Improving WetSpa model to predict streamflows for gaged and ungaged catchments

Alireza Safari and F. De Smedt

ABSTRACT

In the second phase of the Distributed Model Intercomparison Project (DMIP2), the WetSpa model is applied to simulate flows at basin and subbasin scales. Parent basins and their nested subbasins are modeled as gaged and ungaged basins, respectively. Available observations in the subbasins were only used to validate the model predictions. Gaged basins simulation results show that the predictions and observations are in good agreement. However, major peaks are underestimated, as is often the case in runoff modeling. Underestimation of high flows and in particular peak flows indicates that the prediction of actual runoff coefficients in the current WetSpa model needs to be improved. Also, sensitivity analysis of the model parameters reveals that the baseflow recession coefficient is the most sensitive parameter and care should be taken when modeling ungaged basins. Hence, by estimating this parameter for each subbasin separately, the model performance for the subbasins can be improved. To do this, a Boussinesq groundwater flow equation is used to improve the prediction of baseflow recession coefficients in the subbasins. Comparison between the original and the modified WetSpa models shows that the modified model yields relatively higher performances for the subbasins, creating a more accurate model for predicting ungaged subbasins.

Key words | Boussinesq equation, DMIP2 project, runoff modeling, streamflow prediction, ungaged basins, WetSpa model

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INTRODUCTION

The WetSpa hydrologic model was originally developed by Wang *et al.* (1996) to conceptualize a basin hydrological system. Since then, the model has been applied to many basins with different hydrological characteristics: for example, to simulate streamflows and predict floods (Batelaan *et al.* 1996; De Smedt *et al.* 2000; Liu 2004; Safari & De Smedt 2008; Mai 2009; Safari *et al.* 2012), to assess the impact of climate and land use changes on surface runoff and subsurface drainage (De Smedt & Batelaan 2001; Liu *et al.* 2004a, b; Nurmohamed *et al.* 2006; Bahremand *et al.* 2007; Dams *et al.* 2008, 2011; Tavakoli & De Smedt 2012), to predict snowmelt and soil moisture (Zeinivand & De Smedt 2009a, 2010; Tavakoli & De Smedt 2013), to model sediment, phosphorus and phosphates transports on a catchment scale (Liu *et al.* 2006; Rwetabula *et al.* 2007; Zeinivand & De Smedt 2009b), and coupled with a groundwater flow model to simulate groundwater-surface water interactions (Dams *et al.* 2008, 2011; Getachew 2009).

In several cases of these applications underestimations in prediction of high flows, particularly those that lead to flooding, have been experienced. For example, De Smedt *et al.* (2000) applied the adopted WetSpa for flood prediction in a 67 km^2 Belgian catchment to simulate hourly runoff and extreme floods. Although their simulation results compare favorably with measurements, even without any need to optimize model parameters, flows with a return period greater than 20 years were systematically underestimated.

Bahremand *et al.* (2005) applied the WetSpa model to the 4,262 km^2 Hornad basin in Slovakia, and simulated daily hydrographs with a good accuracy, but in some instances underestimated high flows, especially major peaks. Safari (2012) conducted a study to see how the WetSpa model is

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capable of reproducing flows for a broad range from low flows to high flows. PEST predictive analysis functionality was used to investigate the WetSpa model prediction uncertainty. The prediction analysis results showed that the WetSpa model is unable to reproduce high flows, particularly the largest peak discharge; that is, it systematically underestimates peak flows. This underestimation problem of the WetSpa model has been experienced in other model applications as well: Liu (2004), Bahremand (2006), Safari & De Smedt (2008), Getachew (2009), Mai (2009) and Safari *et al.* (2012). Hence, the model systematically underestimates high flows, and should be improved to simulate runoff more accurately, particularly for peak flows. Safari & De Smedt (2008) tested the model forced with radar-based precipitation data and concluded that the calibrated WetSpa model predicted streamflows accurately. However, the model performance was somewhat less for low flows, due to the simplified model descriptor of groundwater flow. This simplification of the groundwater component in the model was also addressed by Bahremand (2006), when modeling the Torysa river basin, Slovakia. In applying the calibrated and uncalibrated WetSpa model to several Distributed Model Intercomparison Project (DMIP2) test basins, Safari *et al.* (2012) reported that for some subbasins the WetSpa model performance was poor or even very poor, whether or not the model was calibrated. Also, Safari (2012) stated that the baseflow recession coefficients obtained from the calibration basins did not apply satisfactorily to the subbasins, leading to lower model performances for the subbasins. Hence, improving the estimation of baseflow recession coefficients on subbasin level could potentially improve the model efficiency, in particular for the ungaged interior locations.

METHODOLOGY

Modifying runoff coefficient estimation in WetSpa

In the WetSpa model (Liu & De Smedt 2004), the runoff coefficient C_{a_t} is obtained by adjusting the potential runoff coefficient (C) as follows:

$$C_{a_t} = C(\theta_t/\theta_s)^{\alpha} \quad (1)$$

where $\theta_t[\mathrm{L^3L^{-3}}]$ is soil moisture at time t, $\theta_s[\mathrm{L^3L^{-3}}]$ is water content at saturation and α is the rainfall intensity adjuster, which depends upon rainfall intensity PI_t, surface runoff exponent m_1 and rainfall intensity scaling parameter m_2 (Table 1), as follows:

$$\alpha = \max[1,\ m_1 + (1+m_1)PI_t/m_2] \quad (2)$$

The values of the potential runoff coefficient (C) depend upon soil type, landuse and slope angle, and are incorporated in the WetSpa model by look-up tables that if needed can be adjusted by the model user. When the soil is saturated, the runoff coefficient C_{a_t} becomes equal to (C), while for unsaturated soils, C_{a_t} becomes much lower than (C) depending upon the value of α (Figure 1).

