A COMPARISON OF THE CURVE NUMBER AND GREEN-AMPT MODELS IN AN AGRICULTURAL WATERSHED

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ABSTRACT. *The curve number and Green-Ampt rainfall-runoff models were compared in the highly agricultural San Joaquin River watershed in California using the Soil and Water Assessment Tool (SWAT). The rainfall-runoff models were left uncalibrated to objectively assess model performances; however, streamflow simulations showed high accuracy compared to observed data caused by the large impact of reservoir releases on streamflow. For daily simulations, the Nash-Sutcliffe model efficiency coefficients were 0.81 for the curve number model and 0.78 for the Green-Ampt model. A Nash-Sutcliffe coefficient of 0.93 was found for both models for the monthly simulations. The Green-Ampt model more accurately predicted large streamflow events than the curve number model, while the curve number model better predicted normal flow events. Both models tended to overpredict streamflow. The average monthly hydrologic components of surface runoff, groundwater flow, lateral soil flow, and the amount of water in the soil column were also compared to quantify the underlying differences between the two rainfall-runoff models. These comparisons yielded equal or comparable average monthly surface runoff values between the two rainfall-runoff models, but higher subsurface flows (lateral soil and groundwater inflows) and soil water volumes for the Green-Ampt model. These results are largely due to the difference in model assumptions, where the curve number model assumes an initial abstraction before surface runoff and the Green-Ampt model assumes surface runoff only when the precipitation rates is greater than the infiltration rate. The selection of the most appropriate rainfall-runoff model should be based on the watershed physical characteristics and the overall goal of the watershed modeling.*

Keywords. *California, Curve number, Green-Ampt, Rainfall-runoff model, SWAT, Watershed hydrology.*

The use of watershed models has become increasingly popular for estimating agricultural runoff in highly agricultural areas. The water quality of aquatic resources has been degraded in much of the world, prompting many countries to assess the historical, current, and future impacts of human activities on these resources. Agricultural runoff, such as sediment, nutrient, and pesticide runoff, is the main contributor to nonpoint-source pollution, adversely affecting surface water and groundwater quality in the U.S. (USEPA, 2000). Accurately modeling agricultural runoff is largely dependent on how well the watershed hydrology is modeled, as surface water, soil water, and groundwater are the vehicles by which pollutants are transported. Therefore, the selection of the best rainfall-runoff model becomes extremely important.

The selection of the rainfall-runoff model is often a compromise between model complexity (simple vs. complex) and the availability of needed input data (King et al., 1999). The merits of simple versus more complex and physically based hydrologic models have been heavily debated (Loague and Freeze, 1985; Michaud and Sorooshian, 1994; Doherty and Christensen, 2011). Several studies have addressed the differences between rainfall-runoff models, especially the popular curve number (e.g., Bales and Betson, 1981) and Green-Ampt models (e.g., Wilcox et al., 1990; King et al., 1999). While both models have been deemed very successful at modeling runoff in watersheds (Wilcox et al., 1990; King et al., 1999), both have limitations due model assumptions and data input needs. Wilcox et al. (1990) compared the curve number and Green-Ampt models on six watersheds in Arizona, Idaho, Nebraska, Oklahoma, and Texas and found that both models simulated similar hydrology. On the Goodwin Creek watershed in Mississippi, King et al. (1999) found that the curve number model simulated streamflow better than the Green-Ampt model, but both models performed satisfactorily.

While the curve number has been deemed to perform satisfactorily, it is a conceptually simple model based on empirical relationships between daily precipitation, land use, and soil type, without considering rainfall intensity or duration of storm events. Conversely, the Green-Ampt model is physically based and can model storm events due to the requirement of subdaily precipitation, a model input that can be difficult to obtain. Even though the Green-Ampt model is physically based, Wilcox et al. (1990) showed that the many regression equations needed to parameterize it

