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Watershed modelling of hydrology and water quality in the Sacramento River watershed, California

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Abstract:

Agricultural pollutant runoff is a major source of water contamination in California's Sacramento River watershed where 8500 km^2 of agricultural land influences water quality. The Soil and Water Assessment Tool (SWAT) hydrology, sediment, nitrate and pesticide transport components were assessed for the Sacramento River watershed. To represent flood conveyance in the area, the model was improved by implementing a flood routing algorithm. Sensitivity/uncertainty analyses and multi-objective calibration were incorporated into the model application for predicting streamflow, sediment, nitrate and pesticides (chlorpyrifos and diazinon) at multiple watershed sites from 1992 to 2008. Most of the observed data were within the 95% uncertainty interval, indicating that the SWAT simulations were capturing the uncertainties that existed, such as model simplification, observed data errors and lack of agricultural management data. The monthly Nash–Sutcliffe coefficients at the watershed outlet ranged from 0.48 to 0.82, indicating that the model was able to successfully predict streamflow and agricultural pollutant transport after calibration. Predicted sediment loads were highly correlated to streamflow, whereas nitrate, chlorpyrifos and diazinon were moderately correlated to streamflow. This indicates that timing of agricultural management operations plays a role in agricultural pollutant runoff. Best management practices, such as pesticide use limits during wet seasons, could improve water quality in the Sacramento River watershed. The calibrated model establishes a modelling framework for further studies of hydrology, water quality and ecosystem protection in the study area.

KEY WORDS California; SWAT; agricultural runoff; water quality; calibration; uncertainty

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INTRODUCTION

Increasing agricultural contamination of surface waters has generated substantial concern since the 1940s (Larson *et al*., 1995). This concern is especially relevant in California's Sacramento River watershed where 8500 km^2 of agricultural land has a large influence on water quality (USDA Forest Service, 2008). Many rivers in the Sacramento River watershed are included in California's 303(d) list of impaired water bodies as a result of multiple pollutants, especially heavy metals and pesticides (U.S. EPA, 2006). This watershed, along with the San Joaquin River watershed, drains into the Sacramento–San Joaquin Delta (Delta), which has shown an appreciable decline in aquatic species, attributed in part to an increase in water pollutant levels (Werner *et al*., 1999). Agricultural land within the Sacramento River watershed receives thousands of tons of pesticides every year (CA DPR, 2006). The primary mode of agricultural non-point source pollution transport is sediment and water runoff, leading to contamination of the Sacramento River and its tributaries (Domagalksi, 1996). Therefore, accurately modelling the characteristics of non-point pollution sources is the first step in agricultural pollutant mitigation.

The use of water quality modelling is a key component for predicting surface water and sediment runoff. Water quality modelling serves as a valuable tool in determining the temporal and spatial variability of agricultural pollutant sources. Various hydrological simulation models have been applied at watershed scales for spatial prediction of hydrological processes and associated water quality (e.g. Luo *et al*., 2008; Wohlfahrt *et al*., 2010). The Soil and Water Assessment Tool (SWAT; Arnold *et al*., 1998), which is used in this study, is one of these hydrologic models that is designed to simulate hydrological and contaminant transport processes at the watershed scale. The model has been used extensively throughout the world for studying streamflow and agricultural pollutant loads (Gassman *et al*., 2007).

Calibration of watershed models is often achieved using inverse modelling (e.g. Kunstmann *et al*., 2006). Inverse modelling is an efficient and objective method to determine the optimum set of parameter values aimed at minimizing differences between observed and simulated output variables (streamflow, sediment loads, nitrate loads etc.). This process is achieved by varying the model parameters within a pre-determined range until the model output best matches observed data. This is a potentially attractive method, as the direct measurement of model parameters describing physical systems is often time-consuming, expensive and potentially error-ridden. Because there may be a wide array of parameters that fit measured output, no hydrological inverse problem is

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uniquely solvable. This is termed ‘model non-uniqueness’, where if one parameter set solution is found, then there may be inherently many more parameter sets that fit the same solution. Therefore, one of the goals of inverse modelling is to characterize the set of models, mainly through assigning distributions having associated uncertainties to parameters that fit the data and also satisfy prior knowledge of the parameter space (Abbaspour *et al*., 2004). To do this, one must consider the uncertainties associated with hydrologic modelling: (1) errors in temporal and spatial observed input data (temperature, rainfall, soil properties, elevation etc.), (2) errors in observed output data (streamflow, sediment concentration etc.) and (3) simplifications in the hydrological and conceptual model (model assumptions, agricultural management timing etc.).

Inverse calibration of a large-scale distributed hydrologic model against one watershed outlet gauge may not accurately capture the temporal and spatial dynamics of individual subwatersheds. Therefore, a multi-criteria calibration should be performed for a better characterization of the varying components of the watershed (Abbaspour *et al*., 2007), while concurrently helping to minimize the non-uniqueness problem by narrowing the uncertainty prediction. If multiple gauge sites with multiple constituents are available for calibration, one can gain better confidence that the entire watershed is being accurately modelled.

In this study, the SWAT model was applied to the Sacramento River watershed for dynamic simulations of streamflow, sediment, nitrate and pesticides. For pesticide fate and transport, chlorpyrifos and diazinon were chosen as the test agents in calibrating and validating the model for pesticide simulation. The objectives of this study were to (1) modify the SWAT code to allow the modelling of flood weir structures and flood water transfers along the Sacramento River watershed, (2) calibrate, validate and assess the uncertainty of the Sacramento River watershed SWAT model at multiple stations for multiple constituents across the watershed by using the calibration and uncertainty analysis program Sequential Uncertainty Fitting Ver. 2 (SUFI-2) and (3) perform a temporal correlation analysis to determine relationships between agricultural pollutants. By characterizing the fate and transport of agricultural pollutants in the Sacramento River watershed, the results could aid in the development of mitigation strategies to reduce the movement of agricultural pollutants to surface waters.

MATERIALS AND METHODS

Study site

The Sacramento River monitoring gauge maintained by the United States Geological Survey (USGS) at Freeport, CA (USGS gauge #11447650) was chosen as the outlet of the simulated watershed. The Sacramento River watershed area, as defined by this study, is approximately 23 300 km^2 (Figure 1). The watershed boundary is bordered by gauge sites directly below dams on the eastern, western and northern sides of the watershed. The western side is bordered by the Black Butte Dam (California Department of Water Resources (CA DWR) ID: BLB); the eastern side is bordered by the Oroville Dam (CA DWR ID: ORO), Yuba River at Marysville USGS gauge (approximately 20 km below Englebright Dam; USGS gauge #11421000), Camp Far West Dam (CA DWR ID: CFW) and Folsom Dam (CA DWR ID: AMF); the northern side is bordered by Shasta Dam (CA