Hence, (C) is the ceiling for the adjusted runoff coefficient C_{a_t}. The underestimation of high flows and in particular peak flows indicates that the actual runoff coefficient should become larger than the ceiling values, which is not possible in the current version of WetSpa unless the default attribute table relating potential runoff coefficient to soil type, land use and slope angle is modified. This would, however, also have an impact on medium and low flows. Hence, to attain an accurate estimation of high flows, the calculation of the runoff coefficient should be

Table 1 | Adjustable WetSpa model parameters and ARIMA error model parameters

Description	Symbol	Unit
WetSpa parameters		
Surface runoff exponent	m_1	–
Rainfall intensity scaling parameter	m_2	mm h^{-1}
Correction factor for potential evapotranspiration	m_3	–
Groundwater storage parameter	m_4	mm
Interflow scaling factor	m_5	–
Groundwater flow recession coefficient	m_6	h^{-1}
New WetSpa parameters		
Aquifer dissipation coefficient	m_6	m^2 d^{-1}
Threshold for antecedent runoff	m_7	mm
Runoff coefficient scaling factor	m_8	mm h^{-1}
ARIMA parameters		
Parameters of the autoregressive part of the model	ϕ_1 to ϕ_4	–

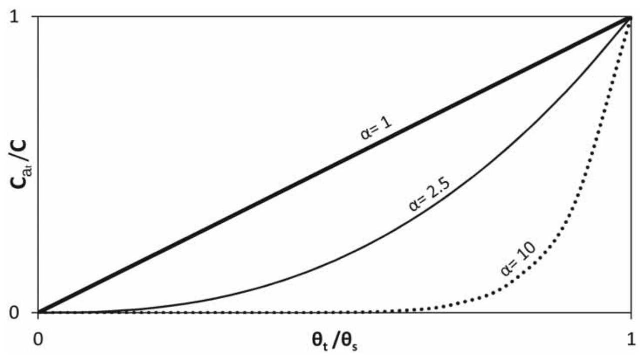

Figure 1 | Relationship between the runoff coefficient and soil moisture for different values of the rainfall intensity adjuster (α) in WetSpa. C_{a_t} is the actual runoff coefficient at time t and C the potential runoff coefficient; $\theta t/\theta s$ is the ratio of soil moisture content at time t to the soil saturated water content.

modified, by taking into account the antecedent effective rainfall. The antecedent effective rainfall, CP_e[L], is the accumulated rainfall volume on the soil surface minus losses by interception, evaporation and infiltration. When CP_e becomes larger than a threshold value, hereafter called parameter m_7[L], the runoff coefficient is estimated using the following expression:

$$C_{a_t} = 1 - e^{-(PI_t/m_8)} \quad \text{for} \quad CP_{e_{t-1}} > m_7 \tag{3}$$

where $m_8[LT^{-1}]$ is a scaling parameter that can be estimated by model calibration. Figure 2 shows the changes in the modified runoff coefficients due to the rainfall intensity. It can be seen that the adjusted runoff coefficients do not have the ceiling limitation of the potential runoff coefficient in Equation (1), and depending upon

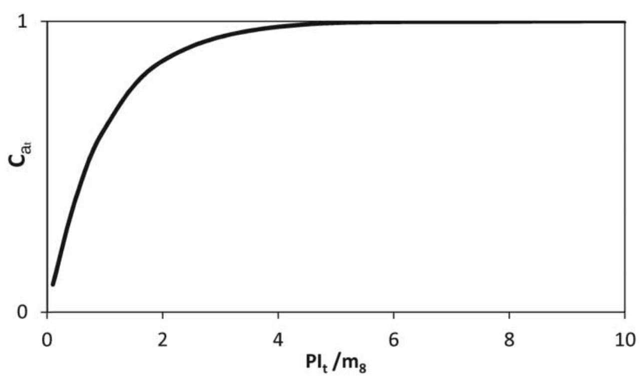

Figure 2 | Schematic illustration of the relationship between runoff coefficient C_{a_t} and rainfall intensity PI_t, when the antecedent effective runoff is larger than a threshold value m_7 in the modified WetSpa model; m_8 is a scaling factor.

the intensity of rainfall, has the possibility to reach 1, which was not possible when using Equation (1). Note that when $CP_{e_{t-1}}$ is less than m_7, the original method of WetSpa (Equation (1)) is used to estimate the runoff coefficient. Safari (2012) showed that use of the modified runoff coefficient (Equation (3)) does not have any effect on low flows.

Modifying baseflow recession coefficient estimation in WetSpa

In the original WetSpa model (Liu & De Smedt 2004), an estimate must be made of the base flow recession coefficients that regulate drainage from groundwater storage to the stream. Since usually little is known about the geology, the simple concept of a linear reservoir is used to estimate groundwater drainage on subcatchment scale as follows:

$$G_s = m_6 G \tag{4}$$

where $G_s[LT^{-1}]$ is the flow generated by groundwater drainage, G[L] is the groundwater storage, and $m_6[T^{-1}]$ is a base flow recession constant. As all WetSpa global parameters are adjustable (Table 1), parameter m_6 can be optimized for the parent basin. However, for simulations of ungaged subbasins there is no guarantee that the groundwater drainage characteristics of a subbasin are similar as for the parent basin and model predictions might be inaccurate.

Hence, it is very likely that the base flow recession characteristics of each subbasin are different, which is not taken into account in the original model and may cause inaccuracies in the prediction of groundwater drainage. To tackle this problem, a Boussinesq-based groundwater flow equation is proposed to estimate the baseflow recession coefficient for each subbasin. The Boussinesq groundwater equation has been applied in a wide range of engineering branches, as well as watershed hydrology and groundwater flow studies, e.g. Troch *et al.* (1993), Szilagyi & Parlange (1998), Lockington *et al.* (2000), Dewandel *et al.* (2003), and Chen *et al.* (2006). Describing flow in porous media led Boussinesq (1877) to conduct a study on the mechanisms of aquifer drainage. A diffusion equation was used by Boussinesq to describe groundwater flow in an unconfined aquifer as follows:

$$\frac{\partial h}{\partial t} = \frac{K}{\phi} \frac{\partial}{\partial x}\left(h \frac{\partial h}{\partial x}\right) \tag{5}$$

where h[L] stands for the water table height measured from the base of the aquifer, t[T] is the time, $K[\mathrm{LT}^{-1}]$ is the hydraulic conductivity, $\phi[-]$ is the effective porosity, and x[L] the horizontal coordinate. The approximate solution to Equation (5) known as the Maillet formula (Maillet 1905) is given by the following equation:

$$Q_t = Q_0 e^{-m_6 t} \tag{6}$$

where

$$Q_0 = \frac{\pi}{2} KHl \frac{h_m}{L} \tag{7}$$

and

$$m_6 = \frac{\pi^2 KH}{4\phi L^2} \tag{8}$$

in which $Q_t[\mathrm{L}^3\mathrm{T}^{-1}]$ is the flow rate at time t, $Q_0[\mathrm{L}^3\mathrm{T}^{-1}]$ the initial flow rate, L[L] the half width of the aquifer, H[L] the depth of the aquifer, h_m[L] is the difference in hydraulic head, and 1[L] the length of the perennial stream. The solution is an approximation in case $h_m \ll H$. These symbols are schematically shown in Figure 3. Hence, Equation (8) enables us to estimate the baseflow recession coefficient m_6 in each subbasin. In the modified WetSpa model, parameter m_6 is calculated using a modified equation (Equation (9)), where $D = KH/\phi$ is a dissipation coefficient $[\mathrm{L}^2\mathrm{T}^{-1}]$, which depends on aquifer properties

$$m_6 = \frac{\pi^2 D}{4L^2} \tag{9}$$

The base flow recession coefficient m_6 in the original model is substituted by the aquifer dissipation coefficient, $m_6 = D$, which can be optimized for the parent basin, and assumed also to be valid for the subbasin. The benefit of this approach is that simulations of subbasins are improved, as the value of the base flow recession coefficient, instead of being estimated by model calibration, is calculated by Equation (9), in which the value of L changes for each subbasin. This value is determined from the area size A of the subbasin and the total length of the river course l, i.e. $L = A/2l$ (Figure 3).

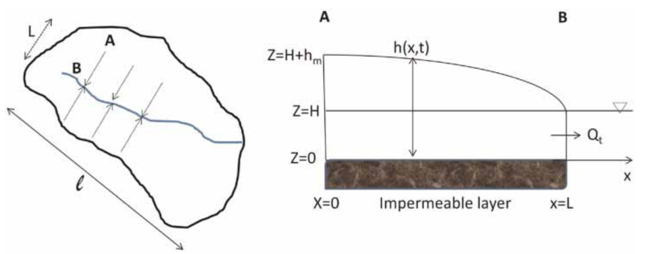

Figure 3 | Schematic representation of the Boussinesq-based model to calculate baseflow. The left panel is a plan view of a catchment with a perennial stream length of *l*, and the right panel a vertical cross-section along the section line A–B. For display purposes, the sketch in the right panel is distorted, whereas in reality *L* is much larger than *H*.

MODEL APPLICATIONS AND RESULTS

This study intends to improve the performance of WetSpa model for modeling streamflows in gaged and ungaged basins. This will be achieved by modifications to the estimation of runoff and baseflow recession coefficients. Reevaluation of the model, hereafter called the modified WetSpa model, is performed in basins (Figure 4 and

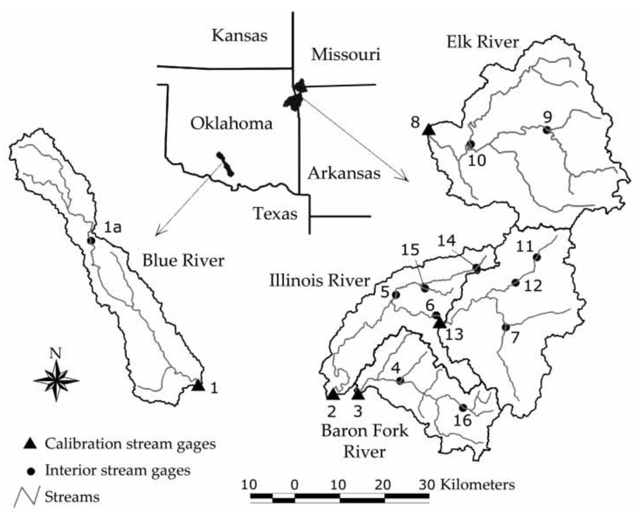

Figure 4 | Distributed Model Intercomparison Project (DMIP2) test basins and stream gages; the name of locations and IDs of the gage stations are given in Table 2.

Table 2) of the second phase of the Distributed Model Intercomparison Project (Smith & Gupta 2012). The DMIP2 parent basins are modeled as gaged basins and the calibrated models are applied to interior subbasins; observations at interior locations are only used to validate the model performance.

Hourly gridded precipitation time series derived from radar (NEXRAD) are divided into two periods: calibration period (from 1 October 1996 to 30 September 2002) and validation period (1 October 2002 to 30 September 2006). Also, prior to the calibration period, 1 October 1995 to 30 September 1996 is used as a 'warm-up' period for the model.

Model performance categories are based on the intervals given by Safari *et al.* (2012), and listed in Table 3. The statistical criterion AM is obtained as follows:

$$\mathrm{AM} = \frac{r_{\mathrm{mod}} + \mathrm{NS} + (1 - |\mathrm{MB}|)}{3} \tag{10}$$

where MB is model bias, NS is the Nash–Sutcliffe efficiency (Nash & Sutcliffe 1970), and r_{mod} is the modified correlation coefficient (McCuen & Snyder 1975). The criteria are given by the following expressions:

$$\mathrm{MB} = \frac{\sum_{t=1}^{N}(Qs_t - Qo_t)}{\sum_{t=1}^{N} Qo_t} \tag{11}$$

$$\mathrm{NS} = 1 - \frac{\sum_{t=1}^{N}(Qs_t - Qo_t)^2}{\sum_{t=1}^{N}(Qo_t - \overline{Qo})^2} \tag{12}$$

$$r_{\mathrm{mod}} = r\frac{\min(\sigma_o, \sigma_s)}{\max(\sigma_o, \sigma_s)} \tag{13}$$

where Qs_t and Qo_t are the simulated and observed streamflows at time t, $\overline{Qo}$ the mean observed flow, σ_o and σ_s the standard deviation of observed and simulated flows respectively, r the correlation coefficient between observed and simulated flows, and N is the number of time steps in the simulation period. An ideal value for MB is 0 and for the criteria NS, r_{mod} and AM is 1.

