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Comparison of the SAC-SMA and API-CONT Hydrologic Models at Several Susquehanna River Headwater Basins

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ABSTRACT

Hydrologic simulation comparisons were made between the Sacramento Soil Moisture Accounting (SAC-SMA) model and the Continuous Antecedent Precipitation Index (API-CONT) model for six Susquehanna River Basin (SRB) headwater basins. Using a 6-hour time step, the difference in cumulative simulation error (stage) between observations and model simulations was calculated over a 19-month period (August 2010-February 2012) to visualize event, monthly, and seasonal model trends. Next, simulated crests (stage) were compared to observed crests for five rain-driven events. Finally, Ensemble Streamflow Prediction (ESP) was used on a daily time scale to provide a long-term (1950-1998) perspective of model performance compared to historical high flow events. Results show that the SAC-SMA model consistently produced more accurate streamflow simulations in terms of the cumulative error in stage over time. However, we could not establish a distinct seasonality (i.e. wet or dry periods, snowmelt) pattern in which one model was consistently more accurate across all basins. The API-CONT model more accurately predicted large event (flood) crests based on the Probability of Detection (POD), False Alarm Rate (FAR), Critical Success Index (CSI), and bias verification statistics. Results suggest that use of the lumped SAC-SMA could improve upon the lumped API-CONT for low and medium flow forecasts, which may be particularly useful for longer lead time applications such as water supply management. However, no improvements would be expected for flood forecasts.

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1. Introduction

Thirteen regional River Forecast Centers (RFCs) within the National Weather Service (NWS) provide a suite of streamflow forecast products. The forecasts predict future stream height and flow and extend from hours (short-term) to months (long-term) into the future. The forecasts aid the general public, community leaders, emergency managers, and reservoir/hydropower managers in making better life- and cost-saving decisions.

Two primary hydrologic (i.e. rainfall-runoff) models, the Sacramento Soil Moisture Accounting (SAC-SMA) model and the Continuous Antecedent Precipitation Index (API-CONT) model, are used within RFCs to produce daily streamflow forecasts. Currently, most implementations of these models are lumped (not distributed) and run operationally on a 6-hour time step. A lumped modeling approach assumes uniformly distributed precipitation and/or melt in both time and space across defined watersheds. Distributed hydrologic models involving non-homogenous watershed characteristics are currently used for developing flash flood guidance but are not widely used for point forecasting on larger rivers. RFCs commonly use hydrologic routing techniques to route flows from headwater sub-basins to downstream points. Where necessary to account for dynamic hydraulic effects, RFCs also use the U.S. Army Corps of Engineers (USACE) Hydrologic Engineering Centers River Analysis System (HEC-RAS) unsteady flow model. During the cold season, a snow accumulation and ablation model (SNOW-17), described by Anderson and Crawford (1964), Anderson (1968), and Anderson (1973), is coupled with the API-CONT and SAC-SMA models to represent and compute physical snowpack processes (i.e. snow water equivalence, snowpack accumulation and melt).

The NWS Middle Atlantic River Forecast Center (MARFC) is currently the only RFC to use the API-CONT model for streamflow prediction. The API model was originally developed by Linsley et al. (1949) to be applied on an event by event basis. In API models, soil moisture gain is tracked by an Antecedent Precipitation Index, which is adjusted for seasonal variations in evaporation and transpiration to produce an estimate of runoff for a given rainfall/melt. The API model consists of empirical relationships derived from historical precipitation, potential evapo-transpiration (PE), and streamflow data, and generates storm runoff based on antecedent moisture conditions, a seasonality function, storm duration and total precipitation (Smith et al. 2000). A continuous API-type model was developed by Sittner et al. (1969) in order to accommodate the need for longer-term water-management forecasts and eliminate some of the calibration challenges involved with an event-based API model. The MARFC API-CONT model is an adaptation of the Sittner et al. (1969) model (NWS, 2013). The API-CONT model computes runoff on an incremental (continuous), not a storm, basis and generates both surface and baseflow runoff amounts.

The SAC-SMA model was initially developed by Burnash et al. (1973) and is used operationally by the remaining 12 RFCs. The model is conceptual and represents the soil profile as a system of two layers (zones), each having a tension water and one or more free water components or reservoirs (Smith et al. 2000). Applied moisture is distributed in a physically realistic manner within the various zones and energy states in the soil, allowing for the preservation of rational percolation characteristics.

The API-CONT and SAC-SMA hydrologic models can be used in conjunction with user-specified modifications (MODS) to account for non-standard conditions and to keep the model states on track (Smith et al. 2000). Warm season model modifications common between both models include the ability to change precipitation amount, runoff volume, and baseflow. Common modifications when using SNOW-17 with either of the two rainfall-runoff models include changing precipitation type (rain or snow), snowmelt rate, snow covered area, and snow water equivalent amount.

The MARFC is considering switching from the API-CONT model to the SAC-SMA model. Incorporating the SAC-SMA model into MARFC forecasting offers several potential advantages. These include: (1) better RFC homogeneity regionally and nationally, (2) increased NWS Office of Hydrologic Development (OHD) and NWS hydrologic contractor support and, (3) receiving, implementing, using new science/technology faster. Costs and calibration time required to implement the SAC-SMA are potential disadvantages that must also be considered. Based on the Northeast River Forecast Center's (NERFC) experience in switching to the SAC-SMA model, a full MARFC transition would likely take at least five years and cost over one million dollars in RFC personnel time or contractor costs (Rob Shedd, NERFC). A better investment may be exploring improved modeling approaches including distributed models. This study does not attempt to weigh these considerations. Rather, the purpose of this study is to help inform MARFC's future modeling decisions via a comparison evaluating the operational performance advantages and disadvantages of both hydrologic forecast models in the Mid-Atlantic region.

More specifically, two primary goals were established at the beginning of this project. First, we wanted to compare the difference in effort needed for maintaining the model states between the two models on an operational (i.e. daily) basis. The second goal was to compare the simulation accuracy of the two models. In this region, flood events dominate the hydrologic forecast focus, not typically drought or low flow conditions, as in other regions of the country where water supply management issues are more common. For this reason, more attention was given to model simulations during high flow events in this study, and less consideration was given to low and medium flow periods.

Six MARFC headwater forecast points in the Susquehanna River Basin (SRB) were used in this study (Fig. 1, Table 1). Each of the six MARFC forecast points is represented by an operating United States Geological Survey (USGS) stream gauge which defines the outlet of each basin. Hydrologic model (API-CONT/SAC-SMA) basin parameters used in this study were calibrated using observed stage/flow data from the USGS stream gauge located at the outlet of each basin. Model performance in this study was evaluated by comparing each model simulation with observed flow/stage at the USGS stream gauge location.

The SRB has a non-tidal influenced drainage area of approximately 27,000 square miles and covers parts of the states of New York, Pennsylvania, and Maryland. Six major sub-basins comprise the SRB: North Branch, Chemung, Upper Main Stem, West Branch, Juniata, and Lower Main Stem. The Susquehanna River is the longest, commercially non-navigable waterway in the U.S., and is the largest tributary to the Chesapeake Bay, supplying roughly 50% of its freshwater inflow (SRBC, 2012). The combination of climate, terrain, and floodplain development make the SRB one of the Nation's most flood-prone areas. Widespread floods are most common during the spring snowmelt and tropical seasons, but flooding can occur anytime during the year (Fig. 2).

Note that "flooding" at a given location depends not only on the hydroclimatology and hydrology of the basin, but also on the NWS flood stage at the outlet which is a function of flood impacts on humans. The SRB has an average annual precipitation of approximately 40 inches. All six headwater points in this study have a drainage area less than 500 square miles and normally crest within 24 hours after a rainfall event begins.

