic cycle, incorporating changing climate conditions, and representing the human managed system with dams, diversions, and hydropower projects. Importantly for our purposes, this platform allows users to incorporate downscaled global climate models and calculate impacts and possible adaptation strategies within one platform (Yates et al., 2009).

Specific objectives of this paper are (1) to present the implementation of the WEAP21 model for 15 west slope Sierra Nevada watersheds from the Feather to Kern Rivers (Figure 1), (2) describe the calibration of the models for unimpaired flows, and (3) to present results of scenarios of temperature increase on snow accumulation and the timing of streamflow.

**METHODS**

In the WEAP21 model, climate, topography, land cover, surface water hydrology, groundwater

![FIGURE 1. Project Watersheds and Topographic Map.](image)
hydrology, and soils data are used to model the natural or unimpaired hydrology of the western slope of the Sierra Nevada. Once the natural hydrology is modeled, infrastructure elements can be added to represent human hydrologic manipulations (Yates et al., 2005). The watersheds modeled, from north to south are the Feather, Yuba, Bear, American, Cosumnes, Mokelumne, Calaveras, Stanislaus, Tuolumne, Merced, San Joaquin, Kings, Kaweah, Tule, and Kern Rivers. The extent of the model covers each contiguous watershed from the Sierran crest to the watershed outlet near the Central Valley floor, an area of roughly $650 \times 125$ km (Table 1). In this section, we present a discussion of the algorithms used to model the hydrologic cycle and a description of the process to delineate “catchments” defined as the modeling units where the terrestrial components of the hydrologic cycle are simulated in WEAP21.

**WEAP21 Algorithms**

The WEAP21 model is a comprehensive, fully integrated water basin analysis system. It is a simulation model that includes a robust and flexible representation of water demands from all sectors and flexible, programmable operating rules for infrastructure elements such as reservoirs, canals, and hydropower projects. It has watershed rainfall-runoff modeling capabilities that allow for calculation of hydrograph components including runoff, interflow, and base flow. Soil moisture storage and snow accumulation and melt are also calculated. Water infrastructure and demand elements can be dynamically nested within the underlying hydrological processes. In effect, this allows the modeler to analyze how specific configurations of infrastructure, operating rules, and priorities will affect water uses as diverse as in-stream flows, agricultural irrigation, and municipal water supply under the umbrella of input weather data and physical watershed conditions. This makes it ideally suited to studies of dynamic change within watersheds, such as climatic shifts.

The physical hydrology model in WEAP21 represents the terrestrial water cycle with a series of simultaneously solved equations. Rainfall is partitioned into snow, runoff, or infiltration depending on temperature, land cover, and soil moisture status. Moisture in the root zone is partitioned into evapotranspiration (ET), interflow, deep percolation, or storage as a function of soil water capacity, hydraulic conductivity, potential ET, and vegetation-specific ET coefficients. Deep percolation enters a second soil compartment and is partitioned into base flow or deep soil moisture storage. This partitioning is a function of the soil moisture storage status, the water holding capacity of the deep compartment, and the hydraulic conductivity of the deep sediments. For a detailed discussion of the model algorithms, see Yates et al., (2005). Due to the importance of snow processes in Sierra Nevada hydrology and modifications to the WEAP21 algorithm used in this effort and not presented in Yates et al. (2005), the snow accumulation and melt module is described here.

WEAP21 includes a simple temperature-index snow-melt model which computes an effective precipitation

