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Parameterization of a Gridded Rainfall-Runoff Model for Southern Australia

PARAMETERIZATION OF A GRIDDED RAINFALL-RUNOFF MODEL FOR SOUTHERN AUSTRALIA

Gibbs M.S.[1], H.R. Maier[2] and G.C. Dandy[3]

***Abstract**: In many locations where rainfall-runoff models are required, there is a lack of streamflow to calibrate the desired models. Many studies have attempted to determine suitable parameter values for conceptual rainfall-runoff models (CRR) where flow data are unavailable for calibration. These use techniques such as donor catchments, or relating the parameter values to characteristics of the catchment. However, the lumped nature of CRRs makes it difficult to directly capture the variation in large catchments that will influence the degree of runoff observed. In this work, a CRR has been applied on a gridded basis to investigate if the spatial distribution of the parameter values allows for a physical basis to be maintained. Different parameter values were adopted for each grid in the catchment, preserving the heterogeneity of the catchment and the physical meaning of the model parameters. The loss model used was the 11 parameter Soil Moisture Accounting (SMA) model in HEC-HMS. Three catchments in southern Australia have been considered, and a number of GIS data sets have been tested to identify if the attribute values are suitable to parameterize the most significant model parameters. The results suggest that, for the catchments considered, many of the surface storage parameters can be determined directly for catchments attributes stored in GIS databases to produce acceptable runoff simulation performance.*

***Keywords**: Hydrologic Modelling; Loss Models; Calibration; Geographical Information Systems; Regionalization.*

INTRODUCTION

In many cases, streamflow records are unavailable to calibrate rainfall-runoff models. A great deal of research has been dedicated to regionalization of conceptual rainfall-runoff models for prediction in ungauged basins, however recent studies suggest that the parameters of these models have little physical meaning (Post et al., 2008), and are therefore unlikely to produce reliable results when extrapolated to ungauged catchments. One of the main reasons for this, especially for large catchments, is the heterogeneity of the catchment. Hence, the physical basis of the model is potentially undermined by attempting to condense the large variation in the rainfall-runoff response of the catchment into a small number of lumped parameter values.

Distributed rainfall-runoff models allow different values of model parameters to be used in

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different areas in the catchment, either through the use of sub-catchments or on a gridded basis (Michaud and Sorooshian, 1994). Beven (1895) outlined the benefits of distributed modeling, including an assessment of the effects of land-use change, allowing for spatially variable inputs and outputs and hydrological response at ungauged sites. Carpenter and Georgakakos (2006) concluded that even under present day parametric and input uncertainties, distributed models offer clear performance advantages. The advantage of a distributed approach is that heterogeneity in the catchment can be represented explicitly. However, in order to implement distributed models, more parameter values are required than for a simple lumped conceptual rainfall runoff (CRR) model, as instead of a small number of parameters to model the overall response of the catchment, there are a small number of parameters for each sub catchment or grid cell. It is unclear how to determine values for the large number of parameters required in distributed models, as there can potentially be more parameters in the distributed model than flow observations, producing an over specified model.

If a rainfall runoff model is applied on a small scale, considering a relatively homogeneous subsection of the catchment, CRR model parameters might retain the physical basis intended in their conceptualization. Also, the proliferation of Geographical Information Systems (GIS) meant that large datasets of catchment attributes are becoming readily available, which may be useful in order to quantify the runoff response of a catchment. If the physical basis that underpins conceptual rainfall runoff models can be retained in by applying them on a smaller scale, many of the parameters may be derived from the catchment information available in GIS databases.

The aim of this paper is to investigate if acceptable performance can be produced by a gridded conceptual rainfall runoff model by determining the parameter values directly from GIS datasets describing the catchment characteristics. The following section outlines the methodology adopted, including the catchments considered, the model implemented, and the datasets used to parameterize the model. This is followed by the results produced by the models, and concluding remarks about the approach used.