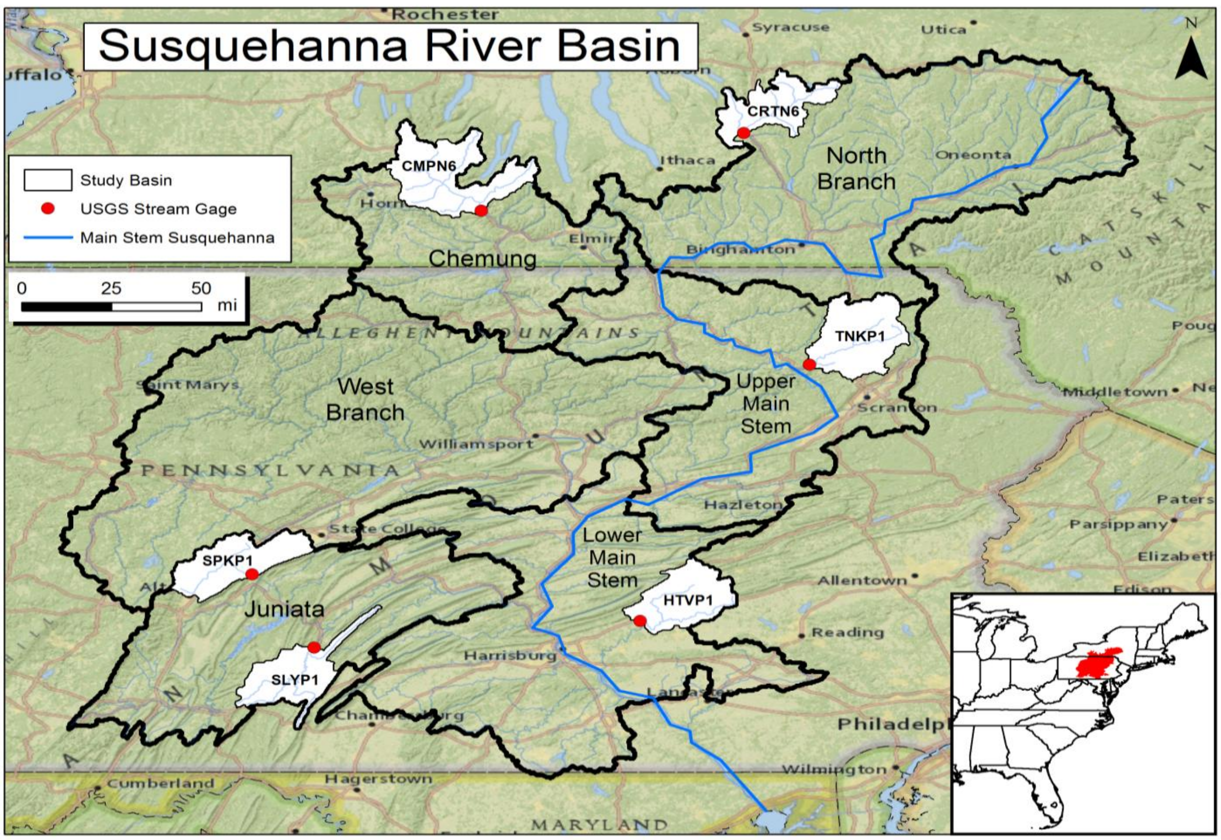

Figure 1. Map showing SRB, study basins, and USGS gauges included in the study.

Table 1. SRB NWS daily streamflow forecast points and sub-basins included in the study.

NWS Forecast Point	Susquehanna Sub-Basin	Stream	State	Crest Time (hr)	Area (mi^2)	Gauge Elevation (ft)	NWS ID	USGS ID
Campbell	Chemung	Cohocton River	NY	18	470	1,016	CMPN6	01529500
Cortland	North Branch	Tioughnioga River	NY	24	292	1,085	CRTN6	01509000
Harper Tavern	Lower Main Stem	Swatara Creek	PA	18	337	357	HTVP1	01573000
Shirleysburg	Juniata	Aughwick Creek	PA	24	301	570	SLYP1	01564512
Spruce Creek	Juniata	Little Juniata River	PA	12	220	751	SPKP1	01558000
Tunkhannock	Upper Main Stem	Tunkhannock Creek	PA	12	383	610	TNKP1	01534000

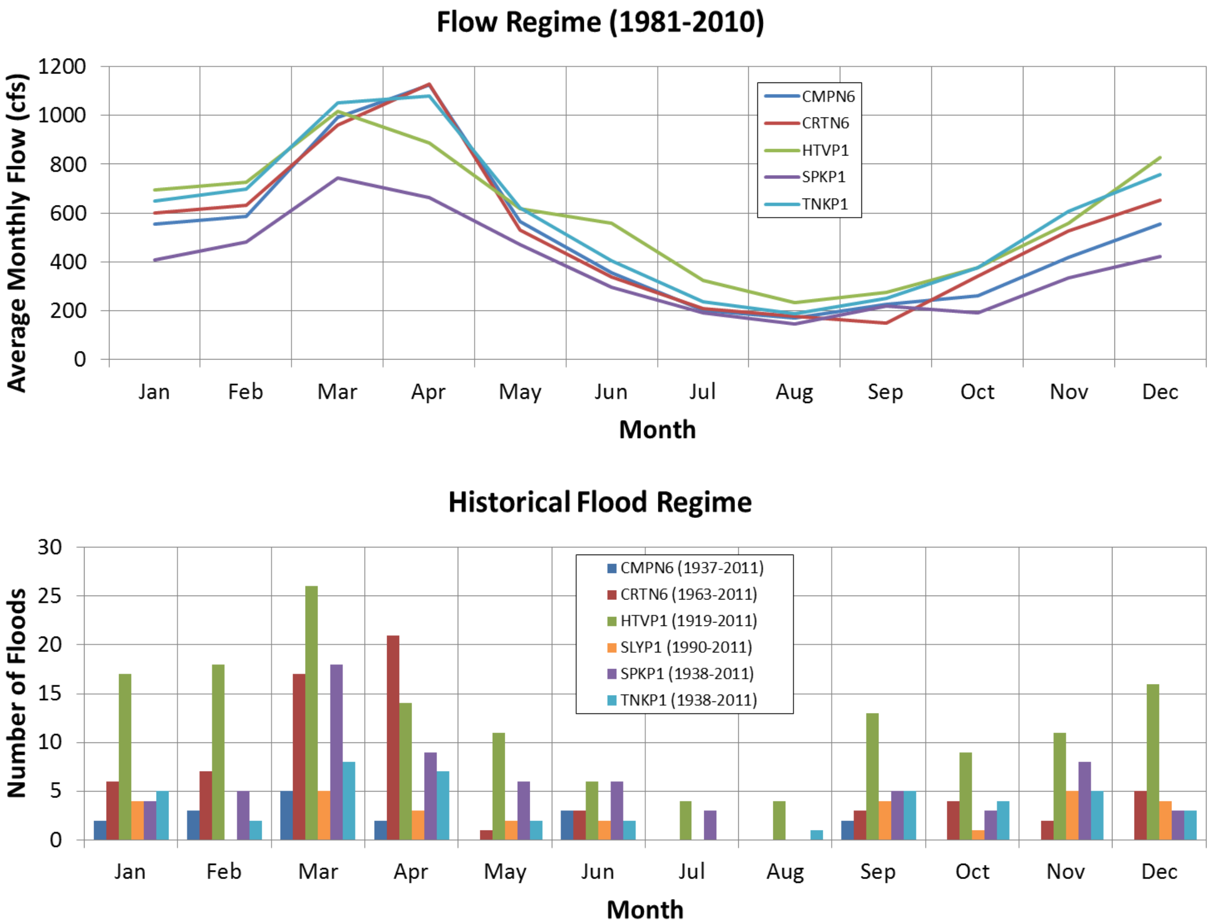

Figure 2. Historical (a) flow regime and (b) flood regime of the basins included in the study. Note that Fig. 2a excludes stream gauge SLYP1 due to its short period of record.

2. Data and Methodology

To gain an operational perspective on the similarities and differences between model components, a senior hydrologist familiar with the API-CONT model applied user-specified MODS to both models. MODS were made on an event basis and only if they were considered necessary by the hydrologist. The differences, challenges, and knowledge required to maintain model states for each of the two models were noted. The hydrologist had limited knowledge of the SAC-SMA model parameters and characteristics. This part of the study was used only to acquire a basic understanding of model response to user-specified MODS and to compare the effort required to similarly maintain the states of both models. However, the "modified simulations," although generated, were not used in this study to quantify the hydrologic performance of the two models. Rather, only "pure simulations" (i.e., no MODS) were used, thereby eliminating any potential forecaster bias.

For quantitative analysis, three streamflow data types were used - USGS stream gauges provided observed data (streamflow and stage; http://www.usgs.gov/water/), while simulated runoff from the two models (API-CONT and SAC-SMA) were used as predicted data. Using the basin unit hydrograph and gauge rating curve, simulated runoff is converted to a simulated flow and stage at the gauge location. The simulation performance of the two hydrologic models was assessed using three different methods over varying time scales. Each of the three methods is discussed in more detail in following paragraphs. In all analyses, model simulations used identical observed mean areal precipitation and mean areal temperature (MAT) forcings. Prior to the actual analysis period (August 2010 through February 2012), both models were run for a minimum of three months to initialize the model states. Model simulations were made using radar-based (derived) Mean Areal Precipitation (MAPX) on a six-hour time scale. MAPX data are created using both radar estimated precipitation and gauge observations. MARFC started using MAPX as the default input precipitation for all daily forecast points in November 2008. Prior to then, MARFC used gauge-based (derived) Mean Areal Precipitation (MAP) on a six-hour time scale as the default input precipitation. Although sometimes forecasters will choose to use MAP data in operations because there can be differences between MAPX and MAP that vary seasonally, we chose to use the MAPX data for the 2010-2012 period in this study because it is the best available for most of the period. For the period 1950 through 1997, "historical" simulations were made using Mean Areal Precipitation (MAP) since MAPX data were not available. MAP data use~~s~~ only precipitation gauge observations and do~~es~~ not include radar-estimated precipitation. Note that both the API-CONT and SAC-SMA models were calibrated using MAP data, so any differences in calibration and validation forcings will be the same for both models. For reference, both Cognitore (2005) and Zhang et al. (2010) report on differences between MAP and MAPX in the MARFC data archives.

