

Assessing the Role of Parameter and Input Uncertainty in Ecohydrologic Modeling: Implications for a Semi-arid and Urbanizing Coastal California Catchment

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ABSTRACT

Ecohydrologic models are a key tool in understanding plant–water interactions and their vulnerability to environmental change. Although implications of uncertainty in these models are often assessed within a strictly hydrologic context (for example, runoff modeling), the implications of uncertainty for estimation of vegetation water use are less frequently considered. We assess the influence of commonly used model parameters and inputs on predictions of catchment-scale evapotranspiration (ET) and runoff. By clarifying the implications of uncertainty, we identify strategies for insuring that the quality of data used to drive models is considered in interpretation of model predictions. Our assessment also provides insight into unique features of semi-arid, urbanizing watersheds that shape ET patterns. We

consider four sources of uncertainty: soil parameters, irrigation inputs, and spatial extrapolation of both point precipitation and air temperature for an urbanizing, semi-arid coastal catchment in Santa Barbara, CA. Our results highlight a seasonal transition from soil parameters to irrigation inputs as key controls on ET. Both ET and runoff show substantial sensitivity to uncertainty in soil parameters, even after parameters have been calibrated against observed streamflow. Sensitivity to uncertainty in precipitation manifested primarily in winter runoff predictions, whereas sensitivity to irrigation manifested exclusively in modeled summer ET. Neither ET nor runoff was highly sensitive to uncertainty in spatial interpolation of temperature. Results argue that efforts to improve ecohydrologic modeling of vegetation water use and associated water-limited ecological processes in these semi-arid regions should focus on improving estimates of anthropogenic outdoor water use and explicit accounting of soil parameter uncertainty.

Key words: Ecohydrology; Modeling; Urban ecology; Plant–water interactions; Semiarid; Sensitivity analysis.

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INTRODUCTION

Semi-arid ecosystems are subject to high inter-annual variation in precipitation and regular water scarcity; both of these characteristics place stress on vegetation. The intensity of storm event precipitation and the length of drought periods in these regions may also increase as atmospheric carbon levels rise (IPCC 2007). Simultaneously, urban populations in semi-arid regions such as the southwestern US are increasing (Mackun and Wilson 2011) and human modifications to the landscape structure and the local water cycle in urban catchments can be extensive (White and Greer 2006; Paul and Meyer 2001). In semi-arid regions, the impacts of urbanization in an ecohydrologic context are of particular interest. Water is often imported to semi-arid and arid urban areas, and irrigation of landscaping vegetation can constitute a significant portion of overall water use. Urban outdoor water use is estimated to represent approximately 20 % of total urban water use in California (Gleick and others 2003); this additional water source acts to boost vegetation growth and productivity. At the same time, increases in impervious area can reduce precipitation infiltration, negatively impacting the amount of water stored and available to vegetation during dry periods.

Ecohydrologic models can serve as useful tools for forecasting the effects of environmental change on vegetation and runoff. Given the current and expected stresses and changes described above, urban catchments in semi-arid regions are a logical setting for implementation of such models. Ecohydrologic models can be used to quantify both the current impacts of urbanization and how the sensitivity of semi-arid ecosystems to future change might be altered by urbanization. We use a semi-arid and urbanizing catchment, Mission Creek, to investigate some of the challenges presented when applying ecohydrologic models to these environments. Located in Santa Barbara, CA, this site typifies the water-scarce and increasingly urban nature of many semi-arid catchments.

A key challenge in hydrologic modeling is determining model sensitivity to uncertainty and developing strategies for reducing or accounting for uncertainties that lead to substantial changes in model predictions. Numerous papers and commentaries highlight the importance of assessing hydrologic model sensitivity to uncertainties in calibrated soil parameters, precipitation uncertainty, and the structure of the model itself (for example, Kirchner 2006; Sivapalan 2009). Although uncertainty is recognized as a challenge in ecological modeling, the

impact of input uncertainty has not been extensively explored (Fuentes and others 2006). If model sensitivity to parameter or input uncertainty is large relative to model predictions of ecosystem response to expected changes in climate, land use, or other potential stressors, those predictions are of limited value. Applying lessons and methods from traditional hydrologic modeling to a broader ecological modeling context is one potential means of better understanding the impacts of uncertainty in ecological modeling.

One of the largest sources of uncertainty in hydrologic modeling is the nature of soil properties, such as hydraulic conductivity and storage. These properties cannot be measured across an entire catchment and many studies have shown that widely available soil maps are poor estimators of these parameters (Zhu and others 2001; Band and Moore 1995). Further, the presence of macropores and preferential flowpaths often leads to higher values of drainage parameters than would be expected given soil classifications (Nieber and Sidle 2010; Holden 2009). Because these properties control infiltration and storage capacities, they can influence water availability during dry periods and thus impact vegetation water use and productivity. However, in urban environments, impervious surfaces limit infiltration and may reduce the importance of the underlying soils; uncertainty in soil parameters may therefore impact model output less in urban catchments than in comparable undeveloped catchments. A common approach to reducing soil parameter uncertainty is calibration using streamflow observations. Although calibration of soil drainage parameters can reduce uncertainty, there are often many parameter combinations that yield equally acceptable reproductions of runoff, a concept referred to as equifinality (Beven and Binley 1992). Model behavior may differ considerably between these equally acceptable parameter sets.

A second source of uncertainty in hydrologic models is that of water and temperature inputs derived from empirical data. We focus our analysis on three sources of input uncertainty: extrapolation of point precipitation data across the catchment, water inputs resulting from outdoor water use (OWU) in urban areas, and the nonlinear change in temperature with elevation that can result from the presence of a marine fog layer and other local controls. As explained below, these sources of uncertainty are especially relevant in the semi-arid, urbanizing, coastal catchments that are found throughout central coastal California and typified by the Mission Creek study catchment.

Accurate spatial extrapolation of precipitation from point data is a long-standing challenge in hydrologic modeling. Previous studies have found that uncertainties in precipitation estimates can significantly impact model estimates of runoff (Moulin and others 2009; Bardossy and Das 2008; Nandakumar and Mein 1997), however, the impact on modeled ET is less studied. Precipitation inputs are typically derived from one or more point measurements and extrapolated across the catchment or, in the case of models driven by global or regional climate model inputs, coarse spatial-scale estimates that must be downscaled by distributing values within local catchments. Although spatially continuous precipitation data (for example, radar) are increasingly used to drive hydrologic models, these data are typically not available for historical periods or future climate scenarios. A variety of methods may be used to extrapolate point data, such as Thiessen polygons, kriging, and development of precipitation isohyets or inverse distance weighting. In this study, we extrapolate precipitation as a function of elevation to calculate precipitation isohyets and then assess the effect of uncertainty in the scaling factor used to define the isohyets. In catchments with significant relief, precipitation is often strongly influenced by elevation (Mair and Fares 2011; Hevesi and others 1992) and previous studies of the Mission Creek catchment have used elevation as a primary variable in extrapolating precipitation (Beighley and others 2005). Because the precipitation–elevation relationship may vary significantly from storm to storm (Dettinger and others 2004), we specifically consider the impact of uncertainty associated with an event-based scaling factor.

In urbanizing catchments, another source of uncertainty arises from estimates of outdoor water use (OWU), which primarily goes to irrigating urban vegetation. In semi-arid areas, OWU can constitute a significant portion of annual water inputs and even contribute to elevated baseflow levels. White and Greer (2006) estimated a 13% increase in dry-season runoff resulting from outdoor water use in a catchment near San Diego, CA. In southern California cities, outdoor water use has been estimated to range from 18 to 35% of total water use (Metropolitan Water District 1996). Outdoor water use peaks during the summer when precipitation levels are low, and the fate of this water (as runoff or ET) is of interest both from a water management standpoint and an ecological perspective. This additional water input likely increases vegetation water use and productivity, but the observation of elevated baseflow suggests

that it is not always efficiently applied and that OWU may be impacting riparian and aquatic ecosystems as well as upslope areas. However, municipal water use is rarely explicitly monitored as indoor versus outdoor use. The modeler must therefore estimate the fraction of total water use that constitutes OWU.