Also, for low-flow evaluation a logarithmic transformed Nash–Sutcliffe criterion $\mathrm{NS_L}$ is used, expressed as follows (Smakhtin *et al.* 1998):

$$\mathrm{NS_L} = 1 - \frac{\sum_{t=1}^{N}(\ln(Qs_t) - \ln(Qo_t))^2}{\sum_{t=1}^{N}\left(\ln(Qo_t) - \overline{\ln(Q_o)}\right)^2} \tag{14}$$

Table 2 | Distributed Model Intercomparison Project (DMIP2) test basins and location of the stream gages, gage identification (ID), basin area (*A*), length of the perennial stream (*l*), and number (No.) as shown in Figure 4

Watershed	Location	ID	*A* (km^2)	*l* (km)	No.
Blue River	Blue, OK	BLUO2	1,233	144.3	1
	Connerville, OK	CONNR	420	61.8	1a
Illinois River	Tahlequah, OK	TALO2	2,484	145.5	2
	Watts, OK	WTTO2	1,645	82.2	6
	Flint Creek near Kansas, OK	KNSO2	285	43.7	5
	Flint Creek at Springtown, AR	SPRIN	37	10.8	14
	Sager Creek near West Siloam Springs, OK	WSILO	49	18.6	15
	South of Siloam Springs, AR	SLOA4	1,489	79.2	13
	Savoy, AR	SAVOY	433	41.1	7
	Osage Creek near Cave Springs, AR	CAVES	90	19.2	11
	Osage Creek near Elm Springs, AR	ELMSP	337	44	12
Elk River	Tiff City, MO	TIFM7	2,258	109.4	8
	Big Sugar Creek near Powell, MO	POWEL	365	47.1	9
	Indian Creek near Lanagan, MO	LANAG	619	71.9	10
Baron Fork River	Eldon, OK	ELDO2	795	67.1	3
	Dutch Mills, AR	DUTCH	105	18.9	16
	Peacheater Creek at Christie, OK	PEACH	65	19.5	4

Table 3 | Model performance categories to indicate the goodness of fit by means of the aggregated measure AM (Equation (10))

Category	Aggregated measure (AM)
Excellent	> 0.85
Very good	0.70–0.85
Good	0.55–0.70
Poor	0.40–0.55
Very poor	< 0.40

and for evaluation of high flows an adopted version of the Nash–Sutcliffe criterion NS_H (US Army Corps of Engineers 1998), i.e.

$$NS_H = 1 - \frac{\sum_{t=1}^{N}\left(Qo_t - \overline{Qo}\right)\left(Qs_t - Qo_t\right)^2}{\sum_{t=1}^{N}\left(Qo_t + \overline{Qo}\right)\left(Qo_t - \overline{Qo}\right)^2} \quad (15)$$

Criteria NS_L and NS_H vary between $-\infty$ and 1, with 1 corresponding to the ideal value.

To investigate the WetSpa model deficiency in predicting flows for interior points, parameters need to be identified that are essential for the subbasins model predictions. This can be done by PEST parameter sensitivity analysis (Doherty 2004), including a Box-Cox transformation to transform flow discharges and an autoregressive integrated moving average (ARIMA) time series model to transform the residuals, as discussed by Safari (2012). PEST implements a robust variant of the Gauss–Marquardt–Levenberg method for parameter estimation, which makes it able to find the minimum of the objective function in fewer model runs than other algorithms such as the shuffled complex evolution algorithm (Duan *et al.* 1992, 1994). Since PEST is a local search method, the choice of the initial guess for the parameter values is crucial (Abbaspour *et al.* 2001). However, this problem can be resolved using a multi search driver developed by Skahill & Doherty (2006). PEST estimates optimum parameter values by minimizing the sum of squared residuals. In order to reduce correlation between residuals and discharges, a Box-Cox transformation was applied to the discharges and to handle residuals interdependence, an ARIMA error model was applied to the residuals. Sensitivities of the WetSpa and ARIMA models for the five calibration basins are given in Table 4. It can be seen that parameter m_6, the base flow recession coefficient, is the most sensitive parameter in all the basins.

Uncalibrated model performances for subbasins are given in Table 5. For interior points CAVES, ELMSP, SAVOY and SLOA4 that are common for the two parent basins Tahlequah and Siloam Springs, Table 5 shows that modeling a subbasin using the same parameter set from the parent basins can yield very different model performances. The parameter sets for the parent basins, Tahlequah and Siloam Springs, are alike, except for parameter m_2 and m_6 (Safari *et al.* 2012; Table 4). Since the difference in m_2 values is of no concern as the default value of m_1 is 1 (see Equation (2)), the uncalibrated model parameter values for the two parent basins only differ for the base flow recession coefficient, m_6. As can be seen in Table 5, the difference in model performances can be significant in terms of model performance category, e.g. compare subbasins CAVES and SAVOY. This can be attributed to the fact that the base flow recession coefficient obtained for the parent basin does not apply to the subbasin.

Model calibration for the modified models is also performed using PEST parameter estimation program in conjunction with Box-Cox transformation and ARIMA error model. For the modified WetSpa models, the appropriate error model types are ARIMA(3,1,0) for the Blue River, ARIMA(1,1,0) for the Baron Fork River, Elk River and Illinois River at Tahlequah, and ARIMA(2,1,0) for the Illinois River at Siloam Springs. In each optimization iteration ARIMA models are fitted to the residuals of the Box-Cox transformed discharges, and the sum of squared errors is minimized by PEST program until the model is calibrated.

Parameter estimates and their sensitivities for the modified WetSpa models obtained by PEST are given in Table 6. It can be seen that the most sensitive parameter for all basins is m_3, the correction factor for the evapotranspiration, whereas for the original WetSpa models (Table 4), the most sensitive parameter was m_6, the base flow recession coefficient. This is likely due to the fact that the base flow recession coefficient is no longer an adjustable parameter, and hence is excluded from the sensitivity analysis of the modified model. Also, the sensitivity of parameter m_6, the aquifer dissipation coefficient, varies from fairly sensitive in the Baron Fork River basin and Illinois River basin at Tahlequah to almost insensitive over the rest of the basins.