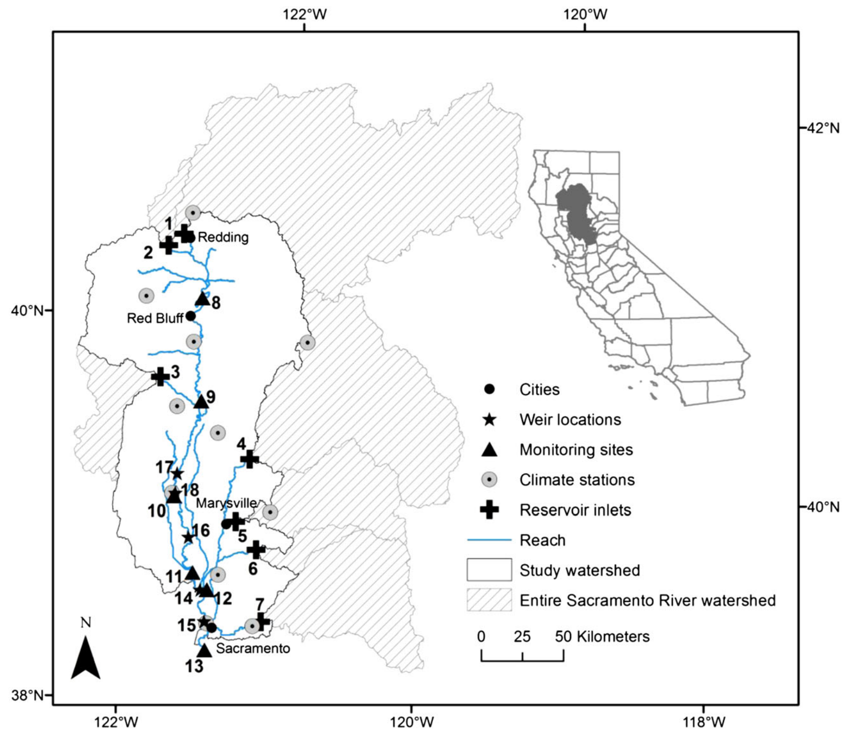

Figure 1. Study area of the Sacramento River watershed in northern California

DWR ID: SHA) and Whiskeytown Dam (USGS gauge #11372000) (Figure 1, Table I). The study area includes the majority of agricultural land in the northern Central Valley from Sacramento to Red Bluff. The majority of the land use in the study area is rangeland composing approximately 62% of the total watershed area, whereas agricultural land composes approximately 33% of the total area. The remaining 5% represents urban land use, waterways/wetlands and forested areas. Almost all agricultural activities impacting water quality of the Sacramento River and its tributaries occur in the Sacramento River watershed that is modelled in this study.

The Sacramento River Valley has a typical Mediterranean climate characterized by hot summers and mild winters, with an average temperature ranging from 4.4 °C in the winter to above 32 °C in the summer (Guo *et al*., 2007). The soils of the valley are mostly fine grained with low permeability (Troiano *et al*., 2001). The mean annual precipitation ranges from 36 to 64 cm, with most of the precipitation occurring during November to April. Hence, the streamflow in the Sacramento River is dominated by winter and spring runoff from snowmelt and rainfall. Additional water requirement for crops grown within the watershed is therefore dependent on irrigation from surface water or groundwater (CA DWR, 1998). Dam and reservoir operations for urban and agricultural uses have greatly disrupted the natural hydrology in this region.

Model description and modifications

SWAT model description. The watershed hydrology and water quality model referred to as SWAT was chosen for this study (Arnold *et al*., 1998). SWAT is a continuous-time, quasi-physically based, distributed water quality model designed to simulate water, sediment and agricultural chemical transport on a river-basin scale. SWAT was designed to be applied for ungauged river basins and therefore can be used to analyze many watersheds using readily available data. SWAT integrates processes for the simulation of climate, hydrology, plant growth, erosion, nutrient transport and transformation, pesticide transport and management practices. The SWAT version 2005/ ArcSWAT version, which is coupled with Environmental Systems Research Institute (ESRI's) ArcGIS version 9.3, was selected for this study. Full details of the SWAT model can be found in Neitsch *et al*. (2005). SWAT model has been applied to numerous agricultural watersheds for hydrology and water quality simulations (Gassman *et al*., 2007; Luo *et al*., 2008). Previous studies suggested that SWAT successfully captured the spatial and temporal variations on watershed hydrology and the impacts of agricultural activities on water quality.

In SWAT, the watershed of interest is divided into subbasins, which are then divided into hydrologic response units (HRUs). The HRUs are intended to represent 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 basis 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. The runoff volume is estimated using the modified Soil Conservation Service (SCS) Curve Number method (SCS, 1984). Sediment discharge at the watershed outlet is calculated using soil erosion and sediment routing equations such as the Modified Universal Soil Loss Equation. Nutrient outputs are estimated by tracking their movements and transformations. The pesticide component in SWAT simulates pesticide transport in dissolved and particulate phases with surface and subsurface hydrologic processes (Neitsch *et al*., 2002).

Table I. Inflows and monitoring sites in the Sacramento River watershed

Map ID	Tributary outlets or river site	Location		Sampling type	
		Latitude	Longitude	Streamflow	Water quality
	Sites for inlet discharge				
1	Shasta Dam	40.601	−122.443	X	X
2	Whiskeytown Dam transfer	40.516	−122.525	X	X
3	Black Butte Dam	39.808	−122.329	X	X
4	Oroville Dam	39.522	−121.547	X	X
5	Yuba River – Marysville	39.176	−121.524	X	X
6	Camp Far West Dam	39.050	−121.317	X	X
7	Folsom Dam	38.683	−121.183	X	X
	Sites for model evaluation				
8	Sacramento River – Bend Bridge	40.289	−122.186	X	X
9	Sacramento River – Hamilton City	39.752	−121.994	X	
10	Sacramento River – Colusa	39.214	−121.991	X	X
11	Colusa Basin Drain	38.844	−121.729	X	X
12	Sacramento River – Verona	38.774	−121.597	X	X
13	Sacramento River – Freeport	38.450	−121.5	X	X

The fate and transport of pesticides are determined by their solubility, degradation half-life and partitioning coefficients (Neitsch *et al*., 2002). For this study, irrigation in an HRU was automatically simulated by SWAT on the basis of the water deficit in the soil. Depending on the subwatershed, irrigation water was extracted from the nearby reach or a source outside the watershed. Fertilization in an HRU was automatically applied on the basis of a plant growth threshold. The type of fertilizer applied in each subbasin was based on a literature review (Carman and Heaton, 1977; Krauter *et al*., 2001).

Modelling of canals, diversions and bypass conveyances in SWAT. The Sacramento River watershed SWAT model in this study includes the major and many minor tributaries and the trans-basin diversion from the Trinity River to the Sacramento Basin. Major irrigation diversions include the Anderson–Cottonwood in the northern part of the watershed and the Tehama–Colusa and Glenn–Colusa canals in the central part of the watershed. These are simulated by water-use volume removals from the geographical point of extraction on the Sacramento River and transferred via a point source to the reach of final conveyance. The average monthly removal and conveyance were based on long-term averages from the CA DWR when observed data were not available.

Flood conveyances within the Sacramento River watershed are an integral part of the watershed stream dynamics. The Sacramento River floodway system is designed to carry large winter season floods, culminating in combined flow of 17 300 m^3/s in the river and bypasses (Roos, 2006). The largest known flood discharge was 17 500 m^3/s, which occurred in February 1986. There are six major flood control structures on the Sacramento River: Colusa Weir, Fremont Weir, Moulton Weir, Tisdale Weir, Sacramento Weir and Colusa Basin Drain Weir. Other minor flood weirs exist but were not explicitly represented in the model. These flood weirs capture streamflow when the river stages are above a certain flood stage. When the river is above this stage value, water spills over the weir structures, capturing streamflow that would have originally remained in the river. The weirs transport water into wetlands, other streams or completely out of the modelled watershed (Yolo Bypass, for example). The Sacramento River flood weir discharge for the six weirs was based on the work by Feyrer *et al*. (2006). Figure 1 shows the location of the flood weirs. A schematic of the Sacramento River flood system from Roos (2006) is found in Figure 2.

The current version of SWAT, SWAT 2005, cannot represent flood conveyances, and therefore, the model code was modified to incorporate this important feature. The SWAT code was manipulated by including a rule-based algorithm in the routing module (Figure 3). If the discharge is above the diversion discharge listed in Table II, the water is routed to the diversion destination. For example, if the Sacramento River simulated discharge is greater than 1841 m^3/s near the Colusa Weir, any amount over this discharge will be diverted to the Sutter Bypass. The Fremont and Sacramento Weirs divert the water to the Yolo Bypass, which is beyond the modelled watershed. Therefore, any discharge above the specified flood discharge is removed from the river and not transported within the watershed. No flood data were available for the Colusa Basin Drain Weir, and therefore, the largest discharge in the dataset was assumed to be the flood diversion discharge. This flood discharge is diverted to the Yolo Bypass. All model runs within this study were simulated using SWAT with the new flood conveyance code. A schematic of the flood conveyance algorithm is shown in Figure 3.