The final source of input uncertainty considered is air temperature. Many models use temperature data directly in computation of evapotranspiration (for example, Priestley and Taylor 1972) or to estimate vapor-pressure deficit (VPD), (Jones 1992; Ward and others 1994), which impacts ET rates derived from the Penman–Monteith equation. In small catchments, temperature can usually be reliably extrapolated from point data using elevation-based temperature lapse rates (Running and others 1987). However, in coastal catchments a marine fog layer can dampen temperature fluctuations and cause non-linear variations in temperature across elevation, introducing error into temperature inputs derived from standard lapse rates. Because the fog layer can be highly variable in space and time, it becomes a potentially major source of uncertainty when estimating temperature inputs in affected catchments.

We quantify the sensitivity of modeled runoff and ET to these four uncertainties using the Regional Hydro-Ecological Simulation System (RHESys; Tague and Band 2004) within the Mission Creek catchment, a semi-arid, urbanizing catchment in Santa Barbara, CA. The model is run across a series of scenarios designed to capture the likely range of uncertainty in each source. Sensitivity of modeled ET and runoff to each source of uncertainty is then analyzed at monthly, annual, and long-term (14-year) time scales. By comparing the contribution of different uncertainty sources to modeled hydrologic behavior within the same analysis, we can assess the relative importance of each. Analysis of both ET and runoff responses highlights differences in the timing and magnitude of sensitivity between these two outputs.

This assessment of model sensitivity provides insight into how soil-drainage properties combine with the timing and magnitude of water inputs to control vegetation water use at different temporal scales. We discuss how our assessment can be used in the design of efficient strategies for reducing parameter and input uncertainty and ultimately in evaluating the utility of the model as a tool for forecasting catchment response to projected environmental change. We are particularly interested in the effect of different sources of uncertainty on vegetation water use, represented by ET. In an

urbanizing catchment such as Mission Creek, accurate modeling of ET is key to understanding the likely effects of further urbanization on vegetation function, including the effects of vegetation water use on streamflow as well as vegetation productivity and biogeochemical cycling of key nutrients such as nitrogen (N). In semi-arid environments, water is a strong limiting factor on vegetation growth (van Wijk 2011; Ochoa-Hueso and Manrique 2010; Austin and others 2004); accurately capturing hydrology is thus especially important to understanding broader ecological and biogeochemical processes.

STUDY SITE AND INPUT DATA

Study Site

The Mission Creek (MC) catchment is a 31-km² catchment located in Santa Barbara, CA (Figure 1). Catchment elevation ranges from 0 to 1,312 m. Land cover is characterized by chaparral in the steep (slopes >20°) headwater regions with suburban and progressively more urban development dominating the base of the catchment. Developed land uses cover approximately 50% of the catchment. Land use is inferred from 1: 42,000 scale aerial photographs taken in 1998 and classified based on Anderson Level III classifications (Anderson and others 1976). According to this classification, developed land use is broadly characterized as areas with 30% or greater area covered by constructed materials. The three dominant developed land classes in the catchment are “developed, open space” (<20% impervious cover), “developed, low intensity (20–49% impervious cover), and “developed, medium intensity

(50–79% impervious cover). The local climate is Mediterranean, with warm, dry summers and the majority of annual precipitation delivered during winter storms. Annual precipitation averages 470 mm y⁻¹ (National Climate Data Center 2002).

Input Data

Basin topography, derived from a USGS 10 m-resolution DEM, is used to subdivide the catchment into a hierarchy of patches, zones, and hillslopes. Land cover, vegetation, and impervious surface cover characteristics are derived from a set of 1998 aerial photographs as described in Beighley and others (2005) and used to assign land surface parameters (see Tague and others 2009; Tague and Pohl 2008; White and others 1997 for details). Daily temperature data for the water years (WY) 1993–2006 were obtained from a National Climate Data Center (NCDC) monitoring station near the base of the catchment (3 m elevation, Figure 1). Hourly precipitation data collected over the WY 1993–2006 study period at a mid-elevation (700 m) gauge operated by the Santa Barbara County (SBC) Flood Control District were used as the point precipitation input for all model runs. Precipitation data from this gauge and seven additional SBC Flood Control gauges on the south (ocean-facing) slopes of the Santa Ynez mountains (Figure 1) were used to calculate the precipitation scaling factors that extrapolate precipitation depths across the catchment.

Monthly water use (WU) data were provided by the City of Santa Barbara for 1990–2007. OWU inputs were calculated following a method previously employed by Johnson (2005), modified to accommodate the multi-year study period. February water use (typically the lowest water use month of the year) was assumed to characterize indoor water use; indoor water use across a year was then derived by assuming a linear change in use from one February to the next. OWU for a given month was calculated as:

$$\text{OWU}_{m,n} = \text{Total WU}_{m,n} - (\text{Feb WU}_n * (1 - (m/12))) - (\text{Feb WU}_{n+1} * (m/12)) \quad (1)$$

where n represents the year in question and m represents month. Note that for these calculations the year begins in February ($m = 1$). We assumed that monthly OWU totals are distributed evenly within each month to estimate daily OWU. OWU estimates were applied uniformly across developed areas (approximately 50% of catchment area) as an additional daily precipitation input. This method of

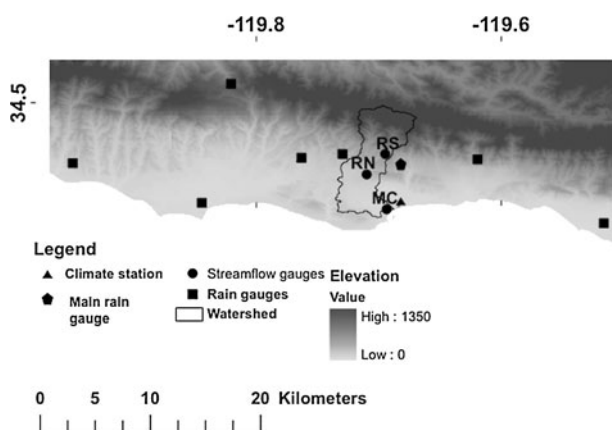


Figure 1. The Mission Creek catchment, streamflow, climate, and precipitation gauging stations used in the study.

OWU estimation resulted in OWU accounting for 26% of total water use over the 1990–2007 period, within the 18–35% range for residential and commercial areas estimated for southern California (MWD 1996).

RHESSys MODEL

All model outputs used in this analysis were generated using the RHESSys model (Tague and Band 2004). RHESSys is a spatially distributed model of coupled hydro-biogeochemical cycling and has been successfully used to model daily runoff and ET in watersheds with similar climate and topography to Mission Creek (Tague and others 2004, 2009; Tague and Pohl 2008). RHESSys models interception, soil and litter evaporation, canopy transpiration, infiltration, and vertical drainage, as well as lateral routing between terrestrial patches. A Penman–Monteith approach is used to estimate evaporation and transpiration fluxes. A detailed description of approaches used to estimate infiltration and lateral–vertical fluxes is provided in Tague and Band (2004).

Model Calibration

In RHESSys, soil parameters that control flow rates through soils and permeable bedrock layers are often calibrated using measured streamflow. In the Mission Creek catchment, we used a multi-step calibration process utilizing data from a set of three runoff gauges (RS, RN, and MC; Figure 1) nested within the catchment. We calibrated two shallow subsurface soil parameters: saturated hydraulic conductivity (k) and decay of k with depth (m). We also calibrated three parameters used to define bypass flow to deeper groundwater stores and groundwater drainage rates: $GW1_{\text{shallow}}$ and $GW1_{\text{steep}}$, the fraction of precipitation automatically routed to groundwater where slope was less than 20° and more than 20° , respectively, and $GW2$, which controls the drainage rate of deep groundwater to the stream. The separation between “steep” and “shallow” regions of the catchment has been used in previous hydrologic modeling of the Santa Barbara region (Beighley and others 2005); steep areas are assumed to generate more quickflow and shallow regions are assumed to generate more groundwater flow. Initially, 15,610 parameter sets were randomly generated. The number of acceptable parameter sets was first narrowed based on streamflow data collected over WY 2001–2007 at the RS gauge. This step calibrates against streamflow from a steep, undeveloped and relatively homogeneous portion of the catchment, minimizing the likelihood

that non-soil surface characteristics, such as impervious surface cover, will be unintentionally co-opted into soil drainage properties. Because slopes in this portion of the catchment are generally greater than 20° , this step also allowed us to focus specifically on calibrating the $GW1_{\text{steep}}$ parameter and separate it from the $GW1_{\text{shallow}}$ parameter. Parameter performance was measured by evaluating the Nash–Sutcliffe efficiency of modeled daily streamflow (NSE) (Nash and Sutcliffe 1970), NSE of the natural logarithm of modeled daily streamflow, and mean percent error of modeled daily streamflow. In the second calibration step, RN1, we took the top 25% of parameter sets from the RS calibration and use them to model streamflow in the RN catchment, calibrating against flow from the WY 2003–2007 period. In this round of calibration, we also randomly varied the $GW1_{\text{shallow}}$ parameter associated with each parameter set. Best parameter sets from this round of calibration were selected and used for two final calibrations, RN2 and MC, which tested the model against a different meteorological record than the RN1 calibration (RN2, calibrating against data from WY 1997–2002) and across a larger geographic area (MC, calibrating over the WY 2001–2007 period).

