Understanding sources of uncertainty in flash-flood forecasting for semi-arid regions

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Abstract About one-third of the Earth's land surface is located in arid or semi-arid regions, often in areas suffering severely from the negative impacts of desertification and population pressure. Reliable hydrological forecasts across spatial and temporal scales are crucial in order to achieve water security – protection from excess and lack of water – for people and ecosystems in these areas. At short temporal scales, flash floods are extremely dangerous hazards accounting, for example, for more than 80% of all flood-related deaths in the USA. Forecasting of these floods requires a connected spatially-distributed hydro-meteorological modelling system which accounts for the specific meteorological and hydrological characteristics of semi-arid water-sheds, e.g. summertime convective rainfall and channel transmission losses. The spatially highly heterogeneous nature of the precipitation and the non-linear response behaviour of the system demand the explicit accounting and propagation of uncertainties into the model predictions. This short paper presents the results of a multi-year study in which such a system was developed for flash-flood forecasting in the semi-arid southwestern USA. In particular, we discuss our effort to understand and estimate underlying uncertainties in such a modelling system. To achieve this we use the GLUE approach to uncertainty analysis, in combination with a variance-based global sensitivity analysis technique. In general, the level of uncertainty found was very high and largely dominated by uncertainty in the radar rainfall estimates. Regarding the model parameters, uncertainties in the hillslope model parameter values had a greater impact on the predictions than the uncertainties in the channel parameters, at least for relatively small basins.

Key words flash floods; semi-arid; uncertainty; sensitivity; GLUE; Sobol's method

INTRODUCTION AND SCOPE

A trend towards an increasingly drier and more variable climate has significantly increased global incidences of intense (extreme) precipitation events in the 20th century at the expense of more moderate events (IPCC, 2001). The impact of this change in climate is particularly felt in semi-arid (annual rainfall is 250–500 mm/year) and arid (annual rainfall is less than 250 mm/year) regions of the world. This change has lead to a continuous increase in damages due to extreme flood events, despite widespread problems of water scarcity (Kundzewicz & Kaczmarek, 2000). Such flood events can be short-fused and of small spatial extent, or they can be widespread and of long duration. Both flood types bring their own severe consequences. Since 1985, more than 350 million people were displaced globally because of widespread flood events. Out of this, during the last 19 years, 44 floods generated the displacement of more than 1 million people each. Most of these major floods were located in Asia and took place during the summer months.

Arid and semi-arid regions span approximately one-third of the global land surface, one-fourth of the contiguous USA, and more than half of the western USA. The semi-arid southwestern USA experiences extremely localized and intense convective thunderstorms during summer months (Roeske *et al*., 1989), often leading to short-fused local flood events. Floods that occur within six hours of the causative rain event are termed flash floods within the USA. More people in the USA are killed annually by flash floods than by any other natural disaster (AMS, 1985). They account for more than 80% of all flood-related deaths and cause a billion US dollars in annual economic loss.

Perhaps the most effective way to mitigate the risk due to flash flood occurrence is through implementing a real-time flood forecast and warning system. Requirements for such a system include a high-resolution spatially-distributed model of the highly non-linear hydrological processes occurring at the land surface in semi-arid regions (Pilgrim *et al*., 1988), driven by spatially-distributed rainfall observations or rainfall predictions, and including estimates of uncertainty (Wagener & Gupta, 2005).