METHODOLOGY

Catchments & Input Data

Three catchments in South Eastern Australia have been used in this study (Fig. 1). Light Detection and Ranging (LiDAR) derived elevation observations on a 10 m grid were available for the region, and these have been used to determine catchment boundaries, as well as flow direction, flow accumulation and local slope grids. The catchment areas are 178 km^2 for the Nalang Creek catchment, 491 km^2 for the Bakers Range catchment, and 700 km^2 for the Mosquito Creek catchment. The dimensionless main channel slope is in the order of 0.0014 for each catchment.

Daily streamflow records are freely available at each catchment outlet from the South Australian Department for Water, Land and Biodiversity Conservation Surface Water Archive (http://e-nrims.dwlbc.sa.gov.au/swa/). Flow has been recorded for a 16 year period between 1977 and 1993 for the Nalang Creek catchment, a 22 year period between 1971 and 1993 for the Bakers Range catchment, and a 39 year period from 1971 to 2009 for the Mosquito Creek catchment.

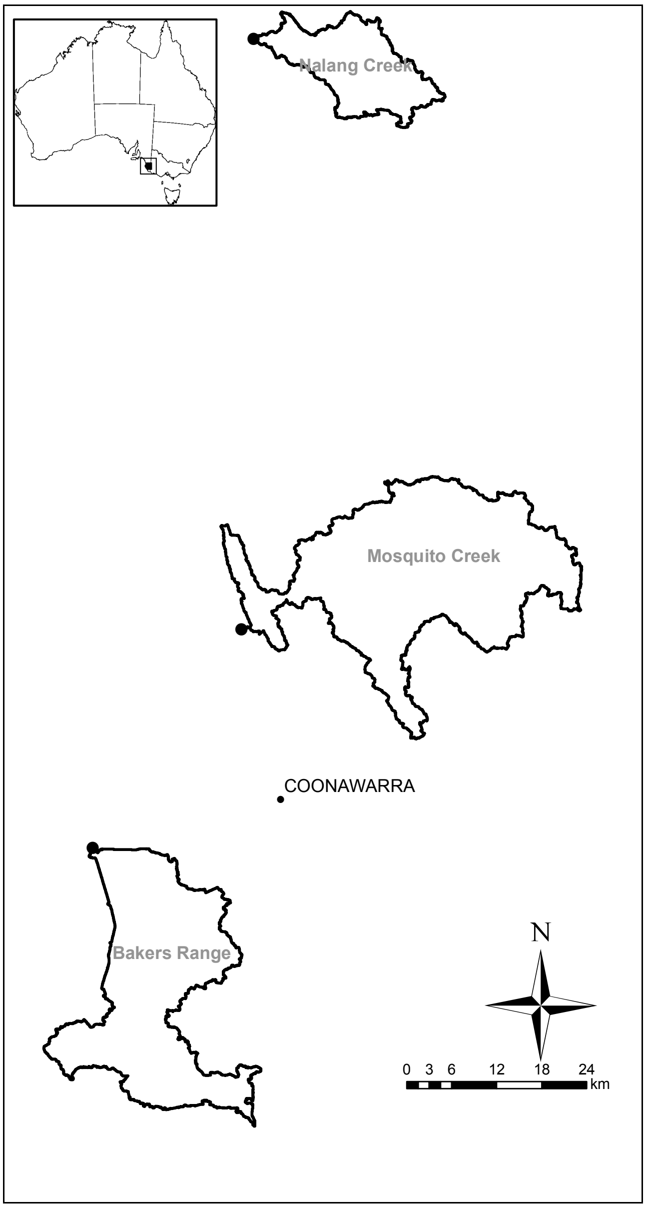

Fig 1. The three catchments considered in the study, and the location of the Coonowora evaporation site.