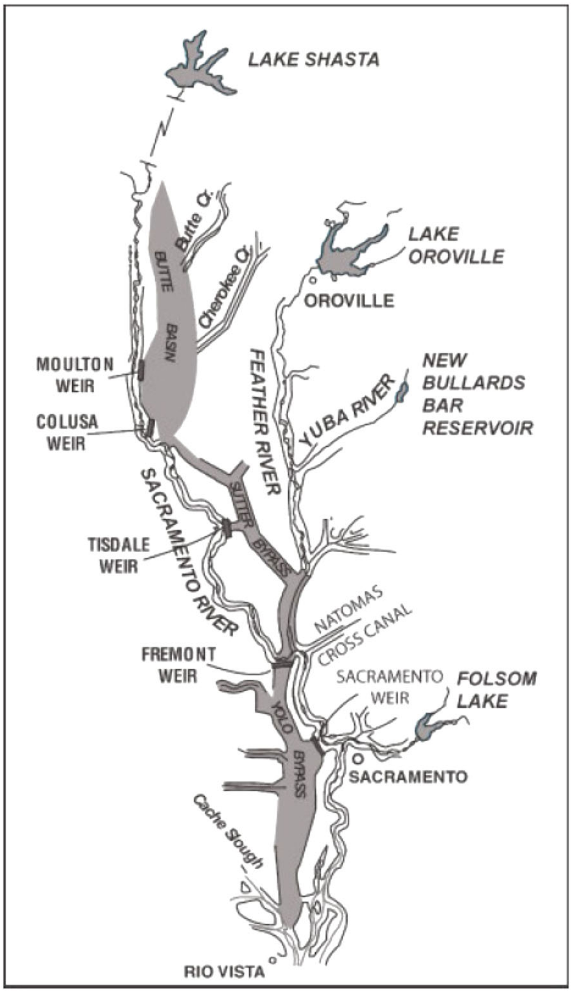

Figure 2. Schematic diagram of the Sacramento River flood routing (from Roos, 2006)

Model initialization

Model input. The SWAT input parameter values such as topography, land use/land cover, soil and climate data were compiled using databases from various state and government agencies. Elevation, land use and stream network data were obtained from the US Environmental Protection Agency's Better Assessment Science Integrating Point and Non-point Sources database. Data included 1 : 24 000 scale land use/land cover data developed by the CA DWR during 1996–2004 (CA DWR, 2009), 1 : 24 000 scale

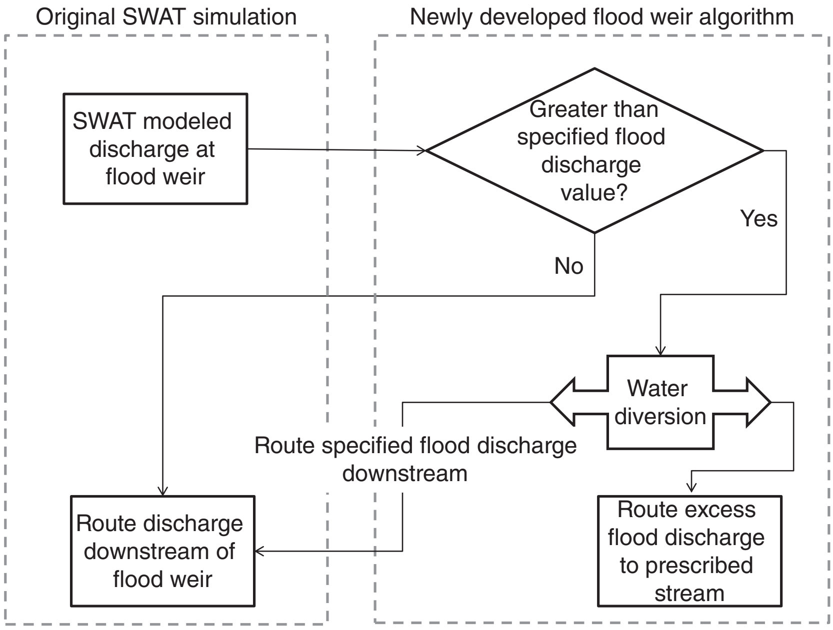

Figure 3. Schematic of the flood conveyance algorithm. SWAT, Soil and Water Assessment Tool

Table II. Flood weir routing values for selected weirs in the Sacramento River watershed

Map ID	Flood structure	Divert when above (m^3/s)	River origin	Divert to	Latitude	Longitude
14	Fremont Weir	2000	Sacramento River	Out of watershed (Yolo Bypass)	38.76	−121.64
15	Sacramento Weir	5000	Sacramento River	Out of watershed (Yolo Bypass)	38.60	−121.56
16	Tisdale Weir	595	Sacramento River	Sutter Bypass	39.02	−121.82
17	Moulton Weir	1274	Sacramento River	Sutter Bypass	39.34	−122.02
18	Colusa Weir	1841	Sacramento River	Sutter Bypass	39.23	−121.99

Digital Elevation Models (DEMs) and 1 : 100 000 scale stream network data from the National Hydrography Dataset. The CA DWR land use data is the highest spatial resolution cropland and irrigation data for California. Cropland information was assumed to have remained unchanged since the date of survey completion. The top five crops in the watershed include rice (9.4% of the watershed area), orchards (5.74%), agricultural row crops (2.26%), general agricultural land (2.06%) and hay (2.04%). Soil properties in the watershed were extracted from the 1 : 250 000 State Soil Geographic database, which is based on soil surveys. Daily weather data, including precipitation and minimum and maximum temperatures, were retrieved from the California Irrigation Management Information System (Figure 1).

Model initialization and evaluation were based on the monitoring data at selected inlet and outlet gauges within the study area (Figure 1, Table I). Data on streamflow and water quality for those gauges were collected from the National Water Information System (USGS, 2008) and the California Surface Water Database (CEPA, 2008). Monthly streamflow values were aggregated from daily values, and long-term monthly averages were used for missing data. Sediment load data were available in a monthly interval at the Sacramento – Freeport watershed outlet and varied for the other gauges within the watershed. The availability of observed nitrate data varied from site-to-site throughout the watershed. Chlorpyrifos and diazinon data were only available at the Sacramento – Freeport outlet. SWAT required continuous data at the dam inlets into the watershed, and therefore, the LOADEST program developed by the USGS was used to predict sediment and nitrate loads at the inlets (Runkel *et al.*, 2004). LOADEST estimates streamflow constituent concentration on the basis of observed data. Because most of the agricultural land is located within the Sacramento Valley, the streamflow at the watershed inlets was assumed to be free of pesticides.

Pesticide application data were collected from the Pesticide Use Reporting system administered by the California Department of Pesticide Regulation (CA DPR). Since 1990, California has required all commercial pest control operators to report all pesticide applications. These reports include information about the pesticide applied, amount, area treated, timing of applications and the subject crop with a spatial accuracy of one square mile. Pesticide use amounts are recorded at daily intervals for each township/range/section in California and are tabulated by each county, then submitted to the CA DPR for compilation and distribution. For this study, use amounts of chlorpyrifos and diazinon were retrieved from the database as weekly averages for each township/range/section and distributed into the agricultural HRUs in each subbasin.

On the basis of available water quality monitoring data, the fate and transport of two organophosphate pesticides, diazinon and chlorpyrifos, were analyzed. Both pesticides are highly used nationwide and listed on the US Clean Water Act Section 303(d) list of products that may cause water body impairment. According to the US Environmental Protection Agency, diazinon and chlorpyrifos are highly toxic to birds, fish and aquatic insects. Depending on the formulation, diazinon and chlorpyrifos also have a low to high toxicity to humans. Diazinon and chlorpyrifos are highly soluble and have a low persistence in soil with a half-life of 2–6 weeks depending on climate. Chlorpyrifos has a higher soil adsorption coefficient (6070) than diazinon (1000), which causes it to adhere to soil particles much more strongly than diazinon. The chemical and physical properties of chlorpyrifos and diazinon were primarily obtained from the built-in pesticide database in SWAT. Other transport coefficients were set at the default values suggested by the SWAT model (Neitsch *et al.*, 2005).

