Calibration of a semi-distributed hydrological model using discharge and remote sensing data

LAL P. MUTHUWATTA[1], MARTIJN J. BOOIJ[2], TOM H. M. RIENTJES[3], M. G. BOS[3], A. S. M. GIESKE[3] & MOBIN-UD-DIN AHMAD[4]

1 *International Water Management Institute, PO Box 2075, Colombo, Sri Lanka*
2 *Water Engineering and Management, Faculty of Engineering Technology, University of Twente, PO Box 217, 7500 AE Enschede, The Netherlands*
m.j.booij@utwente.nl
3 *International Institute for Geo-Information Science and Earth Observation (ITC), PO Box 6, 7500 AA Enschede, The Netherlands*
4 *CSIRO Land and Water, GPO Box 1666, Canberra ACT2601, Australia*

Abstract The objective of this study is to present an approach to calibrate a semi-distributed hydrological model using observed streamflow data and actual evapotranspiration time series estimates based on remote sensing data. First, daily actual evapotranspiration is estimated using available MODIS satellite data, routinely collected meteorological data, and applying the SEBS algorithm. Second, the semi-distributed hydrological model HBV is calibrated and validated using the estimated evapotranspiration and observed discharge. This is done for multiple sub-basins of the Karkheh River basin in Iran. The Nash-Sutcliffe coefficient (NS) is calculated for each sub-basin. Maximum and minimum NS values for the calibration using observed discharge are 0.81 and 0.23, respectively, and using estimated evapotranspiration 0.61 and 0.46, respectively. The comparison of model simulations with multiple observed variables increases the probability of selecting a parameter set that represents the actual hydrological situation of the basin. The new calibration approach can be useful for further applications, especially in data-sparse river basins.

Key words hydrological modelling; SEBS; remote sensing; MODIS; HBV model; actual evapotranspiration; Monte Carlo simulation; Karkheh River basin, Iran

INTRODUCTION

Hydrological models are usually calibrated by using discharge time series observed at one or a few locations in the river basin. However, simulating one variable (e.g. discharge) close to the observed one does not guarantee the satisfactory simulation of other model output such as actual evapotranspiration (Mroczkowski *et al*., 1997; Seibert, 2002). Furthermore, river basins are subject to several activities, one of which is agriculture that uses water from the natural system by means of surface water or groundwater diversions. Part of this diverted water is transferred to the atmosphere by evaporation and transpiration. The rest remains in the system and contributes to the groundwater aquifer and to the river discharge through various flow processes. Therefore, in modelling studies it is crucial to consider the effects of human activities on observed discharge time series. This would increase the trustworthiness of the calibration and eventually help to estimate reliable parameters that represent the catchments under scrutiny. But, acquiring data on water diversions and consumption is often not feasible due to technical, legislative and administrative constraints.

In that respect, using remote sensing (RS) information could be a useful addition to hydrological modelling, since it provides information on ground conditions that could be converted into hydrological variables such as actual evapotranspiration (Bastiaanssen *et al*., 1998; Su, 2002). This provides the volumes of water consumed by different land-use classes both spatially and temporally. Incorporating these spatial and temporal estimates of actual evapotranspiration with hydrological model calibration indirectly incorporates the effects of diversions.

The objective of this study is to present an approach to calibrate a semi-distributed hydrological model using observed streamflow data and actual evapotranspiration time series estimates based on RS data. The study area is the Karkheh River basin in Iran, which is described first. The approach to estimate daily actual evapotranspiration time series using available RS data and routinely collected meteorological data, and the hydrological model HBV to simulate river discharge are then detailed. Finally, the results and discussion are presented.

STUDY AREA

The Karkheh River basin (51 000 km^2) is located in the southwestern region of Iran between 30°N to 35°N and 46°E to 49°E and is one of the most productive agricultural areas in Iran. It covers 9% of Iran's irrigated area and produces 10–11% of the wheat production of the country. The elevation of the basin ranges from less than 10 m a.m.s.l. in the southern areas to more than 3500 m in the hilly parts of the basin. The river drains into the Hoor-Al-Azim swamp, which is a transboundary wetland located at the Iran–Iraq border. The southern part of the basin receives an average annual precipitation of about 150 mm while the northern part receives up to 750 mm. The class A pan annual evaporation, which are the only readily available evaporation data in the basin, ranges from 2000–3600 mm from the north to the south. Precipitation in the area is regarded as insufficient to meet crop water requirements and therefore irrigated agriculture largely depends on water from the Karkheh dam.