In this paper we investigate the predictive utility of a semi-arid flash-flood forecasting system based on high resolution rainfall input into the well-established, event-driven, physically-based semi-arid rainfall–runoff model KINEROS2 (Kinematic Runoff and Erosion; Semmens *et al*., 2005). The system was tested using gauge and radar estimates of rainfall for eight summertime convective thunderstorm events occurring over a sub-basin of the semi-arid USDA-ARS Walnut Gulch Experimental Watershed (WGEW) near Tombstone, Arizona. An approach based on the Generalized Likelihood Uncertainty Estimation framework (GLUE; Beven & Freer, 2001) is used to select suitable parameter sets and to assimilate incoming event information in a forecasting mode. The Sobol variance-based global sensitivity analysis method (VGSA) is applied to explore the influence of uncertainties from sources like rainfall forcing, initial soil moisture conditions and model parameters on streamflow predictions (Saltelli *et al*., 2004). The latter method has been chosen based on results of our earlier research, which suggested that this approach provides more information than some other sensitivity analysis approaches (Tang *et al*., 2007). Research questions addressed here include:

1. How reliable can a semi-arid region flash-flood forecasting model be in the face of the compounding effects of these uncertainties present?
2. To what extent are model predictions of runoff affected by errors in observations of the spatial distribution and the volume biases of the rainfall input?
3. How sensitive are model predictions of runoff to the specification of initial soil moisture conditions, and how complex must an inter-storm model be to meet this need?
4. Which model parameters strongly influence the model predictions of runoff?

DESCRIPTION OF THE RAINFALL–RUNOFF MODEL

KINEROS2 (Semmens *et al.*, 2005; http://www.tucson.ars.ag.gov/kineros) is an event-oriented, distributed, physically-based model developed to simulate the runoff response in basins characterized by predominantly overland flow. The equations in KINEROS2 simulate interception, dynamic infiltration and infiltration-excess surface runoff, with flow routed downstream using a finite difference solution of the one-dimensional kinematic wave equations over a basin conceptualized as a cascade of planes (hillslopes) and channels.

KINEROS2 uses the Parlange 3-parameter infiltration equation (Parlange *et al.*, 1982). This equation is implemented as a dynamic infiltration algorithm interacting with both rainfall and surface runoff in transit. Hence, it is well-suited to model channel transmission in semi-arid ephemeral streams. Microtopographic relief on upland surfaces is represented by a plane-transverse sawtooth relief geometry.

DESCRIPTION OF TEST WATERSHED AND DATA SETS USED

The WG11 study area The WG11 watershed studied here is a sub-basin of the WGEW located in the southwestern USA. The watershed area considered covers 6.4 km^2 and ranges 1430–1525 m in elevation. The WGEW is a highly instrumented study basin (Renard *et al.*, 1993).

Radar rainfall estimates The WSR-88D radar DHR data provide reflectivity estimates that are transformed using an empirical Z-R power relationship into rainfall estimates on a polarimetric 1° × 1 km grid for every radar volume scan (Morin *et al.*, 2005). The variable radar rotational scan speed imparts time-steps ranging from 4 to 6 minutes for events used in the present study.

Gauged rainfall and discharge Since the WGEW has a dense raingauge network, we used rainfall data from 11 weighing raingauges in and near WG11 (aggregated using a Thiessen polygon areal weighting approach), and discharge data for one streamgauge at the sub-basin outlet. These gauge rain estimates corrected the depth bias and the time lag in the radar estimates, and then were averaged with the corrected values to give merged estimates. The breakpoint instantaneous discharge data (finest resolution being 1 minute) was converted to radar timestep values by averaging over time windows delineated by the mid-points of the radar timesteps; this was visually seen to represent the original data time series best (not shown). Table 1 shows details about the events used in this study.

***A priori* parameters from AGWA** *A priori* parameters for KINEROS2 were obtained from the AGWA GIS-based preprocessor using the DEM of the United States Geological Survey (USGS), the soils coverage/shapefile from the State Soil Geographic Database (STATSGO), and the land cover grid from the Multi-Resolution Land Characteristics (MRLC) Consortium - National Land Cover Data (NLCD). All the above data sets were available at or interpolated to 10 m resolution.

Table 1 Table showing observed discharge characteristics and rain comparison statistics for all events.