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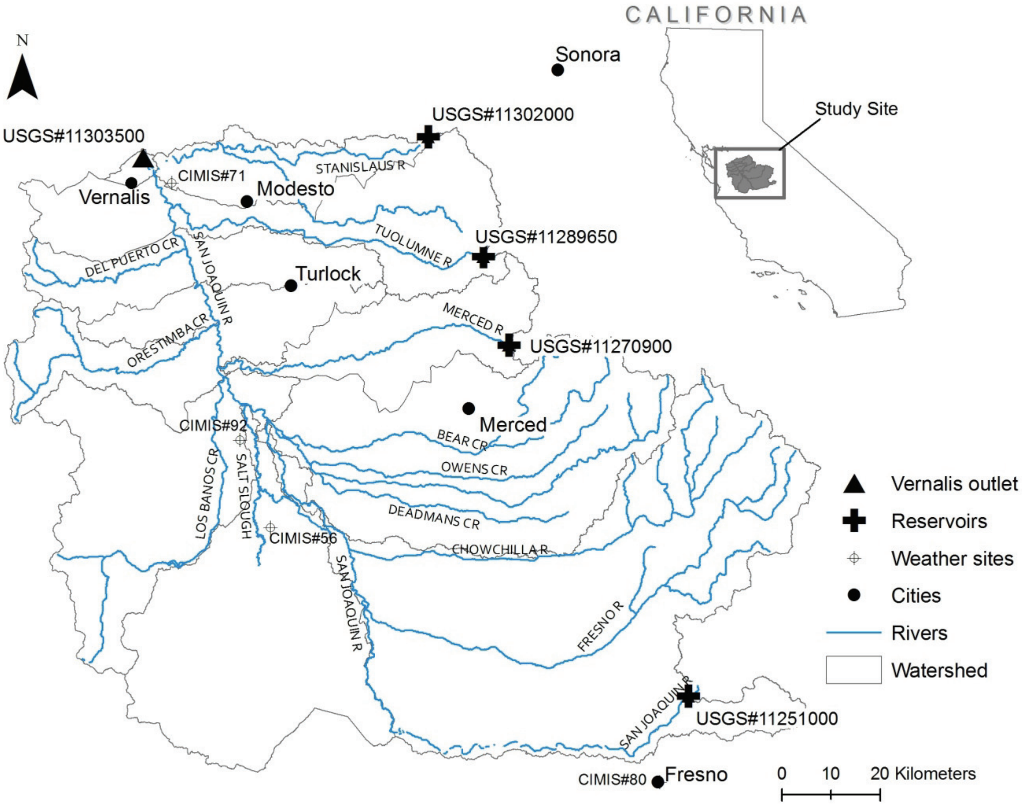

Figure 1. Study area of the northern San Joaquin Valley watershed (from Ficklin et al., 2010).

may dilute much of the "physically based" aspect of the model.

A major limitation for the use of many hydrologic models on agricultural catchments is that many of these catchments are highly managed; therefore, model results may not mimic actual hydrologic characteristics. In this article, we apply and evaluate two very different models (curve number and Green-Ampt) for modeling rainfall-runoff using the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) in the highly agricultural San Joaquin River watershed in California. Most importantly, we determine whether one model predicts streamflow better than the other when land use is highly spatially aggregated and streamflow is heavily regulated, which are characteristics of many highly agricultural watersheds. The average monthly hydrologic components of surface runoff, lateral flow, and groundwater flow are also compared between the two models to determine which hydrologic components are contributing the bulk of the water entering the San Joaquin River. Due to the intensive agriculture in the area, and growing concern about the effects of agricultural pollutants on the Sacramento-San Joaquin Bay Delta ecosystem, large-scale modeling studies of the hydrology and water quality of the San Joaquin River watershed continue to be of interest (Luo et al., 2008; Ficklin et al., 2009; Ficklin et al., 2010). The results will be useful for future modeling studies of watersheds containing a large amount of agricultural land, and will assist water resource and water quality managers in management decisions.

Materials and Methods

Study Site

The test watershed is the San Joaquin River watershed, located in California's Central Valley (fig. 1). The 14,983 km^2 watershed is enclosed by the Coastal Range to the west and the Sierra Nevada foothills to the east. The watershed is highly agricultural and includes the majority of agricultural areas in the counties of Stanislaus, Merced, and Madera, and parts of San Joaquin, Mariposa, Tuolumne, San Benito and Fresno counties. A large portion (95%) of the crops in the study area are fruits and nuts (38%); field crops (36%); truck, nursery, and bean crops (17%); and grain crops (4%) (DWR, 2007).

The San Joaquin River watershed has a typical Mediterranean climate with hot, dry summers and cool, wet winters (fig. 2). Average summer and winter temperatures are approximately 24°C and 10°C, respectively. Average annual rainfall is approximately 200 to 300 mm, with most of the precipitation falling between November and May, while precipitation between June and October is negligible (fig. 2).

Variation in soil characteristics within the study area can be attributed to three main groups of parent materials: (1) east-side granitic alluvium, (2) west-side mixed sedimentary alluvium, and (3) alluvium of mixed sources (Gatzke et al., 2011). Soils east of the San Joaquin River typically have sandy to sandy-loam textures, while soils west of the San Joaquin River typically have loamy to clay textures. Near the San Joaquin River, soils have mixed mineralogy with a wide range of textures. A full description

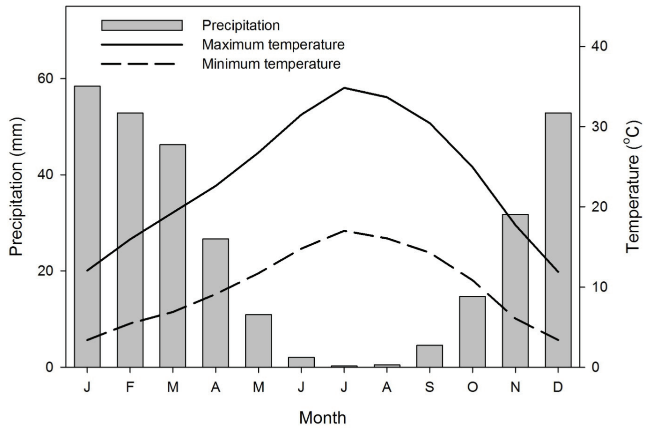

Figure 2. Average monthly precipitation and maximum and minimum temperatures for the San Joaquin River watershed.

of the soils in the study area can be found in Gatzke et al. (2011).