Table 4 | Original WetSpa model parameter sensitivity values and ranks for the five parent basins

Watershed unit	[a]	m_1, –	m_2, mm h^{-1}	m_3, –	m_4, mm	m_5, –	m_6, h^{-1}	ϕ_1, –		ϕ_2, –	ϕ_3, –	ϕ_4, –
Blue River	P_o	11.32	190.8	0.764	113	13.36	0.00034	0.142		0.265	0.094	–
	S_v	1.48E-05	1.57E-04	2.33E-03	1.92E-04	1.22E-05	2.80E-0	1	4.41E-04	4.41E-04	4.41E-04	–
	S_r	8	7	2	6	9	1	5		4	3	–
Baron Fork	P_o	14.17	181.3	0.938	86	3.42	0.00108	0.629		–	–	–
River	S_v	9.81E-06	5.01E-05	2.63E-03	2.19E-04	5.07E-05	5.50E-0	2	4.13E-04	–	–	–
	S_r	7	6	2	4	5	1	3		–	–	–
Elk River	P_o	15.79	291.6	0.839	17	3.54	0.00012	0.421		0.177	–0.010	0.062
	S_v	7.09E-06	6.27E-05	8.54E-04	2.02E-04	4.98E-05	5.55E-0	1	2.64E-04	2.64E-04	2.64E-04	2.64E-04
	S_r	10	8	2	7	9	1	4		5	3	6
Illinois River	P_o	5.22	79.8	0.943	300	5.66	0.00139	0.882		– 0.224	–	–
(Siloam Springs)	S_v	6.11E-05	3.42E-04	8.85E-04	5.74E-05	7.07E-05	5.55E-0	2	3.98E-04	3.98E-04	–	–
	S_r	7	5	2	8	6	1	4		3	–	–
Illinois River	P_o	6.33	144.3	0.942	300	2.48	0.00268	0.743		6.87E-02	–	–
(Tahlequah)	S_v	4.77E-05	1.82E-04	9.94E-04	5.89E-05	1.51E-04	3.47E-0	2	2.19E-04	0.000219	–	–
	S_r	8	5	2	7	6	1	3		4	–	–

[a]P_o is the optimized parameter value, S_v the sensitivity value, and S_r the sensitivity rank. m_1 to m_6 are original WetSpa model parameters described in Table 1 and ϕ_1 to ϕ_4 are ARIMA error model parameters.

Table 5 | Uncalibrated model performances of the common subbasins in the Tahlequah and Siloam Springs basins for the calibration period

Subbasin	Parent basin	MB	r_{mod}	NS	AM	Performance
CAVES	Talo2	−0.34	0.43	0.45	0.52	Poor
	Sloa4	−0.27	0.58	0.62	0.64	Good
ELMSP	Talo2	−0.25	0.49	0.40	0.55	Poor
	Sloa4	−0.29	0.46	0.38	0.51	Poor
SAVOY	Talo2	−0.15	0.57	0.64	0.69	Good
	Sloa4	−0.12	0.66	0.64	0.73	Very good
SLOA4	Talo2	−0.18	0.52	0.65	0.66	Good
	Sloa4	−0.15	0.54	0.69	0.69	Good

MB is the model bias, r_{mod} the modified correlation coefficient, NS the Nash–Sutcliffe efficiency, and AM the aggregated measure.

Based on the AM values, model performance categories given in Table 3 are obtained for the modified and original WetSpa models. Results for the calibration and validation periods are given in Tables 7 and 8 for the original and modified WetSpa models, respectively. Improved values for the model evaluation criteria obtained with the modified WetSpa models are indicated in gray, and degraded performances are outlined in black.

The obtained model performance measure, AM, for the calibration period (Table 7) reveals that for all the parent basins the modified WetSpa model outperforms the original model. In terms of model performance category, this is substantial for the Elk River basin and the Illinois River basin at Siloam Springs. Also, for the validation period (Table 8) the modified model gives better performances than the original model for all parent basins, especially for the Elk River for which the model performance category improves significantly from poor to good. This improvement is illustrated in Figure 5, which shows a graphical comparison between model generated flows and measured flows for the Illinois River basin at Tahlequah. It can be seen that high and low flows are generally predicted more accurately with the modified model. Figure 6 shows a scatter plot of the runoff coefficients predicted by the original model versus modified runoff coefficients. While the modified runoff coefficients can approach 1, actual runoff coefficients predicted by the original model can ultimately only reach their ceiling, i.e. the potential runoff coefficient. The NS_H values for high flows clearly indicate that the modified model outperforms the original model in most cases; that is, four out of five parent basins for both the calibration and validation periods (Tables 7 and 8). Also, the low flow evaluation criterion NS_L shows that the modified model outperforms the original model in four out of five cases for the calibration period, and three out of five for the validation period, although both models poorly predict low flows for the validation period. The lesser performance of the WetSpa model in the validation period is likely due to the fact that the rain and flow regime became much drier in the validation period relative to the calibration period (Safari *et al*. 2012).

In terms of water balance error as represented by MB in Tables 7 and 8, a marked improvement is observed for most basins for both calibration and validation periods. The water balance error improves for Blue River from −15.78 to −12.16%, for Baron Fork River from −16.74 to −8.63%, and for Elk River from −24.39 to −0.82%. However, the water balance errors for the Illinois River basins in the calibration period, and for the Blue River and Illinois River at Siloam Springs in the validation period are not very different.

Calibrated WetSpa models are applied to the subbasins. There are a total of 16 subbasins nested in the five DMIP2 parent basins, of which the Blue River subbasin, CONNR, lacks observed flow data for the calibration period. Hence, the model results for the calibration period can be verified with the observations of 15 subbasins only. Results for these 16 inner measurement river sections are also given in Tables 7 and 8. Note that no further parameter optimization was done for modeling of the subbasins, meaning that the subbasins are assumed ungaged and have been modeled using the calibrated parameters for the parent basins. Model performances for the original and modified WetSpa models are compared based on their aggregated measure values. As can be seen in Table 7, the model performance improves for 10 out of the 15 subbasins. However, in some cases the improvements are not significant. This is also the case for 13 out of 16 nested subbasins for the validation period. Also, the high flow criterion NS_H improves for 14 out of 15 subbasins in the calibration period and 12 out of 16 cases in the validation period, while the low flow criterion NS_L increases only for eight and seven subbasins, respectively, for the calibration and validation periods. Simulation results for the interior locations given in Tables 7 and 8 show that in most cases the modified WetSpa model

Table 6 | Modified WetSpa model parameter estimates and their sensitivities for the five DMIP2 parent basins