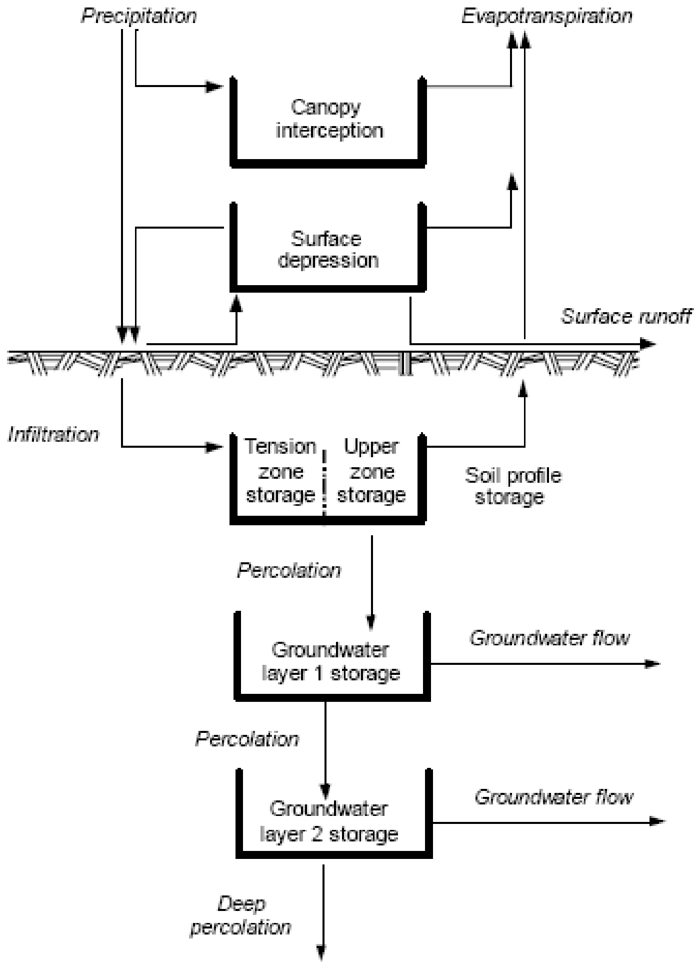

Fig 2. Conceptual layout of the Soil Moisture Accounting Loss Model

The gridded rainfall data produced by the Australian Bureau of Meteorology National Climate Centre for the Australian Water Availability Project (Jones et al., 2007) has been used as an input to the model. The original dataset contains daily rainfall for Australia at a resolution of 0.05°, interpolated from observations at gauging stations. These data have been restricted to the study region, and projected to a 5 km grid size, which has also been adopted for the modelling framework. Monthly average evaporation values have been determined from the Coonawarra station, the location of which can be seen in Fig 1.

Rainfall-Runoff Model

The Soil Moisture Accounting (SMA) loss model (Fleming and Neary, 2004) in the HEC-HMS software package (Scharffenberg and Fleming, 2009) has been used to compute the excess rainfall. As seen in Fig 2, the SMA loss method implements five storages to represent the dynamics of water movement above and in the soil. These layers represent canopy interception, surface depression storage, soil storage, and upper and lower groundwater storage (Scharffenberg and Fleming, 2009). The soil layer is subdivided into two sections, tension and gravity (or upper) zone storage, where only the gravity storage component contributes to the simulated baseflow. In this work, the value for the percolation rate in the soil and groundwater stores has been assumed to be the same. The initial storage conditions have been set to 0%, however the model has been permitted a warm up period of 1 year to remove the influence of the initial storage conditions. Therefore, there are 11 model parameters for calibration, namely the canopy, surface, soil, soil-tension, groundwater 1 and 2 storage depths, infiltration and percolation rate, groundwater 1 and 2 reservoir coefficients and a combined baseflow linear reservoir coefficient.

As part of the distributed modelling approach used, the SMA model is implemented on a grid cell by grid cell basis. Each grid cell receives separate precipitation from the meteorological model. All cells are initialized to the same initial conditions, and then allowed to evolve separately during the simulation based on individual parameter values and precipitation inputs (Scharffenberg and Fleming, 2009).