Important API-CONT and SAC-SMA calibration differences exist in our study. First, the API-CONT model was calibrated for each of the six sub-basins by several MARFC hydrologists over time. Furthermore, the MARFC's primary goal is to most accurately forecast large event (flood) crests. Because of this, the calibrated model parameters tend to be skewed toward high flow events and are consequently less effective in lower flow events. Second, Riverside Technology, inc. (RTi) was tasked with calibrating the SAC-SMA model for use in this study (RTi, 2009). Unlike MARFC's calibration approach, RTI's calibration procedure focused on generating the best overall calibration statistics and was not skewed toward high flow events. RTi's calibration process included developing new unit hydrographs more compatible with the SAC-SMA model's treatment of surface vs. baseflow runoff. In picking events, RTi generally used the following criteria in developing unit hydrographs during their calibration process: (1) an event should be isolated from other events and ideally, there should be several dry days prior to and after the precipitation event, resulting in a smooth and continuous hydrograph with minimal interference from other events, (2) an event should be free from obvious measurement noise, (3) 'medium-sized' events were preferred for analysis, (4) multiple-peaking events should not be used because they are indicative of non-constant runoff rates, and (5) events that are influenced by ice storms or snowmelt should not be used. RTI's evaluation of SNOW-17 and SAC-SMA model parameters was based on the visual closeness of individual observed and simulated hydrographs as well as overall simulation error statistics. During RTi's calibration phase, multiple calibrators reviewed parameters and statistics and worked together to attain appropriate parameter sets. RTi calibrated five of the six sub-basins included in this study (Cortland, Harper Tavern, Shirleysburg, Spruce Creek, and Tunkhannock). The SAC-SMA calibration for Campbell was performed by two MARFC hydrologists during a brief familiarization exercise and is therefore considered incomplete, having not undergone the same rigorous calibration techniques used by RTi. However, Campbell SAC-SMA simulations were still included in this study for comparison purposes.

The first quantitative method that compared the two model simulations used a cumulative simulation error approach. For each of the six streamflow gauges, simulated stream height (stage) was compared to observed stage using a 6-hour time step from August 2010 to February 2012 (19 months), and the respective absolute errors were computed and accumulated over the study period. The benefit to using this approach is that it provides visual insight on model behavior on multiple time scales (i.e. events, wet/dry periods, and seasons). Next, the difference in cumulative simulation error values between models was calculated at each time step, providing an error difference time-series. The slope of the difference time-series is significant because based on whether the slope of the time-series line is positive or negative indicates which model performed better during a particular event, wet/dry period, or season.

The second method made crest comparisons at each streamflow gauge. First, simulated crests (stage and flow) for each model were compared with observed crests for five events from August 2010 to February 2012 (19 months). Events were chosen based on magnitude and precipitation type. The five largest events in which rain was the sole precipitation type (with no snow melt effects) were evaluated at each of the six streamflow gauges independently. Instantaneous (15-minute) observed crest data was compared with 6-hour simulated crest data. Next, a contingency table was used to describe the distribution of simulations and observations in terms of categorical (i.e. flood vs. no flood) frequency (Table 2). Only flood (observed and/or simulated) occurrences within the five chosen events at each gauge were considered for the contingency table. The calibration period for each model did not include the five events used for crest comparisons in this study. Therefore, evaluating each hydrologic model simulation during the five high flow events provided independent verification information.

For the crest analysis comparison, numerous verification statistics were calculated and expressed in percentages (multiplied by 100). Probability of Detection (POD or hit rate) is the proportion of observed floods that were simulated to be floods. POD values (scores) range from 0 (worst) to 100 (perfect). False Alarm Rate (FAR) is the proportion of simulated floods that were not observed to be floods, and values range from 0 (perfect) to 100 (worst). Critical Success Index (CSI or threat score) is the proportion of correctly simulated floods over all floods, either simulated or observed. CSI values range from 0 (worst) to 100 (perfect). Bias is the ratio of all simulated floods over all observed floods. Bias scores range from 0 (low bias) to ∞ (high bias), with a value of 100 being perfect. Model simulation verification scores provided valuable comparison statistics for numerous flood events across multiple gauges.

$$POD = a / (a+c) \qquad (1)$$

$$FAR = b / (a+b) \qquad (2)$$

$$CSI = a / (a+b+c) \qquad (3)$$

$$Bias = (a+b) / (a+c) \qquad (4)$$

Where a, b, and c are defined in the contingency table (Table 2).

Table 2. Contingency table used to calculate the simulated verification scores.

		Event Observed		
		Yes	No	Total
Event Simulated	Yes	a	b	a + b
	No	c	d	c + d
	Total	a + c	b + d	a + b + c + d = n

A two-sample t-test was used for the crest comparison analysis to determine the probability (p-value) that the simulated crest error from one model was significantly different from the simulated crest error of the other model. For the test, a t-value is calculated and compared with a standard table of t-values to determine whether the t-statistic reaches a certain threshold of statistical significance. The two-sample t-test was performed including the Campbell gauge (n = 30 events) and excluding the Campbell gauge (n = 25 events). The absolute value of the simulation error was used for each model during all events.

$$t = (x_1 - x_2) / \sqrt{(s_1^2/n_1 + s_2^2/n_2)} \qquad (5)$$

where:

x = the average model simulation error for all events
s = the standard deviation of the model simulation error for all events
n = total number of events

Finally, for the third method of quantitative comparison, the NWS Extended Streamflow Prediction Analysis and Display Program (ESPADP) was used to compare the hydrologic model simulations on a historic (>30 years) time frame. ESPADP was originally developed to produce probabilistic long lead-time conditional hydrologic model simulations over a user-specified time period for water supply forecasting. ESPADP also has the capability to generate daily historic model simulations for each year of available record using historical observed forcings (MAP/MAT/PE/snow melt). For this study, ESPADP was used to compare model exceedance probability curves with the observed exceedance probability curve at each gauge. For our application, we used the ESPADP option to select the maximum daily flow value in each historical year and then used those values to create an exceedance probability plot. We plotted these exceedance curves for both simulated and observed data. This method is an efficient way to compare simulated and observed flows for numerous (~50) high flow events across many years. Since ESPADP simulations are based on average daily flow, the crest (peak flow) is not captured, which may lead to different results than the crest analysis comparison.

3. Results

a) Maintaining Model States

As stated earlier, a senior hydrologist familiar with the API-CONT model applied user-specified modifications (MODS) to both models on an event basis but only if they were considered necessary. The hydrologist who generated the MODS noted that in general the effort required to maintain model states within each of the two models was similar. Since the hydrologist had only limited knowledge of the SAC-SMA model parameters and characteristics, there was a learning curve associated with making MODS using the SAC-SMA model as well as determining what the effects of those MODS were. However, once a comfort level was achieved, the actual effort in keeping the model states similar for the two models was comparable. More active hydrometeorological periods naturally require more maintenance (i.e., more MODS) in each model, while during less active periods the hydrologist found that the SAC-SMA seemed to require less maintenance than the API-CONT model. In summary, the hydrologist noted no significant difference in terms of time, effort or degree of complexity related to maintaining the model states of each of the two models.

b) Simulation Performance - Cumulative Simulation Error and Error Difference Time Series

Cumulative simulation error results can be interpreted as follows. First, colored lines (API-CONT=blue, SAC-SMA=red) representing modeled cumulative simulation error were plotted over the observed (black) time series (Figs. 3a-8a). The line with the smallest cumulative simulation error at the end of the time series is the more accurate model over the 19-month period (August 2010 through February 2012). Next, the difference in simulation error (red line minus blue line) between both models was calculated and provided an error difference time series (green line; Figs. 3b-8b). The green line has a positive slope when the API-CONT is more accurate and a negative slope when the SAC-SMA model is more accurate. The steepness of the error difference time series should also be considered. The models are in general agreement when the error difference time-series is horizontal. A steep, positive slope indicates a period when the API-CONT model outperformed the SAC-SMA model. A steep, negative slope indicates a period when the SAC-SMA model outperformed the API-CONT model. A bump in the error difference time series indicates an event in which the API-CONT was more accurate while a dip indicates an event when the SAC-SMA was more accurate. The cumulative simulation error and error difference time series are plotted with the observed time series to provide visual analysis of daily model performance for the length of study period.