Watershed unit	[a]	m_1, –	m_2, mm h^{-1}	m_3, –	m_4, mm	m_5, –	m_6, m^{2}d^{-1}	m_7, mm h^{-1}		m_8, mm h^{-1}	ϕ_1, –	ϕ_2, –	ϕ_3, –
Blue River	P_o	11.23	153.5	0.798	300	17.16	567.2	3.39		0.021	0.125	0.217	0.081
	S_v	2.71E-05	1.74E-06	3.07E-03	1.93E-07	7.17E-05	1.73E-0	7	4.57E-05	5.83E-06	4.61E-04	4.61E-04	4.61E-04
	S_r	7	9	1	10	5	11	6		8	2	4	3
Baron Fork	P_o	12.96	115.7	0.933	290	2.68	1,574.5	1.98		2.461	0.631	–	–
River	S_v	4.71E-05	9.78E-04	1.65E-03	3.59E-05	1.58E-04	2.31E-0	4	9.94E-05	4.30E-05	4.32E-04	–	–
	S_r	7	2	1	9	5	4	6		8	3	–	–
Elk River	P_o	20.46	199.9	1.005	300	8.44	4,042.3	1.05		0.268	0.534		
	S_v	1.26E-05	8.96E-08	3.02E-03	6.81E-08	1.10E-04	2.30E-0	8	1.03E-04	3.75E-05	3.81E-04	–	–
	S_r	6	7	1	8	3	9	4		5	2	–	–
Illinois River	P_o	2.41	174.0	0.910	300	23.23	3,802.1	4.46		466.7	0.934	– 0.243	
(Siloam Springs)	S_v	3.70E-03	4.77E-04	4.87E-03	5.61E-05	3.45E-03	2.48E-0	4	1.66E-03	3.17E-04	4.64E-04	4.64E-04	–
	S_r	2	5	1	10	3	9	4		8	6	6	–
Illinois River	P_o	10.59	70.4	0.912	300	10.41	1,918.4	3.81		4.251	0.658	–	–
(Tahlequah)	Sv	8.54E-05	1.99E-03	4.26E-03	5.69E-05	1.98E-04	2.82E-0	4	2.73E-05	1.46E-05	3.03E-04	–	–
	S_r	6	2	1	7	5	4	8		9	3	–	–

[a]P_o is the optimized parameter value, S_v the sensitivity value, and S_r the sensitivity rank. m_1 to m_8 are modified WetSpa model parameters described in Table 1 and ϕ_1 to ϕ_3 are ARIMA error model parameters.

Table 7 | Simulation results of the original and modified WetSpa models for the calibration period

Watershed	Stream gage	Type of simulation	MB	r_{mod}	NS_L	NS_H	NS	AM	Performance
Blue River	**BLUO2**	Original	−0.16	0.49	0.85	0.66	0.66	0.66	Good
		Modified	−0.12	0.54	0.83	0.68	0.67	0.70	Good
	CONNR	Original	–	–	–	–	–	–	–
		Modified	–	–	–	–	–	–	–
Baron Fork River	**ELDO2**	Original	−0.17	0.58	0.69	0.71	0.70	0.70	Very good
		Modified	−0.09	0.60	0.78	0.72	0.74	0.75	Very good
	DUTCH	Original	−0.18	0.30	0.40	0.21	0.25	0.46	Poor
		Modified	−0.09	0.29	0.46	0.21	0.24	0.48	Poor
	PEACH	Original	−0.11	0.63	0.71	0.48	0.33	0.62	Good
		Modified	0.06	0.78	0.37	0.71	0.63	0.78	Very good
Elk River	**TIFM7**	Original	−0.24	0.52	0.68	0.59	0.62	0.63	Good
		Modified	−0.01	0.69	0.69	0.59	0.63	0.77	Very good
	LANAG	Original	−0.25	0.51	0.46	0.25	0.02	0.43	Poor
		Modified	0.01	0.46	0.50	0.33	0.45	0.63	Good
	POWEL	Original	−0.10	0.42	0.84	0.30	0.26	0.53	Poor
		Modified	0.27	0.54	0.59	0.38	0.28	0.51	Poor
Illinois River at Tahlequah	**TALO2**	Original	−0.02	0.80	0.66	0.87	0.84	0.87	Excellent
		Modified	0.03	0.83	0.70	0.91	0.84	0.88	Excellent
	CAVES	Original	−0.13	0.54	−0.83	0.54	0.52	0.64	Good
		Modified	−0.08	0.76	−8.04	0.65	0.53	0.74	Very good
	ELMSP	Original	−0.02	0.61	−1.62	0.41	0.40	0.66	Good
		Modified	0.02	0.68	−1.12	0.51	0.40	0.69	Good
	KNSO2	Original	0.16	0.19	0.30	0.11	0.18	0.41	Poor
		Modified	0.20	0.35	0.68	0.23	0.32	0.49	Poor
	SAVOY	Original	0.03	0.71	0.73	0.70	0.60	0.76	Very good
		Modified	0.07	0.73	0.80	0.74	0.53	0.73	Very good
	SLOA4	Original	0.00	0.62	0.25	0.74	0.72	0.78	Very good
		Modified	−0.02	0.74	0.74	0.85	0.78	0.83	Very good
	SPRIN	Original	0.09	0.19	−1.43	0.10	0.18	0.42	Poor
		Modified	0.16	0.33	−8.77	0.21	−0.72	0.15	Very Poor
	WSILO	Original	−0.10	0.10	0.68	0.08	0.13	0.38	Very Poor
		Modified	0.05	0.19	−0.10	0.14	0.21	0.45	Poor
	WTTO2	Original	−0.05	0.75	0.50	0.83	0.79	0.83	Very good
		Modified	−0.01	0.86	0.74	0.83	0.74	0.86	Excellent
Illinois River at Siloam Springs	**SLOA4**	Original	−0.02	0.69	0.65	0.82	0.78	0.82	Very good
		Modified	0.05	0.87	0.65	0.89	0.80	0.88	Excellent
	CAVES	Original	−0.16	0.58	0.11	0.60	0.58	0.67	Good
		Modified	−0.06	0.65	−1.61	0.70	0.45	0.68	Good
	ELMSP	Original	−0.05	0.64	−0.29	0.47	0.45	0.68	Good
		Modified	0.04	0.58	−4.13	0.59	0.28	0.61	Good
	SAVOY	Original	0.02	0.75	0.80	0.72	0.59	0.78	Very good
		Modified	0.10	0.71	0.82	0.75	0.55	0.72	Very good

MB is the model bias, r_{mod} the modified correlation coefficient, NS_L a logarithmic transformed Nash–Sutcliffe criterion for low flows, NS_H an adapted version of the Nash–Sutcliffe criterion for high flows, NS the Nash–Sutcliffe efficiency, AM the aggregated measure; gaged basins are shown in bold. Improved model evaluation criteria are indicated in gray and degraded performances are outlined in black.

yields lesser bias than the original model. This is obtained for nine out of 15 subbasins for the calibration period and 15 out of 16 for the validation period. It is worth mentioning that the modified correlation coefficient r_{mod} for the calibration and validation periods improves for the modified WetSpa model, which indicates a better capture of the observed hydrographs.