Sacramento River watershed model set-up. The ArcSWAT interface was used for the set-up and parameterization of the model. On the basis of the DEM, stream network and irrigation diversion data, a minimum drainage area of 550 km^2 was chosen to divide the watershed into 33 subbasins. The subbasin delineation in this study is consistent with the subbasins defined by the CA DWR (CEPA, 2007). Inlets into the watershed were based on the dam locations discussed in the Section on Modelling Flood Conveyances Using SWAT. For each subbasin, multiple HRUs were distributed on the basis of the overlap of land use, soil and slope features for landscape characterization at finer resolution. A total of 471 HRUs were defined in the study area on the basis of a 5% coverage threshold of land use, soil and slope features in each subbasin. The median slope of the watershed was 4.9%, and therefore, two slope classes of 0–4.9% and 5.0–291% were used. Model simulations were run from 1990 to 2007, with the first two years excluded for model initialization.

Model sensitivity analysis, uncertainty analysis and calibration

Data and statistics for model calibration. Monthly model calibration was performed for six streamflow and water quality stations (Figure 1, Table I). These stations are distributed throughout the watershed and therefore provide a regional representation of model parameters. Sample totals of 435 for sediment load (four stations), 260 for nitrate (three stations), 139 for chlorpyrifos (one station) and 133 for diazinon (one station) were used for watershed calibration and validation. For pesticide samples with concentrations lower than the detection limit, the concentration was recorded as the reporting limit. Observed data from some of the stations did not cover the entire simulation period, and therefore, different calibration time periods were included in the calibration procedure. For all stations, a split-sample approach was used, where the latter years were used for validation and the prior years were used for calibration. To compare monthly simulated and observed data, the Nash–Sutcliffe (NS; Nash and Sutcliffe, 1970) efficiency coefficient was used as the objective function:

$$NS = 1 - \frac{\sum_{t=1}^{T} \left(Q_{\mathrm{o}}^{t} - Q_{\mathrm{m}}^{t}\right)^2}{\sum_{t=1}^{T} \left(Q_{\mathrm{o}}^{t} - Q_{\mathrm{o}}^{\mathrm{ave}}\right)^2} \quad (1)$$

where NS is the Nash–Sutcliffe coefficient, Q_{o}^{t} is the observed data, Q_{m}^{t} is the simulation data and $Q_{\mathrm{o}}^{\mathrm{ave}}$ is the average of the observed data. Nash–Sutcliffe values can range from negative infinity to 1, where 1 is a perfect match of model data to observed data.

In this study, multiple variables (streamflow, nitrate, chlorpyrifos and diazinon) are used in the objective function, resulting in one NS value for multiple output variables. In this case, the NS objective function is

$$g = \sum_{i} w_i NS_i \quad (2)$$

where g is the NS objective function, w is the weight of the parameter and i is the variable. The objective function determines the 'best simulation' (best average NS coefficient) of all stochastic simulations. For this study, the weights for all parameters were set at 1. Other model efficiency statistics such as the coefficient of determination (R^2), ϕ, and percent bias (PBIAS) were used to further show the goodness of calibration. R^2 was included to show the proportion of variance of the simulated variable that is predicted from the observed variable. ϕ is a slightly modified version of the efficiency criterion defined by Krause *et al.* (2005) where the coefficient of determination, R^2, is multiplied by the coefficient of the regression line, b. This function allows accounting for the discrepancy in the magnitude of two signals (depicted by b) as well as their dynamics (depicted by R^2). Including b guarantees that the over-predictions or under-predictions are reflected in the statistic. ϕ is calculated by:

$$\phi = \begin{cases} |b|R^2 & \text{if } |b| \le 1 \\ |b|^{-1}R^2 & \text{if } |b| > 1 \end{cases}. \quad (3)$$

PBIAS measures the average tendency of the simulated data to be larger or smaller than the observed data (Gupta *et al.*, 1999). An optimal PBIAS value is 0.0%, with a low value indicating an accurate simulation. Positive values indicate model underestimation, and negative values indicate model overestimation. Based on the work by Moriasi *et al.* (2007), a satisfactory PBIAS value is ±25% for streamflow, ±55% for sediment and ±70% for nutrients. No specific ranges are available for pesticides.

Model parameters for calibration and uncertainty analysis. Because SWAT involves a large number of parameters, a global sensitivity analysis was performed to identify the key parameters across the Sacramento River watershed. The sensitivity analysis was performed using a combination of Latin hypercube and one-factor-at-a-time sampling strategy developed by van Griensven *et al.* (2006). This approach has the advantage of being fast compared with similar procedures and therefore does not produce an absolute measure of sensitivity, but rather a ranked list of sensitive parameters. The sensitivity was assessed at the watershed outlet. At first, a large number of parameters were analyzed and then subsequently removed if the parameter was found to be insensitive for the model output. As a result, only the sensitive parameters were used for calibration.

The initial ranges for the selected parameters were based on prior knowledge and a literature review (Luo *et al.*, 2008). For the calibrated parameters, separate values for each region, land use/soil texture or crop were used, which substantially increased the calibration parameters. To obtain a regional calibration, for example, the Curve Number values for subbasins 1–9 were changed to various values, whereas the Curve Number values for subbasins 10–12 were changed to different values. The regional parameter values were manipulated to match the nearest monitoring gauge. To account for the uncertainty in the observed data, a relative error of 10% was assumed (Butts *et al.*, 2004; Schuol *et al.*, 2008a).

Calibration and uncertainty analysis procedure. Hydrologic models are subject to uncertainties from input data (rainfall, soil properties etc.), the conceptual model (simplification of processes, lumping of heterogeneities etc.), model parameters (non-uniqueness, lumped parameters etc.) and measured data (error in discharge, point samples of sediment etc.). Calibration, validation and uncertainty analysis were performed for hydrology and water quality using the program SUFI-2 (Abbaspour *et al.*, 2004; Abbaspour *et al.*, 2007). Yang *et al.* (2008) compared different uncertainty analysis techniques and determined that SUFI-2 needed the fewest amount of model runs to achieve a satisfactory solution. This efficiency is desirable when dealing with computationally intensive, large-scale models, such as the Sacramento River watershed. The calibration parameter ranges were based on previous SWAT calibration procedures using SUFI-2 (Yang *et al.*, 2007; Schuol *et al.*, 2008a; Schuol *et al.*, 2008b; Yang *et al.*, 2008).

The SUFI-2 algorithm provides a platform to conduct calibration and validation, as well as uncertainty analysis. In the SUFI-2 algorithm, known uncertainties are mapped onto the parameter ranges, which are calibrated to bracket most of the measured data in the prediction uncertainty for a confidence level of 95% (95PPU). The overall uncertainty of the model output is quantified by the 95PPU calculated at the 2.5% (L95PPU) and the 97.5% (U95PPU) uncertainty levels of the cumulative distribution obtained through Latin hypercube sampling (Abbaspour *et al.*, 2004). A combination of uncertainties are included in the 95PPU, including model parameter and simplification uncertainties as well as observed data uncertainty, which is assumed to be 10% for this study. Starting with a larger parameter range, SUFI-2 iteratively decreases the parameter uncertainties. After each iteration, new and narrower parameter uncertainties are calculated, where the most sensitive parameters find a larger uncertainty reduction than the less sensitive parameters. For each calibration iteration, a 'best simulation' is found, which is the one simulation with the highest model efficiency using model performance statistics (i.e. NS, R^2, ϕ and PBIAS) compared with observed data.

Two uncertainty indices are used to compare measurement to stochastic simulation results: the *p-factor* and the *r-factor* (Abbaspour *et al.*, 2004; Abbaspour *et al.*, 2007). The *p-factor* is the percentage of measured data bracketed by the 95PPU. The maximum value for the *p-factor* is 1, and an ideal simulation would bracket all measured data in the 95PPU band. The *r-factor* is calculated as the ratio between the average range of the 95PPU band and the standard deviation of the measured data. The *r-factor* represents the range of the uncertainty interval and should be as small as possible. The *r-factor* indicates the strength of the calibration and should be close to or smaller than a practical value of 1. A larger *p-factor* can be found at the expense of a larger *r-factor*, and often a tradeoff between the two is sought (Schuol *et al.*, 2008a).

