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Space–time scale sensitivity of the Sacramento model to radar–gage precipitation inputs

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Abstract

Runoff timing and volume biases are investigated when performing hydrologic forecasting at space–time scales different from those at which the model parameters were calibrated. Hydrologic model parameters are inherently tied to the space–time scales at which they were calibrated. The National Weather Service calibrates rainfall runoff models using 6-hour mean areal precipitation (MAP) inputs derived from gage networks. The space–time scale sensitivity of the Sacramento model runoff volume is analyzed using 1-hour, 4×4 km^2 next generation weather radar (NEXRAD) precipitation estimates to derive input MAPs at various space–time scales. Continuous simulations are run for 9 months for time scales of 1, 3, and 6 hours, and spatial scales ranging from 4×4 km^2 up to 256×256 km^2. Results show surface runoff, interflow, and supplemental baseflow runoff components are the most sensitive to the space–time scales analyzed. Water balance components of evapotranspiration and total channel inflow are also sensitive. A preliminary approach for adjusting model parameters to account for spatial and temporal variation in rainfall input is presented. © 1997 Published by Elsevier Science B.V.

Keywords: Rainfall runoff; Radar data; Sacramento model; Space–time scale; Scale dependence

1. Introduction

The National Weather Service (NWS) distributed modeling project is analyzing the space–time hydrologic model response to high resolution precipitation estimates from next generation weather radar (NEXRAD) (Hudlow, 1988; Klazura and Imy, 1993) in order to improve operational hydrologic forecasting. The use of NEXRAD precipitation estimates is expected to improve hydrologic forecasting because of the distinct advantage of radar over rain gage networks in estimating the spatial coverage of heavy rainfall (Seo and Smith, 1996; Smith et al., 1996). NWS river forecasters also acknowledge that rain gage networks often do not fully capture the intensity and spatial characteristics of heavy precipitation events.

The NEXRAD data known as the 'hourly digital precipitation array' (HDP) are derived from an algorithm called the precipitation processing subsystem (Fulton et al., 1997; Hudlow, 1988; Klazura and Imy, 1993). The HDP products have systematic errors which are inherent to any radar rainfall data, and these errors are well documented by Smith and Krajewski (1994), Seo et al. (1995), and Smith et al. (1996). Because of the known errors in the radar precipitation

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estimates and the fact that the NWS calibrates their rainfall runoff models using gage only mean areal precipitation (MAP) estimates as input, this study uses a multi sensor gridded precipitation estimate known as Stage III. The Stage III data merges the HDP and gage precipitation estimates by using the gage data to remove mean and local biases contained in the radar derived 1-hour precipitation estimates. The interested reader is referred to Shedd and Fulton (1993) for more discussion on the corrections applied. The Stage III data assumes the gage sensor is 'ground truth' precipitation and uses the HDP gridded precipitation estimates to fill in the spatial distribution and rate of rainfall between the gages (Shedd and Smith, 1991). The NWS Hydrologic Rainfall Analysis Project grid system (HRAP) uses a polar stereographic projection grid to merge optimally rainfall estimates from multi-radars and rain gages (Schaake, 1989; Greene and Hudlow (1982) NWS internal publication; Greene et al., 1979). The HRAP grid size is a function of latitude and is approximately $4 \times 4\ km^2$ over the area of study. The multi-sensor HRAP grid precipitation estimates will be referred to as Stage III for the remainder of the paper.

The NWS primarily uses the Sacramento Soil Moisture Accounting (SAC-SMA) model to generate river forecasts on basins with a response time of greater than 12 hours. The SAC-SMA model is a conceptually based rainfall runoff model with spatially lumped parameters (Burnash, 1995; Burnash et al., 1973). It is generally applied to river basins ranging from $300\ km^2$ up to $5000\ km^2$. Basin sizes vary according to hydrologic region, geomorphology, forecast point requirements, and available data. The SAC-SMA model is generally run at a 6-hour time step but can run at any time step. Inputs to the SAC-SMA model are 6-hour mean areal precipitation (MAP) and 6-hour mean areal potential evaporation (MAPE). MAPE is estimated from pan evaporation data or monthly mean potential evaporation, and may also be calculated from synoptic data. The SAC-SMA model parameters are manually and automatically calibrated with the objective of making the model simulation match historical observed discharge data. Calibration usually requires at least 8 years of historical input precipitation data for continuous simulation and comparison to observed discharge (University of Arizona, 1995). An additional 8 years of historical data are recommended for model verification. Therefore, the calibrated parameters are inherently tied to the space–time scale, terrain, geographic location, and gage networks from which they are calibrated.

As a result of the calibration parameters being tied to the historical rain gage network, a direct utilization of the gridded Stage III data cannot be made without understanding how the SAC-SMA model responds to precipitation forcing at various spatial and temporal scales. Optimally, a lumped basin that is disaggregated into sub-basins should be recalibrated to reflect the model's response to a different scale and type of precipitation forcing (i.e. 6-hour gage MAP values vs. 1-hour gridded radar precipitation estimates). Obled et al. (1994) followed this procedure when they modeled a basin in a lumped fashion and then as a collection of 9 constituent sub-basins. However, less than 3 years of Stage III data are available for recalibration of the SAC-SMA model, which is an insufficient length of time for calibration and validation of model parameters. Comprehensive procedures exist within the NWS for the calibration of the SAC-SMA on lumped basins provided there are stream gage data available. However, it is unclear how to recalibrate the model parameters on the disaggregated sub-basins owing to the absence of stream gages at internal points. Thus, the NWS faces the unique problem of using a semi-distributed modeling approach for operational forecasting, without a sufficient period of high resolution Stage III data or observed discharge data with which to calibrate the sub-basins. Until an adequate radar calibration data set is available, improved understanding is required concerning SAC-SMA model parameter adjustments to account for model response to different scales of precipitation inputs.

This paper presents the results of the sensitivity of the SAC-SMA model runoff component volumes to Stage III gridded precipitation estimates at numerous space–time scales. There are no actual hydrographs being presented in this paper, simply the runoff component volumes. Although model parameters are tied to the space–time scale, terrain, and gage network characteristics from which they are calibrated, this paper shows similar model results from a wide range of model parameters. Therefore, the results presented are considered to be generally applicable to the SAC-SMA model response and are not tied to the parameters used. A primary assumption in the analysis is that the 6-hour Stage III MAPs are equal to the historical 6-hour gage MAPs because gage data are used by the Stage III multi-sensor field. In addition, the calibrated SAC-SMA model parameters are assumed to be applicable to input MAPs estimated from Stage III data as well as gage network data.

2. Literature review

Hydrologic model response to precipitation inputs of various spatial and temporal resolutions has been the subject of numerous investigations. Many studies have approached this problem from the standpoint of rain gage sampling and density. Recently, the implementation of radar has enabled hydrologists to begin the evaluation of model response to gridded precipitation estimates. Intuitively, one would hypothesize that the use of higher resolution data leads to better model results. Surprisingly, there does not seem to be a clear trend in the literature that supports this hypothesis.

In an oft-referenced work, Wilson et al. (1979) concluded that ignoring the spatial variability of precipitation input, even when the total depth of rainfall is preserved, can have significant influences on the runoff hydrograph. Their findings were based on the analysis of a 67 km^2 basin and two levels of synthetic precipitation definition: in the first case, one gage was used to define the input to a lumped parameter model, while in the second, 20 gages were used. Based on limited testing, Shanhltz et al. (1981) arrived at a similar conclusion, as did Beven and Hornberger (1982) who suggested that:

> (the) incorporation of distributed inputs would lead to improvements in simulating catchment hydrographs.