Hydrologic Model Description

SWAT is a continuous-time, quasi-physically based, distributed water quality model designed to simulate water, sediment, and agricultural chemical transport at a river-basin scale. SWAT was designed to be applied to ungauged river basins and therefore can be used to analyze many watersheds using readily available data. SWAT integrates processes of several other models, allowing for the simulation of climate, hydrology, plant growth, erosion, nutrient transport and transformation, pesticide transport, and management practices. SWAT 2005 was used for model runs, while ArcSWAT, a SWAT graphical user interface coupled with ESRI's ArcGIS version 9.2, was used to generate SWAT model input files. Full details of SWAT can be found in Neitsch et al. (2005).

In SWAT, the watershed of interest is divided into subbasins, which are then divided into hydrologic response units (HRUs). The HRUs preserve the heterogeneity of the important physical properties of the watershed and are delineated by overlaying topography, soil data, and land use maps in a geographical information system (GIS). This subdivision gives the model the strength to better represent the properties of land uses and/or soils of each subbasin that may have a significant effect on hydrology. The HRU water balance is represented by four storage components: snow, soil profile, shallow aquifer, and deep aquifer. Flow, sediment, and agricultural runoff are summed across all HRUs in a subwatershed, and the resulting flows and pollutant loads are then routed through channels, ponds, and/or reservoirs to the watershed outlet.

Rainfall-Runoff Models

Predictions of runoff are simulated using the Green-Ampt and curve number rainfall-runoff models. Both models are widely accepted and are used in many applications (e.g., Chow et al., 1988; Arnold and Allen, 1996; Mays, 2005). The models were left uncalibrated, as calibration may mask the differences that result from using the different rainfall-runoff models. Additionally, the uncalibrated model results will show how well each model predicts before calibration, an indication of the amount of effort needed to calibrate the model (Geza and McCray, 2008).

The curve number model is an empirical model widely used for determining the amount of runoff from precipitation in a particular area. The model was developed to simulate surface runoff from daily rainfall events. The curve number values are based on the area's hydrologic soil group, land use, management, and initial hydrologic condition, with the hydrologic soil group and land use being the most important variables. SWAT uses curve number values obtained from the USDA Soil Conservation Service's *National Engineering Handbook* (SCS, 1984). In SWAT, the curve number model estimates the amount of runoff first, and assumes that the remaining precipitation will infiltrate. Surface runoff generated from the curve number model is estimated by:

$$Q_{surf} = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)} \tag{1}$$

where Q_{surf} is the surface runoff or rainfall excess (mm H_2O), R_{day} is the rainfall depth for the day (mm H_2O), I_a is the initial abstraction that includes surface storage, interception, and infiltration prior to runoff (mm H_2O), and S is the retention parameter (mm H_2O). S is estimated by:

$$S = 25.4\left(\frac{1000}{\text{CN}} - 10\right) \tag{2}$$

where CN is the curve number value for the day. The initial abstraction (I_a) is commonly approximated as 0.2S. In that case, equation 1 becomes:

$$Q_{surf} = \frac{\left(R_{day} - 0.2S\right)^2}{\left(R_{day} + 0.8S\right)} \tag{3}$$

and surface runoff will only occur when $R_{day} > I_a$.

The Green-Ampt model, on the other hand, is a physically based model. The Green-Ampt solution assumes that there is an abrupt wetting front in the dry soil, rather than a diffuse front where the water potential varies with water content (Green and Ampt, 1911). The Green-Ampt equations are simplified representations of the infiltration process and are considered a preferred model for computing vertical water flow in soil during rainfall events (Chu, 1978). In SWAT, the Green-Ampt model estimates the amount of infiltration first, and the remaining precipitation will become surface runoff. The Green-Ampt model estimates surface runoff and infiltration by:

$$f(t) = K\left[\frac{\psi\Delta\theta}{F(t)} + 1\right] \tag{4}$$

where $f(t)$ is the infiltration rate (mm h^{-1}), K is the hydraulic conductivity (mm h^{-1}), ψ is the wetting front soil suction head (mm), $\Delta\theta$ is the change in moisture content, $F(t)$ is the cumulative infiltration (mm), and t is time (h). $F(t)$ is estimated by:

$$F(t) = Kt + \psi\Delta\theta \ln\left[1 + \frac{F(t)}{\psi\Delta\theta}\right] \quad (5)$$

where all variables have been previously defined. The wetting front soil suction head (ψ) was adapted from a regression analysis on several soils presented by Rawls et al. (1989). They expressed ψ as a function of porosity (*POR*), percent sand (*PS*), and percent clay (*PC*):

$$\begin{aligned}\psi = \exp\Big(&6.5309 - 7.3256POR + 0.001583PC^2 \\ &+3.809479POR^2 + 0.000344PS \times PC \\ &-0.049837PS \times POR + 0.001608PS^2 \times POR^2 \\ &+0.001602PC^2 \times POR^2 - 0.000014PS^2 \times PC \\ &-0.00348PC^2 \times POR - 0.0008PS^2 \times POR\Big)\end{aligned} \quad (6)$$

Both models were run at daily and monthly time steps within SWAT.

Data Collection and Analysis

SWAT input parameter values were compiled from various state and federal government agency databases. Elevation, land use, and stream network data were obtained from U.S. Environmental Protection Agency's Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) database. Data included 30 m resolution digital elevation models (DEMs) and 1:100,000-scale stream network data from the National Hydrography Dataset (NHD). Soil properties were extracted from the Soil Survey Geographic (SSURGO) database developed by the USDA Natural Resources Conservation Service (NRCS). Hydraulic conductivity was assumed to equivalent to 50% saturated hydraulic conductivity, as suggested by Bouwer (1966). Cropland areas were defined based on the land use survey database developed by the California Department of Water Resources (DWR) during 1996-2004 under the assumption that agricultural land use has not change since the survey was completed. Hourly precipitation and daily minimum and maximum temperatures were retrieved from four California Irrigation Management Information System (CIMIS) weather stations located in the study area (fig. 1). Reservoir release data were obtained from the U.S. Geological Survey (USGS; see fig. 1). Both rainfall-runoff models used the same input data.

Statistical Analyses

The mean, median, and standard deviation (SD) were calculated for the daily and monthly streamflow results. The Nash-Sutcliffe coefficient of efficiency (NSE; Nash and Sutcliffe, 1970) was used to evaluate the goodness-of-fit between the simulated and observed streamflow data at the USGS gauge outlet at Vernalis, California (ID No. 11303500). NSE values can range from negative infinity to 1, where 1 is a perfect match of simulated to observed data. The percent bias (PBIAS) statistic was calculated to measure the tendency of the simulated flows to be larger or smaller than the observed flows. The optimal PBIAS value is 0.0; positive values indicate a tendency to underestimate, and negative values indicate a tendency to overestimate. The equations for NSE and PBIAS are:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(y_{obs,i} - y_{sim,i}\right)^2}{\sum_{i=1}^{n}\left(y_{obs,i} - \overline{y}_{obs,i}\right)^2} \quad (7)$$

$$\text{PBIAS} = \frac{\sum_{i=1}^{n}\left(y_{obs,i} - y_{sim,i}\right)}{\sum_{i=1}^{n} y_{obs,i}} \times 100 \quad (8)$$

where $y_{obs,i}$ is the observed streamflow, $\overline{y}_{obs,i}$ is the mean of the observed streamflow and $y_{sim,i}$ is the simulated streamflow. We also compare cumulative streamflow totals to verify long-term model fit.

The Mann-Whitney rank sum test ($p < 0.05$, two-sided) was used to compare the simulated and observed streamflows since they exhibited non-normal distributions (Mann and Whitney, 1947). The Mann-Whitney rank sum test is based on the concept that if two groups come from the same distributions, then the sum of the ranks of the values should be somewhat equally distributed between the two groups.

Results and Discussion

Streamflow Comparisons

We compare streamflow results in the San Joaquin River watershed using the curve number and Green-Ampt rainfall-runoff models. It is important to note that the San Joaquin River watershed is heavily regulated by reservoirs, and any differences in streamflow results between the curve number and Green-Ampt models are from changes in hydrology within the watershed and not from changes in reservoir releases. Further, we again must emphasize that the curve number and Green-Ampt models were not calibrated against observed data, as an attempt to objectively identify the utility of the two models in an ungauged agricultural watershed.

NSE values indicate that all curve number and Green-Ampt simulations resulted in accurate simulations of streamflow, which is caused by the highly managed reservoir releases (table 1). However, the Mann-Whitney significance tests indicate that, for daily simulations, both rainfall-runoff models are significantly different ($p < 0.05$) from the observed streamflow values (table 1). For daily simulations, the curve number model (NSE = 0.81) predicted streamflow more accurately than the Green-Ampt model (NSE = 0.78). The mean, median, PBIAS, and cumulative streamflow statistics indicate overpredictions of streamflow by both models, which were caused by simulated extreme streamflow events not found in the observed streamflow data (fig. 3). The standard deviation and 95th percentiles of daily streamflow from the Green-Ampt simulations were closer to those of the observed streamflow (table 1; fig. 4). This may

Table 1. Descriptive and model efficiency statistics for the curve number and Green-Ampt simulations.