It can also be noted that often poor model performances are obtained for the smaller subbasins, whether or not the model is modified. This indicates a scale dependency of

Table 8 | Simulation results of the original and modified WetSpa models for the validation period; MB is the model bias, r_{mod} the modified correlation coefficient, NS_L a logarithmic transformed Nash–Sutcliffe criterion for low flows, NS_H an adapted version of the Nash–Sutcliffe criterion for high flows, NS the Nash–Sutcliffe efficiency, AM the aggregated measure; gaged basins are shown in bold. Improved model evaluation criteria are indicated in gray and degraded performances are outlined in black

Watershed	Stream gage	Type of simulation	MB	r_{mod}	NS_L	NS_H	NS	AM	Performance
Blue River	**BLUO2**	Original	0.48	0.62	0.56	0.65	0.61	0.58	Good
		Modified	0.51	0.78	0.55	0.70	0.63	0.63	Good
	CONNR	Original	0.11	0.40	−2.51	0.41	0.25	0.52	Poor
		Modified	−0.03	0.53	−0.42	0.50	0.07	0.52	Poor
Baron Fork River	**ELDO2**	Original	−0.21	0.61	−0.64	0.70	0.67	0.69	Good
		Modified	−0.10	0.55	−0.43	0.58	0.62	0.69	Good
	DUTCH	Original	−0.23	0.51	−0.13	0.54	0.32	0.53	Poor
		Modified	−0.09	0.47	0.08	0.46	0.28	0.55	Good
	PEACH	Original	−0.19	0.02	0.22	−0.28	−0.32	0.17	Very poor
		Modified	0.16	0.06	−0.04	−0.50	−1.27	−0.13	Very poor
Elk River	**TIFM7**	Original	−0.46	0.47	−3.51	0.64	0.62	0.54	Poor
		Modified	−0.31	0.59	−1.16	0.69	0.68	0.65	Good
	LANAG	Original	−0.45	0.70	−3.55	0.78	0.68	0.64	Good
		Modified	−0.28	0.43	−1.61	0.47	0.52	0.56	Good
	POWEL	Original	−0.32	0.36	−1.29	0.33	0.42	0.49	Poor
		Modified	−0.14	0.66	−1.50	0.59	0.53	0.68	Good
Illinois River at Tahlequah	**TALO2**	Original	−0.26	0.66	−1.11	0.83	0.81	0.74	Very good
		Modified	−0.20	0.68	−0.78	0.84	0.81	0.77	Very good
	CAVES	Original	−0.53	0.15	−12.53	0.10	0.16	0.26	Very poor
		Modified	−0.48	0.26	−25.00	0.19	0.25	0.34	Very poor
	ELMSP	Original	−0.40	0.25	−7.70	0.12	0.23	0.36	Very poor
		Modified	−0.35	0.36	−5.30	0.26	0.36	0.45	Poor
	KNSO2	Original	0.04	0.35	−6.50	0.22	0.29	0.54	Poor
		Modified	0.08	0.64	−1.42	0.49	0.51	0.69	Good
	SAVOY	Original	−0.32	0.44	0.10	0.49	0.50	0.54	Poor
		Modified	−0.28	0.47	0.49	0.50	0.51	0.57	Good
	SLOA4	Original	−0.29	0.44	−1.84	0.54	0.57	0.57	Good
		Modified	−0.26	0.45	0.48	0.57	0.61	0.60	Good
	SPRIN	Original	−0.28	0.33	−7.36	0.20	0.36	0.47	Poor
		Modified	−0.22	0.32	−8.40	0.11	−1.11	0.00	Very poor
	WSILO	Original	−0.34	0.15	−1.45	0.11	0.18	0.33	Very poor
		Modified	−0.24	0.29	−5.93	0.22	0.31	0.45	Poor
	WTTO2	Original	−0.26	0.66	−1.99	0.81	0.76	0.72	Very good
		Modified	−0.20	0.78	−3.77	0.86	0.79	0.79	Very good
Illinois River at SiloamSprings	**SLOA4**	Original	−0.30	0.48	−0.42	0.58	0.64	0.60	Good
		Modified	−0.22	0.59	−0.42	0.65	0.70	0.69	Good
	CAVES	Original	−0.53	0.18	−5.81	0.15	0.21	0.29	Very poor
		Modified	−0.47	0.37	−30.72	0.27	0.31	0.41	Poor
	ELMSP	Original	−0.41	0.28	−3.45	0.19	0.31	0.40	Very poor
		Modified	−0.33	0.50	−15.85	0.37	0.41	0.52	Poor
	SAVOY	Original	−0.33	0.45	0.60	0.49	0.51	0.54	Poor
		Modified	−0.24	0.54	−1.44	0.53	0.54	0.61	Good

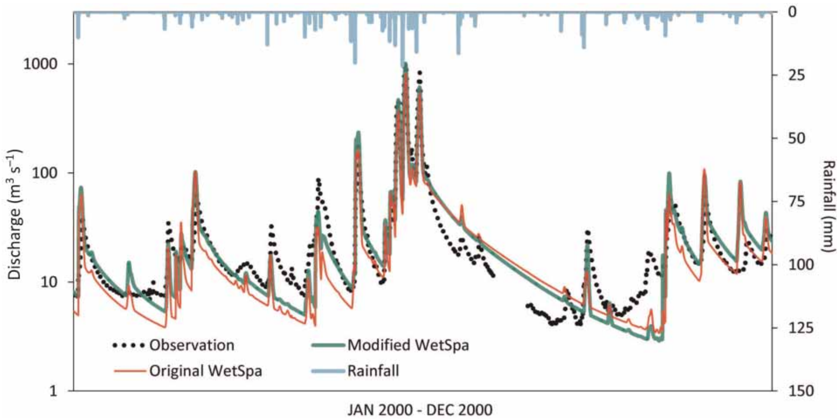

Figure 5 | Simulated and observed hourly flows for the Illinois River at Tahlequah.

