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Proximal watershed validation of a remote sensing-based streamflow estimation model

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Abstract. Remotely sensed time series of landscape biophysical states and radar estimates of precipitation are assessed in a statistical streamflow estimation model in four regionally proximate south-central Texas watersheds. Sandies Creek watershed (1420 km^2) served as calibration of a streamflow estimation model based on 8-day composited time series of land surface (radiant) temperature (LST) and a vegetation moisture stress index (MSI) from MODIS (Moderate Resolution Imaging Spectroradiometer) satellite imagery products. These time series were hypothesized to serve as proxies for soil moisture condition antecedent to streamflow-generating precipitation events as estimated by NEXRAD (Next Generation Weather Radar) precipitation products. A linear multiple regression statistical model yielding estimation equation for observed flows at Sandies Creek was validated in 3 additional proximal watersheds of varying spatial dimension (860 km^2 – 2940 km^2), soils, land cover, and climatology. The validation yielded encouraging results as assessed with Pearson's r, Nash-Sutcliffe's E, and relative volume error or bias. Equivalent performance of the calibrated model was seen in the watershed mostly adjacent to Sandies Creek, the mostly similar one in terms of size, land cover, precipitation, and soils. Performance of the model diminished slightly in the more distal, and climatologically-environmentally dissimilar watersheds. The estimation model was re-calibrated for all three validation watersheds, with positive results. The contribution of LST uncertainty and NEXRAD precipitation bias to model discrepancies were evaluated along with discussion of known sources of model error.

Keywords: surface water hydrology, remote sensing, streamflow estimation, MODIS, NEXRAD.

1 INTRODUCTION

The parameterization of soil moisture, vegetation cover and status, surface temperature, and land use (among others), is key to successful calibration and validation of many physical and conceptual hydrologic models. The spatial and temporal component of these variables can be a limiting factor in the implementation of any model, no matter the simplicity or complexity of model design. Constraints placed on hydrologic models by spatial scaling issues can lead to overgeneralization of hydrologic parameters in one sense (not enough data) and overspecialization in another sense (too much data). The spatial and temporal resolution of soil moisture, for example, can be approached through direct probe analysis at the point and field scale. However, at catchment scales and larger, probe analysis becomes unmanageable and impractical. Soil moisture at these scales must then be inferred statistically from temperature and precipitation records, from moisture proxies such as vegetation state and

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condition, or through remote sensing of reflected or emitted electromagnetic radiation from the land surface.

At various spatial and temporal scales, remote sensing has provided numerous solutions to characterizing land surface biophysical and geophysical processes and properties, many of which relate to hydrologic science [1]. Quick digital delineation of watersheds and surface water flow routing, utilizing Geographic Information System (GIS) analysis, is now possible through the acquisition of surface elevations and subsequent development of digital elevation models (DEM) from laser and radar-ranging satellites and airborne platforms [2,3]. Remotely-sensed spatially distributed precipitation estimates from NEXRAD radar systems are now sufficiently validated to replace gauged and interpolated precipitation as input to hydrologic models [4,5,6]. Soil and vegetation canopy moisture, both key inputs to evapotranspiration models, can be characterized and quantified at various spatial and temporal scales from airborne and satellite-borne visible, infrared, and microwave sensors [7,8,9,10]. While remote sensing can and does provide land surface data relevant to specific hydrologic problems such as streamflow or runoff modeling (such as land use land cover information as input to the curve number method), it was not intuitive that remote sensing alone could parameterize an empirical streamflow estimation model.

Great variability can exist in a single watershed's event to event streamflow response to precipitation. Two otherwise similar precipitation events, in duration and intensity, can result in quite different streamflow responses [11]. This variability most likely stems from the temporal component of the hydrologic variables and not from the spatial component, such as soil type and condition, land use, and land cover. In general, on an event to event basis, soils and land characteristics are sufficiently static and likely fail to account for watershed variability in streamflow response. This is not true of course for small watersheds rapidly urbanizing, for watersheds seriously impacted by fire or other natural hazards, for watersheds with frozen ground, or for watersheds with hydrophobic soil crusting.

For a given watershed, the characterization of soil moisture (spatially and temporally) antecedent to a precipitation event is key to understanding the nature of the variability of the streamflow response to that event [11, 12, 13]. Soil moisture state impacts infiltration dynamics and capacity which in turn impacts runoff response, whether it is Hortonian or saturation overland flow [14]. Variables other than soil moisture state can and do impact streamflow response, such as the spatial distribution and temporal variability of the precipitation event itself.

To address the potential of remote sensing to statistically account for the variation of streamflow events to precipitation events in a south-central Texas study watershed, Weissling and Xie [15] developed and calibrated an 8-day time step streamflow estimation model (model 1) based on a gauged flow record (USGS gauge station), spatially distributed NEXRAD precipitation estimates, daytime land surface temperature, and a vegetation moisture stress index from time series imagery products from the National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS)/Terra and Aqua satellites, for the period of 2002 – 2005. The study watershed, Sandies Creek, encompasses 1420 km^2 of predominately pastoral agriculture, forest, and grasslands in the Guadalupe River Basin, central Texas, a basin with a long history of significant and sometimes catastrophic flood events. For benchmark comparison, a similar statistical model (model 2), also in Sandies Creek watershed, was developed and compared to streamflow estimates derived from the NRCS curve number (CN) method for calendar year 2004 [16]. This latter model employed the same NEXRAD precipitation estimates and land surface temperature (LST) but with a different vegetation index, the Enhanced Vegetation Index (EVI) developed specifically for improved global vegetation monitoring by the MODIS sensor [17]. Correlation of the model 1 calibrated flow series to gauged series (in log space) yielded an r-value of 0.83 and an overall Nash-Sutcliffe estimation efficiency (E) (in log space) of 0.68. The results of validating model 1 for a 15-month period (Jan 2006 to March

2007) yielded an E of 0.45; a satisfactory result considering the 15-month validation period occurred during an extended drought with baseflow conditions predominating in the watershed during most of 2006. The results of model 2 calibration and its comparison to the gauged flow series for 2004 yielded an E of 0.84. The best CN modeled flow series for this same time period yielded an E of 0.62 compared to the gauged series.