In order to make use of the gridded SMA loss model, a modified Clark method provides a linear, quasi-distributed transform method to route surface flow to the catchment outlet. Each grid cell requires an input for the time for runoff to reach the catchment outlet. Travel times for each grid cell have been determined using the method proposed by Noto and LaLoggia (2007), and the calibration method proposed by Gibbs et al. (2009). This procedure allows different velocities to be used on the hill slope and the stream system, and also considers the increase in velocity with flow accumulation. The results from this analysis have also been used to determine the time of concentration and storage coefficient parameters for the modified Clark method used for the transformation of surface runoff to the catchment outlet.

GIS Data for Model Calibration

A number of different databases were considered as potential sources for model parameter values, including the soil landscape mapping database (DWLBC, 2002a), which includes a total of 42 attributes relating to soil moisture, soil structure, soil chemistry, salinity, erosion, land surface type, rooting zone depths and irrigation. In order to determine a parameter value from each dataset, polygon features were converted to raster datasets with 50m cell size. The resulting cell values were averaged to produce the required parameter value at the 5 km cell scale. Different combinations of values based on the GIS datasets were trialed to investigate the impact on model performance. Model performance was assessed using the Nash-Sutcliffe Efficiency (NSE) calculated on simulated and observed monthly volumes over the three catchments considered. The following combination of GIS datasets for each model parameter was found to produce the best overall simulation results.

Canopy Storage

Based on the Australian Land Use and Management Classifications (Version 6), a canopy storage has been assigned to each of the tertiary land use classes based on values suggested by Crockford and Richardson (1990), Dunkerley and Booth (1999) and Fleming and Neary (2004). Hence, plantations and natural vegetation have been classified to have 3 mm, crops 2 mm, and pasture 1 mm of canopy storage.

Surface Storage

To represent the surface storage, depths based on the slope of the land have been used, where a lower slope would be expected to produce a higher surface storage. The Digital Elevation Model (DEM) of each catchment has been used to compute the local slope at each grid cell. The corresponding surface storage depths have been taken from Chow (1964) and the slopes assigned to each depth by Fleming and Neary (2004). Hence, a surface storage size of 19.05 mm have been assigned to flat areas, 12.7 mm to areas with slopes of 5% and 6.35 mm inch to area with a slope of 30%. An exponential equation with $R^2 = 0.81$ has been fitted to these three points producing the equation $s = 15.114e^{-0.031x}$, where s is the surface storage (mm) and x is the local slope (%).

Along with the surface storage expected to occur due to the local slope of the catchment, a depression analysis has also been undertaken to determine the depth of any larger depressions in the landscape. The depression evaluation pre-processing tool in ArcHydro (Maidment, 2002) has been used to compute the depths of depressions in the landscape. The resulting depression depths were added to the surface storages determined from the slope of the local catchment above, to produce the total surface storage.

Maximum Infiltration Grid

The local slope is also expected to influence the maximum infiltration rates for the SMA model. The soil landscape dataset (DWLBC, 2002b) has been used to describe the soil type in the region, which classifies the type of soil from 15 potential groups. Based on United States Department of Agriculture information and values proposed by Chow (1964) and Hillel (1982), the data in Table 1 have been used to determine the infiltration rates, based on the soil type and slope of the catchment at each grid cell.

Table 1. Infiltration rates (mm/hr) based on soil type and local slope

	Local Slope (%)				
Soil Classification	**0—4**	**5—8**	**8—12**	**12—16**	**Over 16**
Sand 23.5		18.75	14	9.5	6
Sandy Loam	18.75	15	11.25	7.5	4.75
Loamy Sand	22	17.5	13.25	8.75	5.5
Clay 3.25		2.5	2	1.25	0.75
Loam 13.5		10.75	8.25	5.5	3.5
Clay Loam	6.25	5	3.75	2.5	1.5
Sandy Clay Loam	7.75	6.25	4.75	3	2

Soil Storage Depth

Fleming and Neary (2004) found that the soil storage depth and related tension zone depth had the most significant influence on the results of the SMA loss model. Consequently, a number of the soil depth parameters available in the soil landscape mapping database (DWLBC, 2002a) were considered for the soil depth parameter, including depth to hard rock, depth to hardpan, deep drainage depth and potential root zone depth for 5 different crop types.