Daily air temperature, sunshine hours, precipitation and discharge data and 3-hourly relative humidity and wind speed for the period 2000–2004 are used. The meteorological data are available for 16 stations and were obtained from the Iranian Meteorological Organization, and the discharge data for seven stations was obtained from the Iranian Power Ministry. Reference evapotranspiration is computed based on the Penman-Monteith method. Catchment average values for the precipitation, reference evapotranspiration and temperature are computed using Thiessen polygons. For the computation of the actual evapotranspiration, 88 cloud free MODIS (MOderate Resolution Imaging Spectroradiometer) images covering the study area are used for the period March 2000 to December 2003 (NASA, 2008).

METHODS

HBV hydrological model

For river discharge simulation, the hydrological model HBV of the Swedish Meteorological and Hydrological Institute (SMHI) is used (Bergström, 1995). This model is a semi-distributed, conceptual hydrological model using sub-basins as the primary hydrological units. It takes into account the area–elevation distribution and basic land-use categories (glaciers, forest, open areas and lakes). HBV uses readily available data (precipitation, potential evapotranspiration and temperature) as inputs and has proven capabilities in simulating large river basins. The large number of applications using this model, under various physiographic and climatological conditions, has shown that its structure is very robust and general, in spite of its relative simplicity (e.g. Lidén & Harlin, 2000; Dong *et al*., 2005). There are a number of parameters included in the model which have to be estimated through calibration with observed data. The model consists of six routines, which are a precipitation accounting routine, a soil moisture routine, a quick runoff routine and a baseflow routine, which together transform excess water from the soil moisture zone to local runoff, a transformation function and a routing routine.

Spatially and temporally distributed actual evapotranspiration

The surface energy balance system (SEBS) algorithm (Su, 2002) is used to estimate spatially and temporally distributed actual evapotranspiration. SEBS translates satellite radiances into surface albedo, vegetation indexes and surface temperature. These land surface characteristics and routinely collected meteorological data are used to solve the instantaneous energy balance equation. Estimation of the actual evapotranspiration using SEBS over the Karkheh River basin is discussed in Muthuwatta *et al*. (2008).

Acquiring MODIS images to estimate the actual evapotranspiration on a daily basis is often not possible due to cloud cover and the satellite overpass time. Therefore, the temporal resolution of suitable images is not consistent with the temporal model resolution. To overcome this problem, Immerzeel & Droogers (2008) used an approach based on the Penman-Monteith equation to estimate actual evapotranspiration for the days that satellite images are not available. In this study, this approach is further developed to incorporate temporal variations of land surface characteristics. All terms in the Penman-Monteith equation can be estimated on a daily basis using routinely collected meteorological data, except two terms: the surface resistance and the aerodynamic resistance. Estimating these two resistances on a daily basis enables the estimation of daily actual evapotranspiration for days when satellite images are not available. Resistances for days with satellite images are calculated using the Penman-Monteith equation and a roughness-length-based equation for the aerodynamic resistance (Immerzeel & Droogers, 2008). Resistances for days without satellite images are estimated by linear interpolation between these spatially distributed maps with resistance values. Daily time series of spatially distributed actual evapotranspiration are finally derived by inserting daily observed meteorological data and temporally interpolated resistance values into the Penman-Monteith equation.

Calibration procedure

Model calibration is carried out using Monte Carlo Simulation (MCS). The eight most important model parameters are selected and corresponding ranges are determined based on previous studies (e.g. Uhlenbrook *et al.*, 1999; Booij, 2005). Parameter sets are randomly drawn from a uniform distribution within the given range for each parameter. At first, 10 000 model simulations are carried out using the parameter sets generated through the MCS procedure. For each simulation, model performance is evaluated using Y (Akhtar *et al.*, 2008):

$$Y = \frac{NS}{1 + |RVE|} \tag{1}$$

where NS is the Nash-Sutcliffe coefficient and RVE the relative volume error (a fraction). For an acceptable model performance, NS should be close to 1 and RVE should be close to 0 resulting in a Y value close to 1. Out of 10 000 simulations, 1000 simulations that give the highest Y values are selected. Then the upper and lower boundaries of the parameter space are adjusted according to the ranges found in these best 1000 parameter sets. The same MCS procedure as in the previous step is applied with the new parameter ranges and the parameter set that produces the highest Y value is selected as the optimal parameter set.