<table>
<thead>
<tr>
<th>Watershed Name and Code</th>
<th>Watershed Outlet</th>
<th>Number of Subwatersheds</th>
<th>Number of Catchments</th>
</tr>
</thead>
<tbody>
<tr>
<td>American R. – AMR</td>
<td>FOLSOM RESERVOIR</td>
<td>46</td>
<td>185</td>
</tr>
<tr>
<td>Bear R. – BAR</td>
<td>CAMP FAR WEST RESERVOIR</td>
<td>6</td>
<td>19</td>
</tr>
<tr>
<td>Calaveras R. – CAL</td>
<td>N HOGAN LAKE</td>
<td>3</td>
<td>14</td>
</tr>
<tr>
<td>Cosumnes R. – COS</td>
<td>COSUMNES R AT MICHIGAN BAR 11335000</td>
<td>5</td>
<td>27</td>
</tr>
<tr>
<td>Feather R. – FEA</td>
<td>LAKE OROVILLE</td>
<td>38</td>
<td>164</td>
</tr>
<tr>
<td>Kaweah R. – KAW</td>
<td>LAKE KAWEAH</td>
<td>8</td>
<td>61</td>
</tr>
<tr>
<td>Kings R. – KNG</td>
<td>PINE FLAT RESERVOIR</td>
<td>15</td>
<td>103</td>
</tr>
<tr>
<td>Kern R. – KRN</td>
<td>RIO BRAVO PP NR BAKERSFIELD CA, 11193010</td>
<td>10</td>
<td>68</td>
</tr>
<tr>
<td>Merced R. – MER</td>
<td>LAKE MCCLURE</td>
<td>6</td>
<td>42</td>
</tr>
<tr>
<td>Mokelumne R. – MOK</td>
<td>PARDEE RESERVOIR</td>
<td>13</td>
<td>56</td>
</tr>
<tr>
<td>San Joaquin R. – SJN</td>
<td>MILLERTON LAKE</td>
<td>38</td>
<td>185</td>
</tr>
<tr>
<td>Stanislaus R. – STN</td>
<td>NEW MELONES RESERVOIR</td>
<td>25</td>
<td>109</td>
</tr>
<tr>
<td>Tulare R. – TUL</td>
<td>LAKE SUCCESS</td>
<td>9</td>
<td>56</td>
</tr>
<tr>
<td>Tuolumne R. – TUO</td>
<td>NEW DON PEDRO RESERVOIR</td>
<td>19</td>
<td>97</td>
</tr>
<tr>
<td>Yuba R. – YUB</td>
<td>DEER CREEK NR SMARTVILLE 11418500</td>
<td>20</td>
<td>82</td>
</tr>
<tr>
<td></td>
<td>AND HARRY L ENGLEBRIGHT LAKE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total number of subwatersheds and catchments</td>
<td></td>
<td>261</td>
<td>1,268</td>
</tr>
<tr>
<td>Average area (±SD)</td>
<td>182.5 km²</td>
<td>37.6 km²</td>
<td></td>
</tr>
</tbody>
</table>
\( P_e \). The model estimates snow water equivalent (SWE) and snowmelt from an accumulated snowpack in the catchment, where \( m_e \) is the melt coefficient given as

\[
m_e = \begin{cases} 
0 & T_i < T_s \\
1 & T_i > T_1 \\
\frac{T_i - T_1}{T_1 - T_s} & T_s \leq T_i \leq T_1 
\end{cases}
\]

with \( T_i \) the observed temperature for period \( i \), and \( T_1 \) and \( T_s \) are melting and freezing temperature thresholds, with the melt rate is given as

\[
m_i = \min(Ac_i m_e, E_m)
\]

Snow accumulation, \( Ac_i \) is a function of \( m_e, m_i \), and the observed total precipitation, \( P_i \)

\[
Ac_i = Ac_{i-1} + (1 - m_e)P_i - m_i
\]

\( E_m \) is the available melt energy converted to an equivalent water depth/time. The available melt energy is computed as

\[
E_m = R_{\text{net}} + E_{\text{other}}
\]

\( R_{\text{net}} \) is the net radiation and \( E_{\text{other}} \) represents additional forms of energy that contribute to snowmelt beyond the incoming solar radiation. This lumped parameter includes sensible, latent, advective, and ground energies. It is calculated as the net radiation, \( R_{\text{net}} \), multiplied by an additional radiation factor, \( R_f \), which was adjusted during calibration. The calculation for net radiation considers the albedo which is modeled using a simple algorithm that decreases albedo through time to represent the “ripening” of the snow surface (USACE 1998, figure 5-5). The model user specifies a “new” snow albedo value, \( A_N \), and the lowest or “old” snow albedo, \( A_O \), value as a fraction. Albedo is set at the “new” value following snowfall, it is then decreased by 0.1 for each simulation week with a minimum of the “old” snow albedo value.