		Streamflow ($m^3\ s^{-1}$)					
		Mean[a]	Median	SD	NSE	PBIAS (%)	Cumulative Streamflow ($m^3\ s^{-1}$)
Daily	Observed	114.86	58.6	158.4	-	-	671,216
	Curve number	115.76*	66.1	145	0.81	-0.78	676,480
	Green-Ampt	124.79*	68.8	160	0.78	-8.65	729,282
Monthly	Observed	115.51	60.5	152.5	-	-	22,178
	Curve number	116.18	68.3	142.9	0.93	-0.58	24,056
	Green-Ampt	125.29*	69.9	156.1	0.93	-8.47	22,307

[a] Asterisk (*) indicates significant difference between model mean and observed mean at $\alpha = 0.05$

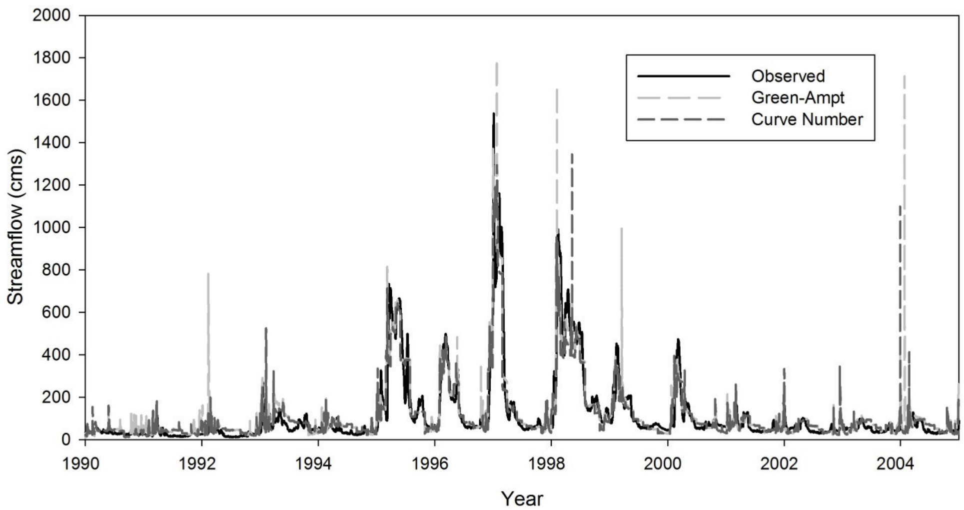

Figure 3. Observed, curve number, and Green-Ampt simulated daily streamflow time series at outlet of San Joaquin River watershed.

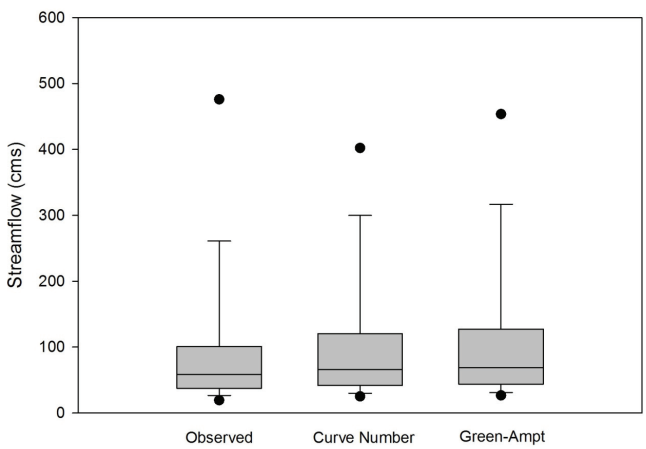

Figure 4. Box plots of observed, curve number, and Green-Ampt simulated daily streamflow results. Whiskers represent 1st and 3rd quartiles, and black circles represent maxima and minima.

suggest that the Green-Ampt model has the capability of predicting large storm events better than the curve number model, while the curve number model may better predict normal flow events.

Similar results were found for monthly simulations. The Green-Ampt model resulted in significantly different streamflow values ($p < 0.05$) compared to the observed data, while the curve number model resulted in statistically similar streamflow values ($p > 0.05$) (table 1). Both rainfall-runoff models produced the same NSE value of 0.93 (table 1). As expected, monthly NSE values were higher than daily NSE values because there is less room for error as data become less aggregated (Wilcox et al., 1990).

As was the case for the daily simulations, the mean and median values for the curve number model were closer to the observed values, while the standard deviation and 95th percentiles using the Green-Ampt model were closer to the observed values (table 1; figs. 5 and 6). Both models overpredicted compared to the observed monthly streamflow statistics.