On the other hand, Obled et al. (1994) used 21 rain gages to define the input to 9 sub-basins representing a 71 km^2 basin. They presumed that providing distributed inputs to the model would improve simulations, especially if parameter re-optimization was allowed. However, their semi-distributed representation of the basin produced slightly worse results than a lumped representation combined with coarser precipitation input, even after recalibration of the model parameters. The authors were unable to prove the value of using distributed rainfall inputs to improve hydrologic predictions, noting that:

> better dynamics expected in the discharge from better information on rainfall pattern is not demonstrated in (the) goodness-of-fit criteria.

Krajewski et al. (1991) saw more influence from temporal resolution of rainfall inputs than from spatial variability. Given the very small size of the basin (7.5 km^2), the authors concluded that their results were reasonable. However, Pessoa et al. (1993) found that simulated hydrographs from an 840 km^2 basin using distributed radar–rainfall inputs were not significantly different than simulated hydrographs produced from lumped radar–rainfall inputs. Significant differences were realized, however, when lumped rainfall inputs were defined as the arithmetic means of up to 5 randomly selected radar pixels.

Kouwen and Garland (1989) examined the effects of radar data resolution on runoff hydrographs produced from a distributed parameter model, and attempted to define guidelines for the appropriate level of rainfall input resolution. They found that coarser resolution radar input sometimes produced better simulation results owing to smoothing of errors present in finer resolution data. However, they also recognized that local circumstances dictate whether radar data smoothed into a coarser grid would be appropriate. Their study also presented significant differences between runoff hydrographs produced by rain gage only data and radar data.

Kenner et al. (1996) recognized the need to identify the scale dependences of critical hydrologic parameters. Preliminary results were obtained when a 963.5 km^2 basin was modeled as a single lumped area and as a collection of 5 sub-basins. In limited tests on a single extreme event, the semi-distributed approach produced better agreement with the observed hydrograph than the lumped approach. However, the results may be affected by the fact that neither approach was calibrated.

In a recent study, Shah et al. (1996) examined the spatial variability of rainfall on a small (10.55 km^2) basin for various levels of antecedent moisture conditions. Spatial averaging of rainfall inputs led to adequate simulations under wet conditions. However, greater errors resulted when spatially averaged rainfall fields were used with dry antecedent moisture

Table 1
Sub-basin scale dimensions and units

Sub-basin size (HRAP bins)	Sub-basin size (km)	Sub-basin size (km^2)	Number of sub-basins representing entire area
1 × 1	4 × 4	16	4096
2 × 2	8 × 8	64	1024
4 × 4	16 × 16	256	256
8 × 8	32 × 32	1024	64
16 × 16	64 × 64	4096	16
32 × 32	128 × 128	16384	4
64 × 64	256 × 256	65636	1

conditions, indicating a linkage between spatial variability of rainfall and the distribution of soil moisture which subsequently controls the generation of runoff.

Ogden and Julien (1994) found severe reductions in peak discharge due to a reduction in rainfall excess which was directly attributed to the aggregation of radar inputs. Their analysis used high resolution radar inputs and a gridded rainfall runoff model on watersheds less than 150 km^2.

Wood et al. (1988) introduced the concept of a representative elementary area (REA) to account for the small-scale heterogeneities in the macro scale models. The REA represents the threshold scale where statistical representations of smaller areas can replace actual patterns of variability. For the 525 km^2 Little Washita catchment Wood (1995) estimated the threshold scale to be on the order of 5 to 10 km^2. However, Fan and Bras (1995) argued that the REA concept has limited utility in hydrology because the REA is scale dependent, and it can vary on individual storm events.

Nalbantis (1995) developed guidelines for adjusting certain hydrologic model parameters to account for changes in temporal modeling scales. He addressed the problem of lumped parameter models calibrated with daily information that were then used at shorter time intervals to simulate flood events. Often, this situation arises when continuous daily rainfall and streamflow data are available for long periods, but an insufficient period of shorter time interval data is available for proper calibration at shorter time intervals. His proposed strategy involved calibrating the model at a daily time step, then adjusting certain time-dependent withdrawal coefficients to derive a model to be used at a 1-hour time step. The daily model would be operated continuously. At the onset of a flood event, the derived hourly model would be initialized using the states of the continuous daily model. His results showed that the prediction of initial values of the 1-hour state variables related to slow response of a basin can be done quite accurately. However, he could not produce an automated method to transfer reliably the rapid response state variables from the daily to the hourly scale without requiring significant tuning.

3. Method

In order to examine the response of the SAC-SMA model to Stage III precipitation inputs at various spatial and temporal resolutions, a collection of synthetic sub-basins is created. The synthetic sub-basins correspond to regular aggregations of HRAP bins within a 64 × 64 HRAP bin matrix. These sub-basins range in size from a 1 × 1 HRAP bin up to 64 × 64 HRAP bins, as shown in Table 1. MAP inputs for the sub-basins are calculated from a 64 × 64 HRAP bin, 1-hour, Stage III precipitation data set that encompasses a calibrated test basin at Eldon, OK. Fig. 1 shows the 64 × 64 HRAP bin experimental data set and the Eldon test basin. Fig. 2(a–g) shows the scaling of MAP inputs for a 1 hour accumulation of a Stage III precipitation field and the resulting areal averaging of the high intensity event over the range of synthetic sub-basin scales analyzed.

Model parameters were taken from a basin calibration of the Baron Fork at Eldon, OK, USA, whose drainage area is 795 km^2. A 6-hour MAP time series for the basin was derived using 11 years of rain gage