### WEAP21 Catchment Delineation

Catchment nodes in WEAP21 represent a specific geographic area in which the distribution of land cover and soil properties are specified. Input weather data are assumed to be uniform over the entire catchment area. To parameterize the catchments, publicly available Geographic Information System (GIS) data including soils, vegetation, and digital elevation models (DEM) were gathered. Catchment definition was achieved using the following steps: (1) delineation of watersheds, subwatersheds, and elevation bands using the DEM; (2) intersection of elevation bands with subwatersheds to create WEAP21 catchments; (3) classification of vegetation and soils; and (4) intersection of soils, vegetation, and catchments to calculate fractional areas for each vegetation-soil combination in each WEAP21 catchment.

To perform the delineation of watersheds, subwatersheds, and elevation bands, 10 m DEMs available from the U.S. Geological Survey (USGS) were used (http://www.seamless.usgs.gov/). Watershed pour points were placed at the watershed outlets listed in Table 1. Subwatershed pour points were chosen based on the location of important infrastructure including dams, diversions, return flow structures, and USGS streamflow gages (Figure 2A). USGS streamflow gages were used if they possessed approximately five years or more of continuous record during the 1982-2001 calibration period. This delineation resulted in 261 subwatersheds throughout the 15 watersheds (Table 1) with an average upstream discrete area of 182.5 km². Elevation bands were delineated for the first 500 meters above sea level and then for every 250 meters up to the crest of the mountain range (500-4,000 m). This level of elevation discretization was chosen to provide resolution in the critical snow accumulation elevation range. The creation of catchments required the intersection of the elevation bands with each subwatershed. The resulting 1,268 geographic regions with an average area of 37.6 km² served as the basic modeling unit where hydrologic processes were modeled in WEAP21. At this base unit of accounting, where a catchment represents the intersection of subwatersheds and elevation bands, climatic data such as temperature, precipitation, humidity, and wind speed were assumed uniform and used as model inputs (Figures 2B and 2C).

Land cover and soils data were obtained from publicly available sources. Land cover information was obtained from the National Land Cover Dataset (NLCD) (Homer et al., 2004). The NLCD vegetation data included 29 land cover classes, which were aggregated into seven land cover types: barren land, trees, agriculture, grasslands, shrubs, urban, and water. The aggregations were based on the similarities in hydrological properties such as transpiration rates and runoff characteristics.

Soil depth classifications of greater than or less than 50 cm were assigned based on Natural Resource Conservation Service soil survey mapping unit minimum component depth to bedrock and the presence of rock outcrop. The Soil Survey Geographic (SSURGO) database was used for 75% of the study area. The remaining 25% of the area was characterized using the coarser resolution State Soil
Geographic (STATSGO) data. The STATSGO data was used for the entire Kern and Calaveras watersheds and portions of the Kings, San Joaquin, Mokelumne, Stanislaus, and Tuolumne watersheds.

The next step was the intersection of land cover and soil depth information with the catchments to create a unique land cover/soil depth combination within each WEAP21 catchment (i.e., trees on deep soils, trees on shallow soils, shrubs on deep soils, shrubs on shallow soils, etc). At this level of spatial intersection, model parameterization for plant and soil characteristics was assumed uniform.

**Weather Data**

Due to the large variation in temperature and precipitation over the Sierra Nevada caused by orographic effects (Meyers and Cotton, 1992; Galewsky and Sobel, 2005) and because observed weather data are relatively scarce, it was necessary to use interpolated weather data as input to the model. The DAYMET dataset (Thornton et al., 1997) was chosen for this application due to its spatial resolution (1 km grid) which is fine enough to provide resolved temperature and precipitation values for catchments that may be in proximity but at very different elevations. The DAYMET dataset included daily average temperature, vapor pressure deficit, and precipitation. DAYMET temperature and precipitation time series were obtained for a single location within each catchment. The locations were determined by placing a point close to the polygon centroid on the mid-elevation contour for the elevation band, i.e., along the 1,125 m contour for the 1,000-1,250 m band. These points were then used to

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**FIGURE 2.** Subwatershed Delineation, Elevation Banding, and Catchment Definition.
obtain and incorporate the weather time series from the DAYMET website.