RESULTS AND ANALYSIS

Modelling flood conveyances using SWAT

The implementation of the flood weir modification for the Sacramento River watershed allowed for much-improved model simulations (Figure 4). With the use of the flood stage discharges based on the work by Feyrer *et al.* (2006), the uncalibrated monthly NS coefficient for streamflow improved from −0.26 to 0.87, thus allowing for a better representation of the managed hydrology in the watershed. The high NS coefficient demonstrates the large effects of reservoir management on streamflow. The reservoirs largely influence the amount of streamflow at any given time, especially during the summer months. Analyzing the results by removing the summer months when rainfall is negligible, the root mean square error improved from 717.2 m^3/s with no flood routing to 219.6 m^3/s with the flood routing implemented. The implementation of the flood weir algorithm can be useful for other studies throughout the world. If enough information is known about the flood weir and its conveyance, the new flood weir modification could be used to improve watershed simulations.

Model sensitivity analysis

Most sensitive input parameters related to model simulations of hydrology, sediment, nitrate and pesticides were identified on the basis of global sensitivity analysis (Table III). Curve Number and the alpha baseflow factor were the most sensitive to streamflow. This is physically

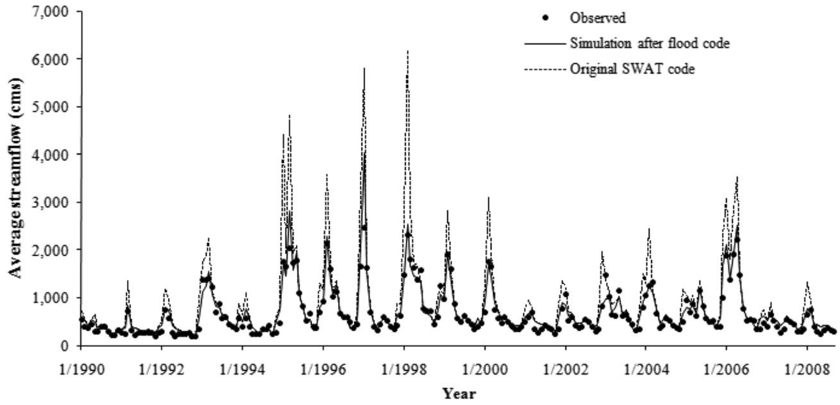

Figure 4. Observed and pre-flood and post-flood code streamflow. SWAT, Soil and Water Assessment Tool

Table III. Sensitive Soil and Water Assessment Tool (SWAT) parameters and the final calibrated values or ranges

Variable	Sensitive parameters	Parameter definition	Final parameter value range
Sensitive to hydrology	v_ALPHA_BF.gw	Baseflow alpha factor	0.07 to 0.84
	r_CN2.mgt	Curve Number	−23% to +20%
	r_CH_N2.mgt	Manning's n value for the main channel	−22% to +21%
	r_CH_K2.mgt	Effective hydraulic conductivity in the main channel	2 to 67 mm/h
	r_OV_N.hru	Manning's *n* value for overland flow	−19% to −1%
	v_LAT_TTIME.hru	Lateral flow travel time	5 to 165 days
	r_SOL_AWC.sol	Soil available water content	−22% to +9%
	r_SOL_BD.sol	Soil bulk density	−18% to +24%
	r_SOL_K.sol	Soil hydraulic conductivity	−20% to +25%
	v_ESCO.hru	Soil evaporation compensation factor	0.09 to 0.82
	v_EPCO.hru	Plant uptake compensation factor	0.19 to 1.00
	v_SURLAG.bsn	Surface runoff lag coefficient	9.88 days
Sensitive to hydrology relating to agricultural management	v_FLOWFR.mgt	Fraction of available streamflow for irrigation	0.01 to 0.92
	v_AUTO_WSTRS.mgt	Water stress threshold that triggers irrigation	0.25 to 0.75
	r_HEAT_UNITS.mgt	Number of heat units to bring crop to maturity	−9% to +10%
Sensitive to sediment	v_SPCON.bsn	Channel re-entrained linear parameter	0.005
	v_PRF.bsn	Sediment routing factor in main channels	0.07
	v_SPEXP.bsn	Channel re-entrained exponent parameter	1.40
	v_ADJ_PKR.bsn	Peak rate adj. factor for sed. routing in the subbasin	0.63
	v_CH_EROD.rte	Channel erodability factor	0.06 to 0.64
	v_CH_COV.rte	Channel cover factor	0.03 to 0.71
	v_USLE_P.mgt	USLE support practice factor	0.15 to 0.87
	r_USLE_C.crop.dat	USLE water erosion factor	−19% to +19%
	r_USLE_K.cov	USLE soil erodability factor	−20% to +10%
Sensitive to nitrate	v_BIOMIX.mgt	Biological mixing efficiency	0.17 to 0.85
	v_ERORGN.hru	Organic N enrichment ratio for loading with sediment	1.15 to 3.90
	v_AUTO_NSTRS.mgt	Nitrogen stress threshold that triggers fertilization	0.15 to 0.65
Sensitive to pesticides	v_PERCOP.bsn	Pesticide percolation coefficient	0.03 for chlorpyrifos 0.14 for diazinon
	v_AP_EF.pest.dat	Pesticide application efficiency	0.65 to 0.80
	v_PST_KG.mgt	Amount of pesticide applied in each HRU	+15% to +35%
	v_CHPST_STL.swq	Settling velocity for pesticide sorbed to sediment	0.37 to 0.95

'v_' indicates a replacement of the original parameter value; 'r_' indicates a relative change from the original parameter value; 'a_' indicates an addition of the original parameter value.
The filename extension in the sensitive parameter column indicates the input file being changed.

reasonable because elevated Curve Numbers represent increased runoff and therefore decreased infiltration, whereas the baseflow factor would lead to higher or lower baseflow contributions during low flow events. Crop and agricultural management parameters such as automatic irrigation and fertilization thresholds, sediment coefficients and pesticide application rates were also sensitive to hydrologic and water quality model output. Table III describes the most sensitive hydrology and water quality parameters. For example, alpha baseflow factor may be 0.1 in the northern portion of the watershed and 0.7 in the southern portion of the watershed. It is important to note that the results of the sensitivity analysis may be site specific and thus are not directly applicable to other sites.

Model calibration, validation and uncertainty analysis

The monthly calibration, validation and uncertainty results are shown in Figures 5–9 and Tables III, IV. Table III displays the final calibration ranges for the sensitive SWAT parameters. A range is displayed because each region in the Sacramento River watershed may have different parameter values. For example, the baseflow alpha factor may have a value of 0.5 in the northern portion of the Sacramento River watershed and 0.25 in the southern portion of the Sacramento River watershed. The shaded region in each figure is the 95PPU uncertainty range. The 95PPU is not calculated where observed data are not available, and thus, no 95PPU ranges are available for periods with no observed data. Table IV presents the calibration results for the regional, multi-site calibration approach. The model efficiency statistics are from the 'best simulation' for the final calibration iteration, which is the best average *NS* coefficient from Equation (2). Given the large amount of uncertainty within the Sacramento River watershed, calibration and validation of the watershed could be qualified as 'good' or 'satisfactory'. The simulation results were considered to be good if the *NS* coefficient was larger than 0.75 and satisfactory if it was between 0.36 and 0.75 (Van Liew and Garbrecht, 2003; Larose *et al.*, 2007). This indicates good quality of the input data as well as an accurate representation of the agricultural management techniques.

Figure 5 displays the SWAT-predicted monthly streamflow at the Sacramento River – Freeport watershed outlet compared with the USGS and CA DWR observed streamflow data. While a large portion of the streamflow is released from the upstream reservoirs, a significant correlation between streamflow and precipitation in the Sacramento River watershed ($p < 0.05$) was found. On average, 60% of the discharge data for the entire simulation period were bracketed by the 95PPU, while the average *r-factor* was 0.30. The low *r-factor* can be attributed to the managed reservoir releases into the watershed, where a low *r-factor* indicates a small thickness of the 95PPU band and thus smaller uncertainty of the input parameters. A low *r-factor* was found for all streamflow gauges. This result shows the effect of the reservoir releases on streamflow, where varying the range of model input parameters leads to a similar streamflow output. A larger *r-factor* would be expected for a completely natural watershed, where a wider range (or collection) of parameters would be expected to have a significant effect on the streamflow.