Overall, the SAC-SMA model was more accurate over the 19-month period at five of the six gauges using the cumulative simulation error method. Campbell was the only location where the API-CONT model outperformed the SAC-SMA model, and this was likely due to the lower quality SAC-SMA calibration process mentioned earlier. However, we could not determine a consistent pattern in which one model outperformed the other at all gauges during a particular season. Instead, results suggest that both models simulate streamflow similarly the majority of the time (i.e. horizontal or relatively flat slope error difference time-series). Our results compare favorably with RTi’s calibration report (RTi, 2009) – that in most cases, the SAC-SMA model is able to simulate the cumulative water balance more accurately than the API-CONT model.

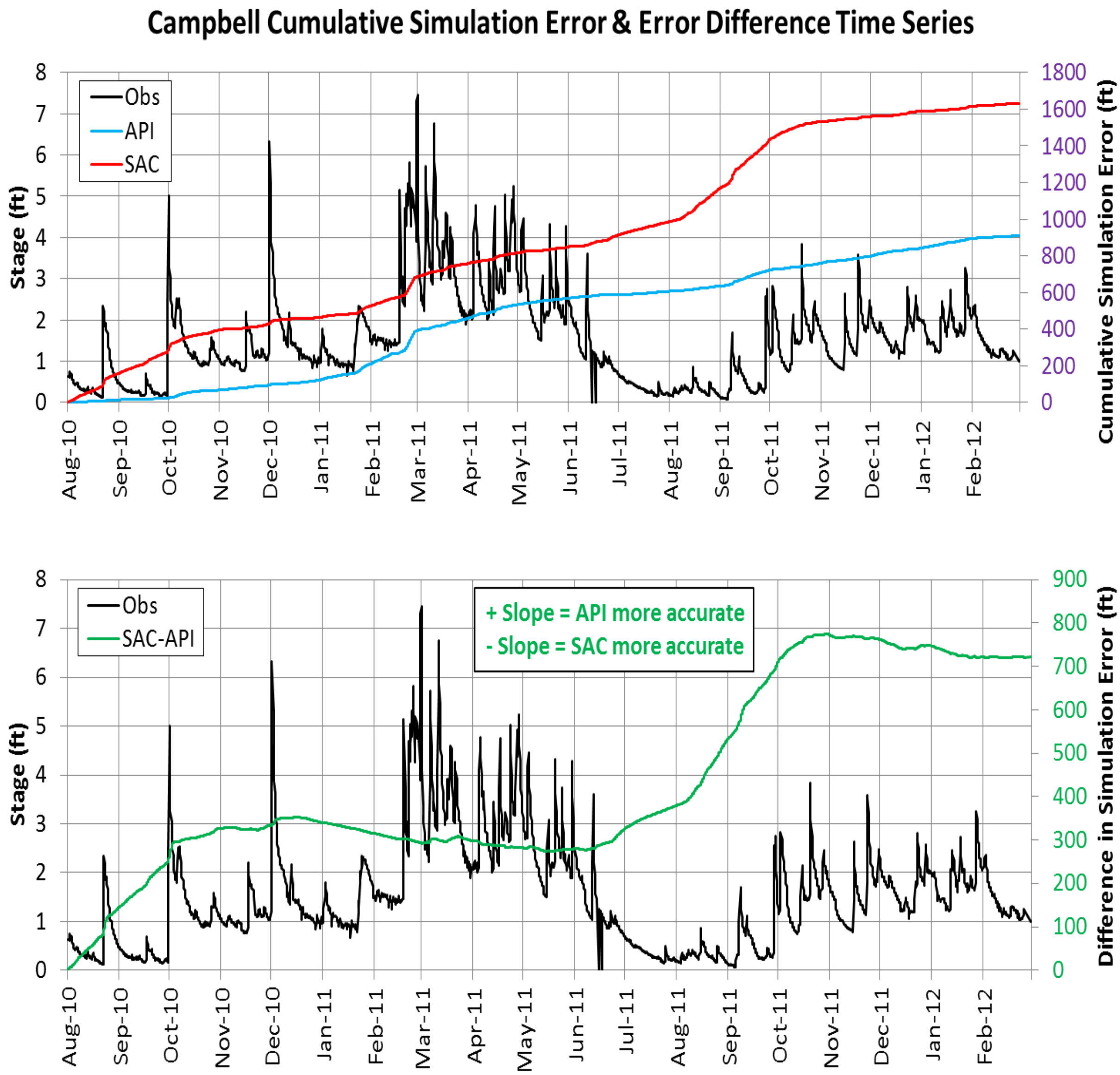

Figure 3. Campbell simulation results. (a) Cumulative simulation error: the API-CONT model had lower simulation error over time; (b) Error difference time series: the models were in general agreement for most of the study period. The API-CONT model outperformed the SAC-SMA model for the July-October months.

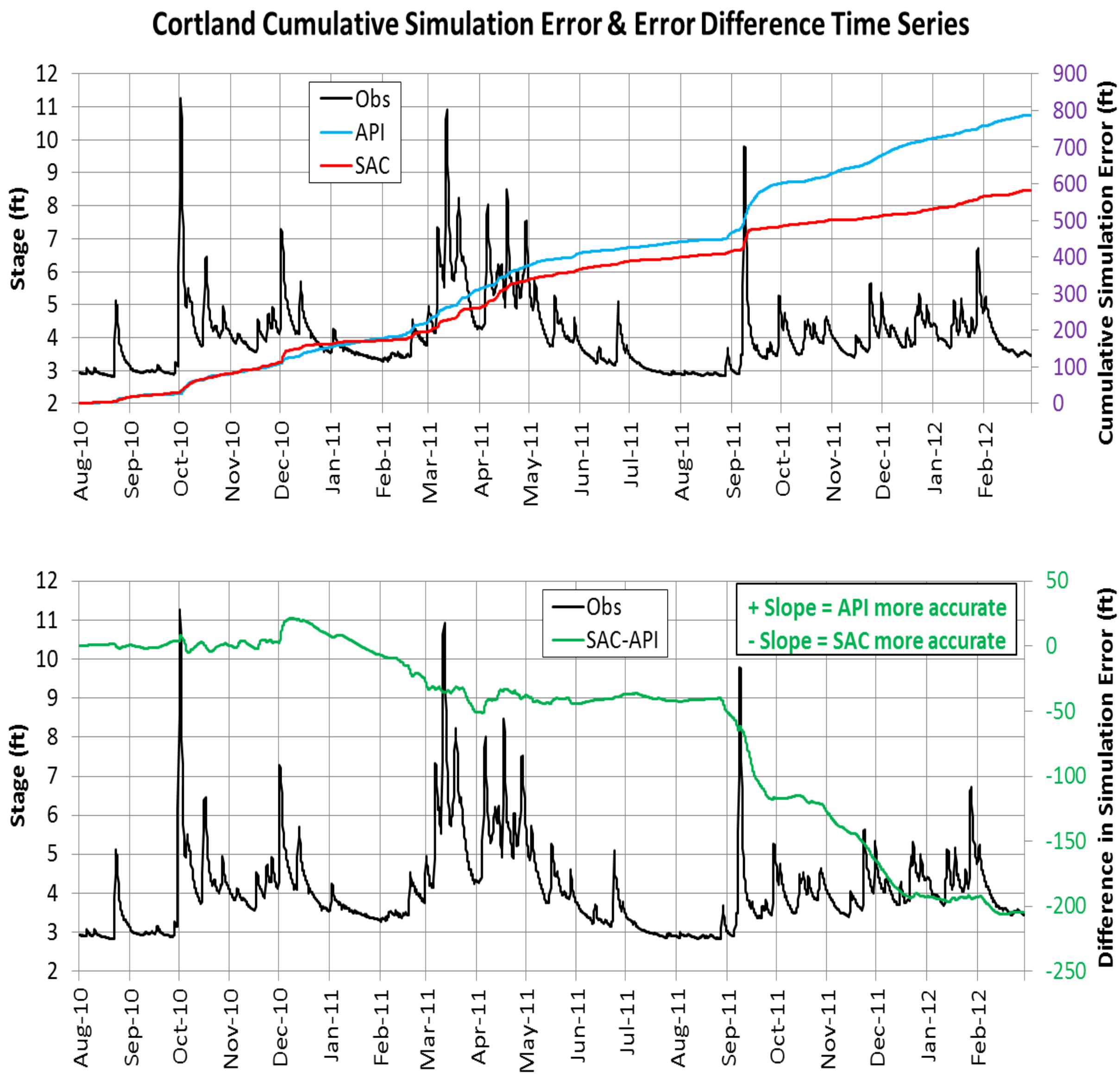

Figure 4. Cortland simulation results. (a) Cumulative simulation error: the SAC-SMA model had lower simulation error over time; (b) Error difference time series: the models were in general agreement for most of the study period. The SAC-SMA model outperformed the API-CONT model from September 2011 through December 2011.