MODEL CALIBRATION

Model calibration was performed using manual calibration techniques targeting observed SWE and computed unimpaired streamflow data obtained from the California Department of Water Resources (CDWR) and California Data Exchange Center (CDEC) webpage. SWE data were obtained for 15 locations. Computed monthly unimpaired streamflows were obtained for the watershed outlets of 13 of the 15 modeled watersheds. Monthly data were used because weekly data were not available during the entire calibration period for several watersheds. No monthly unimpaired flow data were available for the Calaveras or Bear River watersheds.

An initial set of parameters was developed that could be applied across all 15 watersheds and captured the seasonal and inter-annual variability of snow and flow measurements across the Sierra Nevada (Table 2). The most sensitive model parameters were then adjusted on a watershed by watershed basis, including soil water capacity, hydraulic conductivity, melt and freeze temperatures, additional radiation factor, and preferred flow direction (Table 3) to account for fine-scale differences in watershed characteristics not captured by the available data.

The accuracy of the model at predicting snow accumulation and melt is quantified by the correlation coefficients between observed and modeled values of SWE, shown in Figure 3. Pearson’s correlation coefficients were calculated for weeks in which the observational record was non-zero and averaged 0.87, and ranged from 0.71 to 0.94. The largest shift from the uniform set of parameters in the snow model were for the Merced, San Joaquin, and Kings watersheds (Table 3). Potential reasons for these differences include the fact that SWE observations are point measurements and do not necessarily represent the spatial averages computed in the model. Additionally, we suspect underpredictions of precipitation in the input weather data, as will be discussed later in this section, had an effect on the calibrated parameter set.

For streamflow, calibration was based on comparisons between the CDWR unimpaired streamflows and computed flows using the bias, root mean square error (RMSE), and 10th, 25th, 50th, and 75th flow exceedence percentiles. In addition to the 10th flow exceedence percentile, the RMSE of the log transformed flow values (RMSE\textsubscript{log}) was calculated to enable closer scrutiny of the ecologically important low summer and fall flows. Values of the BIAS ranged from −6% to 2% with an average of −1% (Table 4). The RMSE varied from 38% to 65% with an average of 51%. Flow exceedence percentiles were within ±17% of

### Table 2. Uniformly Applied Calibration Parameters.

<table>
<thead>
<tr>
<th>Model Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop coefficient, ( k_c )</td>
<td>1.1</td>
</tr>
<tr>
<td>Runoff resistance factor, RRF</td>
<td>Ag = 8, Bare = 4, Grass = 12, Shrubs = 14, Trees = 20, Urban = 4, Wet = 4</td>
</tr>
<tr>
<td>Albedo, new snow, ( A_N )</td>
<td>0.7</td>
</tr>
<tr>
<td>Albedo, old snow, ( A_O )</td>
<td>0.3</td>
</tr>
</tbody>
</table>