At the watershed outlet, most of the data outside of the 95PPU band were from low flows, indicating that the model might not be fully capturing the dynamics of the groundwater/baseflow component of the hydrologic system. This bolsters the call for the improvement of the simplified soil water and groundwater representations in SWAT (e.g. Gassman *et al.*, 2007; Kim *et al.*, 2008). It is well known that much of the groundwater contamination in California is in shallow aquifers that are directly connected to surface waters (Belitz and Landon, 2010). Understanding how water within the fluvially derived sediments and the stream channel interacts is critical to efforts attempting to protect both groundwater and surface water resources (e.g. Valett *et al.*, 1997; Dahm *et al.*, 1998; Stanford and Ward, 1998). The use of a coupled SWAT and groundwater model would

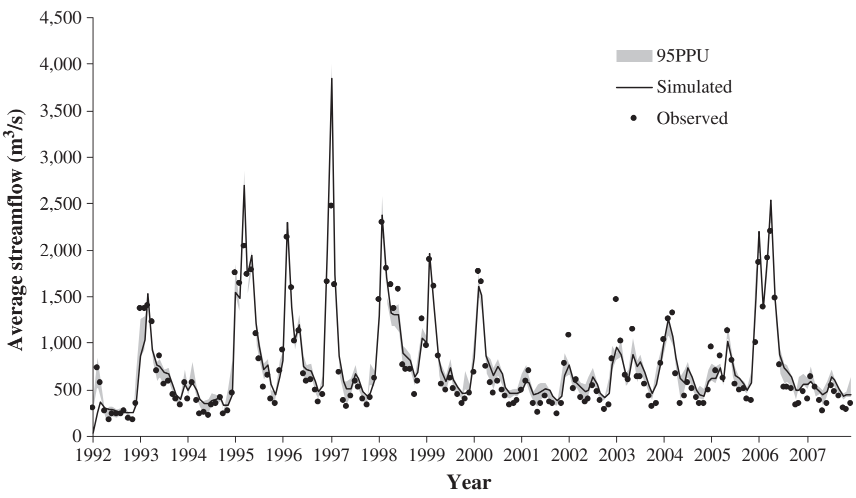

Figure 5. Observed, simulated and the 95PPU uncertainty band of streamflow at the watershed outlet. 95PPU, prediction uncertainty for a confidence level of 95%

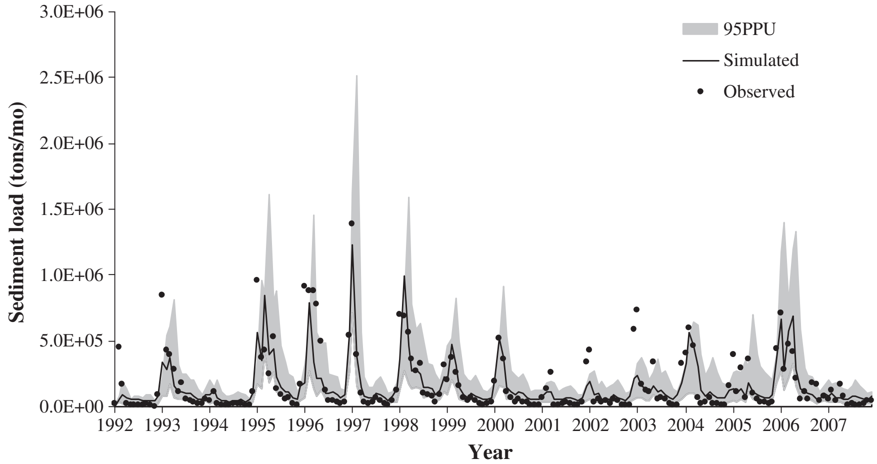

Figure 6. Observed, simulated and the 95PPU uncertainty band of sediment load at the watershed outlet. 95PPU, prediction uncertainty for a confidence level of 95%

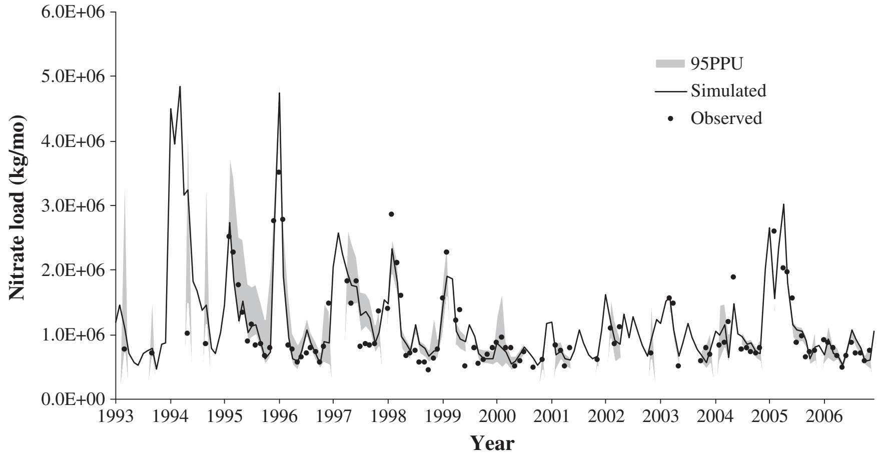

Figure 7. Observed, simulated and the 95PPU uncertainty band of nitrate load at the watershed outlet. 95PPU, prediction uncertainty for a confidence level of 95%

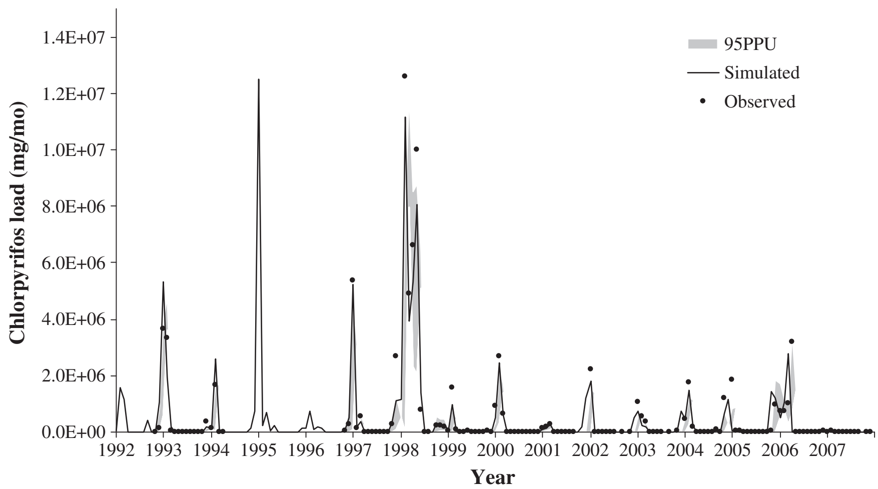

Figure 8. Observed, simulated and the 95PPU uncertainty band of chlorpyrifos load at the watershed outlet. 95PPU, prediction uncertainty for a confidence level of 95%

allow for improved groundwater–surface water simulations, as has been shown by Kim *et al*. (2008).