The United States Department of Agriculture Soil Survey Manual (USDA, 1993) states that the depth of the lowest layer or horizon should be related to the depth of rooting to be expected for perennial plants, assuming that water state and chemistry are not limiting. Of the depths available in the soil landscape mapping database, the potential rootzone depth for crop type CA, which is defined as sensitive perennial horticultural crops, such as citrus and avocadoes, has been adopted as the soil storage depth.

Baseflow Analysis

The parameters pertaining to the groundwater storages have been determined from baseflow analysis. To do this, a flow record is required. However, as individual events are considered, the data requirement is less than that for the calibration of a rainfall runoff model, which is often in the order of 10 years or more of daily flow measurements. Also, baseflow recession parameters determined from nearby catchments that are gauged may be suitable to be adopted in adjacent ungauged catchments.

The observed daily baseflow was determined from the available flow records using the baseflow separation method of Eckhardt (2005) with a BFI_{max} value of 0.5 for ephemeral streams with porous aquifers, and the K value was derived from recession analysis of the flow data (Linsley et al., 1988). The K value has also been used to determine the groundwater coefficient and storage depth for the SMA loss model in HEC-HMS (Fleming and Neary, 2004).

For this study, constant baseflow recession parameter values have been applied in the SMA model, as detailed spatial information about potential changes in the baseflow is unavailable, and as baseflow is expected to be relatively constant across catchments. Hence, the results from the above recession analysis have been averaged to represent the expected groundwater response of the region. The resulting values adopted were 202 hrs for the groundwater layer 1 storage coefficient, 1655 hrs for the groundwater layer 2 storage coefficient, 30 mm for the groundwater layer 1 storage depth and 203 mm for the groundwater layer 2 storage depth.

Tension Storage Depth

As outlined above, the soil profile zone is divided into two regions, the gravity zone and the tension zone. The gravity zone is defined as the portion of the soil profile that will lose water to both evapotranspiration and percolation. The tension zone is defined as the area that will lose water to evapotranspiration only. In order to determine an appropriate depth for the gravity zone, the average volume of baseflow has been used to determine the storage depth required to produce this baseflow volume based on the catchment area. The depths obtained have been averaged across all catchments, producing a depth of 7.2 mm. This depth has been used as an approximation to the component of soil storage that will be influenced by gravity. Therefore, the value required for the tension storage depth has been determined as the soil storage depth at each grid cell minus the average baseflow storage depth of 7.2 mm.

Prior Calibration Studies

Values for the soil percolation rate and baseflow linear reservoir coefficient were derived from an initial calibration study, where a genetic algorithm was used to calibrate all model parameters to simulate both overland flow and baseflow on a daily basis. The average of the percolation rates identified across the three catchments has been adopted, producing a value of 3.77 mm/hr, and for the linear reservoir coefficient a value of 122 hrs. Further work is required to determine if these parameters have a direct physical basis, and can be determined from GIS datasets.

RESULTS AND DISCUSSION

The NSE values based on the simulated and observed monthly volumes are presented in Table 2. It can be seen that acceptable results are produced for both the Mosquito Creek and Bakers Range catchments, while slightly poorer performance is observed for the Nalang Creek catchment. The lower value for the Nalang creek catchment can be attributed to the SMA loss model overestimating the peak flow during runoff events.

Table 2. NSE for Monthly Runoff Volumes

Catchment	NSE
Nalang Creek	0.15
Mosquito Creek	0.61
Bakers Range	0.48

The simulated and observed hydrographs for the period 1979-1989 for the Bakers Range and Mosquito Creek catchments can be seen in Fig. 3 and Fig. 4, respectively. Generally, the timing of the peak flow events is simulated accurately, suggesting that the time-area hydrograph approach adopted to compute travel times for the grids cell is suitable. Some of the error in the simulated hydrograph may be attributed to the errors in input rainfall data, where the interpolation method used to derive the grids of daily rainfall either produced events that were not observed in the catchment, or smoothed out events that were observed. For example, the large spike in flow at the end of 1986 in the Bakers Range catchment may be due to excess rainfall, as are the peaks in flow at the end of 1985 and 1987 for the Mosquito Creek catchment.