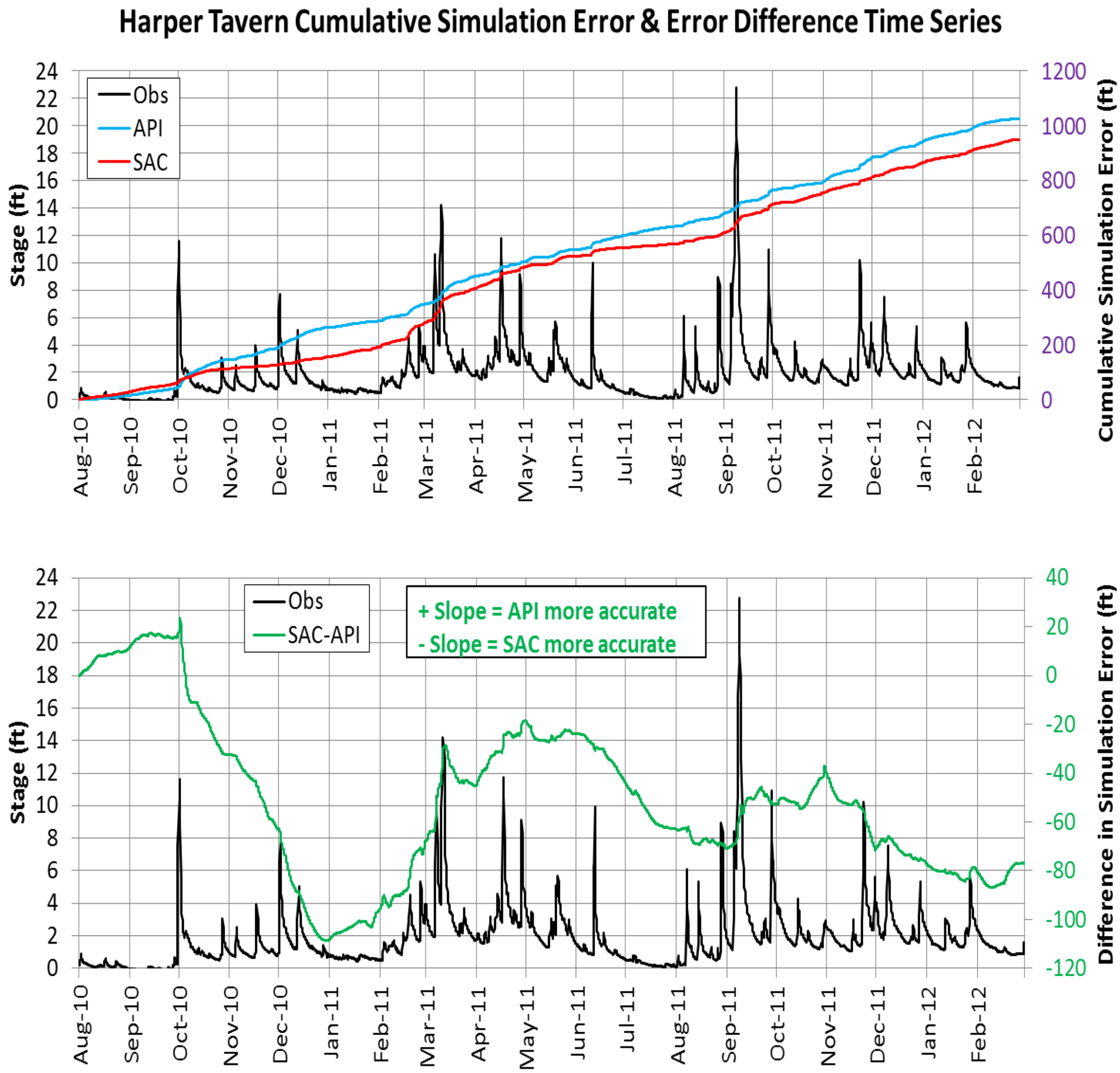

Figure 5. Harper Tavern simulation results. (a) Cumulative simulation error: the SAC-SMA model had slightly lower simulation error over time; (b) Error difference time series: model seasonality patterns were unclear.

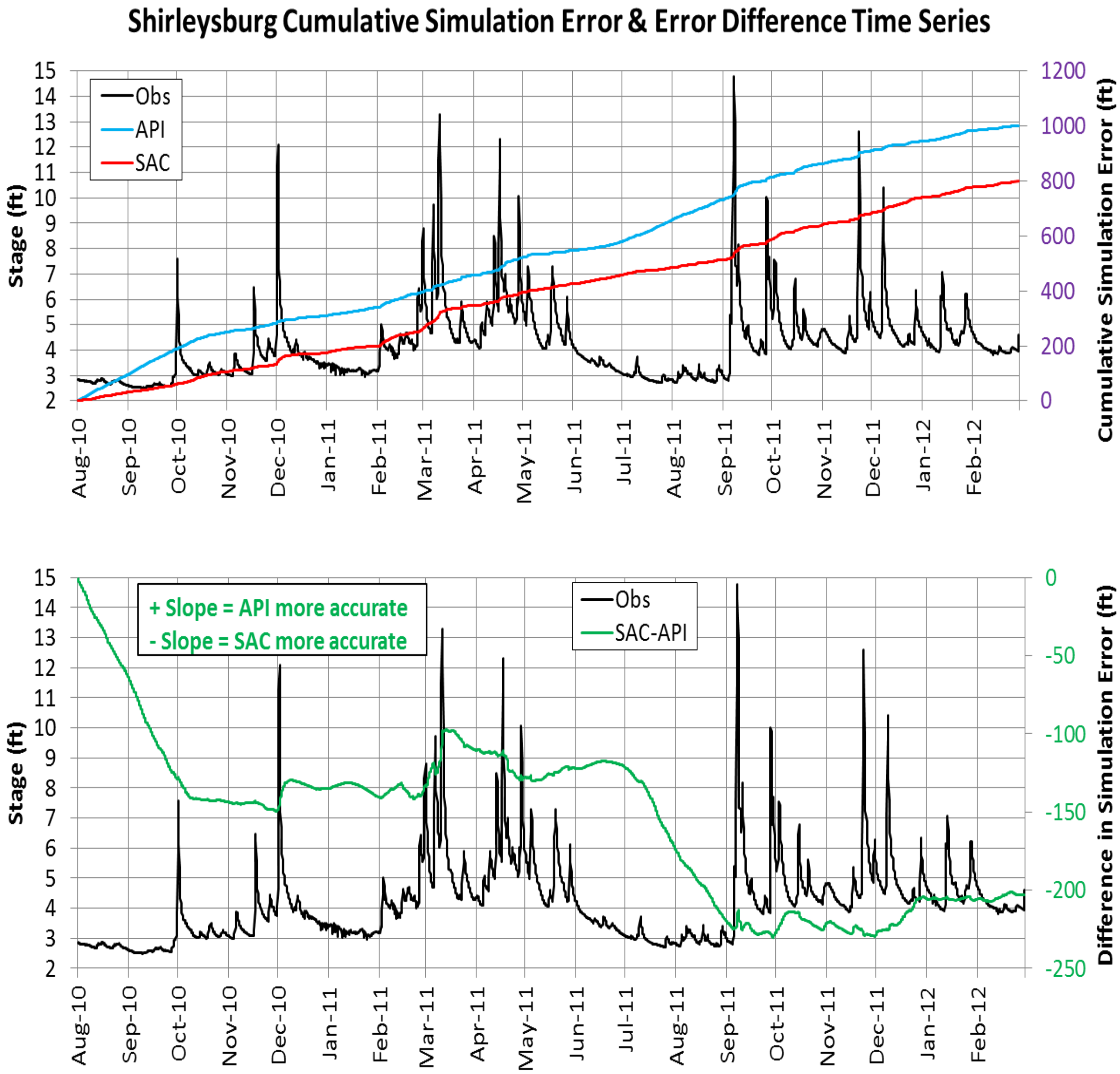

Figure 6. Shirleysburg simulation results. (a) Cumulative simulation error: the SAC-SMA model had lower simulation error over time; (b) Error difference time series: the models were in general agreement for most of the study period. The SAC-SMA model outperformed the API-CONT model for the late summer/early fall months.