SENSITIVITY ANALYSIS

We estimate sensitivity of modeled ET and runoff to uncertainty by varying soil-drainage parameters, precipitation scaling, OWU, and temperature inputs across the estimated range of uncertainty in each of these parameters or inputs. We consider the impact of uncertainty in each input or parameter separately. Although varying all parameter or inputs simultaneously would account for parameter interaction effects, the high-computation time of the required number of model runs made this approach infeasible (run time for a single model run is ~ 30 min for the 14-year study period). We do test sensitivity of precipitation scaling, OWU, and temperature inputs for three different soil-drainage parameter sets, providing some exploration of parameter interaction. The soil parameter sets all showed high levels of performance in comparisons between observed and modeled streamflow. For each source of uncertainty considered, model output from the WY 1993–2006 time period is used to evaluate sensitivity to uncertainty.

Uncertainty in Calibrated Soil Parameters

We focused our evaluation of soil parameter uncertainty on the uncertainty remaining after

calibration against daily runoff. Calibration effectively reduces parameter uncertainty by eliminating “non-functional” parameters, following Beven and Freer (2001). Without calibration, soil parameter uncertainty would be considerably higher. Some form of calibration is typical in hydrologic modeling, even in the case of ungauged catchments where parameter selection may be based upon calibration to nearby gauged catchments (Wagener and Wheeler 2006). We focus our analysis on post-calibration uncertainty, using only parameter sets that yield acceptable streamflow during calibration. A total of 441 soil parameter sets remained following calibration against streamflow observations, from an initial pool of 15,610 parameter sets. A summary of model performance through the calibration process is given in the results section of this paper.

Uncertainty in Precipitation Scaling

A time series of point daily precipitation data was interpolated to compute daily precipitation inputs for each zone in the catchment, where zone is the spatial unit within RHESSys that computes microclimate variables (we used $\sim 5,000$ zones, with a minimum area of 120 m^2 , in the study catchment). Precipitation was interpolated from a single rain gauge based on elevation and precipitation scaling factors (s). Values for s were derived from relationships between pairs of precipitation gauges as:

$$s = [(P_2/P_1) - 1]/(E_2 - E_1) \quad (2)$$

where P_1 and P_2 are daily precipitation (in mm) at two sites, and E_1 and E_2 are elevation (in meters) of the same two sites.

We combined daily data from eight precipitation gauges (Figure 1) collected over the 2000–2008 time period to develop a distribution of s values for daily precipitation. Note that although these stations were used to estimate an event-based time-scale distribution of precipitation scaling factors, they were not complete enough to provide daily time series inputs for simulations. All possible pairings of gauges were considered to provide the maximum possible information about elevation-based differences in precipitation. The minimum elevation between gauge pairings was 50 m. Scaling factors were observed to vary across events, with a slightly larger range in s observed for smaller events ($< 40 \text{ mm}$ at primary gauging station) than for larger events ($> 40 \text{ mm}$) (Figure 2). In each instance, the distribution of s was observed to be roughly lognormal according to the Shapiro–Wilk test of normality. To test model sensitivity to

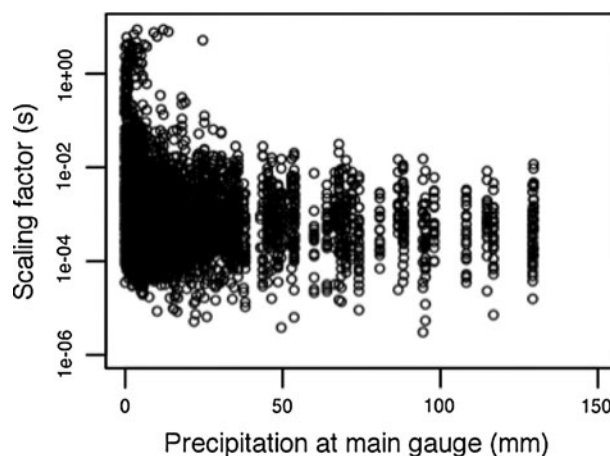


Figure 2. Precipitation scaling factor, s , shown as a function of precipitation falling at the main precipitation gauging station (elevation 700 m). *Smaller* storm events ($< 40 \text{ mm}$) show greater variation in s values than *larger* storm events.

topographic scaling of precipitation inputs, on each day where precipitation was observed at the main precipitation gauge, an s value was selected at random from the distribution of observed s values for either large or small storm events (depending on the magnitude of observed precipitation). Although the difference in distributions between large and small events appears small, we chose to use two separate distributions. Use of a single distribution would expand the tails of the scaling factor distribution for larger storms and generate the potential for larger than expected water inputs and increasing the potential implications of precipitation uncertainty. We preferred to err on the conservative side when determining the magnitude of uncertainty. For each of the three high-performance parameter sets used, 1,000 simulations were run over the WY 1993–2006 period with s varying on a daily basis (3,000 simulations total). The s value was used to extrapolate daily precipitation for a given elevation (P_E) as:

$$P_E = P_{\text{base}} * s(E - E_{\text{base}}) + 1 \quad (3)$$

where E_{base} is the elevation of the main gauge (700 m), and P_{base} is precipitation measured at the main gauge for that day.

Uncertainty in Outdoor Water Use

We examined the effect of uncertainty in water inputs resulting from OWU in urban areas by varying the depth of OWU. First, we removed OWU entirely from the model to determine the contribution of OWU to runoff and ET. We then

explored the impact of varying the depth of OWU to determine if there were critical thresholds at which the fate of OWU within the water balance (runoff vs. ET) displayed significant changes. Five scenarios were considered, one with no OWU inputs and four scenarios adjusting the monthly OWU estimates by $\pm 15\%$ and $\pm 30\%$ of the “base” scenario derived from WU data as discussed above. These changes resulted in a long-term average OWU ranging from 18 to 34% of total water use, consistent with the MWD estimated range of OWU in Southern California.

Uncertainty in Temperature Across Elevation

In RHESSys, temperature is interpolated using an elevation-specific lapse rate. In the absence of direct measurements, VPD is often estimated using the difference between maximum and minimum daily temperature (Running and others 1987; Jones 1992).

We used a single NCDC meteorological station located near the base of the catchment (3 m elevation) for the baseline scenarios and uncertainty analyses not focused on temperature. For the temperature-input sensitivity analysis, additional data from a California Irrigation Management Information System (CIMIS) meteorological station is incorporated to better capture potential fog cover effects. This second station is located at 640 m elevation, about 25 km west of the study catchment (Figure 1). Temperature measurements from the 3 m elevation station (used for baseline simulations) were applied to elevations below 300 m, whereas data from the 640 m elevation station were applied to elevations above 300 m. The 300 m cutoff was selected because the cloud base of most summer fog events in this region is at or below this elevation (Williams and others 2008).