The underlying premise of this empirical approach to estimating streamflow is that information on a watershed's antecedent soil moisture condition does in fact exist in LST and in the biophysical status of the vegetation canopy of a watershed. While the aforementioned paper by Weissling and Xie [15] offers a comprehensive discussion of the theoretical basis for the model parameters, a short summary discussion follows. LST is physically coupled to soil moisture through the efficiency of radiant energy transmission between the surface and atmosphere. The thermal emission of the land surface (as longwave infrared radiation) depends on the composition, roughness, and emissivity of land surface materials. The emissivity is a measure of the efficiency of radiant energy transfer of a material and is directly affected by moisture content. The moisture content of land surface influences the partitioning of atmosphere energy flux into latent and sensible heat. A deficit in precipitation, and thus a depletion of soil moisture, reduces the rate of evapotranspiration. This forces a repartitioning of surface heat flux: a decrease in latent heat flux and increase in sensible heat flux. Increased sensible heat flux requires an increase of surface/boundary layer temperature. Thus short term moisture flux may drive surface temperature anomalies by way of both emissivity change as well as latent/sensible heat repartitioning.

The justification for the inclusion of a vegetation moisture stress index (as one of several biophysical status parameters available from MODIS) is based on the potential for moisture content of the vegetation canopy to serve as a time-delayed proxy for near surface soil moisture state. The canopy is defined as grasses, herbaceous cover, agricultural crop, shrub and tree. Deficits in precipitation necessarily lead to near-surface soil moisture depletion and eventually root zone soil moisture depletion as evapotranspiration progresses. Eventually, moisture stress occurs in the vegetation canopy, to which a high temporal resolution vegetation stress index may be sensitive.

This leads to the hypothesis that a remote sensing-based model, based on proxies for antecedent soil moisture, will account for a significant percentage of the variability of the precipitation - streamflow relation in regionally proximate watersheds for which environmental and climatic conditions are similar. In this paper, the original Sandies Creek watershed streamflow estimation model (model 1) is assessed and validated in three regionally adjacent watersheds of varying spatial dimension for calendar years 2002-05. Utilizing the same model parameters, this validation is compared to the results of re-calibrations of the model specific to each watershed.

2 STUDY AREA

The surface waters of south-central Texas are drained by four regional river basins, the Nueces, San Antonio, Guadalupe, and Lavaca (Fig. 1). These basins encompass a wide range of precipitation, vegetation, land use, and soil regimes. Geographically, they are bounded to the northwest by headwater catchments along the southern margins of the Edwards Plateau and to the southeast by Gulf coast estuaries and bays. Local topographic relief is minimal, though increases substantially as the coastal plain merges with the plateau escarpment.

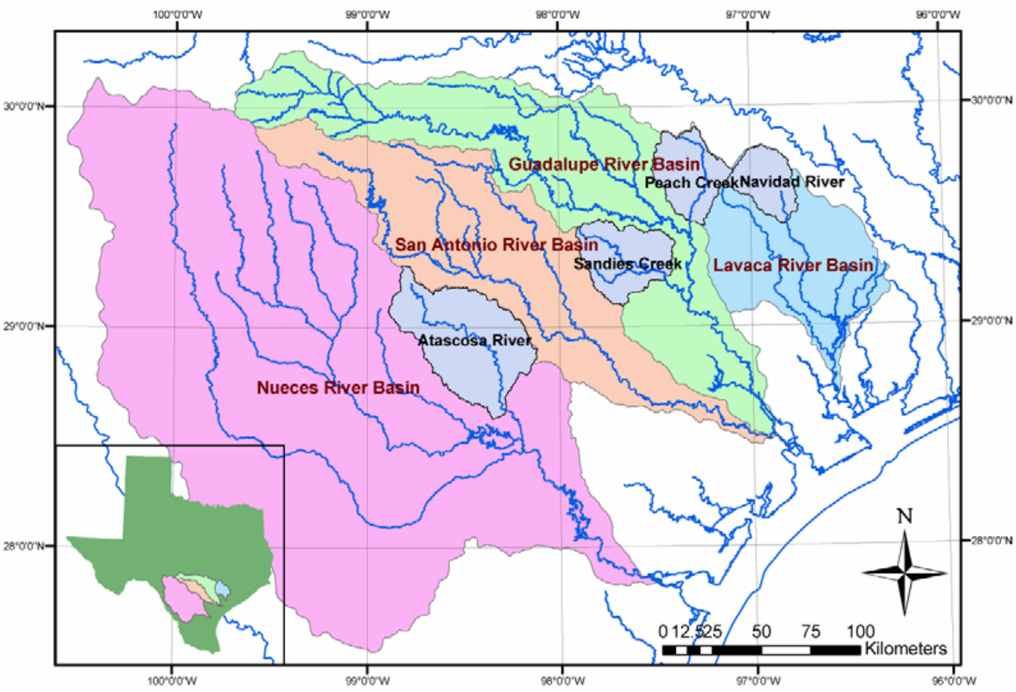

Fig. 1. Location of calibration (Sandies Creek) and three validation watersheds (Peach Creek, Navidad River, Atascosa River) within regional south-central Texas river basins.

Precipitation in the basins is dominated by convective seasonal events, typically associated with converging frontal systems and Gulf of Mexico, Gulf of California and Pacific Ocean moisture masses. Mean annual precipitation across the respective river basins ranges from 750 to 1050 mm, along a west to east gradient. The majority of significant rainfall events occur in late Spring (May – June) and early Autumn (September – October). Flood events are common. The region holds numerous world records for precipitation intensities, from 2-hour events to 2-day events [18,19]. Soil types in the region vary hydrologically from clay-rich, high runoff potential soils of the hydrologic soil groups C and D predominating in the upland and tableland areas of the watershed and sandy, low runoff potential soils of the hydrologic groups A and B predominating in floodplains and along stream courses. An explanation of hydrologic soil groups can be found in Part 630, Chapter 7 of the National Engineering Handbook [20]. Our knowledge of the hydrology of the study area watersheds suggests that streamflow is predominately governed by runoff events. This is evidenced by very low stream baseflow levels, and short recession limbs of event hydrographs. Other than stock ponds and other agricultural impoundments, there are no reservoirs or natural lakes within each of the study watersheds. There is likely some delayed groundwater response to large and/or multiple (back to back) precipitation events, but long-term groundwater outflow is minimal. Depending on precipitation intensity, high runoff potential soils, and soil compaction in areas impacted by pastoral agriculture, infiltration excess overland flow may predominate over saturation excess flow.