### Table 3. Non-Uniformly Applied Calibration Parameters.

<table>
<thead>
<tr>
<th>Watershed Code</th>
<th>FEA</th>
<th>YUB</th>
<th>BAR</th>
<th>AMR</th>
<th>COS</th>
<th>MOK</th>
<th>CAL</th>
<th>STN</th>
<th>TUO</th>
<th>MER</th>
<th>SJD</th>
<th>KNG</th>
<th>KAW</th>
<th>TUL</th>
<th>KRN</th>
<th>Average Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preferred flow direction</td>
<td>0.5</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
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<td>0.8</td>
<td>0.8</td>
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<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.78</td>
</tr>
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<td>Melting threshold (°C)</td>
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<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>6</td>
<td>12</td>
<td>11</td>
<td>5</td>
<td>5</td>
<td>7</td>
<td>6.00</td>
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<tr>
<td>Freezing threshold (°C)</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>−5</td>
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<td>Radiation factor</td>
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<td>4.5</td>
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<td>4.43</td>
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<td>Shallow soil – root zone water capacity (mm)</td>
<td>189</td>
<td>212</td>
<td>212</td>
<td>224</td>
<td>236</td>
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<td>118</td>
<td>82</td>
<td>378</td>
<td>472</td>
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<td>Deep soil – root zone water capacity (mm)</td>
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<td>540</td>
<td>540</td>
<td>570</td>
<td>600</td>
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<td>600</td>
<td>200</td>
<td>200</td>
<td>1,200</td>
<td>3,000</td>
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<tr>
<td>Shallow soil – root zone hydraulic conductivity (mm/week)</td>
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<td>77</td>
<td>77</td>
<td>62</td>
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<td>77</td>
<td>231</td>
<td>154</td>
<td>31</td>
<td>30</td>
<td>30</td>
<td>92</td>
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<td>Deep soil – root zone hydraulic conductivity (mm/week)</td>
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<td>10</td>
<td>10</td>
<td>8</td>
<td>9</td>
<td>8</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>30</td>
<td>20</td>
<td>4</td>
<td>4</td>
<td>4</td>
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<td>12</td>
</tr>
<tr>
<td>Deep water capacity (mm)</td>
<td>300</td>
<td>300</td>
<td>300</td>
<td>200</td>
<td>200</td>
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<td>200</td>
<td>200</td>
<td>200</td>
<td>220</td>
</tr>
<tr>
<td>Deep hydraulic conductivity (mm/week)</td>
<td>20</td>
<td>30</td>
<td>30</td>
<td>35</td>
<td>55</td>
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<td>55</td>
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<td>40</td>
</tr>
</tbody>
</table>
and observed flow rates for each time step (Figure 4). Values of RMSE\(_{\text{log}}\) varied from 1\% to 29\% with an average of 9\% (Table 4). Overall, the model captured the major features of the flow hydrographs at the watershed outlets (Figure 5). However, during the model construction and calibration process, sources of model, parameter specification, and input data error were identified.

Model error was identified during the analysis of the low flows using the RMSE\(_{\text{log}}\) and the 10th flow exceedence percentile. The highest RMSE\(_{\text{log}}\) values were in watersheds that had observed monthly flows of zero during dry summers. This occurred in the American, Cosumnes, Mokelumne, Stanislaus, Merced, and Tule watersheds. The reason for the relatively poor fit in these watersheds is that the continuous mathematical functions of the hydrological algorithms in WEAP21 do not easily represent extremely low flow events. For the watersheds in which there were no observed monthly flows of zero, the average RMSE\(_{\text{log}}\) was 3\%.

A potential source of parameter specification error was identified during the model construction process. As discussed earlier in this section, data from the SSURGO or STATSGO soil surveys were used to characterize soils as either deep or shallow. This classification was based on soil components for which the exact location within the mapping unit is not known. In the case of the higher resolution SSURGO data, the average mapping unit polygon area was 0.7 km\(^2\). As this is more than an order of magnitude smaller than the average catchment size, the spatial uncertainty of component locations was considered unimportant. In contrast, the STATSGO database had an average mapping unit polygon size of 126 km\(^2\), which is over three times the average catchment size. As the entire mapping unit was classified as shallow if one component had a measured bedrock depth less than 50 cm or

### Table 4: Goodness of Fit Statistics for Predicted Monthly Full Natural Flows at Watershed Exits (WY 1982-2000, \(n = 228\)).