The model calibration is carried out for all sub-catchments separately using the procedure mentioned above. The calibration period is from April 2000 to March 2002 and the validation period is from April 2002 to December 2003, taking into account the availability of observed discharge data and MODIS images. Only the discharge generated in each sub-catchment is used for calibration and validation. Three months are taken as a warm-up period.

RESULTS AND DISCUSSION

Calibration and validation using observed discharge

Table 1 presents the model performance for the discharge for seven sub-catchments using observed discharge for calibration and validation. All sub-catchments except Jelogir and Holilan show acceptable NS values (larger than 0.6) for both calibration and validation periods. Jelogir is located in the drier part of the Karkheh River basin and the annual precipitation in this area is low when compared to the upstream areas. Therefore, the observed discharge at the sub-catchment outlet has a relatively large contribution from upstream sub-catchments compared to the discharge generated in Jelogir. The low NS value for Holilan in the validation period indicates that the selected parameter set is not able to represent the hydrological behaviour of this sub-catchment for varying climatological conditions. For all sub-catchments except Jelogir, low RVE values during the calibration period are found, indicating a close agreement of average observed and simulated discharge. In the validation period, Pole Dokhtar shows a high RVE value due to some peaks in the observed data that were not properly simulated by the model.

As an example, Fig. 1 shows the observed discharge and simulated discharge based on discharge calibration and Fig. 2 shows the estimated actual evapotranspiration and simulated

Table 1 Model performance for discharge for seven sub-catchments using observed discharge for calibration and validation.

Sub-catchment	Area (km^2)	Calibration:			Validation:		
		NS	RVE	Y	NS	RVE	Y
Doab	7767	0.81	0.0055	0.81	0.78	–0.018	0.76
Pole Chehr	3122	0.80	0.0030	0.80	0.72	0.029	0.70
Doabe Merek	1286	0.80	0.019	0.79	0.81	0.036	0.78
Ghor Baghestan	4072	0.66	–0.021	0.64	0.68	–0.12	0.61
Holilan	9873	0.62	0.0004	0.62	0.31	0.25	0.15
Pole Dokhtar	9542	0.77	–0.0067	0.77	0.73	–0.16	0.66
Jelogir	4116	0.23	–0.15	0.20	0.23	–0.39	0.17

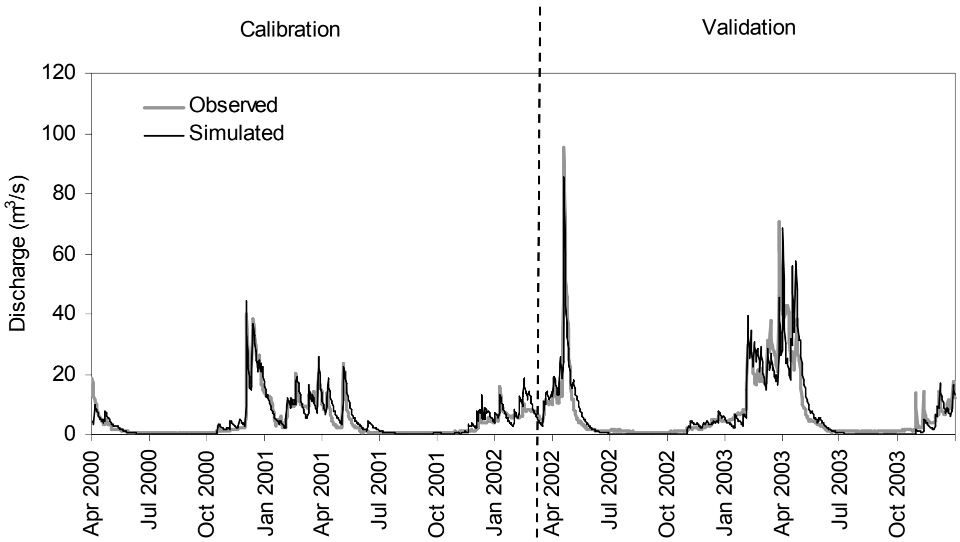

Fig. 1 Observed discharge and simulated discharge based on discharge calibration (HBV) for Doab for calibration and validation period.