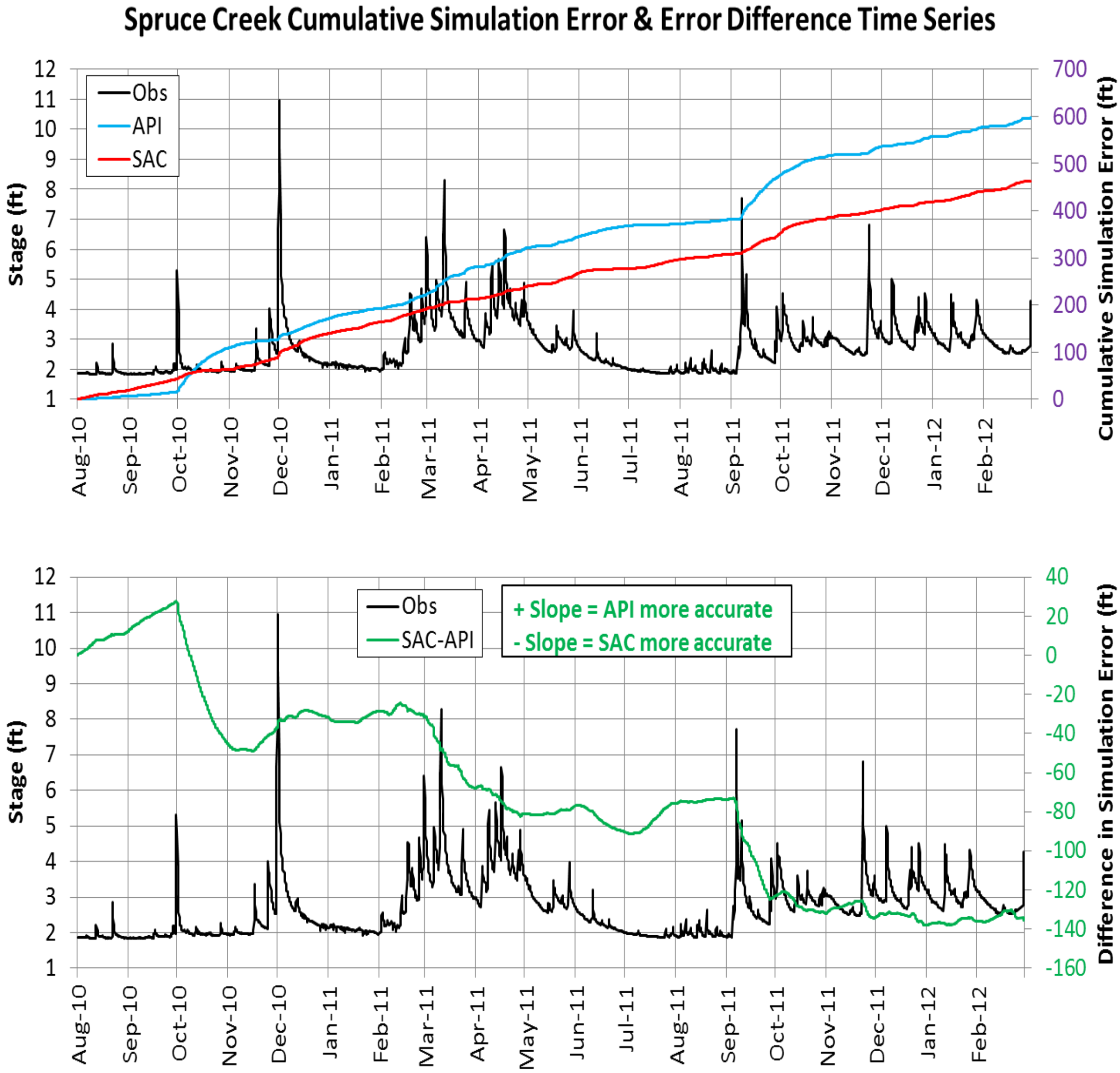

Figure 7. Spruce Creek simulation results (a) Cumulative simulation error: the SAC-SMA model had lower simulation error over time; (b) Error difference time series: the models were in general agreement for most of the study period. Model seasonality patterns were unclear.

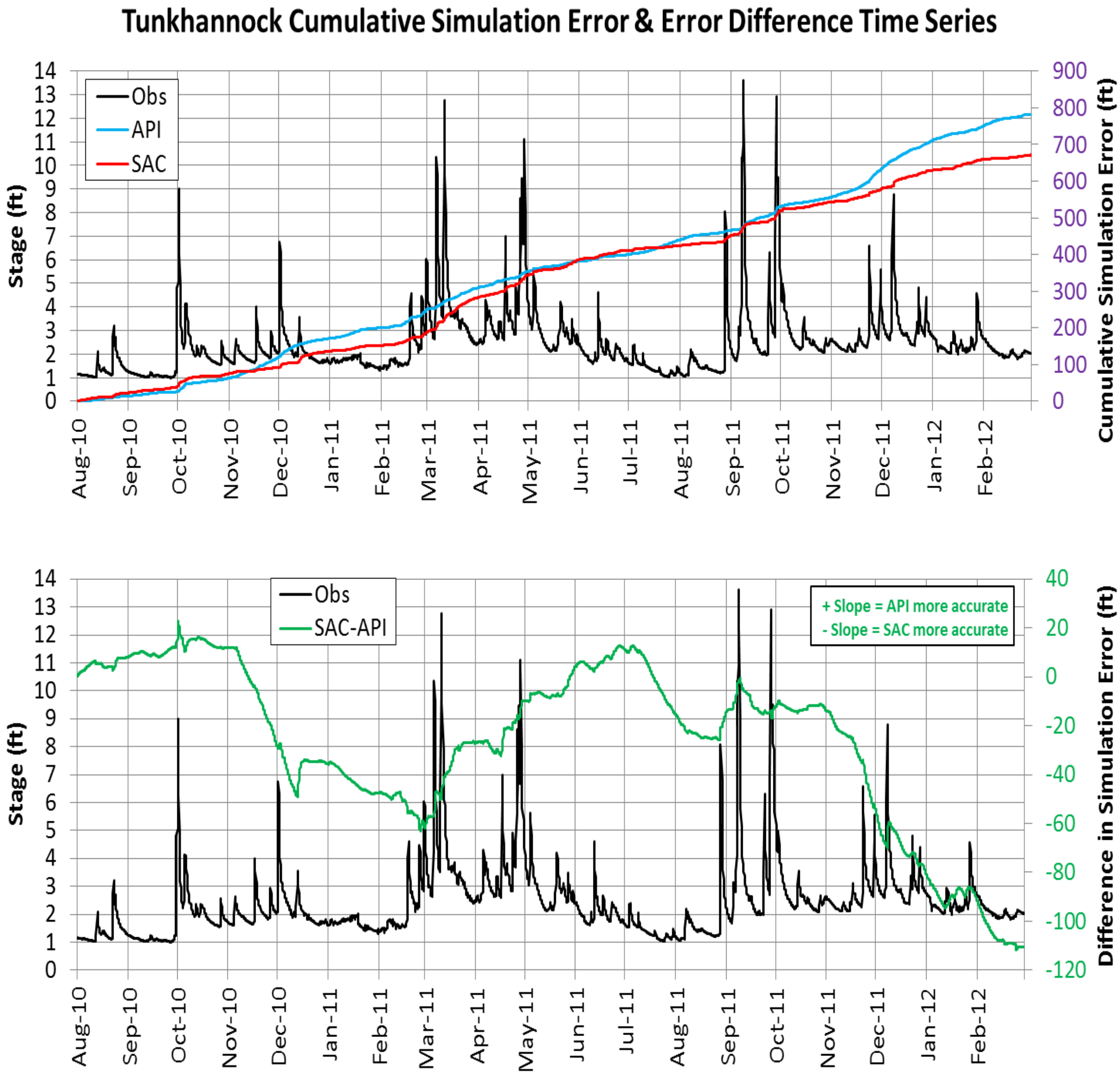

Figure 8. Tunkhannock simulation results: (a) Cumulative simulation error: the SAC-SMA model had slightly lower simulation error over time; (b) Error difference time series: the SAC-SMA model outperformed the API-CONT model during winter months (November-February). The API-CONT model outperformed the SAC-SMA model during snowmelt and early summer months (March-June).

c) Simulation Performance - Crest Analysis

The five largest rain-dominant events were chosen for each basin (independently) from August 2010 to February 2012. All chosen events were common for at least two of the basins and included: Tropical Storm Nicole (October 2010), an early December 2010 rain event, a cold heavy rain event (March 2011), an early summer rain event (April 2011), Tropical storm Lee (early September 2011), a non-tropical event (late September 2011), and a late fall event (November 2011). The Campbell gauge did not experience any observed flooding during the 19-month period. However, at the other five gauges, a minimum of two of the five chosen events were flood events and many times at least four of the five chosen events were flood events. As an example, the procedure for choosing the events and computing the verification statistics are shown in Figure 9 at the Harper Tavern gauge. The average absolute simulated crest error for each model was computed for all events at each gauge and is provided in Table 3.