To examine how well the curve number and Green-Ampt models performed at simulating peak streamflows, we extracted the top 500 observed daily peak streamflows and the top 50 observed monthly peak streamflows and then compared the model efficiency statistics of the curve number and Green-Ampt simulations. For the daily peak streamflows, the Green-Ampt model performed better at simulating high streamflows, with NSE, RMSE, and PBIAS of 0.20, 172 $m^3\ s^{-1}$ and 7.2%, respectively, compared to 0.14, 179 $m^3\ s^{-1}$, and 14.7%, respectively, for the curve number model. The Green-Ampt model also outperformed the curve number model at predicting monthly streamflows, with an NSE value of 0.89 compared to 0.88 for curve number, RMSE of 67.9 $m^3\ s^{-1}$ compared to 69.1 $m^3\ s^{-1}$ for the curve number, and PBIAS of -2.1% compared to 5.4% for curve number.

The streamflow results indicate that the conceptually simple curve number model was able to simulate runoff about as well as the much more complex and physically based Green-Ampt model. This is in agreement with Beven (1989), Anderson and Burt (1985), Wilcox et al. (1990), and King et al. (1999), who point out that increased model complexity does not always increase model accuracy.

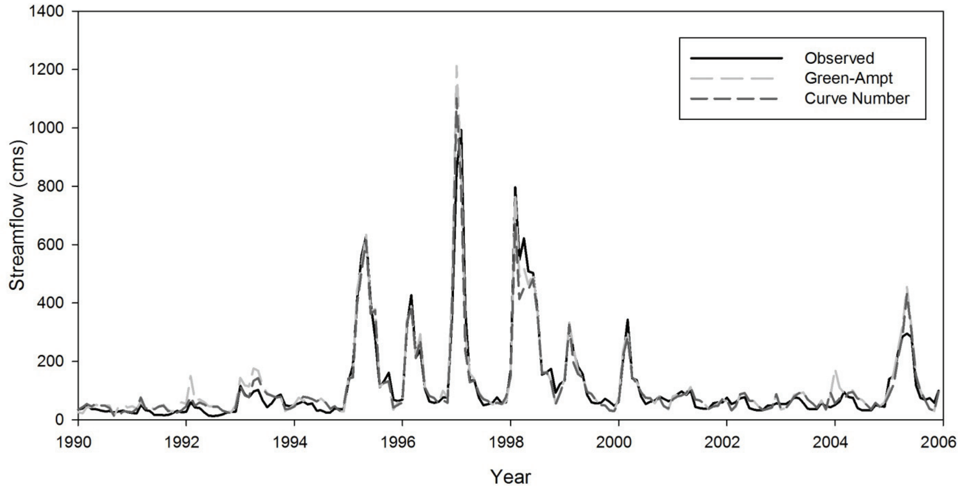

Figure 5. Observed, curve number, and Green-Ampt simulated monthly streamflow time series at outlet of San Joaquin River watershed.

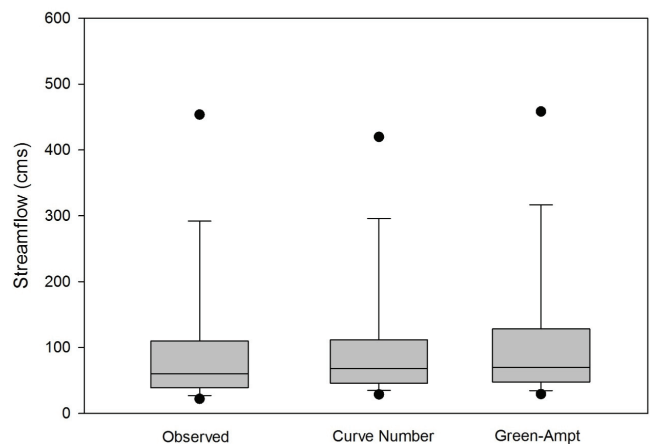

Figure 6. Box plots of observed, curve number, and Green-Ampt simulated monthly streamflow results. Whiskers represent 1st and 3rd quartiles, and black circles represent maxima and minima.

HYDROLOGIC COMPONENT COMPARISONS

It is important to note that no observed surface runoff or subsurface hydrologic data were used for the curve number and Green-Ampt model comparison. However, information can be gleaned from the following hydrologic component comparisons. In a previous study (Ficklin et al., 2012), we showed that the SWAT model adequately simulates surface and subsurface hydrologic components. Further, we view this analysis as a way to show the underlying reasons why the curve number and Green-Ampt models are simulating different streamflows. Therefore, we view this type of analysis as useful information for other SWAT users who are modeling agricultural watersheds.

Average monthly hydrologic component values of surface runoff, groundwater flow, lateral soil flow, and the amount of water in the soil column were plotted to quantify the underlying differences between the curve number and Green-Ampt streamflow results. Two main results can be ascertained from figure 7: (1) equal or comparable average monthly surface runoff values between the two models, and (2) higher subsurface inflows (lateral soil and groundwater inflows) and soil water volumes for the Green-Ampt model.