Sandies Creek, the original calibration watershed of this study, encompasses 1420 km^2 of rural forest, grass and shrub lands on a branch of the Guadalupe River. Land use is agricultural, with hay production and cattle grazing predominating. Sandies Creek watershed is gauged by a United States Geologic Survey (USGS) streamflow gauge station (ID 08175000) (29.2153 N, 97.4494 W).

Peach Creek watershed, encompassing 1240 km^2, is located on a branch of the Guadalupe river in the central section of the Guadalupe River basin. Approximately adjacent to Sandies Creek watershed, Peach Creek watershed bears many similarities to Sandies Creek with respect to precipitation means, land use land cover (LULC), and soil hydrologic group. It is predominately rural with pastoral agriculture dominating land use. The Peach Creek watershed is gauged by a United States Geologic Survey (USGS) streamflow gauge station (ID 08174600) (29.4741 N, 97.3167 W).

The Navidad River watershed is a headwater catchment in the Lavaca River basin. It is the smallest of the validation watersheds, encompassing 866 km^2, and the most humid due to its proximity to the Gulf coast and greater annual mean precipitation. Rural pastoral agriculture dominates land use. The Navidad river watershed is gauged by a USGS streamflow gauge station (ID 08164300) (29.4669 N, 96.8128 W).

Atascosa River watershed, the largest of the validation watersheds, encompasses 2940 km^2 of rural land on a branch of the Nueces River, southeast of the city of San Antonio. It is the driest of the study watersheds, the least forested, but with the largest percentage of type A, high infiltration rate soils. The Atascosa River watershed is gauged by a USGS streamflow gauge station (ID 08208000) (28.6222 N, 96.8128 W).

For each watershed, details of National Land Cover Dataset (NLCD) LULC classifications (online reference: http://landcover.usgs.gov/classes.php), hydrologic soil group designations, and mean annual precipitation for the study period are described in Table 1.

Table 1. National Land Cover Dataset classification of LULC (in %), hydrologic soil group designation (in %), and mean annual (2002 – 2005) precipitation (mm) for Sandies Creek, Peach Creek, Navidad River,and Atascosa River watersheds. FU, SL, GL, and HC denotes forested upland, shrubland, grassland, and herbaceous cultivation respectively.

	NLCD Land Use Land Cover Class (%)				Hydrologic Soil Group %				Mean annual precipitation (mm)			
	FU	SL	GL	HC	A	B	C	D	‘02	‘03	‘04	‘05
Sandies Creek	28	21	19	31	9	13	21	57	1417	658	941	501
Peach Creek	39	14	24	22	6	16	22	55	1445	884	1168	565
Navidad River	19	15	32	32	1	27	22	50	1527	934	1270	638
Atascosa River	14	37	10	35	19	4	50	22	1308	723	881	413

3 MODIS DATA AND PREPARATION

The National Aeronautics and Space Administration’s (NASA) Moderate Resolution Imaging Spectrometer (MODIS)/Terra satellite images the earth’s surface on a near daily basis in 36 spectral bands from the visible to the thermal infrared (online reference: http://modis.gsfc.nasa.gov). The Earth Resources Observation Systems (EROS) data center of the USGS provides MODIS raw data (Level 1A and 1B) and processed products (Level 2, 3 and 4) at spatial resolutions ranging from 250 m to 1000 m. Two level 3 MODIS data products comprise the remote sensing data component of this validation study: the Land Surface Temperature/Emissivity (MOD11A2) 8-day (1 km spatial resolution) composite product, and the Vegetation Indices (MOD13A2) 16-day (1 km) composite product. The MOD11A2 product provides a day and night average surface temperature estimation of the composited vegetation canopy and soil, with an accuracy of 1 degree Kelvin [21]. The MOD13A2 product provides 16-day composited MODIS reflectivity bands 3 (blue, 0.459 – 0.479 μm), 1 (red, 0.620 – 0.670 μm), 2 (near infrared, 0.841 – 0.876 μm), and 7 (shortwave infrared, 2.105 – 2.155 μm). The latter two bands were used to generate a vegetation Moisture Stress Index (MSI). Rock et al. [22] developed the original MSI based on the Landsat Thematic Mapper sensor’s band 4 (near infrared or NIR), a band insensitive to

moisture change in vegetation, and band 5 (middle infrared or MidIR), a band that responds dramatically to moisture change in vegetation. The MSI index utilized in this study is a modified version based on another region of the middle infrared, the wavelength channel centered at 2.10 µm, MODIS band 7. Band 7 is also dominated by vegetation water absorption and is thus sensitive to variations of vegetation water content [23].
This modified MSI is calculated as:

$$MSI = \frac{MidIR_{MODISband7}}{NIR_{MODISband2}} \qquad (1)$$

Depending on geographic location and vegetation type, the spectral response of vegetation, as measured with vegetation indices, is likely to be significantly influenced by seasonal change such as dormancy, senescence, and budding. Clearly, a vegetation indice such as the MSI becomes irrelevant if all green vegetation in a landscape goes into winter dormancy. However, in the south-central Texas region, the vegetated landscape remains sufficiently "green" through the winter season with the growth of cold-season grasses and herbaceous species, conifers, and some deciduous tree species such as live oaks that retain their leaves until spring bud-break. Nevertheless, there will still be a seasonal signal in vegetation indices in this region. The removal of this signal from the time-series of vegetation indices, known as deseasonalizing the series, is warranted if issues of co-linearity with other seasonal parameters, such as LST, are to be avoided in the regression analysis [10]. Deseasonalizing is accomplished by subtracting the long-term mean (if available) time series of a particular parameter from the specific time series associated with the period of analysis. For this validation study, the 2004 MSI time series was deseasoned by the 2002-05 mean series.