Event #	Event date (UTC)	Flow start time (UTC)	Flow duration (min)	No. peaks	Peak flows (m^3/s)	Flow vol. (m^3)	Max. rain intensity (mm/h) Gauge	Max. rain intensity (mm/h) Radar: Morin Z-R	(Radar/ gauge) rain depth ratio	Radar gauge time-step lag
1	29 Jul. 03	21:38	83	1	0.94	1153	80.8	45.6	0.35	0
2	25 Aug. 03	19:16	159	2	0.76, 1.14	3006	80.8	74.9	1.33	0
3	28 Aug. 03	0:00	200	2	1.62, 1.89	5929	76.2	32.6	0.39	0
4	9 Aug. 05	4:34	44	1	0.10	82	54.8	11.0	0.23	2
5	9 Aug. 05	22:57	96	1	1.89	2948	106.7	33.3	0.38	2
6	29 Jul. 06	5:59	197	2	5.08, 1.98	9224	126.5	49.7	0.41	2
7	30 Jul. 06	14:30	78	2	0.44, 0.48	1054	45.7	23.9	0.34	1
8	31 Jul. 06	12:05	88	1	1.49	2611	47.3	25.4	0.38	2

METHODOLOGY FOLLOWED

Table 2 shows the spatial modifiers (e.g. multipliers) on the factors that were used to condition the spatially-distributed parameter field of the AGWA-based *a priori* estimates against the observed streamflow using the GLUE approach. The spatial relative magnitudes in each factor field therefore did not change, only their absolute values. The modifier space was searched using Monte Carlo sampling. The impact of each factor was evaluated using the Sobol's variance-based global sensitivity analysis approach.

Table 3 shows the objective functions (OFs) that were transformed into likelihoods (LFs) in such a way that better parameter sets would achieve higher LF values and that all likelihoods would sum up to one. The LF notations in this study are the same as the corresponding OFs, with an L prefix included. Modifier sets were deemed behavioural if their simulated flows were within error ranges around the observed flows that were assumed desirable in flash-flood forecasting (details not shown), with the corresponding LF denoted as LFB. Two methods for combining likelihoods were employed to arrive at weights to be used in both the GLUE and VGSA analyses. Across different objectives, the multi-objective LF (LFM) was obtained by multiplying the individual shape-based LFs. However, for likelihood updating across events, the LFs were combined (updated) by addition, thereby acknowledging and allowing for model inconsistency across events, i.e. modifier sets able to simulate one event or the other, but not both. In this latter method, each hydrograph-likelihood was weighted by the number of behavioural simulations obtained for that hydrograph before combining.

RESULTS, CONCLUSIONS AND FUTURE WORK

There is a clear and pressing need for improvements in the ability to generate operational flash-flood forecasts in the semi-arid southwestern USA. This study

Table 2 Modifiers used on spatially distributed KINEROS2 parameters and initial states, and on rainfall.

Modifier #	Corresponding uncertainty source type	Modifier notation*	Corresponding parameter description	AGWA/user-provided parameter value/range	Modifier range
1	Plane element model parameter	PKsM	Soil saturated hydraulic conductivity	8.44 mm/h	0.4–2.5
2		PnM	Soil surface roughness	0.055-0.057	0.4–2.5
3		PCVM	Coeff. of variation of PKsM's parameter	0.95	0.4–2.0
4		PGM	Soil net capillary drive	Regressed against PKsM's parameter	0.67–1.5
5		PRocM	Soil volumetric rock fraction	0.43	0.75–1.25
6		PIntM	Maximum interception depth	2.97–3 mm	0.75–1.25
7		PDistM	Soil pore size distribution index	0.3	0.7–1.3
8		PPorM	Soil porosity	0.459	0.75–1.25
9		PRillDA	Microtopographic rill depth	16.8 mm	0–72.5 mm
10		PRillSA	Microtopographic rill spacing	68.35 mm	0–254 mm
11		PCanM	Surface intercepting cover fraction	25.00%	0.75–1.25
12	Channel element model parameter	CKsM	Soil saturated hydraulic conductivity	210 mm/hr	0.8–1.1
13		CnM	Soil surface roughness	0.035	0.4–2.5
14		CCVA	Coefficient of variation of CKsM's parameter	0	0–2.0
15		CGM	Soil net capillary drive	Regressed against CKsM's parameter	0.4–2.5
16		CRocA	Soil volumetric rock fraction	0	0–0.1
17		CDistM	Soil pore size distribution index	0.545	0.7–1.5
18		CPorM	Soil porosity	0.44	0.85–1.15
19		CWCoM	Woolhiser coefficient	0.15	0–3
20		CWidM	Bottom width	5.7-14.3 m	0.33–0.7**
21		CTortF	Channel tortuosity	300–1901 m width, 0.009–0.026 slope	0.95–1.1**
22	Plane element initial condition	PSMIA	Initial soil moisture	Event-dependent	0.2–0.6
23	Channel element initial condition	CSMIA	Initial soil moisture	Event-dependent	0.2–0.6
24	Merged rain input	RainM	Merged gauge-radar rain	–	0.2–1.35