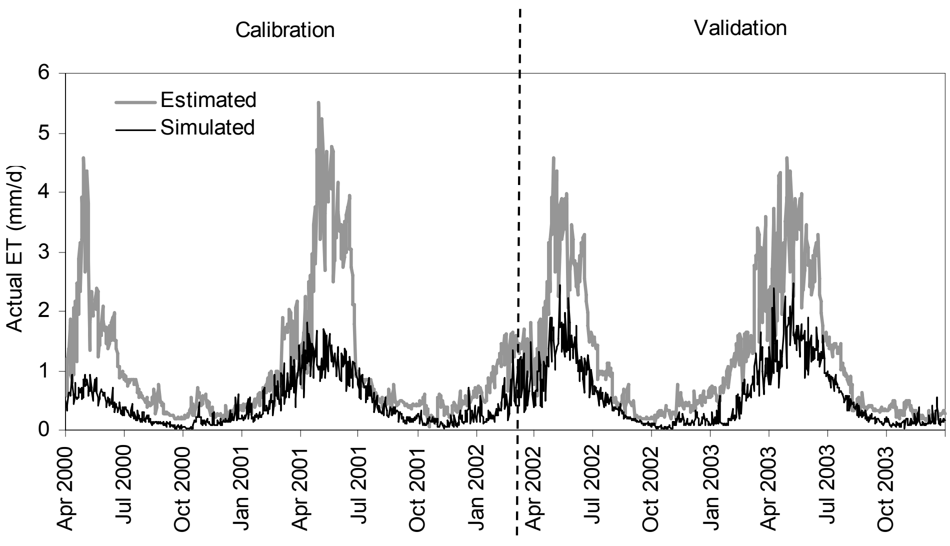

Fig. 2 Estimated actual evapotranspiration (SEBS) and simulated actual evapotranspiration based on discharge calibration (HBV) for Doab for calibration and validation period.

Table 2 Model performance for actual evapotranspiration for seven sub-catchments using estimated actual evapotranspiration for calibration and validation.

Sub-catchment	Area (km^2)	Calibration:			Validation:		
		NS	RVE	Y	NS	RVE	Y
Doab	7767	0.57	–0.069	0.53	0.75	–0.064	0.74
Pole Chehr	3122	0.51	–0.24	0.41	0.64	–0.21	0.53
Doabe Merek	1286	0.56	–0.082	0.52	0.33	–0.10	0.30
Ghor Baghestan	4072	0.65	–0.046	0.62	0.75	0.0022	0.75
Holilan	9873	0.46	0.12	0.41	0.71	0.089	0.65
Pole Dokhtar	9542	0.66	–0.12	0.59	0.66	–0.17	0.56
Jelogir	4116	0.61	–0.24	0.49	0.63	–0.19	0.53

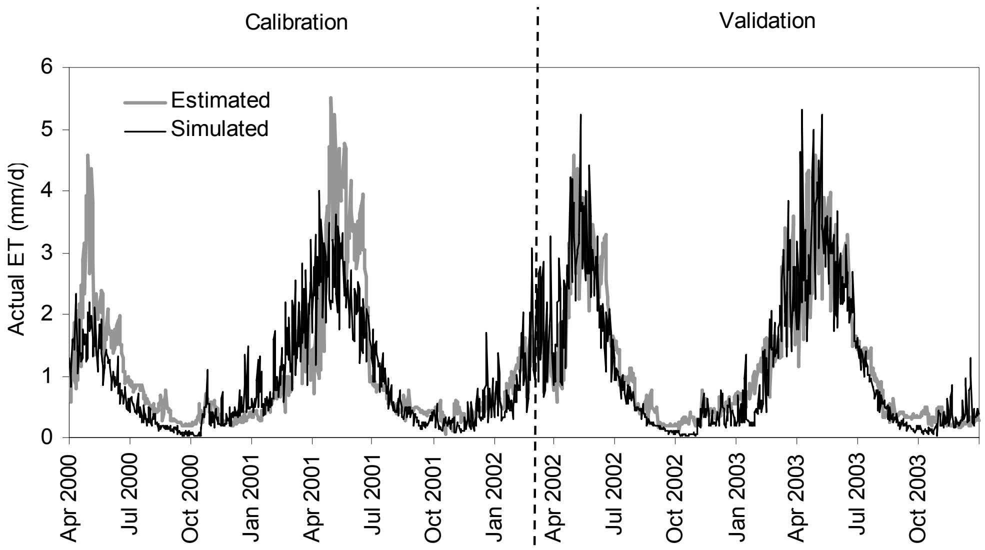

Fig. 3 Estimated actual evapotranspiration (SEBS) and simulated actual evapotranspiration based on actual evapotranspiration calibration (HBV) for Doab for calibration and validation period.