RESULTS

Model Calibration

When compared against observed runoff data from the full Mission Creek catchment for the WY 2001–2006 period (Figure 3), the 441 best parameters ultimately selected for the soil parameter uncertainty analysis were found to have daily NSE values of 0.45–0.56, NSE of the natural logarithm of streamflow (considered an indicator of the model’s ability to capture baseflow) of 0.22–0.41 and percent error of 14–33%, performance comparable to previously used models in the same catchment (Beighley and others 2005). A monthly water

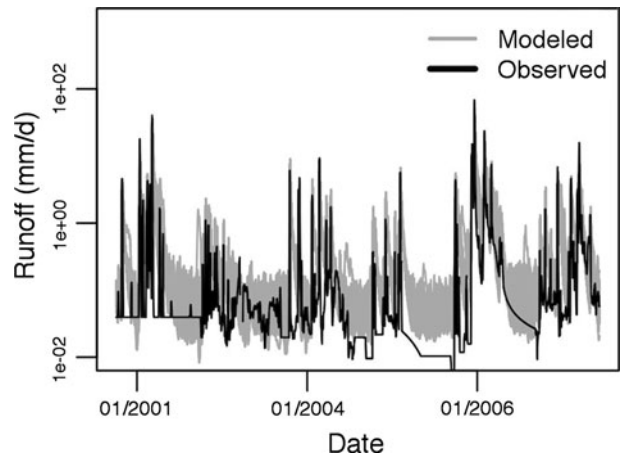


Figure 3. Observed and modeled streamflow for the 441 best parameter sets used to evaluate model sensitivity to calibrated soil parameter uncertainty, WY 2001–2007. Each gray line represents modeled streamflow associated with one of the best parameter sets.

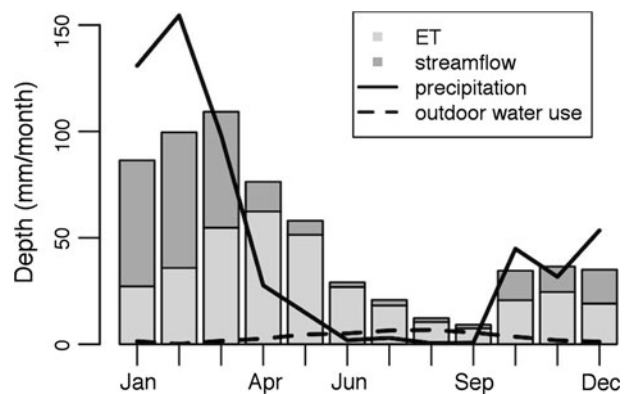


Figure 4. Mean monthly inputs and modeled outputs over the 14-year study period, averaged across the 441 best calibrated soil parameter sets.

balance showing average water inputs and average modeled streamflow and ET outputs over the 14-year study period (Figure 4) shows that the majority of streamflow occurs in the winter months, when the bulk of precipitation also occurs, whereas ET rates reach a maximum in the early spring. The steep soils of the catchment limit storage capacity, and both ET and streamflow quickly decline during the summer months. A summary of model performance at each step of the calibration process can be found in Table 1. A potential concern with the calibrated model is the tendency toward streamflow overprediction that is seen when parameters calibrated against the nested RS and RN subcatchments are applied to the full MC catchment. In part, we believe some of this overprediction, especially of low flows, may be attributable to

Table 1. Summary of Performance Metrics of Selected Best Parameter Sets from Calibration and Validation

	Number of parameter sets	Area, time period	NSE	Log (NSE)	PE
RS calibration	3,903	RS, WY 2001–2007	0.63 (0.46–0.78)	0.35 (0.22–0.59)	0.05 (–14.52–13.20)
RN calibration 1	1,667	RN, WY 2003–2007	0.44 (0.38–0.66)	0.52 (0.27–0.58)	–3.26 (–9.92–4.95)
RN calibration 2	441	RN, WY 1997–2002	0.58 (0.40–0.66)	0.56 (0.38–0.66)	34.68 (7.20–52.44)
MC calibration 1	441	MC, WY 2001–2007	0.51 (0.45–0.56)	0.33 (0.22–0.41)	27.77 (13.65–33.22)

Values are shown as mean (minimum, maximum).

errors in observed baseflow measurements. Summer low flows are known to be difficult to measure accurately in this watershed and lack of precision in baseflow measurements can be observed during low flow periods (Figure 3). Uncertainty in precipitation data is also a key source of model error as discussed in more detail below. Overall, we believe that for this analysis the level of model error is acceptable, as our goal is to determine model sensitivity to different sources of uncertainty rather than to use the model in a predictive capacity.

Sensitivity of Model to Soil Parameter Uncertainty

Over the 14-year study period, model estimates of ET and runoff displayed considerable sensitivity to calibrated soil parameter uncertainty. Long-term mean ET across soil parameter sets ranged from 343 to 396 mm y^{-1} , a range representing 14% of long-term mean annual ET (Figure 5A). Long-term mean runoff ranged from 222 to 253 mm y^{-1} , a range representing 13% of mean runoff (Figure 5B). We note that this sensitivity is only to uncertainty in calibrated soil parameters that met acceptability criteria. Sensitivity across the full range of potential parameters would likely be greater. For individual years, variation in annual ET across soil parameter uncertainty ranged between 4.1% (WY 2006) and 28% (WY 1998) of mean annual ET. Sensitivity of annual ET estimates to soil parameter uncertainty showed some relationship with precipitation; wetter years displayed greater sensitivity to soil parameter uncertainty (Figure 6A). This relationship with precipitation is non-linear; ET sensitivity increases sharply when annual precipitation exceeds 700 mm. This jump suggests that in wetter years, soil conductivity, and groundwater drainage rates play a greater role in determining model output than they do under drier conditions, when the limiting variable is water supply (that is, precipitation).

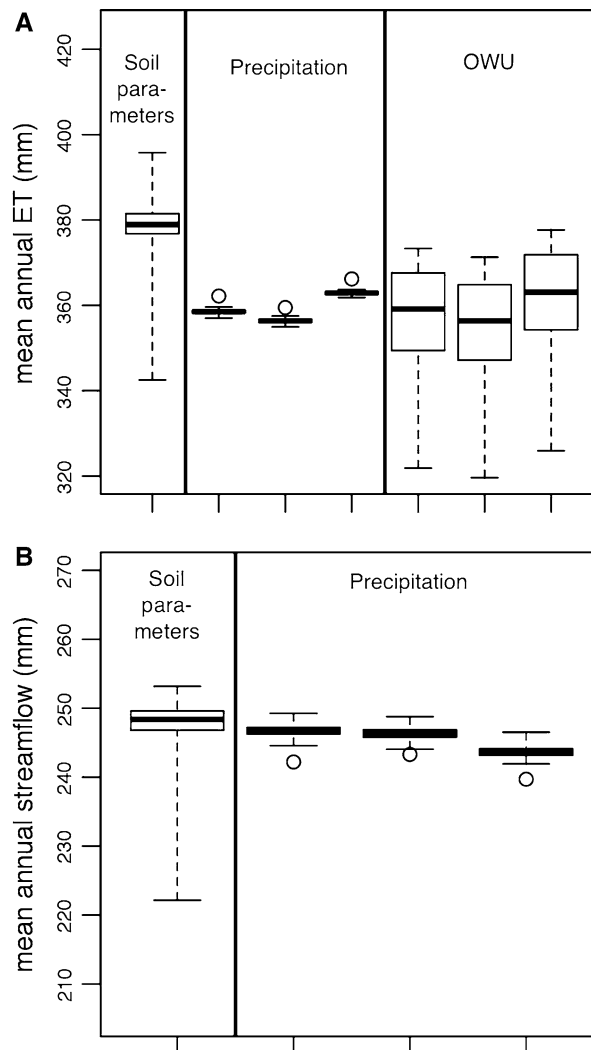


Figure 5. **A, B** Range of long-term mean annual **A** ET and **B** runoff across (left to right) soil parameters (first boxplot), stochastically varied precipitation scaling scenarios (boxplots 2–4, each plot representing results across one of three parameter sets), and OWU scenarios (boxplots 5–7, not shown for runoff as no sensitivity was observed). Black circles represent mean annual ET and runoff estimated using the same parameter set but static precipitation scaling. Sensitivity to incorporation of a high-elevation climate station is not shown as there are only two data points.