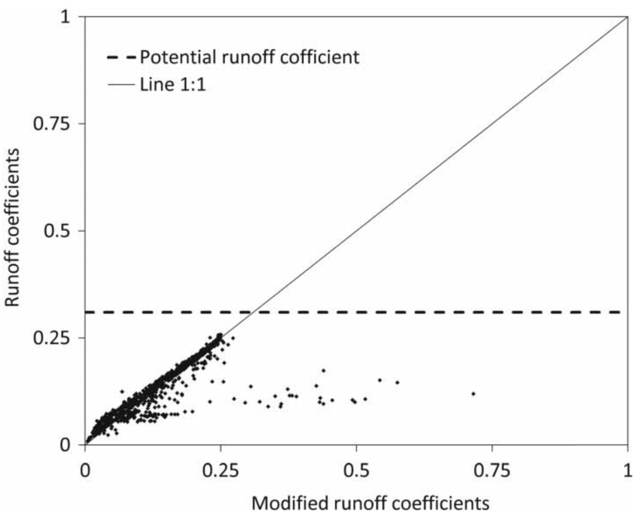

Figure 6 | Runoff coefficients predicted by the original WetSpa versus modified runoff coefficients for the Illinois River basin at Tahlequah in 2000.

other model parameters. To investigate this in detail, the Illinois River basin at Tahlequah with its eight subbasins is chosen to verify if the WetSpa model results are significantly area-scale dependent. Scatter plots of the aggregated measures against area for the eight subbasins are shown in Figure 7. Correlation coefficients for the original and modified WetSpa model runs for both the calibration and validation periods are calculated and with a 95% confidence limit are found to be statistically significant for the original model. This implies that the original WetSpa model is area-scale dependent, and care should be taken when modeling smaller ungaged subbasins. However, for the modified WetSpa model the scale dependency of the model is not statistically significant, yet the model performance for the smaller subbasins is generally lower.

CONCLUSIONS

This study intended to develop improvements for simulating high flows and groundwater drainage in the WetSpa model. Literature review and individual research show that the WetSpa model systematically underestimates high and peak flows through under-prediction of runoff coefficients. Also, groundwater drainage is often inaccurate due to the assumption of a constant baseflow recession coefficient. This highly sensitive model parameter is estimated by model calibration for the parent basins, and when used to model ungaged subbasins results in low model performances. It is suggested to correct the deficiencies in the WetSpa model by inclusion of an improved estimation of the runoff coefficient in case of near saturated soil moisture conditions and by a baseflow recession coefficient at basin and subbasin level as a function of the groundwater flow dissipation coefficient that is calibrated for the parent basin and used without modification for the subbasins. The performance of the modified WetSpa model for the DMIP2 parent basins and their subbasins for the calibration and validation periods is shown to be superior compared with the original WetSpa model.

Also, scale dependency of the performance of the modified WetSpa model is shown to be statistically not significant, whereas this is not the case for the original

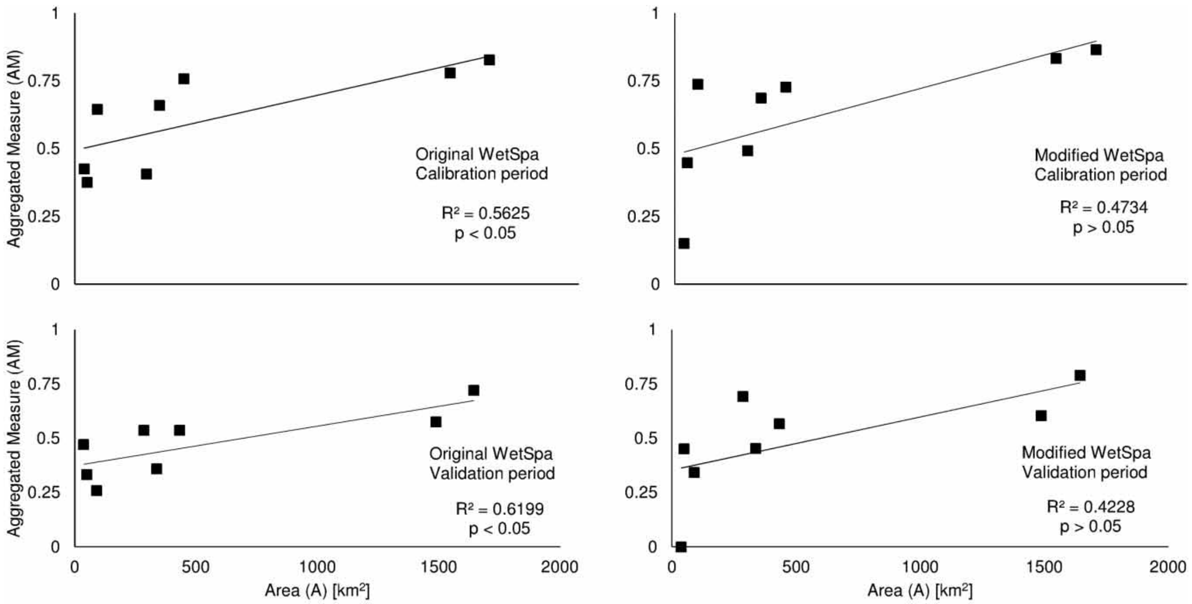

Figure 7 | Model performance versus area for the subbasins of the Illinois River basin above Tahlequah.

model, likely due to the high sensitivity of the base flow recession coefficient. The overall modifications of the WetSpa model presented in this paper make the modified WetSpa model well-suited for simulation of ungaged basins. Also, as the correction factor for evapotranspiration is the most sensitive parameter of the modified model, model applications should focus on the enhancement of spatially potential evaporation input data to obtain better predictions of discharge hydrographs, especially where gaging stations are sparsely distributed over the study area.

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