As was described earlier, the MOD11A2 product provides estimates of mean 8-day composited LST for a 1 x 1 km^2 cell under clear sky conditions. For any given cell, a minimum of two clear sky observations is necessary to generate an 8-day composite product. Cells that fail to meet this criterion are flagged as "no data" in the Level 2 products. If at any 8-day time step, the cumulative number of "no data" cells exceeded 70% of the total number of cells in a particular watershed, then that time step was excluded from the analysis. This was less of a problem with the 16-day composite MOD13A2 product, from which the 8-day MSI parameter was produced by a simple interpolation. Conversion of the 16-day vegetation products to 8-day was accomplished by assigning the second half of a 16-day period to the mean of that period and the follow-on period. All MODIS pixel values for a given 8-day timestep were then composited for the watershed.

4 PRECIPITATION DATA AND PREPARATION

This study utilizes precipitation estimates from the National Weather Service (NWS) NEXRAD Stage III and MPE (Multisensor Precipitation Estimator) data products. Both Stage III and MPE precipitation products represent composites of precipitation rates from multiple weather radars for a River Forecast Center (RFC). They are both bias corrected with multiple surface precipitation gauges [24], and in the case of MPE an additional correction through the incorporation of satellite precipitation estimates and an improved mosaic scheme in overlapping radar cells [25, online reference – http://www.nws.noaa.gov/oh/hrl/dmip/stageiii_info.htm)]. The NWS provides both Stage III and MPE hourly precipitation estimation products in a 4 x 4 km polar stereographic grid (HRAP projection) for an entire RFC and are distributed via the internet in compressed binary (XMRG) format monthly files. A multi-step process for conversion of these bundled monthly files to hourly precipitation rates for specific cells within the study watersheds (given specific geographic map projections) is explained by Xie et al. [26].

Hourly precipitation estimates were composited to an 8-day mean to correspond to the model's 8-day time step. Prior to compositing, however, the precipitation event records were advanced 3 days to account for the maximum lag time observed between significant precipitation events and the subsequent streamflow or runoff events over the 4 year study period. The 3-day advance was found sufficient to ensure that the majority of precipitation events would fall within the same 8-day aggregation period as the ensuing streamflow event during the model calibration and development [15]. It was unavoidable, however, that in each calendar year there were a small number of precipitation events that fell within the preceding time step of the ensuing streamflow event, or were of such duration that the event spanned more than one time step.

5 BASIS OF THE MODEL

The original streamflow estimation equation for Sandies Creek watershed was developed through the regression of the three significant parameters (LST, MSI, and NEXRAD precipitation) against the log-transformed gauged streamflow on an 8-day mean time step for a four-year period of analysis (2002 - 2005). Weissling and Xie [15] describe the selection of these three parameters from an initial parameter set (16 remote sensing parameters plus precipitation) evaluated for significance in a forward stepwise multiple regression approach. LST in this model specifically refers to an 8-day mean daytime land surface temperature, offset or advanced two time steps. For example, the January 17-24 time step in the model incorporates the daytime LST for the January 1-8 time period. This LST parameter was significant at $P < 0.0001$ and accounted for 23.5% of the variation of log-space streamflow in the original Sandies Creek calibration model. MSI specifically refers to an 8-day deseasoned mean of MSI, synchronously with the model time step (no offset). This MSI parameter was significant at $P < 0.0001$ and accounted for an additional 10.5% of the variation of log-space streamflow in the original model. Finally, NEXRAD precipitation, 3-days advancing to the steamflow, accounted for the greatest percentage of log-space streamflow variation at 35.7% and was significant at $P < 0.0001$.

The calibrated streamflow estimation model was based on the following generalized equation for a least squares multiple regression model.

$$Est(\log Y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \qquad (2)$$

where $Est(\log Y)$ is the estimate of log-transformed model response, X_i are the predictor variables or regressors, and β_i are the parameter estimates.

The final estimation equation for the calibrated streamflow model became [15]:

$$\log Q = 1.978 + 0.293P + -0.120T - 6.174I \qquad (3)$$

where Q is 8-day composited daily mean streamflow in m^3s^{-1}, P is 8-day composited daily mean precipitation in mm (advanced 3 days prior to compositing), T is 8-day composited mean LST in °C, and I is 8-day composited mean MSI.

The overall estimation efficiency for the calibrated 2002 - 05 Sandies Creek flow series was 0.68, with efficiencies ranging from 0.48 to 0.79 for individual years. Overall bias for the calibrated flow series was 21%. It must be noted that this overestimate of gauged flow was found to be largely dependent on a single extreme flood event in July 2002. If considered to be a statistical outlier, removal of the time step associated with this event resulted in an overall bias of -47%.

To evaluate the effects of removing this event from the time series regression model, a second calibrated estimation equation was produced:

$$\log Q = 1.909 + 0.343P + -0.121T - 5.742I \qquad (4)$$

The estimation efficiency (E) of this model applied to the 2002-05 Sandies Creek flow series was unchanged at 0.68 while the overall underestimate bias was -30.6%, a considerable improvement. This latter equation (4) served as the standard of model validation for the three testing watersheds, Peach Creek, Navidad River, and Atascosa River. Given obvious dissimilarities of the three validation watersheds to the original Sandies Creek watershed, such as size and location, and subtle dissimilarities such as micro-climatology, LULC, and soils, re-calibrations of the original regression model (ie. new regressions of the original parameters, P, LST, and MSI) for each validation watershed were conducted and evaluated.