The higher subsurface inflows and soil water volumes for the Green-Ampt model are largely due to differences in model assumptions and formulations. The curve number model assumes an initial abstraction that is related to the initial curve number value. The water that is not part of this initial abstraction is assumed to be surface runoff. Curve number initial abstraction is often considered to be 20% of the curve number value, as is the case for SWAT. This value represents an average because of the degree of scatter, and some authors (e.g., Aron et al., 1977) suggest it should be less than 20%. The Green-Ampt model assumes that if the precipitation rate is less than the infiltration rate, then all precipitation will infiltrate during the time period. Therefore, the results displayed in figure 7 reflect the Green-Ampt assumption that if the precipitation rate is lower than the infiltration rate, then more infiltration and subsurface hydrologic activity will occur. It is important to note that annual percolation, which in SWAT is the water that leaves the soil column and enters the deep aquifer, was eight times higher for the Green-Ampt model compared to the curve number model (not shown). Additionally, annual evapotranspiration was 10% higher for the Green-Ampt model, which is a result of more water in the soil column for plants to use and transpire (not shown).

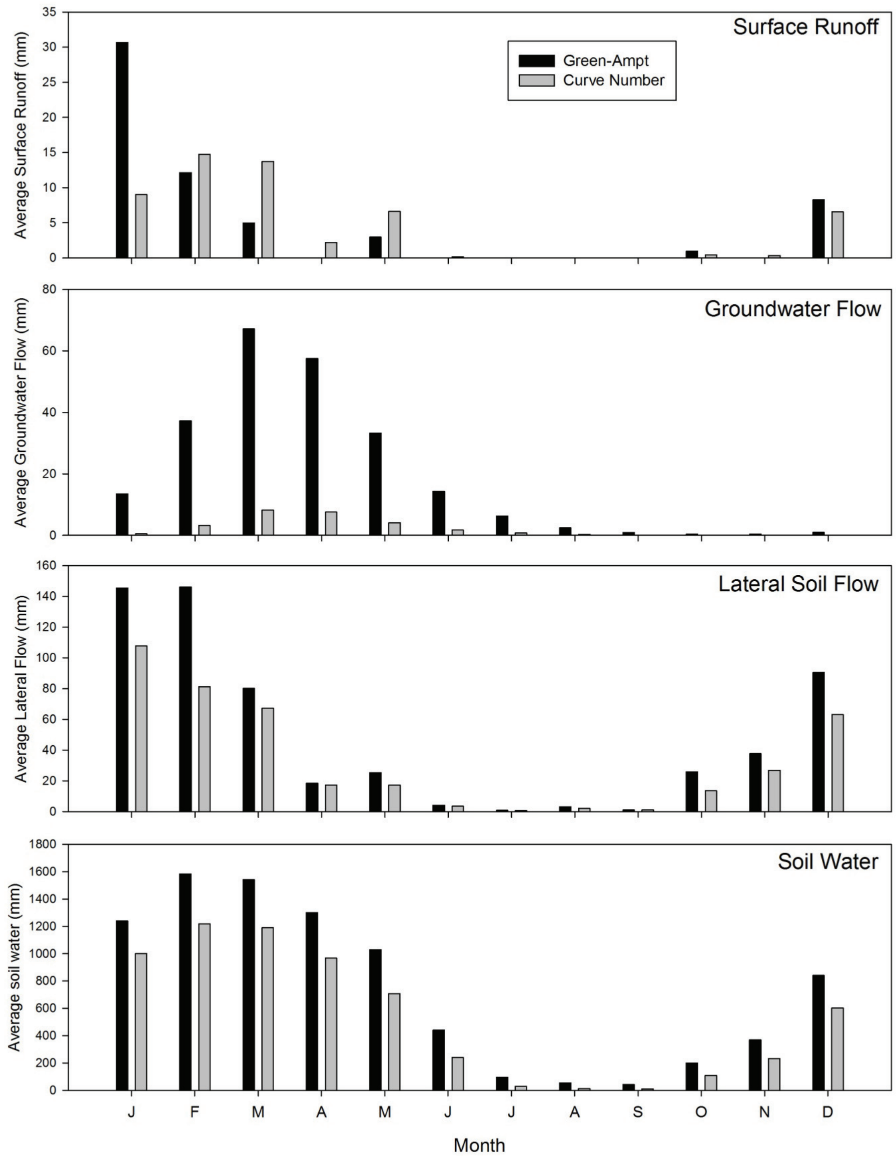

Figure 7. Average monthly hydrologic components simulated by curve number and Green-Ampt methods.