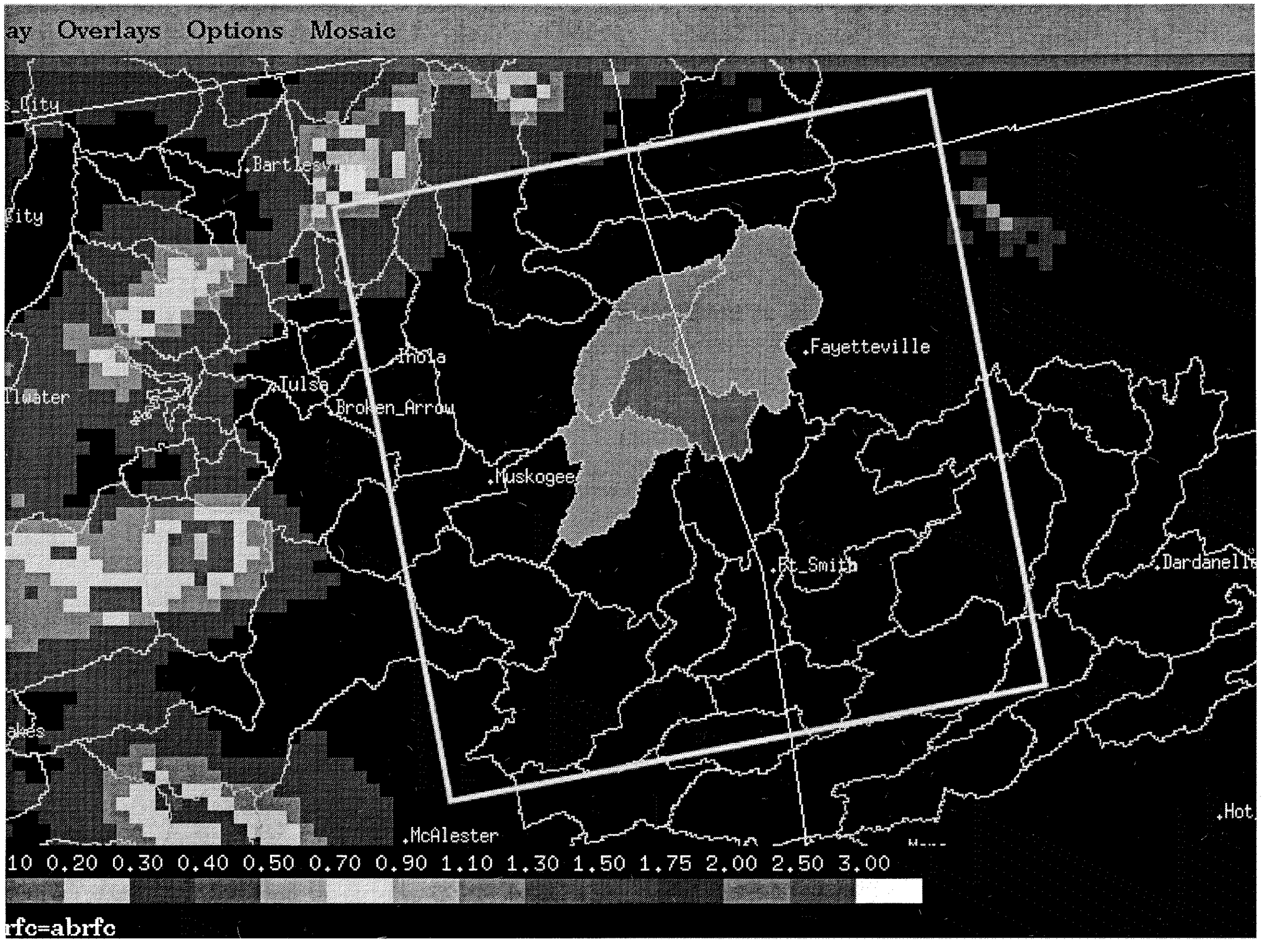

Fig. 1. Location of the Illinois River basin (lightly highlighted) and the calibrated test basin of the Barron Fork of the Illinois River at Eldon, OK (darker highlighting). The basin is in the state of Oklahoma, which is located on the southern plains of the United States. The 64 × 64 HRAP bin Stage III test data set is shown by the square area surrounding the test basin. Precipitation is present to the west and north of the experimental area.

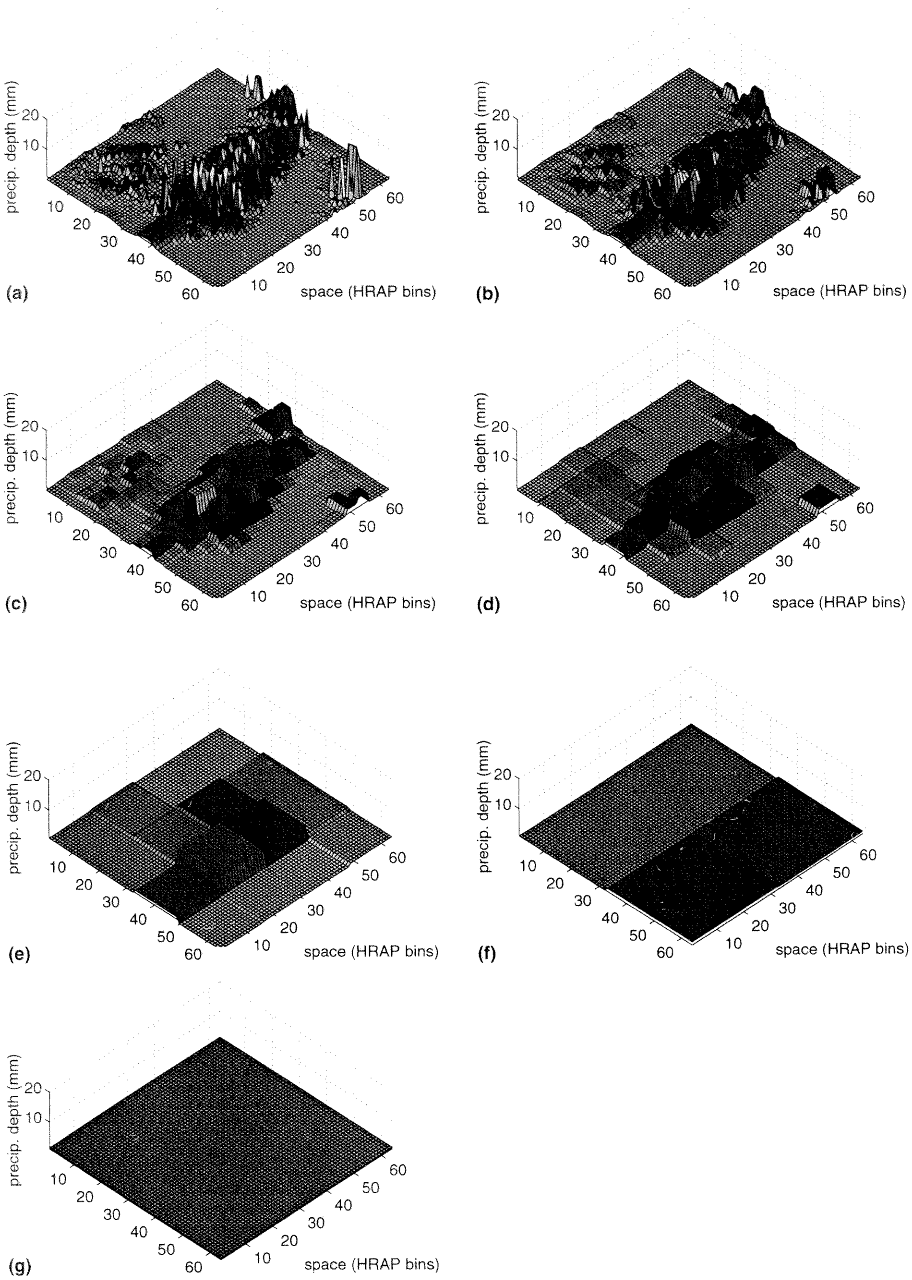
precip. depth (mm)
20
10
10 20 30 40 50 60
10 20 30 40 50 60
space (HRAP bins)
(a)
(b)
(c)
(d)
(e)
(f)
(g)

Fig. 2.

data. Observed mean daily flow records for the stream gage at Eldon were obtained from the US Geological Survey. The calibration time step was 6 hours. It is worth emphasizing that these SAC-SMA parameters, calibrated at 6 hours, and for a 795 km^2 basin, were applied without change to each of the synthetic sub-basins in the subsequent analyses. It should also be noted that the drainage area of the Baron Fork corresponds roughly to the 8×8 HRAP bin area. The calibrated parameters are assumed to be reasonable for the entire 64×64 HRAP bin area, and the area is assumed to have similar rainfall runoff processes throughout.

Within this framework, the sensitivity of the SAC-SMA runoff components to precipitation forcing at various scales is analyzed. The SAC-SMA model is run in a continuous mode for the entire 9-month period using model time steps of 1, 3, and 6 hours, and for each of the spatial scales listed in Table 1. The Stage III data set covers the eastern portion of the Tulsa, OK, river forecasting region and spans from May 7, 1993 through January 31, 1994. This time period records the very wet summer which resulted in the 'Great Flood of '93' in the Midwestern United States. Soil moisture accounting is performed over the entire 64×64 HRAP bin area and is maintained independently for every sub-basin and at each space–time scale analyzed.