* M: multiplier, and A: adder, to uncertainty source field values. TortChF (#21) affects channel length (multiplied) and slope (divided).

**Based on ratio between available information and AGWA values for field-measured sections.

investigated the uncertainty present in a physically-based, distributed semi-arid rainfall–runoff model driven by high-resolution radar rainfall input. In particular, we found the following:

Figure 1 Merging of high spatio-temporal resolution rainfall estimates from gauge and radar has the potential to improve the model forecasting ability.

Figure 2 The uncertainty due to depth/volume bias in the rainfall estimates almost completely dominates the uncertainty in the modelled response.

Figure 3 In general, all the influential model parametric sources of uncertainty are either located in the infiltration equation, thus affecting hydrograph magnitudes or

Table 3 Different OFs considered in this study. These OFs have later been used to derive likelihood functions (LFs).

OF #	OF notation	OF type	OF description
1	FQF	Magnitude-based	Relative deviation from observed ratio of inflection to peak magnitude
2	FQP		Relative deviation from observed peak magnitude
3	FQI		Relative deviation from observed inflection magnitude
4	FSDQ	Slope-based	Relative deviation from slope angle of observed driven part
5	FSNQ		Relative deviation from slope angle of observed non-driven quick part
6	FSNS		Relative deviation from slope angle of observed non-driven slow part
7	FTS	Based on time relative to rain event	Relative deviation from observed time to start
8	FTP		Relative deviation from observed time to peak
9	FTE		Relative deviation from observed time to end
10	FTR	Hydrograph time duration-based	Relative deviation from observed time of rise
11	FTF		Relative deviation from observed time of fall
12	FS		Relative deviation from observed hydrograph skew
13	FVU	Volume-based	Relative deviation from observed peak volume if multi-peak
14	FV		Relative deviation from observed event volume
15	NSC	Observation series error-based	1 – (Nash-Sutcliffe Efficiency, i.e. NSE)