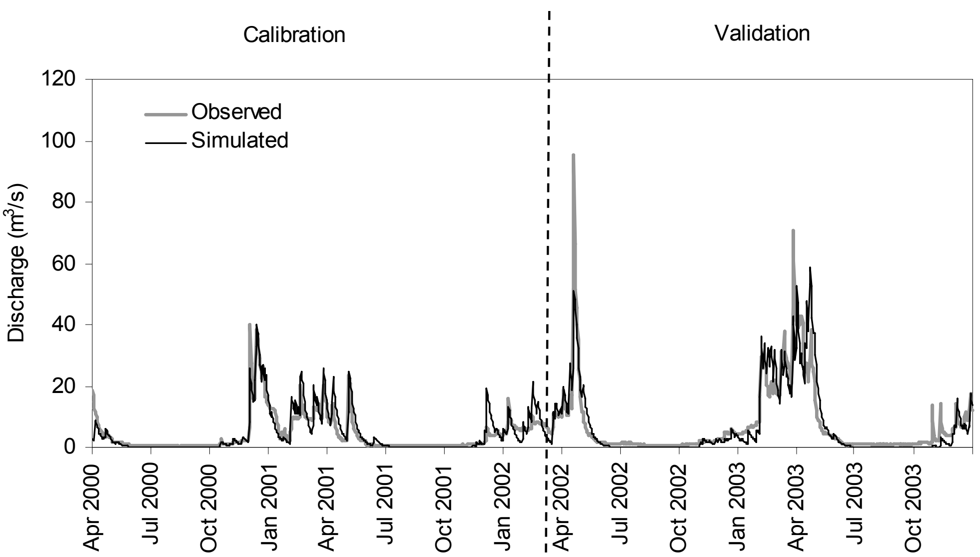

Fig. 4 Observed discharge and simulated discharge based on actual evapotranspiration calibration (HBV) for Doab for calibration and validation period.

actual evapotranspiration based on discharge calibration for Doab for the calibration and validation period. Peak discharges and the recession part of the hydrograph is slightly over-estimated by the model. However, the overall discharge behaviour is well simulated (see also Table 1). In contrast, Fig. 2 shows a poor simulation of the annual evapotranspiration cycle when the model is calibrated using discharge data. The model consistently underestimates evapotranspiration, particularly in the summer.

Calibration and validation using estimated actual evapotranspiration

Table 2 presents the model performance for the actual evapotranspiration for seven sub-catchments using estimated actual evapotranspiration for calibration and validation. Three sub-catchments show acceptable *NS* values in the calibration period, while for six sub-catchments acceptable *NS* values are obtained in the validation period. The *RVE* values are comparable in both periods. Figure 3 shows the estimated actual evapotranspiration and simulated actual evapotranspiration based on actual evapotranspiration calibration, and Fig. 4 shows the observed discharge and simulated discharge based on actual evapotranspiration calibration for Doab for the calibration and validation period. In Fig. 3, the average difference between estimated and simulated evapotranspiration during the simulation period is 0.4 mm/d, while the maximum difference is 2.7 mm/d. However, in more than 90% of the days the difference is less than 1 mm/d. These largely random differences are justifiable as SEBS uses distributed inputs to compute the actual evapotranspiration, while HBV mainly uses point data. Both graphs follow the same pattern. However, during the calibration period, the difference between the two graphs is relatively larger than in the validation period, because of the significant mismatch between the two graphs at the beginning of the simulation possibly due to an insufficient long warm-up period.