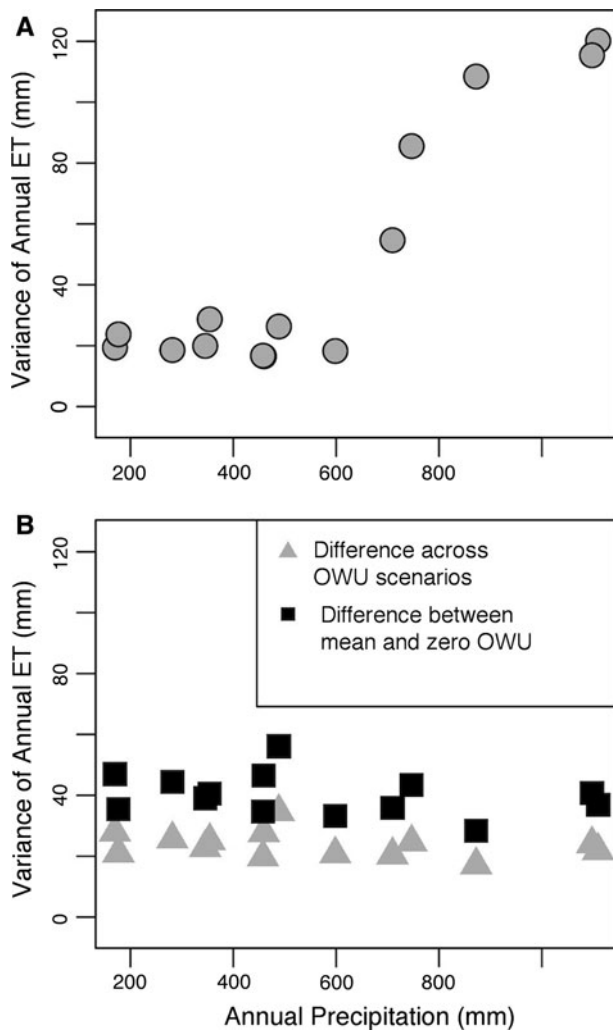


Figure 6. A, B Sensitivity of annual ET to parameter and input uncertainties as a function of annual precipitation. Figures show variance or change in annual ET **A** across calibrated soil parameter sets, **B** between a no OWU and the baseline OWU scenario, and across five possible OWU scenarios (baseline, ± 15 and $\pm 30\%$ of baseline). Results are not shown for analysis of ET sensitivity to stochastic variation in precipitation or the addition of a high-elevation climate station as they show no relationship with annual precipitation.

Monthly ET showed the most sensitivity to soil parameter uncertainty during the spring and summer (Figure 7A). During the remainder of the year, ET sensitivity to soil parameter uncertainty was low. For individual months, ET sensitivity rarely (6 out of 168 months) exceeded 100% of mean ET; median sensitivity was 13%. In contrast to ET, runoff showed more sensitivity to soil parameter uncertainty during the fall and winter (Figure 8A).

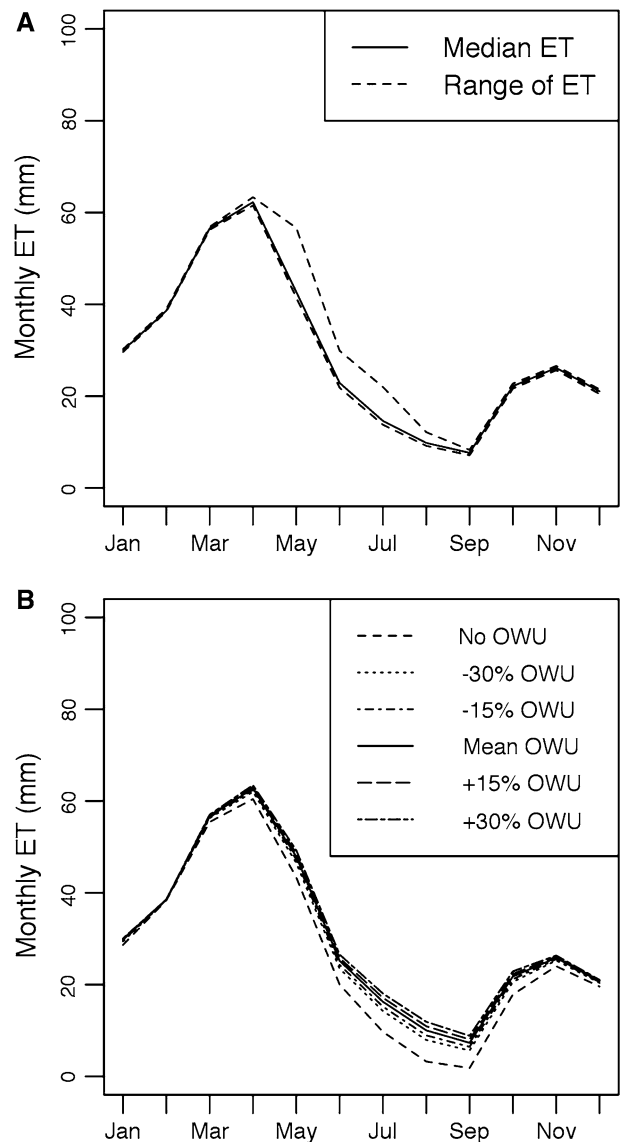


Figure 7. A, B Sensitivity of long-term mean monthly ET to parameter and input uncertainty. Ranges of monthly ET are shown across **A** calibrated soil parameters and **B** a range of OWU scenarios. In each case, ET shows the greatest sensitivity to uncertainty during the summer months, corresponding to the peak growing season. Sensitivity to stochastic precipitation scaling and incorporation of a high-elevation climate station are not shown as the monthly sensitivities are extremely small. Note that these graphs show only mean values for each month across the 14-year study period; sensitivity of individual months could in some cases be larger or smaller.

Precipitation Scaling

Over the 14-year study period, total precipitation showed very little variation when precipitation scaling was varied on an event-by-event basis, with the long-term mean precipitation input ranging

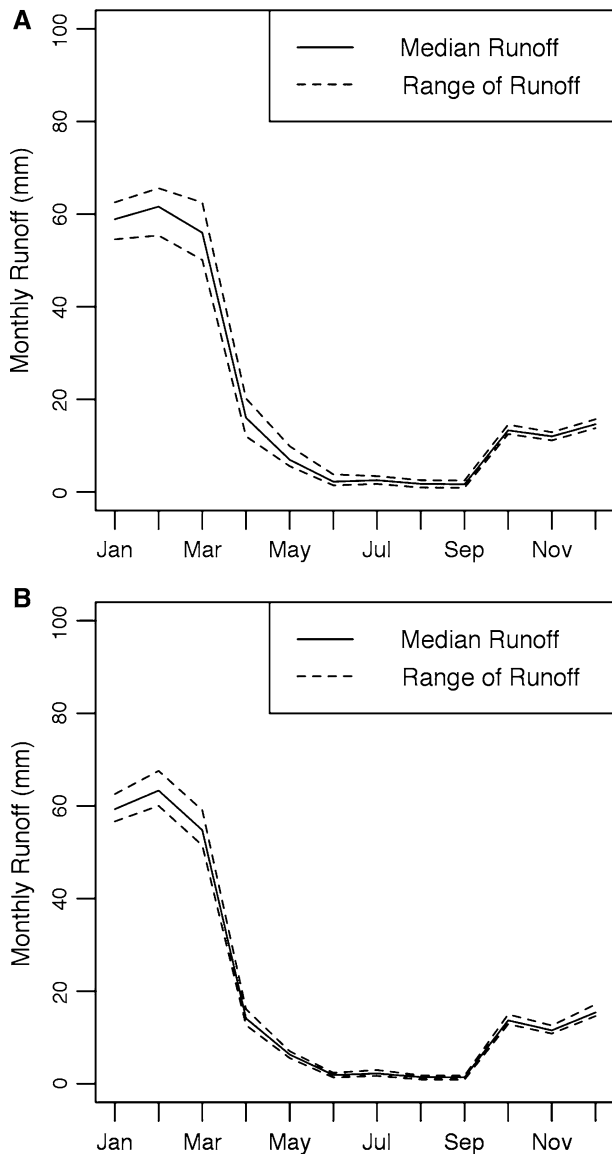


Figure 8. A, B Range in mean monthly streamflow across **A** calibrated soil parameters and **B** a range of stochastically varied precipitation scenarios. Sensitivity to OWU levels and incorporation of a second climate station are not shown as the monthly sensitivities are nonexistent or extremely small. Note that these graph show only mean values for each month across the 14-year study period; sensitivity of individual months could in some cases be larger or smaller.

from 561 to 564 mm y^{-1} . On a year-to-year basis, variation in precipitation inputs was somewhat higher, averaging 15 mm y^{-1} (3.2%), and ranged from 3.3 (WY 2002) to 43 mm y^{-1} (WY 2006) (Figure 9). Variation in annual precipitation depth across the distribution of precipitation scaling uncertainty was strongly tied to annual precipitation observed at the main gauge: years with higher

precipitation showed a greater absolute range in precipitation inputs when the stochastic scaling factor was implemented. However, the most variability by far was seen at the event (daily) time scale. For days when precipitation occurred, precipitation inputs varied by 12% of mean precipitation for the day and were as high as 83% when a stochastic scaling factor was implemented.