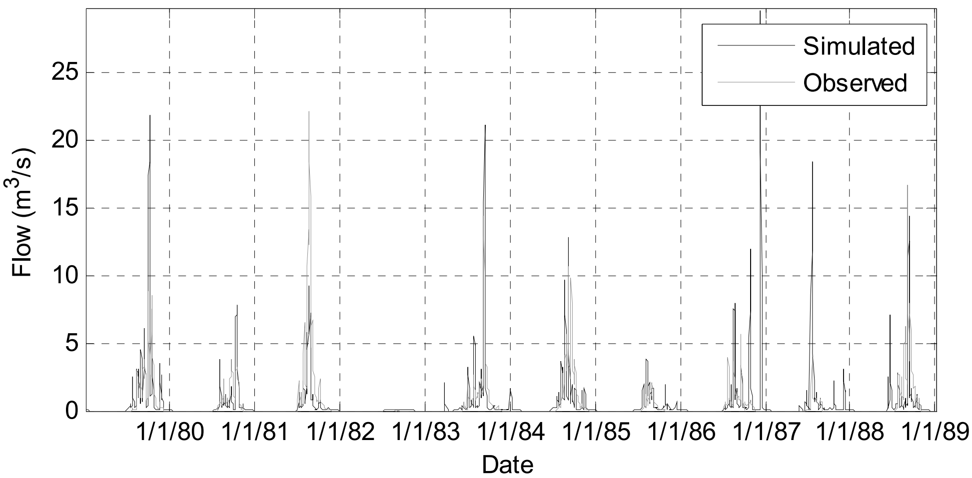

Fig. 3. Bakers Range simulated and observed hydrographs for the period 1979 – 1989.

The simulated and observed hydrographs for the Nalang Creek catchments can be seen in Fig. 5. Again, the timing of the peak flow events is simulated accurately, however most peaks are overestimated by the SMA model. It should be noted that the magnitude of flow at this site is much lower than that observed at the Bakers Range and Mosquito Creek catchments, with 99.1% of the daily flow measurements being below 1 m^3/s. These low flows may have contributed to the lower NSE observed at this site. Also, there is a simulated flow event in 1985 which does not have a corresponding observed flow event, suggesting that this period in the flow record may be missing, also contributing to the poorer performance computed for this catchment.

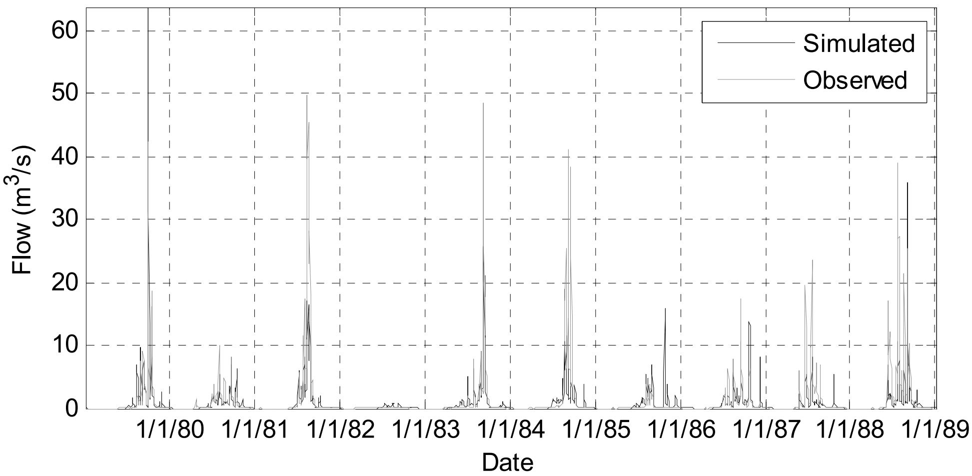

Fig. 4. Mosquito Creek simulated and observed hydrographs for the period 1979 – 1989.