6 RESULTS

Streamflow estimation equation (4) was applied to 8-day mean time series of precipitation, LST, and MSI to generate an 8-day mean flow series for the validation period 2002-05 for the three test watersheds. Results of comparisons of modeled to observed streamflow were assessed with Pearson's correlation coefficient (r), the Nash-Sutcliffe estimation efficiency (E), and the relative volume error or bias (B). These were then compared to the same assessment criteria as used for the calibration watershed, Sandies Creek. Assessments results for each calendar year for all watersheds are shown in Table 2. It should be noted that the ensuing description of an 8-day mean modeled or observed streamflow as an "event" is one of convenience and is not an event in the true hydrologic sense of the word. Therefore, our description of streamflow events should not be confused with a true streamflow peak or hydrograph.

Table 2. Summary of all Eq. 4 assessment criteria, Pearson's correlation coefficient (r), Nash-Sutcliffe's estimation efficiency (E), and relative volume error or bias (B) of modeled vs. observed flow series for Sandies Creek (SC) calibration watershed, and Peach Creek (PC), Navidad River (NR), and Atascosa River (AR) validation watersheds.

	r				E				B			
Year	SC	PC	NR	AR	SC	PC	NR	AR	SC	PC	NR	AR
Overall	0.83	0.79	0.80	0.78	0.68	0.59	0.47	0.41	-0.31	0.23	0.02	-0.30
2002	0.80	0.85	0.79	0.81	0.61	0.63	0.48	0.55	-0.10	0.18	0.53	-0.37
2003	0.73	0.60	0.66	0.64	0.46	0.24	0.18	0.18	-0.43	0.20	-0.29	-0.24
2004	0.86	0.81	0.85	0.74	0.74	0.73	0.53	0.40	-0.43	0.59	-0.24	-0.13
2005	0.89	0.91	0.86	0.83	0.79	0.75	0.59	0.33	-0.60	-0.72	-0.65	-0.55

6.1 Peach Creek

Peach Creek is the watershed most similar to the Sandies Creek calibration watershed in terms of dimension, LULC, and climatology. It is also the only watershed of the study located in the same river basin as Sandies Creek, situated on a neighboring branch of the Guadalupe River. Streamflow estimation equation (4) applied to the 2002-05 time series (n = 180, inclusive of July 2002 event) at Peach Creek yielded assessments of modeled to observed streamflow (log space) quite similar to assessments of the calibration model. Overall, there was a slight loss of model performance, in both the r and E statistic, from the

Sandies calibration to the Peach Creek validation (Table 2). Individual years varied, such as a slight increase in performance for 2002 for both r and E, but a substantial decrease in 2003. Very different results were seen, however, in the B statistic, where a 31% underestimation for the 4-year flow volume at Sandies Creek compared to a 23% overestimation at Peach Creek. This overestimate bias was found to be largely dependent on a single large precipitation event in November of 2004, where modeled flow for the event was 508 m^3s^{-1} compared to 61 m^3s^{-1} for observed flow. Exclusion of this event from the validation resulted in a new overall bias of -20%, a figure more consistent with the Sandies Creek calibration bias.

The 4-year validation time series of modeled vs observed streamflow (linear space) at Peach Creek, including precipitation, is shown in Fig. 2 (Panel A) including a scatterplot of all model and observed streamflow data pairs and corresponding trendlines, by year. The overestimation bias, discussed above, is seen clearly in the first cluster of significant streamflow events, from July 2002 to March 2003. With the exception of the large November 2004 event, where modeled flow (for a two time-step event) overestimated observed flow three-fold, modeled flow during the second cluster of events, from March 2004 to May 2005, underestimated observed flow.

Recalibration of the streamflow estimation model for Peach Creek produced the parameter estimates listed in Table 3. The overall model was significant at $P < 0.0001$, with an r^2_{adj} of 0.63.

Table 3. Re-calibration parameter estimates for Peach Creek, Navidad River, and Atascosa River watersheds.

	Intercept (β_o)	Precipitation (β_1)	LST (β_2)	MSI (β_3)
Peach Creek	2.017	0.320	-0.135	-9.956
Navidad River	2.453	0.212	-0.108	-6.847
Atascosa River	0.276	0.305	-0.038	-5.881

The July 2002 precipitation event, although extreme, was not considered an outlier in the regression analysis and so was included in the model. The assessment of the correlation of modeled and observed streamflow yielded r values virtually unchanged from the validation (Table 4).

Table 4. Summary of re-calibration assessment criteria, Pearson's correlation coefficient (r), Nash-Sutcliffe's estimation efficiency (E), and relative volume error or bias (B) of modeled vs. observed flow series for Peach Creek (PC), Navidad River (NR), and Atascosa River (AR) watersheds.

	r			E			B		
Year	PC	NR	AR	PC	NR	AR	PC	NR	AR
Overall	0.80	0.81	0.82	0.64	0.66	0.68	-0.11	-0.40	0.05
2002	0.85	0.78	0.85	0.69	0.61	0.72	-0.21	-0.38	0.04
2003	0.63	0.72	0.76	0.36	0.51	0.52	0.20	-0.21	0.16
2004	0.81	0.87	0.77	0.72	0.76	0.63	0.12	-0.54	0.11
2005	0.92	0.83	0.87	0.75	0.73	0.81	-0.77	-0.44	-0.40

The E criteria, though, improved slightly after recalibration, to an overall series E of 0.64 from the validation E at 0.59. The most notable improvement of E was in the 2003 series, an improvement of 50%. Bias shifted from an overall overestimate of 23% to an underestimate of 11%. Year 2004 produced the most significant improvement in bias, from +59% to +12%. The 4-year recalibration time series of modeled vs observed streamflow (linear space) at

Peach Creek, including precipitation, is shown in Fig. 2 (Panel B) including a scatterplot of all model and observed streamflow data pairs and corresponding trendlines, by year.