Storm characteristics are difficult to describe for the large 64×64 HRAP bin area, however, some general storm information is useful to understanding the regional climate in the study area. Rain was detected in the 64×64 study area for 2163 hours of the 6480 total hours of data between May 7, 1993 and January 31, 1994. The average hourly precipitation coverage was 22% of the total area with a mean hourly precipitation depth of 0.37 mm/64×64 HRAP bins, given the presence of rain. There were approximately 45 events in the 9-month period that had a storm peak with greater than 40% coverage in the 64×64 area and had a mean peak depth in the covered area of greater than 4 mm.

For comparison, runoff volumes generated by sub-basins within a given level of disaggregation are spatially averaged over the entire 64×64 HRAP bin area. Routing of the runoff components through a unit hydrograph or channel network is not performed in this analysis. The precipitation inputs for the 3-hour and 6-hour time scale analysis are derived from summing the 1-hour data.

The model components analyzed include the following: precipitation depth, impervious runoff, direct runoff, surface runoff, interflow, percolation, total evapotranspiration, supplemental baseflow, primary baseflow, total channel inflow, water balance errors, and evapotranspiration demand. Fig. 3 shows the contribution of the various runoff components of the SAC-SMA model to the runoff hydrograph. Fig. 4 shows the fundamental conceptualization of the SAC-SMA model, including all soil moisture storages, runoff components, and exchanges between the atmosphere and land surface components. The names of the model components are specific to the conceptual formulation of the SAC-SMA model and

Fig. 2. Spatially aggregated Stage III precipitation field over northeastern Oklahoma, January 16, 1994, 20:00z.(a) Stage III 1-hour precipitation field in units of millimeters (z-axis) and over a spatial extent of 64×64 HRAP bins. Each bin has an individual value relative to its neighbors, and is used as input to the lumped SAC-SMA hydrologic model. Thus, 64^2 or 4096 individual SAC-SMA model runs are used over this area for every hour of model simulation (maximum value 19.01 mm). (b) Same data as shown in (a) except they have been averaged in 2×2 HRAP bins. This field has $64^2/2^2 = 1024$ individual values and will require the same number of SAC-SMA model runs to analyze. Notice that the averaging procedure reduces the peaks of actual values shown in (a) (maximum value 15.73 mm). (c) Same data as shown in (a) except they have been averaged in 4×4 HRAP bins. This field has $64^2/4^2 = 256$ individual values. Notice that each individual group appears as a 'tic-tac-toe' board or grid boxes. This may create the false impression that values have been grouped 3×3 rather than 4×4. The values being plotted are at the corner of each square, not centered upon the square, thus a tic-tac-toe board has 16 corners rather than 9 squares (maximum value 11.56 mm). (d) Same data as shown in (a) except they have been averaged in 8×8 HRAP bins. This field has $64^2/8^2 = 64$ individual values. Notice that this field only very coarsely resembles the original field shown in (a) and this is the scale at which the Eldon, OK test basin most closely represents (maximum value 9.11 mm). (e) Same data as shown in (a) except they have been averaged in 16×16 HRAP bins. This field has $64^2/16^2 = 16$ individual values (maximum value 6.32 mm). (f) Same data as shown in (a) except they have been averaged in 32×32 HRAP bins. This field has $64^2/32^2 = 4$ individual values. This field is arguably a poor representation of the original spatial distribution of data (maximum value 2.11 mm). (g) The entire field has now been averaged into a single 64×64 value requiring only a single run of the SAC-SMA model. This corresponds to the lumped model run for the entire 64×64 HRAP bin experimental area (maximum value 1.45 mm).

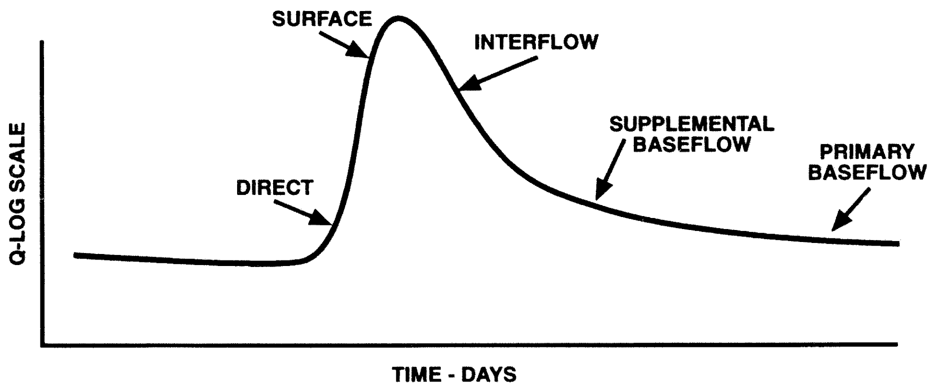

Fig. 3. Sacramento soil moisture accounting model runoff components' contribution to the runoff hydrograph (figure reproduced with permission from River Side Technology, Fort Collins, CO).

are not general terms of hydrologic science. Output summary statistics are calculated over the 9-month period for all 13 model components and all sub-basin scales analyzed. Statistics include mean, variance, maximum, minimum, and cumulative depth values at all sub-basin scales. The analysis in this paper only presents certain statistics, runoff components, and time scale cases in order to highlight the most significant results.

4. Results

4.1. Spatial analysis

Perhaps the most extreme change in modeling strategy for a River Forecast Center would be to convert from 6-hour lumped parameter modeling using gage-derived precipitation estimates to 1-hour semi-distributed modeling using precipitation estimates

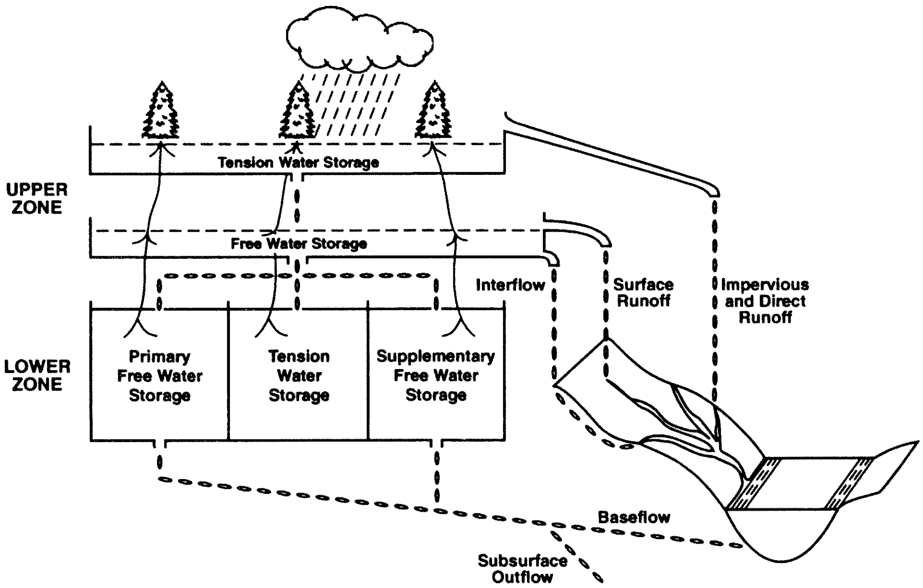

Fig. 4. Conceptualization of the SAC-SMA model illustrating the soil moisture storages, runoff components and land surface–atmosphere exchanges.