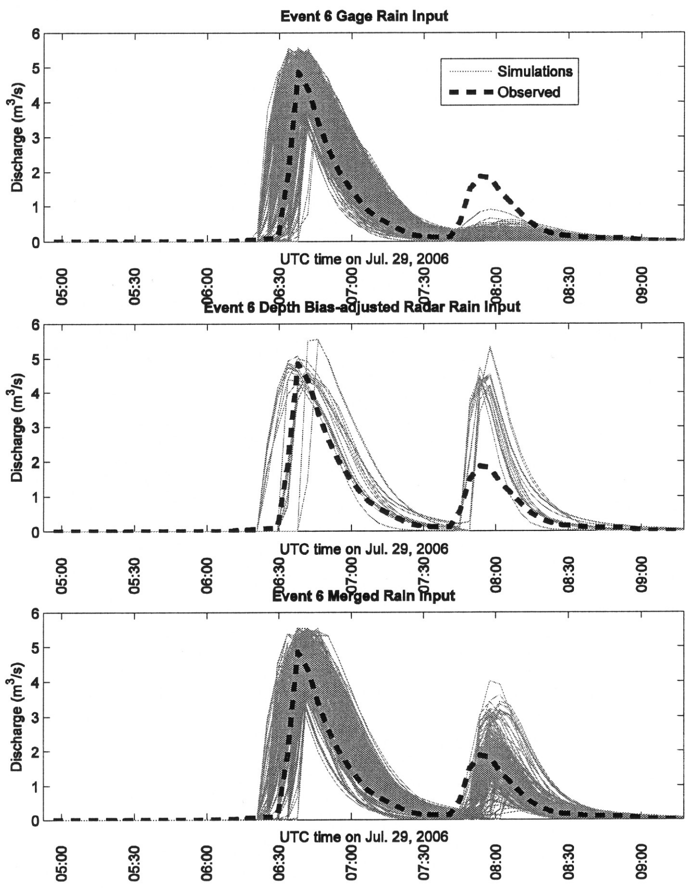

Fig. 1 Simulations behavioural to the 1st (left) peak examined for their behaviour on the 2nd (right) peak during Event 6 using different rainfall input. Merged case shows more modifier set consistency across peaks, where such consistency is defined as behavioural simulation by the same modifier set across peaks.

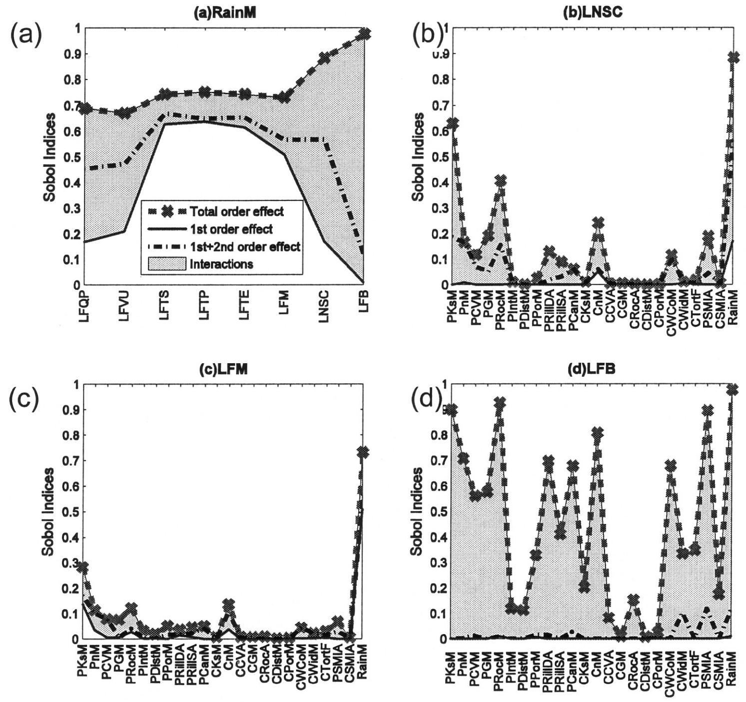

Fig. 2 Net rain influence across all events on model response (RainM). Subplots show fractional influence on: (a) different LFs, (b) Nash-Sutcliffe efficiency (rightmost modifier), (c) multi-objective LFM (rightmost modifier), and (d) behavioural LFB (rightmost modifier).