In summary, the API-CONT model had a lower average simulated error at all gauges (Table 3). In Figure 10, the 'crest' verification statistic was based on all chosen events and indicated the percent of time that each model simulated the crest more accurately. The POD, FAR, CSI, and Bias statistics required either observed or simulated flooding to occur, which represented 25 of the 30 events when the Campbell gauge was included (Fig. 10a) and 22 of 25 events when the Campbell gauge was excluded (Fig. 10b). When including the Campbell gauge in the analysis, the API-CONT model outperformed the SAC-SMA model for all of the event verification statistics. Excluding the Campbell gauge in the analysis resulted in improved SAC-SMA verification statistics, but the API-CONT model still outperformed the SAC-SMA model for all of the event verification statistics except FAR. Furthermore, the two-sample t-test indicates that the difference in API-CONT and SAC-SMA simulation errors is statistically significant. Including the Campbell gauge resulted in a p-value < 0.02, meaning there is a 98% probability that the API-CONT outperformed the SAC-SMA model during the 30 selected crest events. Excluding the Campbell gauge resulted in a p-value < 0.05, meaning there is a 95% probability that the API-CONT outperformed the SAC-SMA model during the 25 crest events. The API-CONT model most likely outperforms the SAC-SMA model during high flow events due to the previously mentioned difference in calibration approaches. Our results agree with RTi's calibration report - that MARFC's current API model often provides similar or better simulations of large precipitation events.

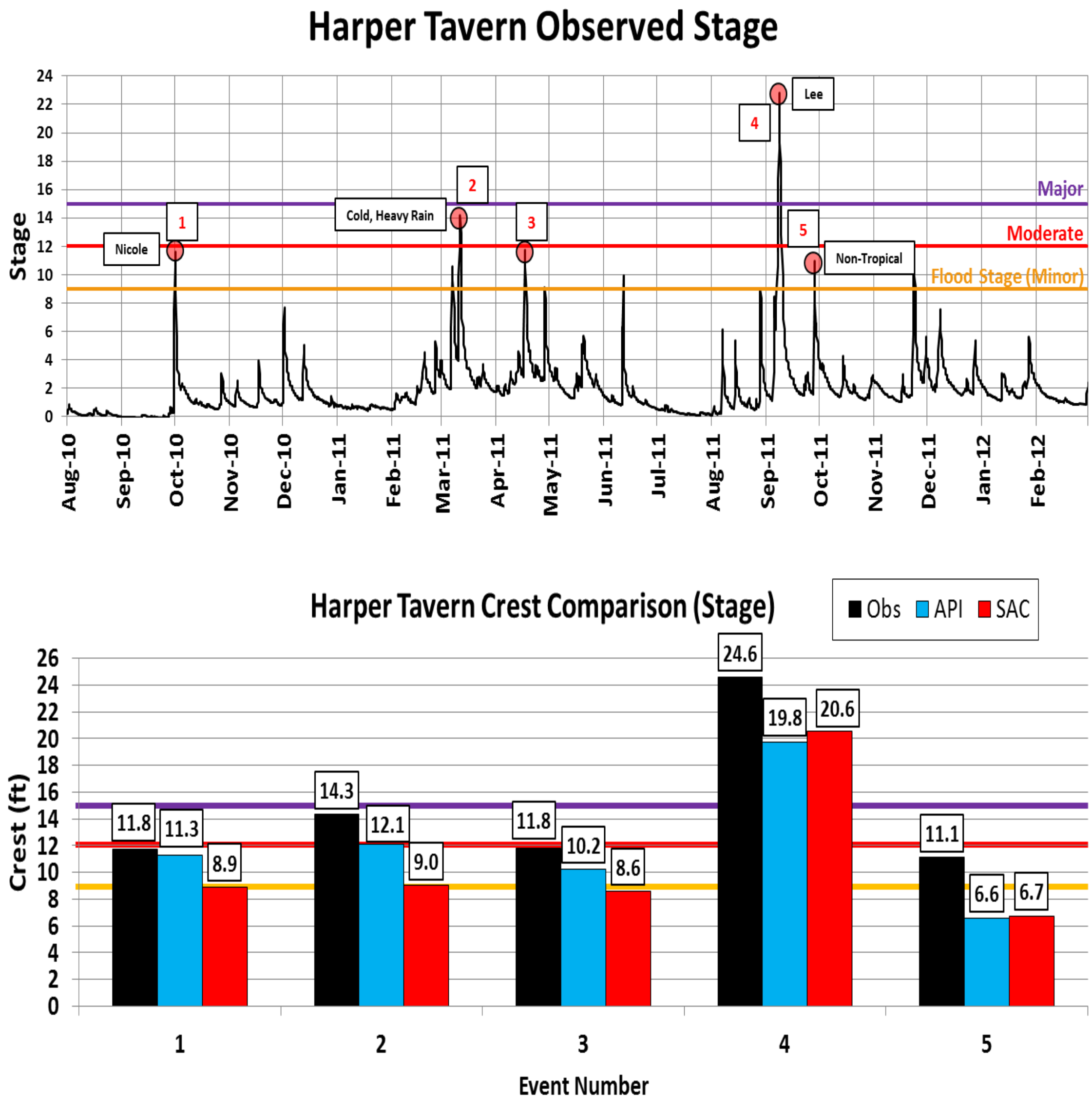

Figure 9. Choosing the five largest rain driven events at the Harper Tavern gauge. (a) Five chosen events which were all flood events. (b) Crest comparison results (Observed = black, API-CONT = blue, SAC-SMA = red). A similar procedure was used at all gauges.

Table 3: Average absolute crest error (ft) for the 5 chosen events at each gauge.

Location	API-CONT	SAC-SMA
Campbell	0.57	1.60
Cortland	0.98	2.09
Harper Tavern	2.71	3.95
Shirleysburg	1.46	3.08
Spruce Creek	1.36	1.63
Tunkhannock	1.59	1.87

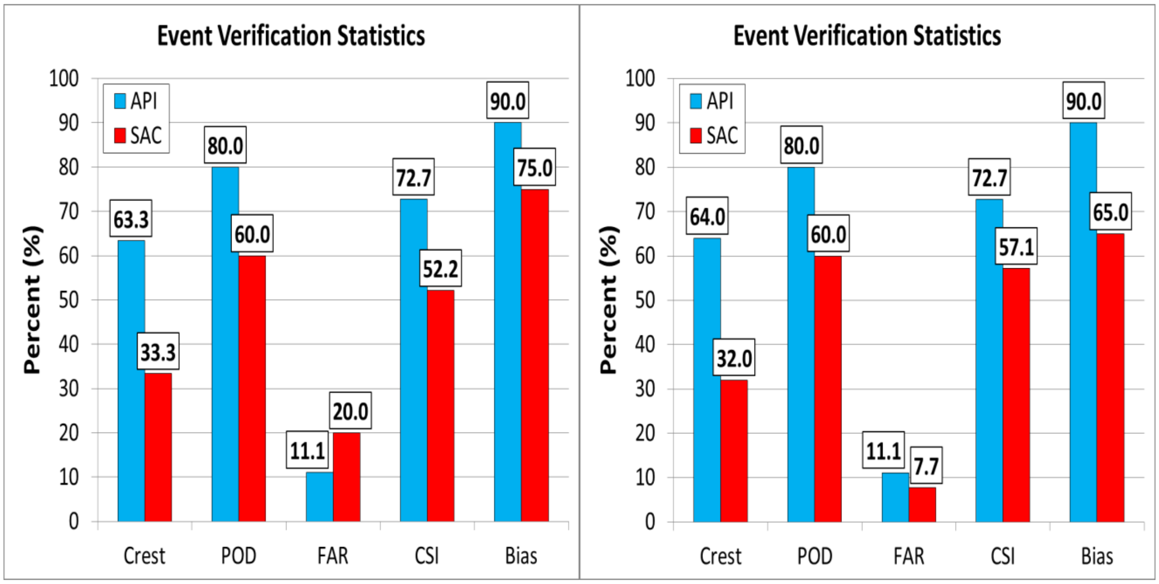

Figure 10. Event verification statistics (a) including Campbell and (b) excluding Campbell.

d) Simulation Performance - Extended Streamflow Prediction (ESP) Analysis

The historical data period in ESP varied at each gauge. Campbell, Cortland, Spruce Creek, and Tunkhannock ESP analysis included the period from 1950 to 1997 (48 years). The period from 1950 to 1988 (39 years) was used at Harper Tavern. Shirleysburg was not included in the ESP analysis due to limited historical gauge data. Three exceedance probability curves (observed, API-CONT, SAC-SMA) were created for each gauge. The curves were based on annual maximum daily flow values. Increased flow corresponds to decreased exceedance probability. For example, if 50 years of historical data are available, the 2% exceedance probability flow would correspond to the year (trace) with the largest observed maximum daily flow. Since ESP includes one value per year in the output, the 98% exceedance probability value would correspond to the year (trace) that included the 50th largest maximum daily flow value.