The sensitivity of runoff to uncertainty in precipitation scaling varies with the time scale considered. As with precipitation, the long-term mean annual runoff showed little sensitivity to precipitation scaling uncertainty, varying by only 4.5–5 mm y^{-1} , considerably less than the range observed across soil parameter uncertainty (Figure 5B). Implementation of a stochastic precipitation scaling factor did result in a small (3–5 mm y^{-1}) but consistent increase in modeled mean runoff over runoff modeled using a static scaling factor (Figure 5B). Sensitivity for individual years was much larger (Figure 9); sensitivity of annual runoff across precipitation scaling scenarios averaged 30 mm y^{-1} (14%) and ranged from 7.0–30% of mean modeled runoff for the same year (5–60 mm y^{-1} , Figure 9). Sensitivity of mean monthly runoff across the entire study period ranged from 0.14 (September) to 4.9 mm mo^{-1} (March) and averaged 1.7 mm mo^{-1} (8.3%, Figure 8B). For individual months, runoff sensitivity averaged 5.4 mm mo^{-1} (26%), but was as high as 260% in one instance (February 2006). In terms of absolute sensitivity of runoff depths, most

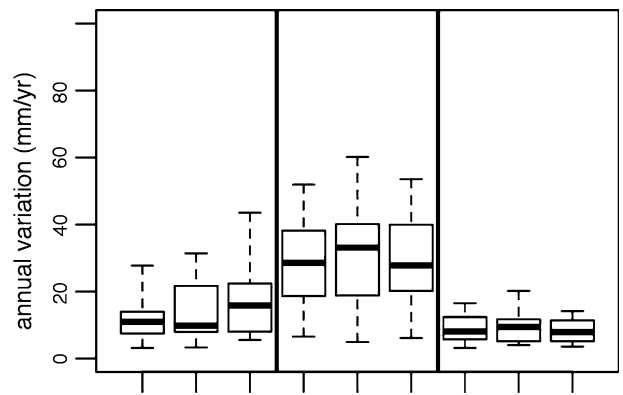


Figure 9. Boxplot of inter-annual variation in the range of annual precipitation (boxplots 1–3), streamflow (boxplots 4–6), and ET (boxplots 7–9) across stochastic precipitation scaling scenarios for each year in the 14-year study period when a stochastic precipitation scaling factor is implemented. Each of the three plots represents results across one of three parameter sets used for the precipitation uncertainty analysis. Streamflow is highly sensitive to precipitation variation, whereas ET shows only moderate sensitivity.

sensitivity was observed in January–March (Figure 8B). The impact of precipitation uncertainty on rainy season runoff is greatest at the event scale. In the 14-year study period, daily runoff on days with precipitation (549 days) averaged 3.4 mm d^{-1} , whereas runoff sensitivity on these days averaged 1.4 mm d^{-1} (43% of the mean) and was as high as 35 mm d^{-1} in one instance. In percentage terms, daily runoff sensitivity to precipitation scaling uncertainty peaked at 570%.

ET showed much less sensitivity than runoff to uncertainty in precipitation scaling. The sensitivity of long-term mean ET was low, only 2.6 mm y^{-1} (0.7%). Within individual years, sensitivity of annual ET averaged 9 mm y^{-1} (2.5%), and ranged from 3.2 (1.8%, WY 2002) to 20 mm y^{-1} (5.4%, WY 2000) (Figure 9). Sensitivity of ET to precipitation scaling uncertainty increased at finer time scales, but was consistently less than runoff sensitivity. Sensitivity in mean monthly ET averaged only 0.4 mm mo^{-1} (1.2%), ranging from 0.15 (September) to 0.9 mm mo^{-1} (May). Within individual months, mean sensitivity of monthly ET across precipitation scenarios was 1.2 mm mo^{-1} (5.4%). In some individual months, ET sensitivity was as high as 18%, but in over 75% of months sensitivity was less than 10%. We note that annual ET is sensitive to annual precipitation (Figure 10),

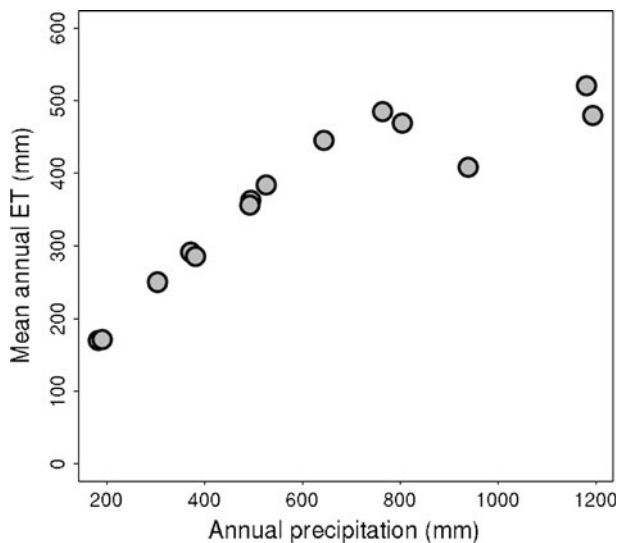


Figure 10. Mean ET with static precipitation scaling versus annual precipitation. The steep soils in the headwaters of the catchment strongly limit storage capacity, whereas the concentration of precipitation in the winter months limits opportunities to replenish water stores. These two factors combined create the leveling-off in annual ET seen when annual precipitation exceeds 600 mm.

particularly below a precipitation threshold of 700 mm y^{-1} . This threshold likely reflects the amount of seasonal precipitation generally required to insure that soils are saturated at the end of the rainy season.

Outdoor Water Use

All scenarios with OWU inputs showed increases in ET, with increases between the no OWU and mean OWU scenarios averaging 40 mm y^{-1} (13%). No appreciable changes in runoff were observed. The sensitivity of ET estimates to uncertainty in OWU was similar in magnitude to sensitivity associated with soil parameters (Figure 5A).

Unlike sensitivity to uncertainty in calibrated soil parameters or precipitation scaling, sensitivity of ET to OWU uncertainty showed no relationship with annual precipitation (Figure 6B). On a monthly basis, maximum changes in ET were observed during the summer (Figure 7B), coinciding with peak OWU. Between the zero OWU and mean OWU scenarios, mean ET increases of $5\text{--}7 \text{ mm mo}^{-1}$ were observed over June–September. These increases represented a 20–75% change in mean monthly ET, depending on the month in question. The general seasonal patterns of ET are not sensitive to OWU uncertainty. Increases in ET were relatively linear with change in OWU over the range of uncertainty in OWU estimates. We might expect that at higher levels of OWU, a threshold would be reached at which increasing OWU would no longer increase ET. However, the current range of OWU rates appears to be below that threshold.

Nonlinear Effects of Elevation on Temperature

The impact of temperature estimates on modeled eco-hydrologic fluxes is predominately expressed through VPD. VPD estimated from temperature data observed at 640 m is typically lower than VPD estimated using temperatures extrapolated from the 3 m elevation station using a linear temperature lapse rate. The differences in VPD estimates also change on a seasonal basis, with differences in VPD near zero in the summer but growing throughout the fall and winter.