<table>
<thead>
<tr>
<th>Watershed</th>
<th>BIAS (%)</th>
<th>RMSE (%)</th>
<th>RMSE(_{\text{log}}) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FEA</td>
<td>0</td>
<td>53</td>
<td>3</td>
</tr>
<tr>
<td>YUB</td>
<td>0</td>
<td>47</td>
<td>3</td>
</tr>
<tr>
<td>AMR</td>
<td>0</td>
<td>39</td>
<td>14</td>
</tr>
<tr>
<td>COS</td>
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<tr>
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</table>

Note: RMSE, root mean square error. BIAS = 100\((\bar{Q} - Q_{\text{obs}})/Q_{\text{obs}}\), and RMSE = \(\sqrt{\frac{1}{n} \sum_{i=1}^{n} (Q_{\text{sim}} - Q_{\text{obs}})^2}\), where \(Q_{\text{sim}}\) and \(Q_{\text{obs}}\) are simulated and observed flow rates for each time step (\(i\)).

![Figure 3: Observed and Simulated (dashed lines) Snow Water Content Values for 15 Sites in the Sierra Nevada. Graph titles provide watershed name, CDEC station code, elevation, and correlation coefficient.](image-url)

FIGURE 5. Simulated (dashed line) and CDWR Estimated Average Monthly Full Natural Flows at Watershed Outlets 1982-2000.
was rock outcrop, an overestimation of the shallow soil extent was likely. This was most prevalent in the Kern and Calaveras watersheds which only had STATS GO data and is evident in the calibrated parameters for the Kern watershed, which has the highest calibrated root zone water capacity of all watersheds.

The relatively high root zone water capacity in the Kern watershed is also likely caused by bias in the input precipitation data. Analysis of the seven CDEC stations in the Kern watershed reveal that input DAYMET precipitation data for the study period has an average positive bias of 19% at those locations. Presumably this precipitation bias extends to areas where there are no CDEC gages as the calibration required a relatively large root zone water capacity and low hydraulic conductivity to increase transpiration and thereby reduce bias in predicted annual streamflow at the watershed outlet. Additional examples of bias in the input precipitation data were found in the San Joaquin watershed where a negative bias (underprediction) was found at CDEC gages Green Mountain (GRM) and Volcanic Knob (VLC) during 1993 and 1995. The volume of annual precipitation in the input data is less than the observed SWE at these locations. Additionally, during 1981-1984, 1986-1987, and 1991 the total input rainfall volume for the watershed above the streamflow gage on the San Joaquin River at Miller Crossing (#11226500) is less than the reported USGS streamflow. This negative precipitation bias resulted in different melting threshold and radiation factors in the snow accumulation and melt model for the Merced, San Joaquin, and Kings watersheds.

In general, interpolation of point observations of precipitation into spatially distributed fields useful for watershed modeling is difficult. In the case of the Sierra Nevada, it is especially difficult in the higher elevation catchments due to the lack of observational data and pronounced orographic effects (Daly, 2006). Previous efforts at modeling rainfall-runoff in this region have encountered similar problems (Knowles, 2000; Koczot et al., 2005) and have adjusted the precipitation inputs to enable a better match between observed and simulated streamflow values.

To assess model accuracy within the boundaries of the watersheds, weekly flows from USGS streamflow gages that measure runoff from undeveloped subwatersheds were compared to model predictions (Figure 6 and Table 5), resulting in an average bias value of \(-1.3\%\) for the 19 unimpaired flow gages (range \(-41\%\) to \(-60\%\)). Model bias was within \( \pm 10\% \) for five gages and \( \pm 20\% \) for 14 gages. RMSE values ranged from \(70\%\) in the Kings watershed to \(203\%\) in the Mokelumne watershed. Values of \( \text{RMSE}_{\log} \) ranged from \(3\%\) to \(19\%\) with an average value of \(8\%\). While these statistics indicate a reduced goodness of fit when compared with the values at the watershed exits (Table 4), it is important to note these gage records were not used in the calibration process and instead were used to independently assess intra-basin model performance.