The API-CONT model simulated the historic flow regime more accurately at Campbell, Harper Tavern, and Spruce Creek (Fig. 11). The SAC-SMA model simulated the historic flow regime more accurately at Cortland and Tunkhannock. The API-CONT model simulated the 2% exceedance flow more accurately at every gauge. ESP analysis confirms that both models simulated the upper end of the historical daily flow regime at each gauge with similar trends.

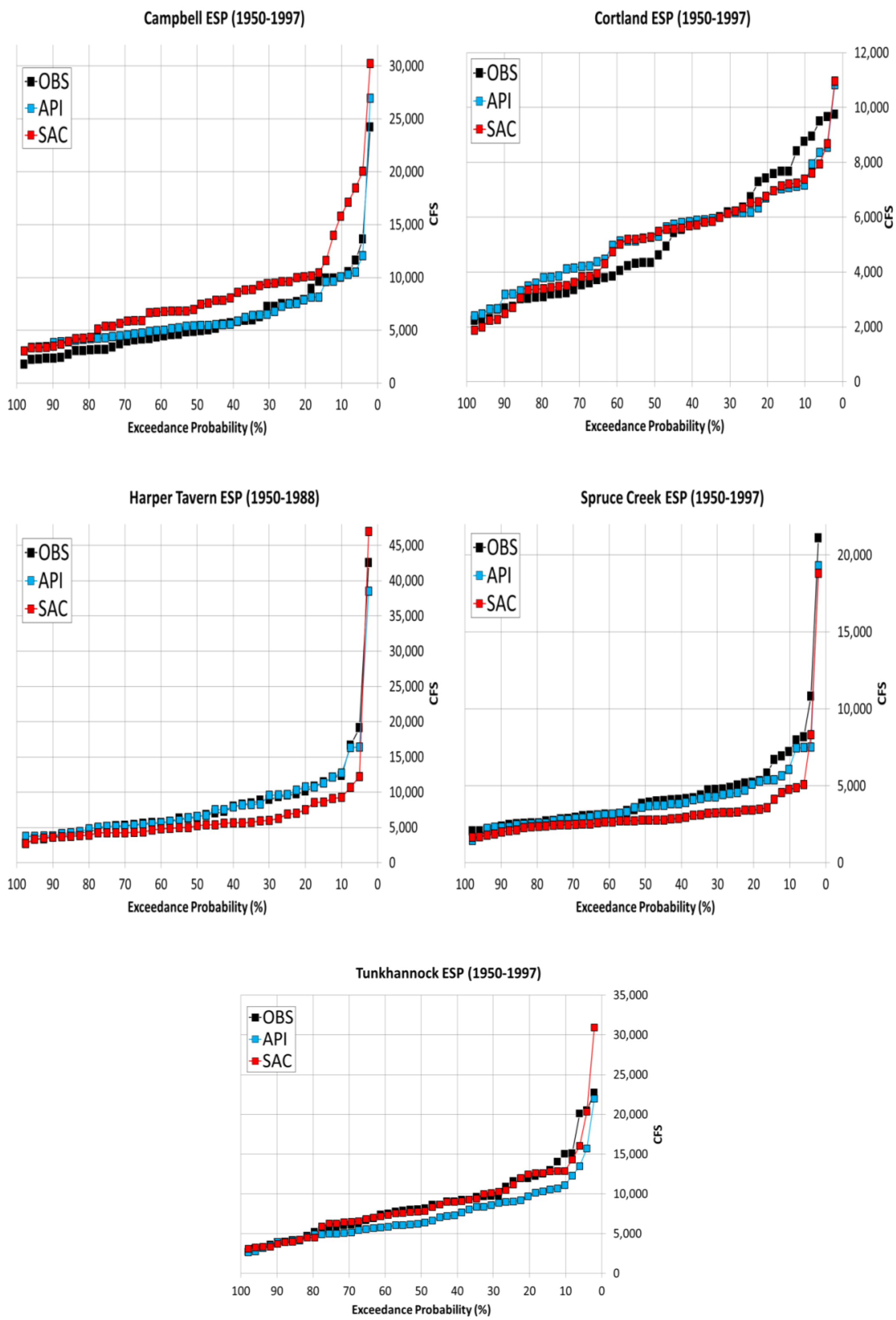

Figure 11. ESP results for (a) Campbell, (b) Cortland, (c) Harper Tavern, (d) Spruce Creek and, (e) Tunkhannock. Plots show the largest (one per year) simulated or observed values.

4. Conclusions

We performed a comprehensive comparison study between the API-CONT and SAC-SMA hydrologic models at six headwater basins in the SRB. The SAC-SMA model simulated streamflow more accurately on a daily basis over a 19-month period (August 2010 through February 2012) using a cumulative simulation error and error difference time series method of analysis. The API-CONT model simulated large event crests more accurately as shown by verification statistics including POD, FAR, CSI, and Bias. Finally, using ESP, both models simulated the upper end of the historical daily flow regime for each basin similarly. The results are consistent with the calibration goals that were established for each of the models. Unfortunately, the results would be more meaningful if both models were calibrated by a single entity and followed a similar calibration process, but that preference was not possible. If desired, MARFC could likely make adjustments to the SAC-SMA calibration parameters to better simulate high flows while limiting the simulation performance at low to medium flows. With respect to the effort required to reasonably maintain the operational model states of the two models by using forecaster-generated MODS, we found no important difference. Naturally, there is a learning curve associated with using the SAC-SMA model (and in making and understanding the MODS) for hydrologists and RFCs that have never used the model (i.e., MARFC).

Smith et al. (2000) performed a similar study at a total of 3 stream gauges (two in Iowa and one in Georgia). They evaluated the advantages of the continuous SAC-SMA model over an event API model. Using hydrograph shape error and peak error, they found that the SAC-SMA model simulated flow more accurately across all of the gauges for a majority of chosen flow intervals. Compared with Smith et al. (2000), our results suggest that a continuous API model simulates peak flows comparable to the SAC-SMA model. One reason our results differ may be due to using continuous API model simulations instead of event based API model simulations. Another reason may be due to significant differences in basin size, topography, and rainfall-runoff response time.

Predictions of water across the United States are important to making decision on water management, recreation, and natural hazards. RFCs have different forecast verification goals based on regional water needs and concerns. In the Western U.S., long-term water supply forecasting plays an important role in RFC operations, and the SAC-SMA model is more suited for the region. Eastern U.S. RFCs, such as MARFC, are currently more concerned with flood crest forecasting and water supply forecasting plays less of a role. Our analyses indicate that the MARFC calibrated API-CONT model outperformed the RTi calibrated SAC-SMA model when forecasting large event crests. This agrees with MARFC forecaster experience and flood event reviews that indicate the API-CONT model has continued to be an effective tool for MARFC flood forecasting.

During the last few years, major advances have been accomplished within the NOAA/NWS operational hydrologic forecasting framework. The implementation of a new software modeling and operational infrastructure known as the Community Hydrologic Prediction Service (CHPS) is expected to be the foundation which will help NOAA/NWS meet goals for hydrologic technology transfer and improved hydrologic operations, services, and products in the future (Roe et al. 2010). Essentially, CHPS is an open, modular hydrologic forecasting system that allows existing and new hydraulic and hydrologic models and data to be utilized and ultimately shared by members of the hydrologic community.

Within NOAA/NWS, CHPS brings a new flexibility to operational hydrology. With proper implementation and configuration, CHPS should allow for the real-time operational use of multiple hydrologic models. In the context of this paper, CHPS should allow for both the API-CONT and SAC-SMA hydrologic models to be run concurrently so that comparisons of the output (i.e., hydrologic forecasts) of the two models can be made in a near real-time operational environment. This "ensemble" approach would be analogous to that being utilized in the NOAA/NWS operational meteorology environment, where viewing and interpreting the output from multiple atmospheric models concurrently in near real-time is already being done. As such, possible future work to build upon this paper might include MARFC adding, configuring and running the SAC-SMA in CHPS for these same five basins for use in daily operations. The running of two distinct hydrologic models within CHPS would be a valuable test of the presumed flexibility that the system should provide and would also allow for direct comparison of model performance over all flow ranges and in a real-time operational environment. An added benefit would be MARFC staff exposure to (and experience gained in using) the SAC-SMA model. Depending on the results and consideration of the advantages and disadvantages mentioned in the introduction, MARFC could then consider expanding the number of calibrated SAC-SMA basins for future operational use.

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