A comparison of output generated with one versus two climate stations showed small long-term differences in modeled ET. Over the study period, mean ET decreased by 7.9 mm y^{-1} (1.7%) when the 640 m temperature inputs were incorporated and runoff increased by a corresponding amount (2.6% increase in mean runoff). Absolute change

in annual ET or runoff for individual years ranged from below 1 to 22 mm y^{-1} , whereas the percent changes ranged from below 1 to 4.5% (ET) and below 1 to 8.1% (runoff). ET in wetter years appeared to exhibit slightly more sensitivity, but the increase was not consistent.

At a monthly time scale, ET exhibited low sensitivity to temperature uncertainty. Mean monthly ET increased from May to August when data from the 640 m station were added, and decreased during the remainder of the year. Absolute differences in mean monthly ET, however, were small, ranging from less than 0.01 (September) to 2.7 mm mo^{-1} (February). Percent difference in mean monthly ET between the two scenarios reached a maximum of 8.9% in January. The pattern of increasing summer ET and declining ET in other months with the addition of the 640 m climate station corresponds to the observed differences in estimated VPD. Over the study period, monthly differences in ET were small, with a median increase or decrease of 4.4 mm mo^{-1} (3.8%). None of the 168 months in the study period displayed changes in ET above 20%.

DISCUSSION

The impact of input and parameter uncertainty varies with the output (ET vs. runoff), time scale and season of interest. Periods of “peak sensitivity” reflect changes in the dominant control on catch-

ment eco-hydrology and the timing of peak inputs (Figure 11). In this semi-arid coastal catchment, there is a seasonal shift from a period of low vegetation growth and water demand, and high precipitation inputs (winter) to a period of low precipitation inputs (winter) to a period of low precipitation inputs, high vegetation growth, and high vegetation water demand (summer). Key transitions occur during rewetting of soils as winter rains begin and during the gradual drying of soils in the spring and summer. Corresponding to this seasonal bioclimatic pattern, model estimates shift from a phase of high sensitivity to soil parameters early in the water year as soils wet up to a phase of high sensitivity to precipitation uncertainty in the winter (both manifested primarily as sensitivity in modeled runoff), return to a phase of high sensitivity to soil parameters in the spring (manifesting as sensitivity in both runoff and ET), and finally shift to a phase of high sensitivity to OWU in the summer (manifesting exclusively as sensitivity in ET).

A key finding was the difference in sensitivity of ET and runoff to parameter uncertainty. This distinction is important given that a model’s ability to reproduce observed runoff is often a primary measure of performance. Thus, use of these models to provide insight into ecological processes such as ET may tend to overlook biases attributable to the specific effect of parameter uncertainty on ET. ET and runoff show interesting differences in sensitivity to uncertainty in calibrated soil parameters,

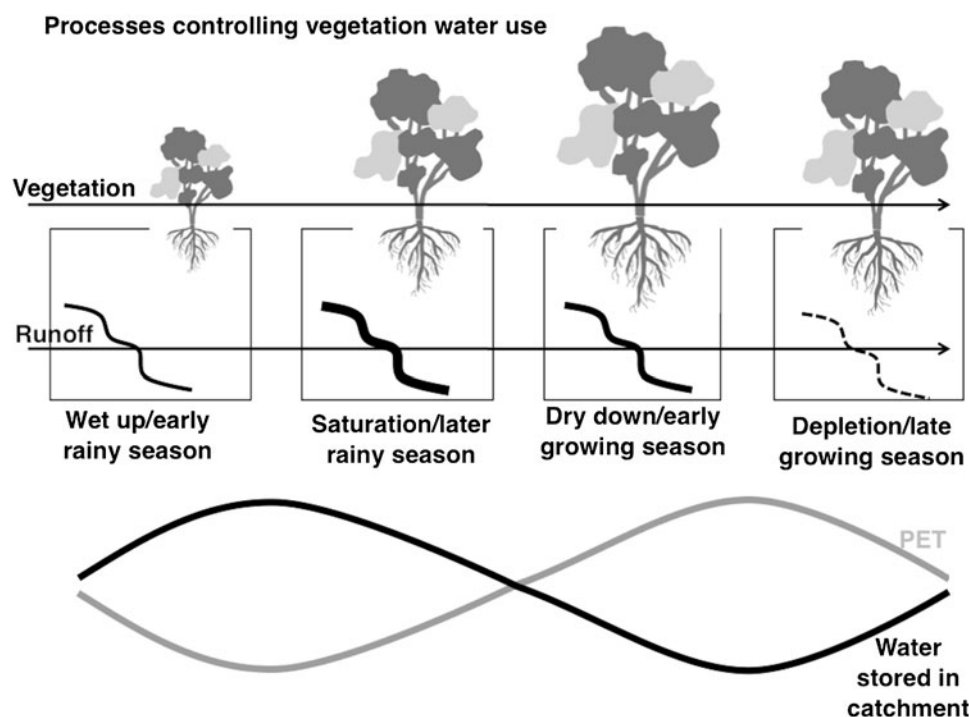


Figure 11. Controls on vegetation water use shift through the water year. In the fall, the system is initially water-limited. It becomes saturated through the winter rainy season and vegetation water use is then limited by demand. Vegetative demand for water rises through the growing season and water stores deplete, returning the system to a water-limited state at the end of the water year.

which reflect the episodic, winter-dominated precipitation regimes of semi-arid systems in a Mediterranean climate. Despite the presence of impervious surfaces reducing potential infiltration in developed areas, high sensitivities to calibrated soil parameters were observed for both runoff and ET. However, the timing of peak sensitivity to calibrated soil parameters differed between the two. At the beginning of the water year when soils are dry, runoff production is largely controlled by soil storage capacity; early season runoff is thus highly sensitive to soil parameters. However, after storage capacities are exceeded during the early rainy season, runoff is controlled primarily by the amount of precipitation available and thus transitions to a period of higher sensitivity to event-scale uncertainty in precipitation scaling but lowered sensitivity to calibrated soil parameters. In contrast, ET depends on water stored during the growing season, and thus sensitivity to drainage parameters is expressed during the spring and summer. If soils drain slowly and storage rates are high, more water is available during the growing season.

ET and runoff also differ in their sensitivity to uncertainty in precipitation inputs. ET sensitivity to uncertainty in event-scale precipitation was relatively low. Unlike runoff, ET is insensitive to the amount by which soil moisture storage capacity is exceeded and shows little sensitivity to event-scale uncertainty in precipitation scaling. In contrast, uncertainty in spatial scaling of precipitation at an event scale did significantly alter runoff estimates. For studies focused on response of runoff or riparian and stream ecosystems to environmental change, there is a greater need to account for this type of uncertainty, as these investigations are most dependent on accurately capturing runoff. We do note that ET is sensitive to total seasonal rainfall, especially in years where annual rainfall is below 700 mm (Figure 10). If we had considered the possibility of a long-term bias in scaling factor, ET likely would have shown greater sensitivity to precipitation uncertainty, as we would have then considered uncertainty in seasonal precipitation totals. A correction for long-term bias in annual precipitation can be estimated from bias in annual streamflow whereas event-scale uncertainty is more difficult to account for. Fortunately, the low sensitivity of ET to event-scale precipitation scaling suggests that, for ecological studies that focus on ET and vegetation response to climate variability in areas similar to our study region, this source of uncertainty is not critical. A key implication of this finding is that for these semi-arid coastal watersheds, vegetation water use responses to small

changes in storm spatial patterns and, in particular, changing storm intensity potentially associated with a changing climate in this region (Cayan and others 2008) are likely to be small. Given that predicting fine-scale (<km) changes in storm patterns associated with climate change remains a key challenge for regional climate models, this finding is encouraging. It is important to note that because the insensitivity of ET to precipitation scaling uncertainty is largely attributable to the seasonal timing of precipitation, ET might become much more sensitive to scaling uncertainty if the seasonal timing of precipitation was to change. However, efforts to predict changes in seasonal precipitation timing for California (Cayan and others 2008) have suggested that these changes in timing will likely be quite minor for the region around Mission Creek. ET will also likely be sensitive to other effects of climate change, such as increased temperature or increased CO₂ availability; fortunately these changes are less difficult to forecast.