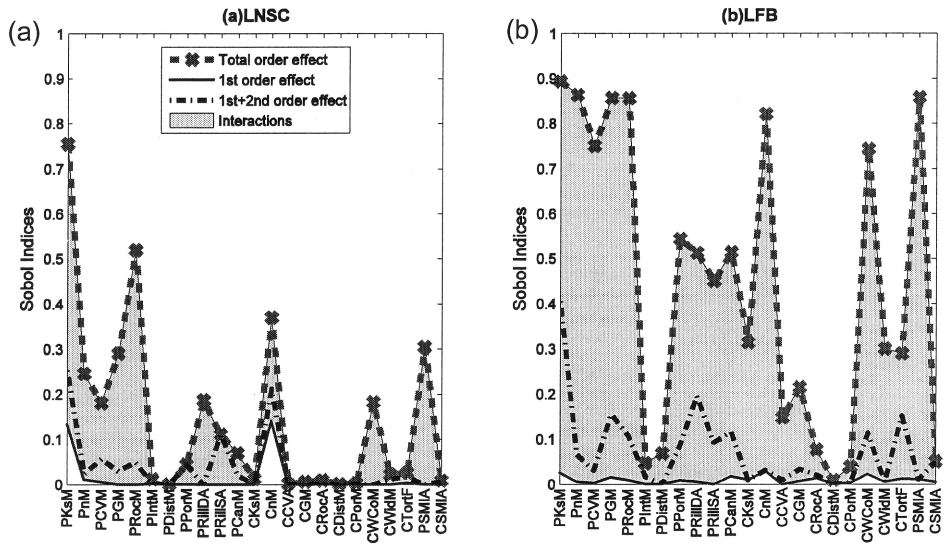

Fig. 3 Relative influence of model parameters and initial conditions on model response. Subplots show fractional influence on: (a) Nash-Sutcliffe efficiency, and (b) behavioural classification.

volume, or are the soil surface roughnesses affecting the timing. Uncertainties in the hillslope model parameter values had a greater impact on the predictions than the uncertainties in the channel parameters, at least for relatively small basins. For the model plane elements, the three most influential parameter uncertainties were in the

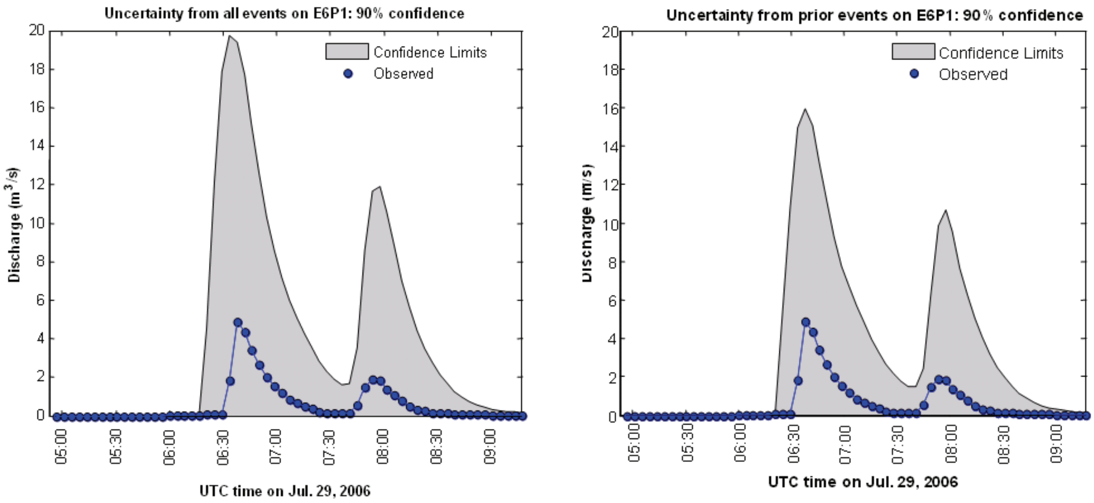

Fig. 4 Predicted 90% confidence intervals for hydrograph of the 29 July 2006 event using behavioural factor sets from: (a) all events, and (b) prior events. In E6P1, E denotes event and P denotes peak in this multi-peak event.

soil saturated hydraulic conductivity, the soil volumetric rock fraction and the soil surface roughness. For the model channel elements, the influential uncertainties were in the soil surface roughness and the Woolhiser coefficient. The latter reduces the effective wetted perimeter for infiltration during low flows, where a trapezoidal channel simplification introduced some error.