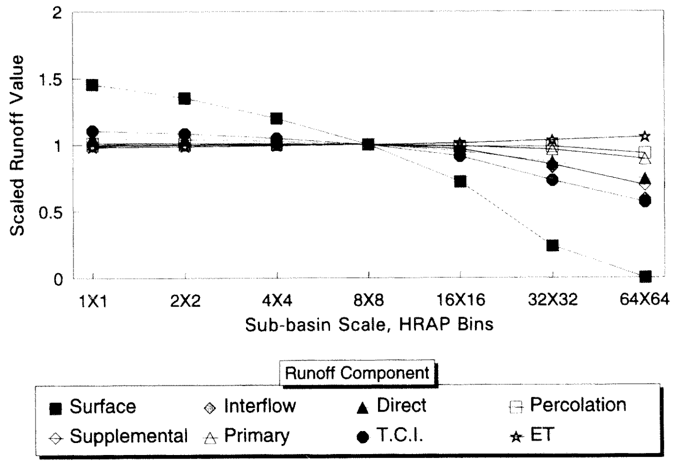

Fig. 5. Relative changes in SAC-SMA model runoff component volumes vs. size of sub-basins using 9 months of 1-hour Stage III precipitation data. Runoff volumes are scaled to the values produced at the 1-hour time scale and the 8 × 8 spatial scale which is approximately the size of the calibrated test basin whose parameters are used for the simulation experiment. Surface runoff is the most sensitive runoff component, followed by interflow and supplemental baseflow. These changes in runoff components cause the resultant increase in total channel inflow as the spatial scale decreases.

derived from NEXRAD. This first series of analyses addresses such a dramatic change.

Fig. 5 clearly shows the sub-basin scale sensitivities of the relative change in SAC-SMA model runoff component volumes for the 1-hour model time step. Recall that the SAC-SMA parameters are uniformly applied to each sub-basin. Each increase in basin resolution results in a 4 fold increase in the number of sub-basins being used to model the 64 × 64 HRAP bin test area. The runoff components are scaled relative to their value generated at the 8 × 8 spatial scale because that is the approximate spatial scale of the calibrated test basin. The SAC-SMA model generates surface runoff when the two storage reservoirs, tension and free water storages, representing the upper soil layer become saturated. Fig. 3 shows

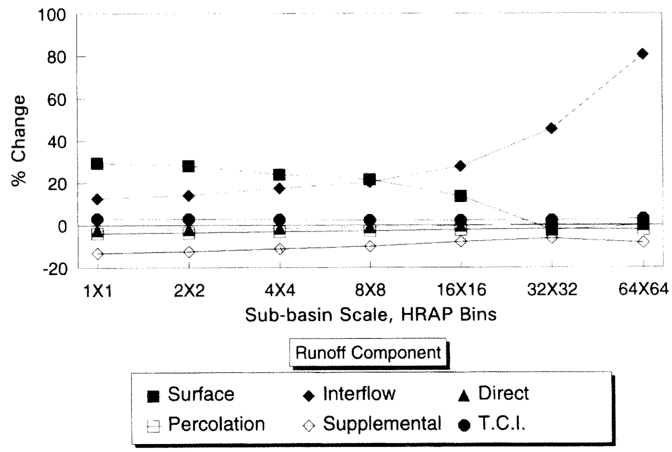

Fig. 6. Percentage change in 9 month total SAC-SMA model runoff component depths resulting from changing from a 6-hour time scale to a 1-hour time scale using 9 months of Stage III data. At the 8 × 8 HRAP bin spatial scale, surface runoff increases 21% from 23.7 mm at a 6-hour time scale, interflow increases 20% from 16.5 mm, supplemental baseflow decreases 9% from 50.1 mm, and total channel inflow (TCI) increases 3% from 119.0 mm.

surface runoff is the fast response rising limb of the hydrograph. As seen in Fig. 5, surface runoff is the most spatially sensitive component of the SAC-SMA model, and decreases to zero as the spatial scale increases to 64 × 64 HRAP bins. Surface runoff is also very sensitive at the finer spatial scales analyzed.

Interflow is the second fastest responding runoff component in the model followed by supplemental baseflow. These runoff components represent the falling limb of the hydrograph as shown in Fig. 3. Interflow is conceptualized as the lateral flow from the upper soil layer and is generated from the upper zone free water storage reservoir. Supplemental baseflow is the fast responding baseflow component and is generated from the lower zone free water reservoir. Fig. 5 shows interflow and supplemental baseflow are also quite sensitive to spatial scale and they both decrease as the sub-basin scale increases. However, they do not prove to be very sensitive at spatial scales less than the 16 × 16 sub-basin size. The figure shows how the reduction of surface runoff, interflow, and supplemental baseflow contribute to the overall reduction of total channel inflow as the sub-basin scale increases. Percolation, direct runoff, and primary baseflow also exhibit a decrease in runoff volume as the spatial scale increases. Capturing the spatial precipitation intensity characteristics exhibited in the Stage III data by using smaller sub-basins without parameter recalibration accentuates the fast response runoff components, while having less impact on the slower response components of the SAC-SMA model.

Evapotranspiration decreases as the sub-basin scale decreases, as shown in Fig. 5. The long-term water balance is maintained in the SAC-SMA model because the increase in total channel inflow, produced at the finer spatial scales, results in less soil water available for evapotranspiration during the drying periods. The SAC-SMA model scale dependence displayed in Fig. 5 is primarily attributed to the spatial averaging of high intensity precipitation events that produce significant runoff (see Fig. 2(a–g)). Increasing the sub-basin scale decreases the mean areal precipitation (MAP) to the extent that it does not satisfy the SAC-SMA upper zone tension and free water storages, which decreases the frequency and runoff volume from those events which produce runoff at the smaller spatial scales. Therefore, increasing the spatial scale increases the volume of precipitation held in tension water storage where it evapotranspires into the atmosphere and reduces total channel inflow. Georgakakos et al. (1996) also noticed that a lumped application of the SAC-SMA model holds more water in storage as compared to a semi distributed application of the model. The results shown in Fig. 4 for surface runoff agree with those generated by Famiglietti and Wood (1994) on an 11.7 km^2 basin. However, Pessoa et al. (1993) detected very little difference in hydrologic model response generated from a lumped versus fully distributed implementation of radar rainfall data on an 840 km^2 basin.

The spatial analysis indicates that parameters derived from the 6-hour MAP inputs at a given spatial scale cannot be distributed to sub-basins of different spatial scales and a 1-hour model time step, without introducing significant biases in the volume and timing of SAC-SMA model runoff components. Therefore, disaggregating a basin to capture the spatial variability of precipitation must be accompanied by recalibration to remove biases in model simulation. All results presented must be viewed according to the fundamental assumptions and limitations of the analysis and may vary geographically.

4.2. Temporal analysis

The time scale analysis is performed to investigate the effects of changing from the 6-hour model time step, most commonly used for current operational forecasting, to the 1-hour time step of the Stage III precipitation data. In the NWS a 6-hour MAP typically represents the lower bound in temporal resolution because the rain gage networks currently used for forecasting procedures are too sparse and do not report frequently enough to produce meaningful hourly precipitation estimates. The temporal analysis assumes the 6-hour MAP from the Stage III products are similar to the 6-hour MAPs derived from gage data. This assumption is reasonable because Stage III precipitation estimates are merged with 'ground truth' gage data.