Future users of this model should consider the calibration results outlined above in determining how to apply the model. Depending on the question to be addressed by the model there are varying levels of confidence in its accuracy. Overall, the calibration results indicate that the model is most accurate at predicting streamflows at the watershed exits and snow accumulation and melt which is to be expected as this was the focus of the calibration effort. Values of streamflow RMSE at the watershed exits, which weights high flows more than low flows, indicate that the worst fit to the observed data was in the San Joaquin, Mokelumne, and Tule watersheds. Values of \( \text{RMSE}_{\log} \), which weights low flows more than high flows, show that the Cosumnes, Mokelumne, American, Stanislaus, and Tule watersheds had the lowest performance. An indication of model performance at the subwatershed scale is provided by the comparison with 19 USGS flow gages. Values of RMSE indicate subwatersheds in the Mokelumne, San Joaquin, and Feather watersheds had the lowest performance. Values of \( \text{RMSE}_{\log} \) indicate that subwatersheds in the Feather, Tule, and Mokelumne watersheds had the worst low flow performance. With respect to predicted streamflow center of mass timing, a majority of the subwatersheds are within one week of the correct time (Table 5), however, subwatersheds in the Feather, Stanislaus, and Tuolumne are less accurate. This information is useful in assessing the submonthly performance of the model and is directly relevant to the results presented below.

**TEMPERATURE INCREASE EFFECTS ON SNOW ACCUMULATION AND STREAMFLOW TIMING**

Changes in the magnitude of snow accumulation and timing of runoff in the Sierra Nevada have been studied from both historical and predictive perspectives. Analyses of the historical streamflow record have shown that the timing of the runoff center of mass has trended to earlier in the year for many Sierra Nevada watersheds over the past 50 years (McCabe and Clark, 2005; Regonda et al., 2005; Stewart et al., 2005). This change has been correlated to increases in spring and summer atmospheric pressure and temperature (McCabe and Clark, 2005; Regonda et al., 2005). The inter-annual variability in spring runoff timing has been partially accounted for by the cycles of the Pacific decadal oscillation. Of the remaining
variability, a large fraction appears to be related to observed increases in global temperatures (Stewart et al., 2005). Looking into the future, researchers have found a continued shift in runoff center of mass to earlier in the year is to be expected as projected increases in temperature affect snow accumulation and melt.
Shifts of one to two months in the timing of the mean monthly peak flow are expected under a future scenario in which the temperature increases by 5°C (Miller et al., 2003). Changes in runoff timing are related to the loss of snowpack which is expected to occur mostly in the 1,300-2,700 m elevation range (Knowles and Cayan, 2004). Depending on the CO$_2$ emissions scenario used, others have found changes in runoff center of mass are expected to vary from one to seven weeks by 2100 (Maurer, 2007).

For this analysis, we chose to focus on simple temperature increase scenarios similar to the method employed in Miller et al. (2003). The model is capable of easily incorporating downscaled weekly climate data however in this first step we wanted to explore the sensitivity of the model outputs to simple temperature increases. This was based on the conclusion that the most common warming projections in global circulation models for California show an increase of about 5°C during the 21st Century. The expected change in rainfall is less certain but is expected to be modest (Dettinger, 2005). To explore how changes wrought by increasing temperatures may evolve over time and space and affect hydrologic responses we added fixed increases of 2°C, 4°C, and 6°C to the historical 1982-2001 input temperature time series.

### Snow Accumulation

The study area average change in snowmelt volume as a function of elevation for the three temperature increase scenarios is presented in Figure 7A. Similar to other studies (Miller et al., 2003; Knowles and Ca-
the 1,750-2,750 m elevation range experienced the largest reduction in snowmelt. The peak reduction in snowmelt occurred in these mid-elevations because lower elevations (<1,750 m) have less snow accumulation initially and higher (>2,750) elevations are cold enough that the modeled temperature increases have less of an overall effect.

In another view of the same information, the percent reduction in snowmelt (Figure 7B) varied from 70% at the lowest elevations to less than 10% at the highest elevations under the 2°C warming scenario. With an increase of 4°C, over 75% of the low elevation (0-1,750 m) snowpack was lost and at the highest elevations around 20% was lost. In the 6°C warming scenario over 90% of the snowpack is lost in the elevation range of 0 to 2,000 m and at the highest elevations (>3,750 m) there was a loss of 25%.