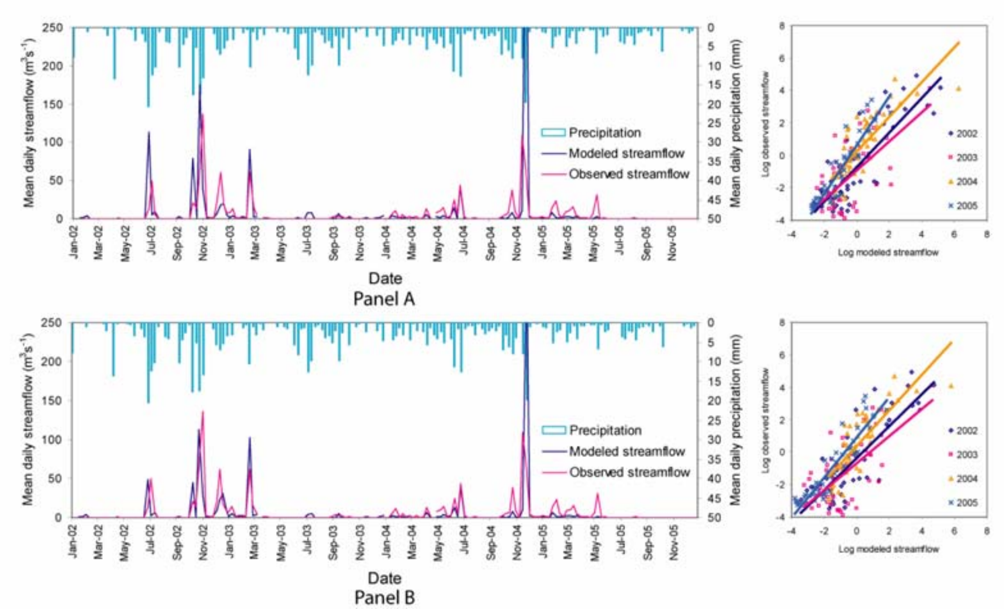

Fig. 2. Validated (Eq. 4) time series (Panel A) and re-calibrated time series (Panel B) with associated scatterplots (log space) of modeled and observed streamflow, and precipitation for Peach Creek watershed.

6.2 Navidad River

Navidad River watershed, in the Lavaca River basin, is the smallest of the validation watersheds, at about 60% of the area of the Sandies Creek watershed. For the period of analysis, Navidad River watershed received approximately 24% greater precipitation than Sandies Creek. The application of Eq. (4) to the 2002-05 time series (n = 179) at Navidad River yielded correlation coefficient assessments (r) of modeled to observed streamflow only slightly less than assessments of the Sandies Creek calibration model (Table 2). E assessments of performance were considerably less, however, with an overall E performance of 0.47 compared to 0.68 for Sandies Creek. The overall bias of the model at Navidad River, however, was close to zero (0.02), with individual year biases ranging from 0.53 to -0.65.

The 4-year validation time series of modeled vs observed streamflow (linear space) at Navidad River, including precipitation, is shown in Fig. 3 (Panel A), including a scatterplot of all model and observed streamflow data pairs and corresponding trendlines, by year. A similar pattern of overestimation bias (to that of Peach Creek) in the July 2002 to March 2003 events and underestimation in the March 2004 to May 2005 events can be seen in the time series plots. The large November 2004 event, spanning two 8-day event periods, was modeled quite well with a cumulative model flow rate of 151 m^3s^{-1} and a cumulative observed rate of 160 m^3s^{-1}.

Recalibration of the streamflow estimation model for Navidad River produced the parameter estimates listed in Table 3. The overall model was significant at $P < 0.0001$, with an r^2_{adj} of 0.65. All large precipitation events, including the July 2002 precipitation event, were included in the regression analysis. There was no significant improvement in r values between the validation and recalibration, with the exception of some improvement in 2003 (Table 4). The E values, however, improved substantially after recalibration, from an overall series validation E of 0.47 to the recalibration E of 0.66. For the 2003 series, E increased almost 3-fold, from 0.18 to 0.51. Bias results for the recalibration were all negative, shifting to -40% for the overall series, albeit with less variance year to year. The 4-year re-calibration time series of modeled vs observed streamflow (linear space) at Navidad River, including precipitation, is also shown in Fig. 3 (Panel B) including a scatterplot of all model and observed streamflow data pairs and corresponding trendlines, by year.

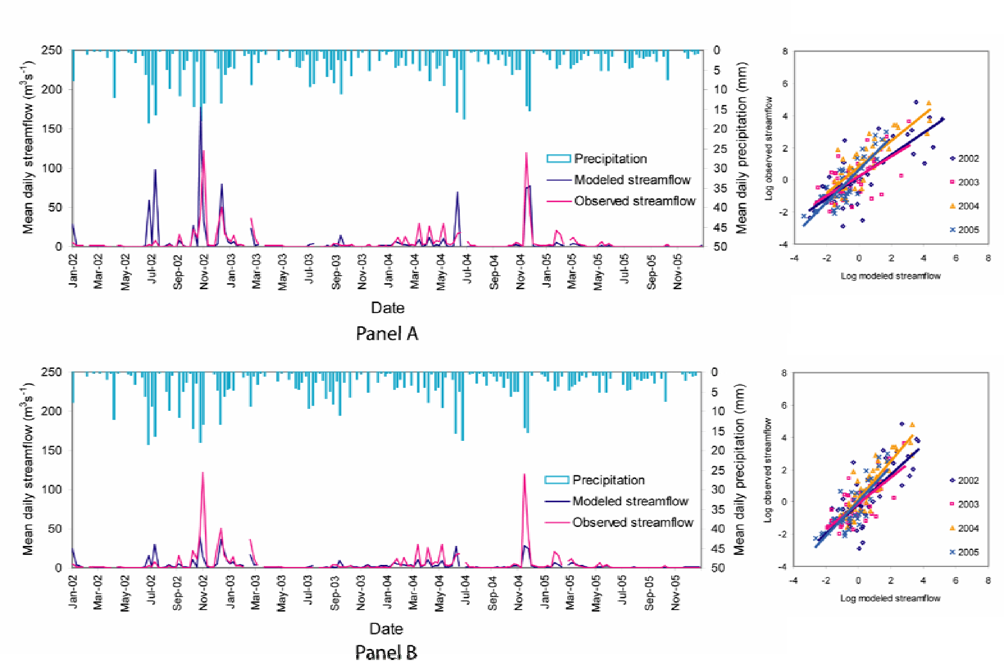

Fig. 3. Validated (Eq. 4) time series (Panel A) and re-calibrated time series (Panel B) with associated scatterplots (log space) of modeled and observed streamflow, and precipitation for Navidad River watershed.