The average *NS* coefficient of the sites for streamflow discharge was 0.79 for calibration and 0.82 for validation, indicating a good simulation of surface water hydrology at the watershed level. As shown in Figure 5, SWAT over-predicted the baseflow for the Sacramento River – Freeport gauge but satisfactorily simulated the peaks and the

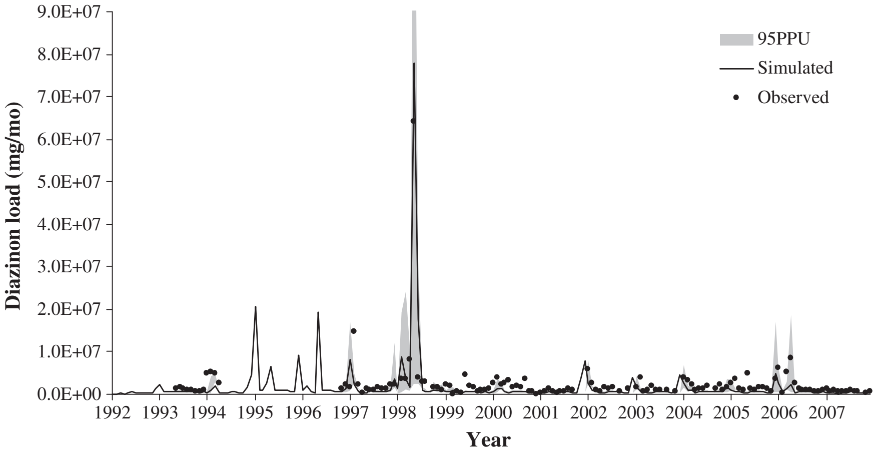

Figure 9. Observed, simulated and the 95PPU uncertainty band of diazinon load at the watershed outlet. 95PPU, prediction uncertainty for a confidence level of 95%

Table IV. Monthly calibration, validation and uncertainty statistics for the streamflow and water quality sites in the Sacramento River watershed

			Calibration					Validation				
Station	*p-factor*	*r-factor*	Dates	*NS*	R^2	Φ	PBIAS (%)	Dates	*NS*	R^2	Φ	PBIAS (%)
Streamflow												
Red Bluff	0.77	0.33	1992–2002	0.89	0.94	0.89	−10.0	2003–2007	0.9	0.9	0.82	−3.0
Hamilton City	0.61	0.3	1992–2002	0.91	0.91	0.82	7.1	2003–2007	0.85	0.86	0.72	−6.4
Colusa	0.64	0.38	1992–2002	0.71	0.88	0.71	−10.3	2003–2007	0.81	0.86	0.86	−11.1
Colusa Basin Drain	0.27	0.45	1992–2001	0.48	0.56	0.32	−51.4	2002–2007	0.64	0.67	0.37	−21.9
Verona	0.66	0.19	1992–2002	0.89	0.89	0.77	−6.7	2003–2007	0.84	0.86	0.71	−11.2
Freeport	0.66	0.17	1992–2002	0.87	0.87	0.8	−6.5	2003–2007	0.86	0.86	0.71	−12.0
Sediment load												
Colusa Basin Drain	0.38	0.36	1995–2000	0.11	0.19	0.04	24.6	2001–2003	0.18	0.21	0.04	19.9
Verona	0.89	1.02	1996–1997	0.86	0.91	0.64	−2.9	1997–1998	0.63	0.72	0.52	5.5
Freeport	0.67	0.8	1992–2002	0.66	0.67	0.42	0.6	2003–2007	0.64	0.64	0.41	−14.1
Nitrate load												
Red Bluff	0.56	0.39	1996–1997	0.82	0.87	0.61	−15.5	1997–1998	0.5	0.58	0.25	12.3
Verona	0.39	0.26	1996–1997	0.71	0.73	0.46	0.3	1997–1998	0.43	0.57	0.18	5.6
Freeport	0.63	0.43	1993–2004	0.69	0.74	0.67	−8.1	2004–2007	0.51	0.59	0.48	10.8
Chlorpyrifos												
Freeport	0.63	0.87	1993–2000	0.72	0.76	0.67	−9.6	2001–2007	0.63	0.45	0.23	20.0
Diazinon												
Freeport	0.68	0.77	1993–2001	0.79	0.81	0.75	21.1	2002–2007	0.5	0.59	0.48	−55.1

NS, Nash–Sutcliffe; PBIAS, percent bias.

mid-range flows. The presence of flood diversions directly above the Sacramento River – Colusa gauge led to an *NS* coefficient of 0.71 for the calibration period, which is lower compared with those of the other gauges on the Sacramento River. The lowest *NS* coefficient was 0.48 for the Colusa Basin Drain subbasin calibration period. SWAT model performance for the Colusa Basin Drain subwatershed is related to the characterization of irrigation water diversion and agricultural management practices in the watershed. The lack of knowledge about agricultural management practices (water transfers, irrigation of crops, collection and release of water for rice ponding etc.) within this region is the reason why this part of the model did not perform as well as the other gauged basins.

Because of the lack of irrigation water-use data in the Sacramento River watershed, we opted to use the automatic irrigation algorithm in SWAT. The automatic irrigation in SWAT limits the amount of irrigation water that can be applied to satisfy soil field capacity for any HRU. When the soil field capacity is reached, irrigation is no longer needed and is therefore no longer applied. This assumption assumes full irrigation efficiency (no wasted water) and likely underestimates the agricultural drainage to streams during the irrigation season, which can be a large amount in the agricultural regions in the Sacramento River watershed (Colusa County Resource Conservation District, 2008). This is one potential reason why the simulation accuracy of the Colusa Basin Drain subbasin was low.

Results of the monthly sediment load simulation in the streamflow discharge are shown in Figure 6 and Table IV. On average, approximately 65% of the observed sediment data are bracketed by the 95PPU; the *r-factor* equaled 0.73. This result shows a good balance between the uncertainty measures used in the calibrated model. As with the streamflow discharge, a large amount of the observed sediment data missing the 95PPU band was during low flow conditions. The calibration and validation of sediment loads for the Sacramento River watershed were deemed satisfactory with an average *NS* coefficient of 0.54. Again, the lowest *NS* coefficient belonged to the Colusa Basin Drain region and can be largely explained by reasons previously discussed. Although the *NS* coefficient for the Sacramento River – Freeport gauge was 'satisfactory' with a value of 0.66 and 0.64 for the calibration and validation periods, respectively, the model over-predicted the sediment loads during the dry season throughout the simulation period. This can be explained by the over-prediction of baseflow, as previously discussed. A larger baseflow contribution will result in higher sediment loads because of increased channel scour. The SWAT model also under-predicted the peak sediment loads from 2001 to 2004, which can be attributed to the under-prediction of the same peaks for discharge at the Sacramento – Freeport gauge.

Results of the nitrate load simulation in the streamflow discharge are shown in Figure 7 and Table IV. On average, 53% of the observed data were within the 95PPU band. For the three sites, the average *r-factor* value was 0.36. Similar to the streamflow and sediment load simulations, a large amount of the data not captured by the 95PPU band was during low streamflows. However, the peaks and mid-range nitrate loads were generally within the 95PPU band. The average nitrate *NS* coefficients for the calibration and validation periods were 0.74 and 0.48, respectively, indicating a good simulation of nitrate loading throughout the watershed. This result indicates that SWAT can adequately simulate nitrogen management techniques.

Results of the pesticide load simulations in the streamflow discharge are shown in Figure 8 for chlorpyrifos, Figure 9 for diazinon and Table IV for both. Only data at the watershed outlet were used because of the lack of observed continuous data throughout the watershed. Approximately 63% of the observed data for chlorpyrifos and 68% for diazinon were bracketed by the 95PPU band. The *r-factors* for chlorpyrifos and diazinon were 0.87 and 0.77, respectively, indicating a good balance between the *r-factor* and *p-factor*. For the model simulations, the pesticide database properties such as Koc (sorption coefficient) and half-life were kept at their default values. Varying these parameters will likely increase the 95PPU band and thus capture more of the observed data, but we assumed these default parameters as our calibration values. The *NS* coefficient was 0.72 for chlorpyrifos and 0.90 for diazinon for the calibration period and 0.65 and 0.50 for the validation period, respectively. As with the nitrate simulation, the accuracy of the results indicates that the large number of different pesticide management techniques are represented well by SWAT.