A finding with particular implications for urban environments was that, at annual and monthly time scales, the sensitivity of ET for the entire Mission Creek catchment to uncertainty in OWU inputs was comparable to uncertainty in soil parameters (Figure 7A), despite the fact that OWU inputs are only applied to developed portions of the catchment (~50% of total catchment area). These comparable levels of sensitivity are likely attributable to the water-stressed nature of the catchment and seasonal timing of precipitation. When soil water stores have been exhausted, as is consistently the case during the summer months, calibrated soil parameters can no longer exert a strong influence on ET. In a catchment where precipitation is more evenly distributed throughout the growing season, we would expect the sensitivity to uncertainty in calibrated soil parameters to exceed the model's sensitivity to OWU uncertainty.

Long-term mean ET was also substantially more sensitive to uncertainty in OWU than in precipitation scaling. Although OWU inputs are much lower than precipitation, the timing of peak OWU application coincides with peak vegetation demand. The impact of OWU inputs is also insensitive to prior wet season conditions, reflecting the temporal separation between peak periods of OWU and precipitation. In a climate where precipitation coincides more closely with the peak growing season, OWU might display greater sensitivity to precipitation, as watering rates would decline during a wet summer or increase during a dry one. In water-scarce areas such as the study site, it might be expected that watering restrictions could cause an

occasional precipitation-OWU connection if such restrictions were only implemented during very dry years. However, municipal water supplies in semi-arid areas are rarely dependent solely on local supplies. In Santa Barbara, for example, water can also be obtained via the California State Water Project. Thus, a drought would need to extend across a large region and last over multiple years before watering restrictions are implemented. In Mission Creek, the most recent watering restrictions occurred during the 1986–1991 period (County of Santa Barbara 2007). It was also interesting that our analysis found no sensitivity of runoff to OWU uncertainty. This finding was surprising as a study of another Southern California catchment found that baseflow levels had increased as a result of urbanization (White and Greer 2006). In this instance, our estimates of OWU show peak inputs occurring in the summer, when vegetative water demand is highest, meaning that OWU may be quickly taken up by vegetation before it can significantly impact baseflow. Finally, although OWU inputs are significant, they are still small compared to annual precipitation, and are inputted over only half of the catchment. We suspect that other water inputs resulting from urbanization, such as leaking sewer lines (which we do not currently model), would have a greater impact on runoff levels given their typically close proximity to stream networks.

Finally, sensitivity to uncertainty in temperature lapse rates was small despite the difference in VPD estimates derived from high- and low-elevation climate stations. These results suggest that for semi-arid systems, ET is rarely limited by VPD, unlike more humid systems or sites with different precipitation regimes where ET is more sensitive to fine-scale differences in temperature and VPD (Irmak and others 2006). Given that capturing spatial patterns of temperature lapse rates with dynamics of coastal fog is challenging, the finding that model predictions of ET and runoff are not sensitive to these small changes in temperature is reassuring. However, studies have shown that fog interception and direct uptake of fog water can be an important water source in semi-arid coastal ecosystems (Fischer and others 2009); this effect was not included in this model. Future work will investigate the potential magnitude of this effect.

In summary, we demonstrate that, for this semi-arid urbanizing catchment, key sources of uncertainty for ET estimates include soil parameters and outdoor water use. For these parameters, the sensitivity of ET estimates to uncertainty leads to biases in predictions that are on the same order of mag-

nitude as estimates of climate change impacts on vegetation water use in semi-arid environments (Tague and others 2009; Serat-Capdevila and others 2011). For example, Tague and others (2009) used the RHESSys model to estimate that a 4°C temperature increase would result in an average 10% change in mean annual ET for a semi-arid chaparral ecosystem. Sensitivity of long-term mean annual ET to soil parameter and OWU uncertainties in this study were 10 and 13%, respectively. Reducing uncertainty in OWU is likely to be more tractable than reducing uncertainty in soil parameters. In addition, its importance suggests that efforts to accurately quantify anthropogenic water inputs may be as or more important than accurately quantifying precipitation inputs. OWU estimates for developed areas could be improved with additional measurements, such as monitoring indoor/outdoor water use separately for a random sampling of households and using this data to refine estimates.

Given the high sensitivity observed for both ET and runoff, soil parameter uncertainty is also clearly a concern. However, as discussed earlier, soil properties are difficult to measure directly and are highly heterogeneous across most catchments. Significant reduction of uncertainty through improved soil data is therefore an unrealistic goal. Given this limitation, techniques such as the generalized likelihood uncertainty estimator (GLUE) approach (Beven and Binley 1992) can be used to provide upper and lower bounds on model predictions across a range of likely parameter/input uncertainty. The GLUE approach is widely used in hydrology to quantify the impact of parameter uncertainty on runoff estimates (for example, Choi and Beven 2007; Kumar and others 2010; Winsemius and others 2009), but has not had the same level of use in studies focused on using models to quantify vegetation response to environmental change.

Although ET showed relatively low sensitivity to event-scale precipitation uncertainty, the high sensitivity of runoff to precipitation uncertainty also has implications for calibrating soil-storage and -drainage parameters and thus indirectly for ET estimates. Because runoff estimates are highly sensitive to the precipitation scaling factor, calibration against daily streamflow will be sensitive to this uncertainty. Inaccurate estimates of precipitation scaling can bias the selection of soil parameters during calibration. This finding suggests that calibration focused only on matching observed runoff, particularly storm events, may not be ideal for selecting soil-drainage parameters in systems with

intense and episodic precipitation. For studies focused on ET, the highest sensitivity to soil drainage occurs during spring and early summer, suggesting that calibration of soil-drainage parameters should focus specifically on ET during this period. Ideally, estimates of ET derived from remote sensing data (Winsemius and others 2008) or eddy flux measurements could be used to calibrate the model, further reducing soil parameter uncertainty. In addition, using baseflow alone as an additional calibration metric (Cao and others 2006; Spruill and others 2000) could reduce soil parameter uncertainty, as baseflow will be less sensitive to uncertainty in individual storm events and more sensitive to soil properties and uptake of water by vegetation.

CONCLUSIONS

As water availability in semi-arid systems can strongly influence both vegetation growth (van Wijk 2011; Ochoa-Hueso and Manrique 2010; Austin and others 2004) and biogeochemical cycling (Xiang and others 2008; Miller and others 2005), accurately modeling ET is important in a broader ecological context. Our findings highlight the sensitivity of catchment-scale estimates of ET to uncertainty that is directly attributable to the strong seasonality and water-limited characteristics of coastal, semi-arid systems. As the catchment transitioned from a wet rainy season to a dry growing season and summer, sensitivity to sources of uncertainty also transitioned. Runoff shifts between high sensitivity to soil-drainage parameters and high sensitivity to precipitation uncertainty as the catchment wets up, whereas ET is most sensitive to calibrated soil parameters in the spring and shifts to high OWU sensitivity in the summer. The temporal disconnect between rainy and growing seasons limits the importance of storm-event precipitation uncertainty in modeling ET. However, precipitation uncertainty may influence selection of soil parameters and exert an indirect influence on modeled ET. The sensitivities of model output to soil parameter and precipitation uncertainty in particular highlight the utility of a GLUE-type approach, which allows the modeler to capture a spectrum of likely responses across a range of uncertainty and better quantify confidence in model predictions.

Our analysis highlights some of the characteristics of semi-arid, coastal, and urbanizing catchments that can impact eco-hydrologic modeling efforts. Sources of uncertainty not traditionally considered in hydrologic modeling, such as OWU, can exert a strong

control on vegetation water use in developed catchments. At the same time, precipitation uncertainty, a major source of uncertainty in runoff modeling, exerts a less direct influence on ET due to a combination of climate characteristics and anthropogenic management. However, some traditionally recognized sources of uncertainty, such as calibrated soil parameters, still exert a strong control on modeled ET, showing that despite the many structural differences in developed and undeveloped landscapes, there are areas of common challenge. Given the importance of hydrology to vegetation productivity and biogeochemical cycling in semi-arid ecosystems, reducing, and accounting for uncertainties that impact catchment hydrology are key to successfully capturing the broader ecological response that can be expected from these environments as they experience change.

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