Despite the reduction of the *NS* value for the discharge simulation from 0.81 (see Table 1) to 0.78 (not shown), visual comparison of Figs 1 and 4 shows no significant differences, while the simulation of the actual evapotranspiration significantly improved (compare Figs 2 and 3). Therefore, the parameter set that resulted in a higher model performance for both discharge and actual evapotranspiration can be regarded as a better representation of the sub-basin than the optimal parameter set from the calibration using observed discharge data. Calibration using both observed discharge and actual evapotranspiration in a weighted or fuzzy multi-objective function might yet improve this result.

CONCLUSIONS

This study presents the potential of satellite remote sensing based actual evapotranspiration for semi-distributed conceptual model calibration. The approach to compute daily actual evapotranspiration time series using available satellite images proposed in this paper is useful, especially in data scarce areas. The unavailability of, for example, spatial data on evapotranspiration, limits large-scale modelling applications to conventional calibration based on discharge data at one or a few locations in a basin. The method proposed in this study could be one answer to that problem. However, long time series data, which were not available in this study area, with a longer warming-up period, could have resulted in a better model performance in the actual evapotranspiration calibration. The MODIS satellite data used in this study are freely available on the Internet and this shows the feasibility of applying the same approach in other river basins cost effectively.

This study presents a daily calibration of a semi-distributed hydrological model using satellite data and observed discharge data. Using more than one output variable for model calibration provides a better way to select a parameter set that represents the hydrology in a modelled spatial domain and provides stable outputs for both the calibration and validation periods. Discharge simulated by using the parameter set that gives the highest model performance for the evapotranspiration calibration shows how well this approach can be used to simulate discharges for sub-catchments where observed discharge data are not available. In that context this study will be a useful contribution to the on going PUB (Predictions in Ungauged Basins) initiative.

REFERENCES

Akhtar, M., Ahmad, N. & Booij, M. J. (2008) Use of regional climate model simulations as input for hydrological models for the Hindukush-Karakorum-Himalaya region. *Hydrol. Earth System Sci. Discussions* **5**, 865–902.

Bastiaanssen, W. G. M., Menenti, M., Feddes, R. A. & Holtslag, A. A. M. (1998) A remote sensing surface energy balance algorithm for land (SEBAL): 1. Formulation. *J. Hydrol.* **213**, 198–212.

Bergström, S. (1995) The HBV model. In: *Computer Models of Watershed Hydrology* (ed. by V. P. Singh), 443–476. Water Resource Publications, Highlands Ranch, Colorado, USA.

Booij, M. J. (2005) Impact of climate change on river flooding assessed with different spatial model resolutions. *J. Hydrol.* **303**, 176–198.

Dong, X., Dohmen-Janssen, C. M. & Booij, M. J. (2005) Appropriate spatial sampling of rainfall for flow simulation. *Hydrol. Sci. J.* **50**, 279–298.

Immerzeel, W. W. & Droogers, P. (2008) Calibration of a distributed hydrological model based on satellite evapotranspiration. *J. Hydrol.* **349**, 411–424.

Lidén, R. & Harlin, J. (2000) Analysis of conceptual rainfall-runoff modelling performance in different climates. *J. Hydrol.* **238**, 231–247.

Mroczkowski, M., Raper, P. G. & Kuczera, G. (1997) The quest for more powerful validation of conceptual catchment models. *Water Resour. Res*. **33**, 2325–2335.

Muthuwatta, L. P, Ahmad, M. D., Bos, M. G. & Rientjes, T. H. M. (2008) Assessment of water availability and consumption in the Karkheh River Basin (Iran) using remote sensing and geo-statistics. *Water Resour. Manage.*, under review.

NASA (2008) 88 cloud free MODIS images for the period March 2000–December 2003. http://ladsweb.nascom.nasa.gov, accessed at 1-8-2008.

Seibert, J. (2002) On the dialog between experimentalist and modeler in catchment hydrology: Use of soft data for multicriteria model calibration. *Water Resour. Res*. **38**, W1241, doi:10.1029/2001WR000978.

Su, Z. (2002) The surface energy balance system (SEBS) for estimation of turbulent heat flux. *Hydrol. Earth System Sci.* **6**, 85–89.

Uhlenbrook, S., Seibert, J., Leibundgut, C. & Rodhe, A. (1999) Prediction uncertainty of conceptual rainfall-runoff models caused by problems in identifying model parameters and structure. *Hydrol. Sci. J.* **44**, 779–797.