Figures 2 and 3 These figures consistently show that initial soil moisture specification in the channels (CSMIA modifier) is not important to match the modelresponse. However, the hillslope initial soil moisture (PSMIA modifier) can be important, and especially in case of flash-flood forecasting-related LFB, where it is almost as influential as PKsM. We therefore conclude that initial hillslope soil moisture can have a dominant effect on the predicted response. Hence, sophisticated inter-storm model components are probably required to track it with a high degree of accuracy.

Figure 4 Given the typical level of uncertainty in the magnitude bias of currently available radar rainfall estimates, model parameters and initial conditions, the predictive uncertainty in the modelled flash-flood response is often likely to be much higher than acceptable for accurate flash-flood forecasting. However, the hydrological model is still able to provide a valuable quantitative risk-based tool to forecasters for timely issuance and cancellation of flash-flood warnings and alarms.

This study illustrates the considerable difficulties involved in the identification of models for flash-flood forecasting in semi-arid regions. The most pressing concern is that improved real-time bias-free rainfall estimates are necessary for achieving reduced uncertainty in flood forecasts.

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REFERENCES

AMS (1985) Flash floods – a statement of concern by the American Meteorological Society. *Bull. Am. Met. Soc.* **66**(7), 858–859.

Beven, K. J. & Freer, J. (2001) Equifinality, data assimilation, and uncertainty estimation in mechanistic modeling of complex environmental systems using the GLUE methodology. *J. Hydrol.* **249**, 11–29.

IPCC (2001) *Third Assessment Report*. Cambridge University Press. Available at http://www.grida.no/climate/ipcc_tar/wg1/).

Kundzewicz, Z. W. & Kaczmarek, Z. (2000) Coping with hydrological extremes. *Water International* **25**(1), 66–75.

Morin, E., Maddox, R. A., Goodrich, D. C. & Sorooshian, S. (2005) Radar Z-R relationship for summer monsoon storms in Arizona. *Weather and Forecasting* **20**(4), 672.

Parlange, J.-Y., Lisle, I., Braddock, R. D. & Smith, R. E. (1982) The three-parameter infiltration equation. *Soil Science* **133**(6), 337–341.

Pilgrim, D. H., Chapman, T. G. & Doran, D. G. (1988) Problems of rainfall–runoff modelling in arid and semiarid regions. *Hydrol. Sci. J.* **33**(4), 379–400.

Renard, K. G., Lane, L. J., Simanton, J. R., Emmerich, W. E., Stone, J. J., Weltz, M. A., Goodrich, D. C. & Yakowitz, D. S. (1993) Agricultural impacts in an arid environment: Walnut Gulch case study. *Hydrol. Sci. Tech.* **9**,145–190.

Roeske, R. H., Garrett, J. M. & Eychaner, J. H. (1989) Floods of October 1983 in southeastern Arizona. *US Geol. Survey Water-Resources Investigations Report 98-4225-c*.

Saltelli, A., Tarantola, S., Campolongo, F. & Ratto, M. (2004) *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models*. John Wiley & Sons Ltd, Chichester, UK.

Semmens, D., Goodrich, D. C., Unkrich, C. L., Smith, R. E., Woolhiser, D. A. & Miller, S. N. (2005) KINEROS2 and the AGWA modeling framework. Chapter 6 in: *The GWADI International Modeling Workshop.* UNESCO on-line publication, http://gwadi.org/shortcourses/chapters/Semmens_L6.pdf.

Sobol, I. M. (1993) Sensitivity estimates for nonlinear mathematical models. *Math. Modeling Computational Experiment*, **1**, 407–414.

Tang, Y., Reed, P., Wagener, T. & Van Werkhoven, K. (2007) Comparing sensitivity analysis methods to advance lumped watershed model identification and evaluation. *Hydrol. Earth Syst. Sci.* **11**, 793–817.

Wagener, T., & Gupta, H. V. (2005) Model identification for hydrologic forecasting under uncertainty. *Stochastic Environ. Res. Risk Assess.* doi:10.1007/s00477-005-0006-5.