**Shift in Runoff Center of Mass Timing**

Similar to previous studies (Miller et al., 2003; Knowles and Cayan, 2004; Maurer, 2007), the reduction in snowpack results in a shift in the runoff center of mass to earlier in the year (Figure 8). This is a result of more precipitation falling as rain and directly becoming runoff instead of remaining in storage within the snowpack and due to earlier initiation of snowmelt. The higher spatial resolution of this model enables a distributed analysis of the change in runoff center of mass. Impacts of temperature warming are geographically non-uniform (Figure 9). Under the 2°C scenario, the upper elevations of the Feather, Yuba, and American River watersheds will be affected most as they fall predominantly in the 1,750-2,750 m range. Shifts in runoff center of mass timing will exceed four weeks at some elevations in these watersheds. In contrast, the higher elevation mountainous regions in the southern portion of the study area will be impacted less in the 2°C scenario due to lower baseline temperatures. This indicates that as the climate warms the highest elevations in the northern portion of the study area will be impacted first. If temperatures continue to increase the higher elevation mountains of the southern portion of the study area will also be impacted. In the 4°C scenario, shifts in runoff timing of more than six weeks will occur in the highest mountains of the Feather River through Tuolumne River watersheds. Further south, the middle elevation portions of the Stanislaus River through Kings River watersheds will experience shifts greater than six weeks. In the 6°C scenario, nearly all the highest mountains (>1,750 m) in the watersheds from the Feather to the Kings River have a shift in runoff timing greater than six weeks. The Kern River watershed shows less sensitivity to the changes in snowmelt. This is an artifact of the calibrated soil water storage capacity, discussed above, which was nearly an order of magnitude larger than most other watersheds (Table 3).

**Management Implications**

The effects of increasing air temperature result in non-uniform hydrological responses over the region of study. Analysis of the results presented in Figure 9 and Table 6 reveal the importance of spatial scale in climate change analysis for the Sierra Nevada. For managers of the large terminal reservoirs located at the outlet of most watersheds, the model shows that a 2°C warming will result in an average shift in the
center of mass of the runoff hydrograph of 1.8 weeks. However, relative shifts internal to the watersheds reveal that some regions will experience a shift of up to five weeks under a 2°C warming. Knowledge of the magnitude and location of such changes will be important to resource managers operating at scales smaller than the watershed. For instance, many Sierra Nevada hydropower projects rely on runoff originating in the elevation bands most sensitive to temperature changes and aquatic species that rely on runoff from mid-elevation bands may be the first impacted by climate change. These observations illustrate the utility of our modeling approach by providing scenario-based simulations critical to decision making within a localized context.

In future studies this model can be used to estimate the change in overall ET and its effect on runoff volumes. After infrastructure elements such as dams and diversions are added, modification of operations rules can be studied as a response to the shift in runoff timing. Model predictions of streamflow, soil moisture conditions, and ET will be useful in studying changes in physical habitat for terrestrial and aquatic environments. Potential changes in terrestrial habitat due to climate change are related to changes in the local hydrologic balance and the resultant soil water content available to sustain vegetation cover necessary for species survival (van Mantgem and Stephenson, 2007). Potential changes in aquatic habitat due to climate change are related to changes in streamflow temperature, volume, and timing which affect in-stream habitat for aquatic organisms (Poff, 2002).

**CONCLUSIONS**

A rainfall-runoff model that predicts natural flows has been developed for the western slope of the
Sierra Nevada including watersheds from the Feather River in the north to the Kern River in the south. The model provides the ability to analyze climate change induced alterations in the hydrologic cycle within individual watersheds. The analysis shown here indicates that the impacts of warming temperatures will be experienced in a time and space varying manner that is largely a function of the distribution of elevation in the Sierra Nevada. The model has been constructed in the WEAP21 framework which lends itself to the inclusion of the human operated system and therefore will be a powerful tool in assessing climate change impacts and adaptations for resource managers at the subwatershed scale.

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LITERATURE CITED