The high January surface runoff value for the Green-Ampt model can be explained by the extremely rainy January of 1997. This storm, termed the the New Year's Day storm of 1997, was a short-duration, high-intensity storm, which for some regions led to 20 cm of precipitation in a 24 h period. This storm occurred during a particularly wet winter season, attributed to an extremely strong El Niño event. Throughout the San Joaquin River watershed, dozens of levees failed, resulting in widespread flooding. Excluding this January value from the average monthly surface runoff calculation would result in an average January surface runoff value of 16 mm.

These findings have implications for simulating agricultural runoff, and the user should have an understanding of the relevant pollutants to be modeled in the watershed. For example, pesticides and fertilizers with low Koc values show weak soil adsorption and high solubility, and are thus more mobile in runoff waters. The U.S. Environmental Protection Agency indicates that pesticides with a high potential for groundwater leaching will have Koc values less than 1900 mg g^{-1} and solubility greater than 3 ppm (PAN, 2004). For the agriculturally intensive San Joaquin River watershed, the Green-Ampt model simulates a much more hydrologically active subsurface than the curve number, so it may more accurately model pesticide leaching. Nitrate is an agricultural pollutant often found in groundwater, where nitrate sources include fertilizer applications or livestock manure. Shallow and deep groundwater nitrate pollution is often found below soils lacking a significant amount of anion exchange capacity, allowing the nitrate to remain soluble and move with soil water and groundwater flows. This type of groundwater contamination is also prevalent in areas with extensive irrigation, and these models can help water quality managers understand surface runoff risks from irrigation applications.

Advantages and Disadvantages

When modeling large watersheds, the user must consider the overall goal of the modeling outcome. For example, is the user interested in daily or monthly results? As King et al. (1999) notes, an increase in watershed drainage area and temporal aggregation will smooth the streamflow peaks, and thus the Green-Ampt model may become ineffective. This is likely the case for the San Joaquin River watershed because of its large size; however, as we previously discussed, the Green-Ampt model does a better job simulating peak streamflows. Further, the widely used curve number model was not designed for use in non-event watershed modeling. While the curve number model can be used successfully as a calibration parameter in hydrological models, it was developed for use in determining streamflow for single storm events, and not for day-to-day analysis. Thus, the user must be aware of this limitation when using the curve number, as it is just a simple way to match observed rainfall data to predicted streamflow. Further, the curve number was developed using data from a limited number of regions in the U.S. and may not be applicable for all regions.

The current version of SWAT provides user access to the curve number and Green-Ampt models. For the curve number model, the user must provide spatial land use, soils, and elevation coverages, along with daily precipitation data. The Green-Ampt model in SWAT uses the same spatial coverages, but the user must also provide less readily available subdaily precipitation records and detailed soil information. This can present a large obstacle for minimally gauged watersheds. While the Green-Ampt model is more physically based than the curve number model, the Green-Ampt model is not appropriate for simulating watersheds that contain large saturated areas, due to its assumption that precipitation infiltrates into relatively dry soil. This assumption is important when modeling the relatively flat San Joaquin River watershed, which contains large areas of seasonally flooded wetlands in winter. This is likely the reason for the large amount of surface runoff during the New Year's Day storm of 1997 using the Green-Ampt model. However, the amount of flooded wetland also depends on reservoir management, as the reservoirs collect a large amount of the flood runoff.

Conclusions

The curve number and Green-Ampt rainfall-runoff models were compared in the highly agricultural San Joaquin River watershed in California using SWAT. The models were left uncalibrated in an attempt to objectively identify the utility of the two models. For all simulations, Nash-Sutcliffe efficiency (NSE) values indicate accurate simulations of streamflow, which is largely due to the highly managed reservoir releases. For daily simulations, the curve number model more accurately predicted streamflow as compared to the Green-Ampt model, with NSE values of 0.81 for the curve number model and 0.78 for the Green-Ampt model. However, the Green-Ampt model gave better predictions of runoff associated with large storm events. Similar results were found for monthly simulations comparisons.

The average hydrologic components of surface runoff, groundwater flow, lateral soil flow, and the amount of water in the soil column were also compared to quantify the underlying differences between the two rainfall-runoff models. Two main results were found: (1) equal or comparable average monthly surface runoff values between the two models, and (2) higher subsurface flows (lateral soil and groundwater inflows) and soil water volumes for the Green-Ampt model. These differences are largely due to the model assumptions; the curve number model assumes an initial abstraction before surface runoff, and the Green-Ampt model assumes surface runoff only when the precipitation rate is greater than the infiltration rate.

The most appropriate rainfall-runoff model should be chosen based on the watershed physiography and the reason for modeling. The Green-Ampt model is likely to provide better daily simulation results due to its better simulation of large storm events. However, streamflow peaks will smooth out with increased watershed size and temporal aggregation, making the Green-Ampt less effective than the curve number model. Further, the Green-Ampt model is not appropriate for simulating watersheds that contain a large amount of saturated areas, such as the San Joaquin River watershed during large precipitation and flood events.

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