Temporal analysis

Statistically significant Pearson's correlation coefficients ($p < 0.05$) were found between all output variables as monthly averages (Table V). As expected, sediment loads were highly correlated ($r > 0.7$) to streamflow, whereas nitrate and chlorpyrifos were moderately ($0.4 > r > 0.70$) and diazinon ($0.2 > r > 0.4$) was weakly correlated with streamflow. This indicates that although runoff events are a factor in determining the fate and transport of nutrients and pesticides, the timing of applications may play a larger role. This is especially true for the pesticide time series shown in Figures 8 and 9, where the pesticide load peaks are not necessarily aligned with streamflow and sediment load peaks. For example, streamflow peaks in March 1995 (Figure 5), whereas chlorpyrifos and diazinon peak in January 1995 (Figures 8 and 9, respectively). Further, predicted chlorpyrifos and diazinon loads at the watershed outlet were significantly correlated to the applications over the watershed ($p < 0.05$). Limiting the amount of pesticide applied during the wet months (December through March) significantly reduces large pesticide runoff events. Although the majority of pesticide applications are during the summer growing season, the correlation between pesticide applications and loads during the growing season was not significant ($p > 0.05$). This is largely due to the lack of significant runoff events for pesticide transport during the summer season. This result is in agreement with other pesticide runoff studies in California's Central Valley (e.g. Dubrovsky *et al*., 1998; Luo *et al*., 2008).

The correlation between nitrate, chlorpyrifos and diazinon loads to sediment loads was also expected. Surface water runoff events generate sediment losses while concurrently generating nitrate, chlorpyrifos and diazinon loses. Therefore, the relationship between pollutant loads and sediment losses may represent co-variance between streamflow and sediment loads. Both chlorpyrifos and diazinon are attracted to sediment particles, and therefore, a positive correlation is physically based and represented in the model. As expected, based on their soil adsorption coefficients, chlorpyrifos loads were better correlated to sediment loads than diazinon.

DISCUSSION

Calibration of models at the watershed scale is a challenging task because of the large number of uncertainties that may exist. The Sacramento River watershed includes data and

Table V. Correlation coefficient matrix between the simulated monthly model outputs

	Streamflow	Sediment	Nitrate	Chlorpyrifos	Diazinon
Streamflow	1				
Sediment	0.95	1			
Nitrate	0.47	0.47	1		
Chlorpyrifos	0.44	0.55	0.32	1	
Diazinon	0.23	0.22	0.09	0.55	1

Significant correlations ($p < 0.05$) were found between all variables.

conceptual model uncertainties such as (1) lack of water diversion data for agricultural and human consumption (as well as wastewater discharge), (2) lack of irrigation use, agricultural management and crop planting data within the watershed, (3) lack of complete understanding of surface and groundwater interactions and (4) lack of knowledge of construction projects that could produce large amounts of sediment, as well as other unknown human activities that will have a large impact on hydrology and water quality. For some cases, the effects of these uncertainties may render modelling of a watershed impossible. In this study, parameters with uncertainties in agricultural management practices, such as the amount and timing of fertilization, were varied for each crop and subbasin. For example, the parameters affecting fertilizer application, such as the amount and application timing, were varied for each crop and subbasin. This technique allows for spatial variation of management techniques that in turn provide better agricultural management representation.

Two points are worth noting regarding calibration and validation. Firstly, the *NS* objective function contained 14 observed variables (streamflow, sediment, nitrate and pesticides for multiple gauging stations), and calibrating the model for any one variable would have produced much better results for that variable at the expense of the other variables. For example, calibrating for sediment load at the Colusa Basin Drain outlet alone produced an *NS* of 0.41 during calibration, but decreased to 0.11 when all other variables were included in the objective function. Gatzke and Zhang (2011) developed a SWAT model for the southern portion of the Colusa Basin Drain that resulted in an *NS* of 0.43 for sediment concentration. This type of phenomenon is termed the 'conditionality problem', where the results from one variable are allowed to suffer so that other output variables have more accurate results. In SWAT, this is due to the presence of global parameters (single parameters that represent the whole watershed). Examples of these parameters in SWAT are SURLAG (surface runoff lag time coefficient) and SPCON (channel re-entrained linear parameters). The goal, therefore, is to achieve the highest possible *NS* coefficients for all variables and gauging stations.

Secondly, ignoring the calibration constraints may also produce better calibration and validation results but may result in unrealistic model parameterization. For example, our initial constraint was to vary the Curve Number by $\pm 25\%$ from the original value (SCS, 1984) to better represent agricultural management techniques. Varying the Curve Number by $\pm 50\%$ may result in better simulation statistics by increasing or decreasing surface runoff/infiltration by a large amount, but the land use representation may not be realistic. An example of this misrepresentation would be increasing the Curve Number from 69 to 98 (representing a pasture to paved parking lot transition) to increase the amount of water runoff. Although the simulation results may appear accurate, the representation of the land use is not. This is a problem of model non-uniqueness, where the combination of multiple parameter sets may give similar results. This is why expert knowledge is needed prior to model construction to ensure the model adheres to constraints of the conceptual model.

The 95PPU represents a combined model prediction uncertainty, which includes uncertainty resulting from the non-uniqueness of model parameters, conceptual model uncertainties and input data uncertainties. For this paper, the combined effect of all uncertainties is depicted by the *p-factor* and *r-factor* uncertainty statistics. In the initial calibration iteration, 99% of the sediment loads at the Sacramento – Freeport gauge were within the 95PPU band, but the *r-factor* was very large (2.26). This result illustrates that the uncertainty in the hydrologic or conceptual model is great with respect to determining sediment loads at this location. The large *r-factor* for the initial calibration iteration is likely due to two reasons: (1) initial calibration iterations have large parameter ranges and thus large uncertainties and (2) an omission of modelled agricultural management practices (best management practices, tilling etc.) that have an effect on sediment losses. In the final iteration, 67% of the observed data were bracketed by the 95PPU band, and the *r-factor* was 0.80. Therefore, a balance was found between parameter representation and the amount of prediction uncertainty. This is largely due to a refinement (decrease) in the sediment and agricultural management parameter ranges, leading to a more accurate simulation of sediment.

SUMMARY AND CONCLUSIONS

The SWAT was applied and evaluated on the Sacramento River watershed in northern California. Streamflow and agricultural pollutants, such as sediment, nitrate, chlorpyrifos and diazinon, were calibrated and validated at multiple sites throughout the watershed using the SUFI-2 uncertainty analysis and calibration program. Considering the conceptual model uncertainty (e.g. water transfers, agricultural management practices), as well as input data and model parameter uncertainty in such a large-scale hydrological and water quality model, SWAT satisfactorily simulated streamflow, sediment, nitrate, chlorpyrifos and diazinon loads. The incorporation of a flood weir routing methodology into the SWAT code greatly increased the pre-calibration *NS* coefficient at the watershed outlet from -0.26 to 0.87.

The SWAT satisfactorily captured a large amount of uncertainty within the Sacramento River watershed. The uncertainty analysis results indicate that most of the observed data were within the corresponding 95PPU band for streamflow and agricultural pollutants, whereas the *r-factor* results reflected the amount of uncertainty in each model parameter. Varying model input parameters did not lead to a large 95PPU band for streamflow. This indicates that the reservoir inflow to the watershed has a larger influence on streamflow than does the model parameters. The 95PPU bands for the agricultural pollutants were large, indicating that there is large uncertainty in the conceptual model of the pollutant parameters, as well as the representation of the parameters themselves. This study provides a strong basis for further studies using uncertainty analysis to calibrate and validate hydrologic models. Also, the simulation of hydrology and agricultural pollutant loads was of reasonable accuracy, allowing the Sacramento River watershed model to be used for further scenario analysis.

Temporal analysis indicated that all output variables (streamflow, sediment, nitrate, chlorpyrifos and diazinon loads) were significantly correlated to each other ($p < 0.05$). Sediment is highly correlated to streamflow, whereas nitrate, chlorpyrifos and diazinon were only moderately correlated to streamflow. This indicates that the timing of agricultural management practices likely plays a large role in agricultural pollutant fate and transport. This is especially true for chlorpyrifos and diazinon, where a significant correlation was found between pesticide application and pesticide load ($p < 0.05$). Limiting the amount of pesticide applications during the wet, winter season will reduce pesticide runoff.

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