Modeling at finer time steps is expected to increase forecast lead times and increase forecasting accuracy in fast response basins. For example, if a 6-hour time step is used, the NWS River Forecasting System (NWSRFS) must collect and process data for the entire time interval before the data are run through the models to generate a river forecast. NWSRFS uses a fixed time interval and data are generally reported at fixed times, there is no means for a sliding type of time interval. If a rain event occurs in the first 2 hours of the 6-hour time step, then all 6 hours must elapse before the data are posted to the system for processing. In this example, a 1-hour time step increases the forecast lead time by approximately 4 hours while more accurately representing the intensity of the precipitation.

Fig. 6 displays the percentage change in SAC-SMA model runoff component volumes when changing from a 6-hour time scale to a 1-hour time scale while holding the model parameters constant. Values in Fig. 6 represent the differences in 9-month totals in each of the runoff component volumes. The figure shows that surface runoff is the most temporally sensitive model component at the finer sub-basin scales. Surface runoff at the 8×8 spatial scale increases by over 21% when changing to the shorter 1-hour time scale. Interflow at the 8×8 spatial scale is shown to increase by 20% when changing from the 6-hour to the 1-hour time scale, but is not as sensitive as surface runoff at the finer spatial scales. Supplemental baseflow decreases with decreasing time scale and is more sensitive at the finer spatial scales analyzed. Total channel inflow also increases when changing from a 6-hour to a 1-hour time step and is more sensitive at the finer spatial scales.

The results shown in Fig. 6 are primarily attributed to the temporal averaging of high-intensity, short-duration precipitation events which tend to produce surface runoff. This temporal sensitivity of the SAC-SMA runoff volumes could suggest that the hydrologic processes in the region are operating at a finer time scale than 6 hours. The temporal information contained in the 1-hour Stage III products may possibly be used to improve hydrologic forecasting. Moreover, the temporal analysis indicates that the parameters calibrated at the 6-hour time step cannot be applied at the 1-hour time step without introducing the volume biases shown in Fig. 6. Changing the model time scale and keeping the model parameters fixed redistributes runoff between the rising limb (surface) and the falling limb (interflow) of the runoff hydrograph, as well as between near surface and groundwater runoff components. These runoff volume biases are particularly important because they are most significant in the fast response surface runoff and interflow components of the hydrograph, which are the most critical model elements in flood forecasting. In general, the results displayed in Figs. 5 and 6 indicate that the utilization of finer space–time scale precipitation estimates, without parameter adjustments, introduces SAC-SMA runoff volume and timing errors. These runoff volume and timing errors could potentially result in degradation of the predictive ability of the model if used at finer time scales.

4.3. Adjustment of parameters for space–time scales

One possible method for applying SAC-SMA model parameters at different space–time scales is to make adjustments to parameters in order to minimize the biases created by changing the precipitation intensity (precipitation depth/event duration) across space–time scales. The previous section established that surface runoff is the most sensitive runoff component to space–time scales. The following sections analyze the sensitivity of the runoff components to changes in the upper zone free water maximum (UZFWM) and upper zone tension water maximum (UZTWM) threshold parameters which are known to dominate the generation of surface runoff in the SAC-SMA model. Almost every parameter in the SAC-SMA model could potentially affect surface runoff but they were not analyzed in this work. Caution should be exercized because UZFWM and UZTWM also control interflow, percolation, supplemental baseflow and evapotranspiration components of the SAC-SMA model. Percolation changes have an impact on lower zone free and tension water storages, which directly affect supplemental and primary baseflow recharge and evapotranspiration.

Obled et al. (1994) disaggregated a lumped basin into 9 constituent sub-basins and recalibrated the parameters of their semi-distributed hydrologic model using 9 distinct runoff events over a 16 year period to account for the higher resolution rainfall input fields. However, the 9 months of Stage III data available for the present study are not sufficient for a recalibration of the SAC-SMA parameters, as continuous simulation over an 8 year period is recommended to obtain parameters that are insensitive to the data period selected (University of Arizona,

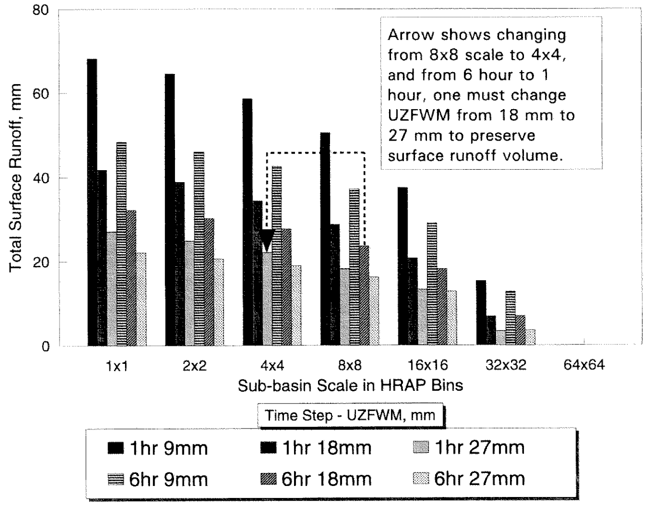

Fig. 7. Effects of changing the SAC-SMA model upper zone free water maximum (UZFWM) parameter on the total surface runoff volume over 9 months of continuous simulation using Stage III precipitation data. Surface runoff is very sensitive to both increases and decreases in the UZFWM parameter at all spatial and temporal scales analyzed.

1995). Until a sufficient length of record of data is available to calibrate the SAC-SMA model for various space–time scales using Stage III precipitation inputs, alternative approaches to adjusting model parameters need to be developed.

4.3.1. Upper zone free water parameter

The separation of fast responding surface runoff and interflow from the slow response baseflow runoff is primarily controlled by the upper zone free water maximum parameter (UZFWM). Bae and Georgakakos (1994) identify this parameter as the most sensitive when examining high flows, where lowering the parameter value has more influence than increasing the value. Their results indicate that the influence of UZFWM is reduced when both high and low flows are considered.

An analysis of upper zone processes is performed by changing the relative size of the upper zone free water maximum parameter. The UZFWM is calibrated at 18 mm and trial runs are made at 50% increases and decreases, 27 mm and 9 mm respectively. Fig. 7 illustrates that the UZFWM parameter derived at one scale is not applicable across different scales because surface runoff volumes are not preserved. Fig. 7 shows that UZFWM must be increased when modeling at finer space or time scales in order to accommodate the higher intensity precipitation events and preserve surface runoff volumes. This affect is more pronounced when the UZFWM parameter is small, which is in agreement with Bae and Georgakakos (1994). The figure also shows that surface runoff is sensitive to UZFWM at both the 1-hour and 6-hour model time steps. Consider an example illustrated in Fig. 7 in which a basin at the 8 × 8 HRAP bin scale is calibrated at a 6-hour time step. If one chooses to disaggregate the basin into 4 sub-basins (i.e. a move to the 4 × 4 scale) the UZFWM must be increased from 18 mm to approximately 27 mm in order to preserve the same volume of surface runoff.