6.3 Atascosa River

The Atascosa River watershed is the largest of the validation watersheds with an area twice that of Sandies Creek. For the period of analysis, it received an average of 830 mm annual precipitation, slightly less than the 880 mm at Sandies Creek. The application of Eq. (4) to the 2002-05 time series ($n = 179$) at Atascosa River yielded slightly lower correlation coefficient assessments (r) of modeled to observed streamflow, 0.78 versus 0.83 for the overall calibration series r assessment at Sandies Creek (Table 2). E assessments of validation performance at Atascosa River followed a similar trend as those at Navidad River with an overall E of 0.41 with individual years ranging from 0.18 to 0.55. The overall bias of the Atascosa River validation model is virtually identical to the Sandies Creek calibration model at -30% and -31% respectively. It must be noted that the modeled response to the July 2002 extreme precipitation event (the July 4 – 11th time step) is not included in the validation model assessment. This one event, clearly beyond the bounds of the stability of the equation, led to a 100-fold overestimate of observed flow. The inclusion of such an event would have rendered the assessment criteria useless.

The 4-year validation time series of modeled vs observed streamflow (linear space) at Atascosa River, including precipitation, is shown in Fig. 4 (Panel A) including a scatterplot of all model and observed streamflow data pairs and corresponding trendlines, by year. Not unlike the other watersheds, a consistent overestimate bias was seen in the July 2002 to March 2003 modeled events. Mixed results were seen in the March 2004 to May 2005 events, with smaller events being underestimated by the model and the single large July 2004 event (a 2 period event) being overestimated more than two-fold.

Recalibration of the streamflow estimation model for Atascosa River produced the parameter estimates listed in Table 3. The overall model was again significant at $P < 0.0001$, with an r^2_{adj} of 0.68. Amongst all watershed recalibrations, Atascosa River had the most significant improvement in r values between the validation and recalibration, from 0.78 to 0.82 for the overall model (Table 4). Year 2003 series r-value increased to 0.76, a notable improvement. A corresponding dramatic improvement in E values were seen after recalibration, with an overall series E of 0.68 compared to 0.41 for the validation. Year 2005 was much more accurately modeled with its E assessment increasing from 0.33 to 0.81. The bias assessment of the overall series resulted in a change from a 30% underestimate to a 5% overestimate. There was less bias variance from year to year as well. The 4-year validation time series of modeled vs observed streamflow (linear space) at Atascosa River, including precipitation, is shown in Fig. 4 (Panel B) including a scatterplot of all model and observed streamflow data pairs and corresponding trendlines, by year.

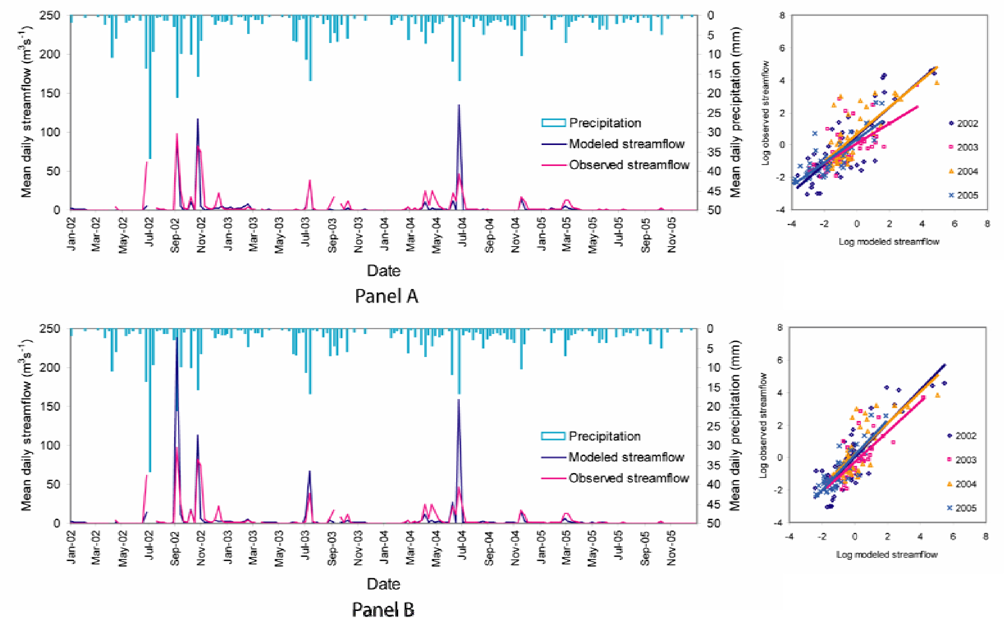

Fig. 4. Validated (Eq. 4) time series (Panel A) and re-calibrated time series (Panel B) with associated scatterplots (log space) of modeled and observed streamflow, and precipitation for Atascosa River watershed.

7 DISCUSSION

The performance assessment of any hydrologic model, in this case streamflow estimation, must be taken in context of the modeling objective and approach. The assessment criteria presented in this study are offered not as guides to compare results to performance of other empirical or physical streamflow estimation approaches, but as guides to assist the reader in assessing this model's spatial and temporal performance. Performance of this model did vary considerably from year to year, and watershed to watershed. The watershed most similar to Sandies Creek, for which the model was originally calibrated, was Peach Creek. As expected, validation results as assessed with the Nash Sutcliffe E criterion more closely tracked the original calibration. With increasing spatial separation of evaluated watersheds, and increasing dissimilarities of precipitation pattern, LULC, and overall size, it was not surprising that the assessments of model validation deteriorated. However, when each watershed was recalibrated, the r^2 assessment of the multiple regression model (for identical parameter sets) was consistent at approximately 65%. This alone indicates that the model approach is perhaps partly independent of location, at least regionally, and to some degree independent of the spatial and temporal pattern of precipitation. The explanation for the remaining 35% of variation in the model, specifically variation in observed streamflow not accounted for by the three parameters evaluated, is most likely rooted in uncertainties of the model parameters, in error induced by the nonsynchronous nature of the precipitation-streamflow event pairs, and in the stochastic component of the precipitation-streamflow relation itself. Although the latter two sources of error are not quantified, a discussion on error and uncertainty due to the three model parameters follows.