Secondary effects of UZFWM adjustments are presented in Figs. 8–10. Fig. 8 shows that interflow is very sensitive to changes in UZFWM for all spatial scales analyzed, and at both the 1-hour and 6-hour time steps. Increasing UZFWM increases interflow at all spatial scales, which is the opposite effect that the parameter change has on surface runoff. Figs. 7 and 8 clearly illustrate how the UZFWM parameter controls the contribution of runoff from surface (rising limb of hydrograph) or interflow (falling limb) because an increase in surface runoff results in a decrease in interflow. Changing UZFWM has a wide range of impacts on percolation across the numerous

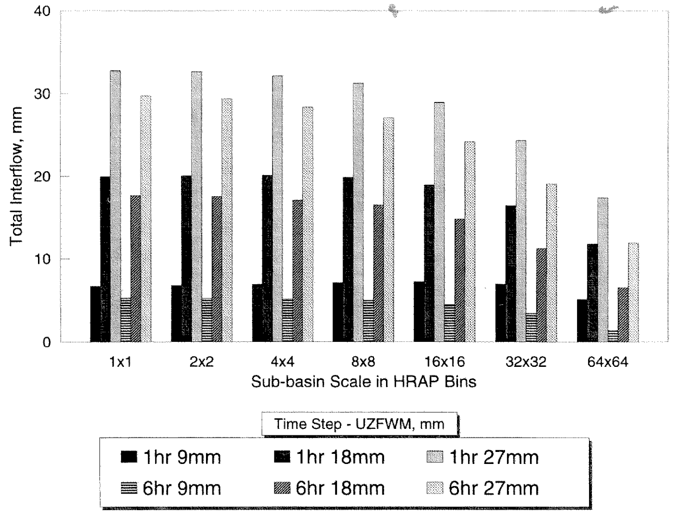

Fig. 8. Effects of changing the SAC-SMA model upper zone free water maximum (UZFWM) parameter on total interflow runoff volume over 9 months of continuous simulation using Stage III precipitation data. Interflow is very sensitive to both increases and decreases in the UZFWM parameter at all spatial and temporal scales analyzed.

space–time scales presented in Fig. 9. UZFWM affects both the volume of water available for percolation and the rate of percolation in the SAC-SMA model. The results in Fig. 9 show no clear relationship between scale, UZFWM, and percolation, which indicates a more in-depth percolation analysis is required. Fig. 10 shows that supplemental baseflow is sensitive to the UZFWM parameter across all space–time scales analyzed and in much the same way the parameter affects percolation. This model

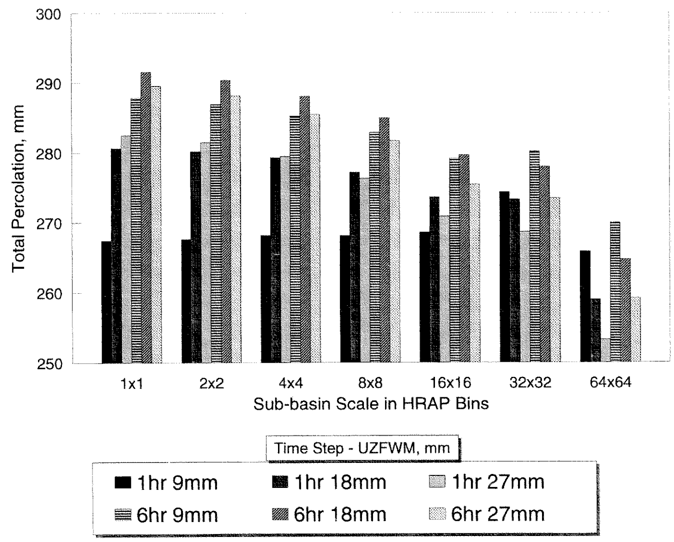

Fig. 9. Effects of changing the SAC-SMA model upper zone free water maximum (UZFWM) parameter on the total percolation of soil water from the upper zone to the lower zone soil moisture reservoirs. The results are obtained from 9 months of continuous simulation using Stage III precipitation data. The UZFWM parameter has a wide range of effects on percolation across the numerous spatial and temporal scales analyzed. Although a clear trend does not exist across scales, the sensitivity of percolation to UZFWM changes is significant.

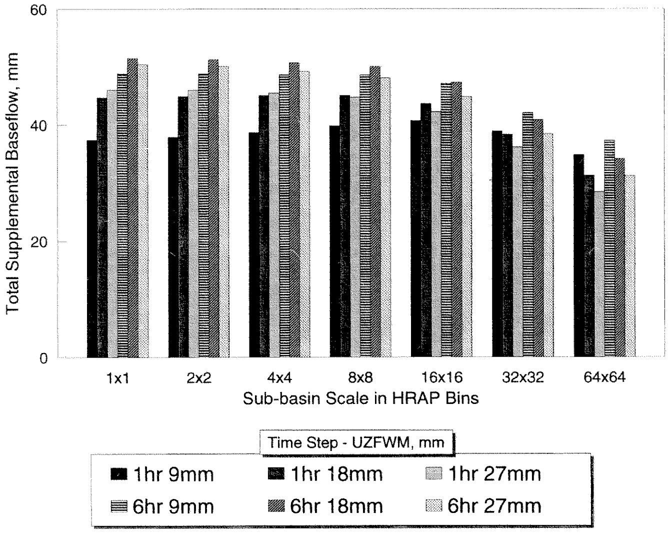

Fig. 10. Effects of changing the SAC-SMA model upper zone free water maximum (UZFWM) parameter on the total supplemental baseflow over 9 months of continuous simulation using Stage III precipitation data. The UZFWM parameter has a wide range of effects on supplemental baseflow across the numerous spatial and temporal scales analyzed. Although a clear trend does not exist across scales, the sensitivity of supplemental baseflow to UZFWM changes is significant and is clearly related to the parameter-induced changes to percolation (see Fig. 9).

behavior is expected because soil water percolates from the upper zone free water reservoir down to the lower zone soil moisture reservoirs, one of which is the lower zone free supplemental baseflow reservoir.

Adjustment of the SAC-SMA model UZFWM parameter is shown to be capable of compensating for biases created from applying the model at space–time scales different from which it is calibrated. However, adjusting the UZFWM parameter also has a significant and opposite effect on interflow, and a wide range of effects on percolation and supplemental baseflow. These complex interactions affect the timing, volume, and shape of the resulting runoff hydrograph. Thus, adjusting UZFWM affects the exchange of water between fast and slow response runoff as well as between the upper and lower zone soil moisture. Figs. 7–10 demonstrate the complex problems inherent to recalibrating model parameters when distributing them spatially and temporally.

4.3.2. *Upper zone tension water parameter*

Upper zone tension water maximum storage capacity (UZTWM) must be satisfied in the SAC-SMA model before precipitation enters the upper zone free water storage where interflow and percolation take place. The tension water storage also controls evapotranspiration, which accounts for 77% of the losses in the water balance for the 9-month simulation period. Therefore, UZTWM also controls runoff generation in the SAC-SMA model in much the same way the UZFWM parameter does, and may also be recalibrated to account for runoff volume biases caused by applying model parameters across different space–time scales. The UZTWM parameter is calibrated at 40 mm for the test basin and trials are run for values of 20 mm, 40 mm, 60 mm, and 80 mm.

Fig. 11 shows that increasing UZTWM decreases surface runoff for all space–time scales analyzed. However, the effects of UZTWM on surface runoff also exhibit the complex interaction with interflow, percolation, and supplemental baseflow, just as the UZFWM parameter does in Figs. 7–10. Surface runoff is more sensitive to the UZFWM parameter than the UZTWM parameter, but either may be used to adjust surface runoff volumes at all space–time scales analyzed.