There is no physical meaning to the moisture stress index (or to any vegetation index), so there is no quantification of uncertainty. For the MODIS LST product, there is a published uncertainty of ± 1 degree K [21]. An analysis of the sensitivity of the original calibration model (at Sandies Creek) to a change in LST of 1 degree (-1 degree due to the negative correlation of LST with Q), resulted in an improvement in the bias for the overall calibration period (2002-05) from 31% to 22%.

Uncertainty in the NEXRAD precipitation estimates likely plays a significant role in model error. While Stage III and MPE precipitation products are to some degree bias-corrected with co-located surface gages, various studies have found remaining underestimate and overestimate bias. Jayakrishnan et al. [27], in a 1995-99 study of 545 weather stations in the West Gulf River forecast center, a region encompassing the Texas gulf coast, found a general underestimate bias of Stage III product precipitation. Bias estimates at Federal Aviation Administration weather stations (n = 24) during the 5 year study ranged from -2% to -50%, and at Texas Corp of Engineer sites (n = 20) from -3% to -45%. Bias in a select group of twenty Cooperative Observer weather stations, however, ranged from -57% to +61% for the period of study. A recent study by Wang et al. [25] of Stage III and MPE radar and gaged precipitation in the upper Guadalupe River basin (a basin encompassing both Sandies Creek and Peach Creek watersheds) found a 19.5% overestimate of Stage III radar precipitation for 2001, but an underestimation of the MPE product precipitation of 7.2% for 2004. An analysis of the sensitivity of the Sandies Creek calibration model (Eq. 2) to a precipitation bias indicated that a mean increase in precipitation of 11% was sufficient to account for the 31% underestimation in modeled streamflow for the 2002 – 05 period. Precipitation during the Sept 6, 2002 time step (8 days) at Atascosa River (21 mm daily mean) generated a modeled streamflow rate of 238 m^3s^{-1} (daily mean) compared to an observed flow rate of 98 m^3s^{-1}, a bias of + 143%. Given the existing LST and MSI for that time step, a 14.0% reduction in precipitation is sufficient to accurately model the observed flow. As the aforementioned studies indicated, individual station bias within single NEXRAD coverages varied greatly, spatially and temporally. Therefore, actual error in precipitation event and event class (light, heavy, storm type, etc) estimates, in both spatial and temporal domains, are probable and must be considered. Any long term systematic and linear bias in the precipitation product (or in any model parameter) during the study period would not likely explain the cumulative modeled flow bias, since parameter bias would be accounted for in the regression. As there was no clear trend in the cumulative modeled flow bias for any watershed (before or after recalibration), and given the fact that reporting bias on an annual basis is a rather artificial and arbitrary construct, it is our conclusion that the bias criteria is inconclusive for the assessment of efficiency of this model.

One source of known error is the potential mismatch of precipitation event and subsequent streamflow event (viz. compositing the events in different time steps), an unavoidable problem with structuring the model on an 8-day fixed date cycle. An examination of major precipitation events during the study period demonstrated that the majority of events were fortuitously paired to their respective flow event in a single time-step, though many were not. The impact of these non-paired events on the r and E performance assessments is likely substantial.

Despite the known sources of error, the likelihood of parameter uncertainty, and the generalizing nature of the model itself, the consistency of results of this research indicate that streamflow can be reasonably estimated for large regionally proximate watersheds, based on a single calibrated watershed. Recalibration of adjacent watersheds makes the model even more extensible. What is perhaps more promising in this modeling approach is not the model's ability to reasonably predict a flow response from a significant 8-day event, but is its ability to predict the total absence of a response given landscape moisture conditions, as assessed with LST and MSI. An examination of any of the time series plots of modeled and gaged streamflow and precipitation clearly demonstrates this successful attribute. Significant 8-day precipitation events in all watersheds and in all seasons consistently generated negligible modeled streamflow, confirmed by the observed flow records. This alone validates the intent and promise of the research efforts.

8 CONCLUSION

Four years of MODIS time series imagery of land surface temperature (LST) and a vegetation moisture stress index (MSI) (as biophysical proxies for landscape moisture condition) and NEXRAD precipitation estimation products were assessed for their ability to statistically estimate observed streamflow in three south-central Texas watersheds, as validation of a previously calibrated model for Sandies Creek watershed in the Guadalupe River basin. The initial stage of this research generated a three parameter empirical model derived from stepwise and multiple regression of sixteen primary raw and deseasoned remote sensing derived parameters hypothesized to be sensitive to or indicative of antecedent moisture condition. Validation performance was assessed with Pearson's correlation coefficient (r), Nash-Sutcliffe's estimation efficiency (E), and relative volume error or bias (B). The best model validation results were for the most proximal watershed, Peach Creek, the watershed also most similar to the calibration watershed in terms of size, land use land cover, and climatology. Validation performance results deteriorated somewhat for the more distal watersheds, Navidad River and Atascosa River, though were still encouraging. All three watersheds were recalibrated utilizing the original parameter set and were assessed for model significance and performance. New multiple regression models yielded r^2 values that ranged from 63 – 68%, all significant at $P < 0.0001$. For the overall series and for individual years, recalibrations of the three watersheds resulted in slight performance gains for Peach Creek and much improved performance assessments for Navidad and Atascosa Rivers. Levels of uncertainty in the MODIS temperature product and bias error in the NEXRAD precipitation products were explored for their potential to account for the validation and recalibration bias. Known sources of model error were also discussed as well as the influence of a generalizing model in accounting for observed flow variability.

From this and previous studies, it is concluded that time series satellite imagery holds significant promise for development of an operational model for estimating a watershed's streamflow response to precipitation events on a generalized 8-day cycle. Future research in watersheds with differing climatology (arid, humid, tropical) and with differing land use land cover is anticipated for validation of this remote sensing-based streamflow modeling concept.

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