Fig. 12 shows that evapotranspiration, ET, is sensitive to recalibration of the UZTWM parameter for all space–time scales analyzed. In general, ET is

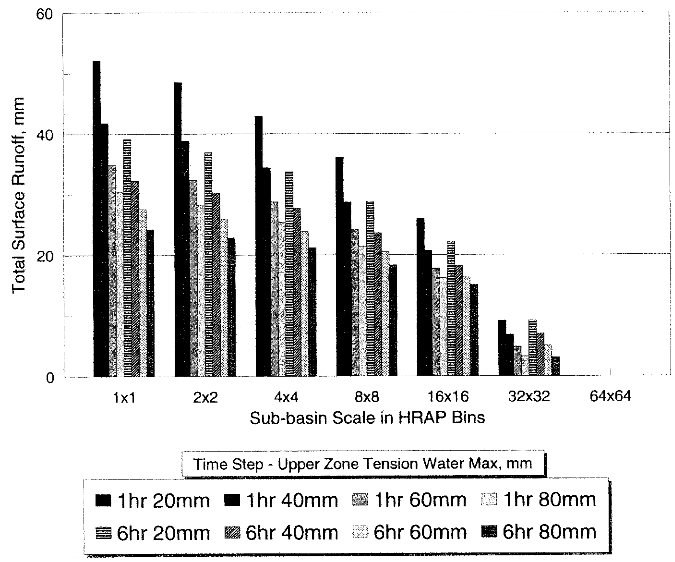

Fig. 11. Effects of changing the SAC-SMA model upper zone tension water maximum (UZTWM) parameter on the total surface runoff volume over 9 months of continuous simulation using Stage III precipitation data. Surface runoff is very sensitive to both increases and decreases in the UZTWM parameter at all spatial and temporal scales analyzed.

maximized at the calibrated UZTWM value of 40 mm and ET decreases as the parameter is either increased or decreased. ET is shown to increase as the sub-basin spatial scale increases and when changing from the 1-hour to 6-hour time step. Both observations are related to more precipitation residing in tension water storage as opposed to becoming runoff. Although a clear trend of ET as a function of UZTWM is not present in Fig. 12, the effect of space–time scales on ET is of the same order of

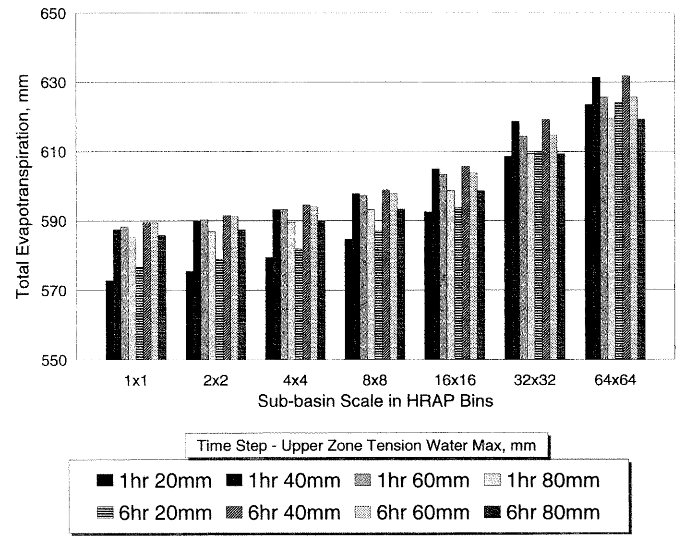

Fig. 12. Effects of changing the SAC-SMA model upper zone tension water maximum (UZTWM) parameter on the total evapotranspiration, ET, over 9 months of continuous simulation using Stage III precipitation data. Evapotranspiration is generally sensitive to UZTWM parameter changes across the space–time scales analyzed. ET tends to be a maximum at the value for which it is calibrated, UZTWM equal to 40 mm.

magnitude as the changes in the other most sensitive SAC-SMA model components. In fact, any increases in ET are balanced by decreases in total channel inflow across all space–time scales. This result strongly suggests a more in-depth study of scale impacts on ET and the long-term soil water balance is required. Figs. 11 and 12 further illustrate that SAC-SMA model parameter adjustments can correct for certain biases created from applying the model at space–time scales for which the parameters are not calibrated. However, changing model parameters causes a complex and poorly understood redistribution of water between the various runoff components in the model which results in new volume and timing biases in both the short-term storm runoff and the long-term water balance.

5. Conclusions

The sensitivity of the SAC-SMA model to precipitation inputs at various space–time scales while holding the parameters constant was explored by developing a rainfall runoff scale driver. The results presented within were realized when running a continuous version of the SAC-SMA model in a lumped fashion at many different space–time scales while using mean areal precipitation inputs derived from gridded Stage III data.

The SAC-SMA model runoff components were found to be sensitive to both spatial and temporal scales of the Stage III precipitation inputs. The analysis revealed a general increase in surface runoff, interflow, supplemental baseflow, and total channel inflow when moving to finer spatial scales and maintaining constant hydrologic model parameters. Evapotranspiration decreased as the spatial scale decreased which offset the increase in total runoff in the 9-month water balance. Decreasing the time scale of the model from 6 hours to 1 hour, while holding the spatial scale constant, resulted in a significant increase in surface runoff, interflow, and total channel inflow. Decreasing the time scale caused a decrease in the supplemental and primary baseflows.

These space–time scale effects on the SAC-SMA hydrologic model response may be attributed to the space–time averaging of high intensity, short duration, runoff generating precipitation events. And this space–time scale sensitivity suggests that potential improvements to the SAC-SMA model simulations may be possible by using the Stage III gridded precipitation estimates and modeling at finer space–time scales. Future research will explore these possibilities by evaluating the finer resolution simulated hydrographs as compared to observed hydrographs.

Adjusting model parameters was shown to be a method for preserving volume biases in a single runoff component when biases were created from applying the SAC-SMA model parameters to space–time scales for which the model was not calibrated. However, simple parameter changes resulted in a complex exchange and redistribution of water in other model runoff components and cannot account for space–time scale effects on the overall volume, timing, and shape of the SAC-SMA runoff hydrograph.

The results presented highlight the need for a greater understanding of the space–time distribution of SAC-SMA model parameters. The analysis indicated that parameters derived at a given space–time scale cannot be applied at different scales without introducing significant runoff volume biases. These biases were displayed in the redistribution of runoff volume between fast and slow response components, as well as between near surface and groundwater response. All results presented must be viewed according to the fundamental assumptions and limitations of the analysis and may vary geographically.

6. Future research

Future research will focus on methods for space–time distribution of SAC-SMA model parameters that do not introduce significant runoff volume and timing errors. A more in-depth study of the effects of changing model parameters on percolation, evapotranspiration and the complex interactions between the various SAC-SMA model runoff components is required. Work has begun on a potential method to adjust existing model parameters for their application across different space–time scales. Research is also underway at the NWS on reformulating the SAC-SMA model to account for the spatial variability in Stage III precipitation fields. Once calibrated, the reformulated SAC-SMA model and its parameters are expected to be less sensitive to spatial scale than the current model version. Alternative models, with parameters derived from existing and new physiographic data sets, should also be investigated. Research will also be focused on deriving synthetic unit hydrographs and developing channel routing procedures for ungaged areas. All model developments will be verified on real basins and evaluated based on their contribution to operational river forecasting accuracy.

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