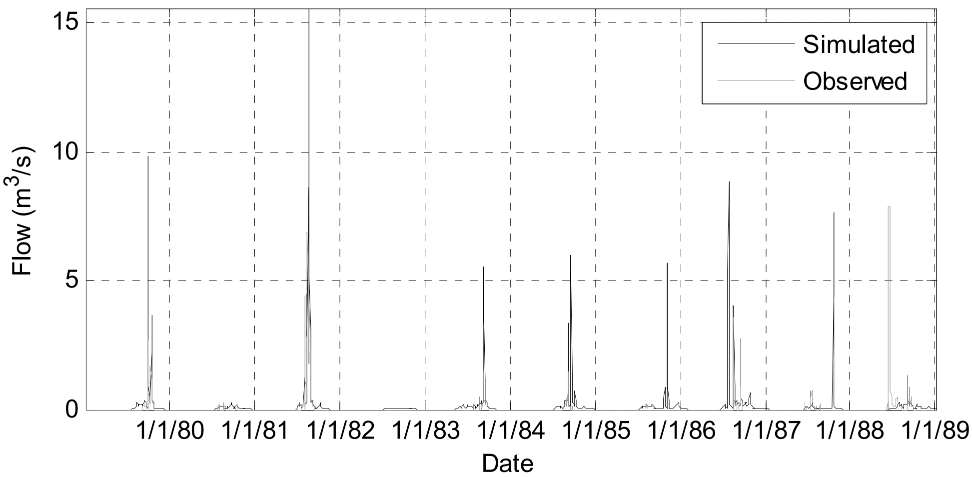

Fig 5. Nalang Creek simulated and observed hydrographs for the period 1979 – 1989.

One of the results of the Distributed Model Intercomparison Project (DMIP) (Smith et al., 2004) was that smaller catchments have less capacity to dampen out inputs and corresponding input errors (Reed et al., 2004), most likely in the magnitude and spatial distribution of rainfall events. This observation could also explain the poorer performance of the SMA loss model on the Nalang Creek catchment. Similarly, the Bakers Range catchment has a smaller area than the Mosquito Creek catchment, and also a lower NSE, which supports this observation.

While a number of parameter values have been determined from the flow record or prior calibration studies, the values adopted from these studies were constant across the three catchments, suggesting that for ungauged catchments suitable values for these parameters may be able to be adopted from nearby gauged catchments or nearby calibrated models. Also, Flemming and Neary (2004) undertook a sensitivity analysis on the SMA loss model, and found that the maximum infiltration rate, the maximum soil depth, and the tension zone depth caused the most variation in simulated streamflow when adjusted. The proposed approach derives values for these three most significant parameters directly from catchment information, indicating that the most significant parameters may be able to be derived directly from GIS datasets.

Improved model performance would most likely be obtained by calibrating all of the derived model parameter values. These adjustments would account for many factors, including the inability of the model equations and parameterizations to represent the true catchment physics and heterogeneity, scaling effects, and the existence of input forcing errors. However, it could be questioned whether or not the calibrated model would outperform the uncalibrated model, based on GIS derived parameter values, in the absence of these biases (Reed et al., 2004). Smith et al, (2004) questioned whether easier parameterization of a physically based distributed parameter model would warrant its use, even when it might not provide improvements over simpler lumped conceptual models. For gauged sites the increase in complexity for a distributed model may not be justified, and many of the results of the DMIP project indicate better performance can be achieved with a simple lumped loss model (Reed et al., 2004). However, in the case of ungauged sites, the parameterization of lumped model parameters may not be able to determined, because of the varying hydrologic response of large catchments, and in this case distributed models may be justified. Further work will attempt to parameterize lumped models with averaged values based on these results, to investigate the difference in performance.

CONCLUSIONS

A methodology to calibrate the distributed SMA model based on soil and land use data has been proposed. Values for the most significant soil and surface parameters have been derived directly from GIS datasets and applied on a gridded basis. Groundwater parameters have been determined from recession analysis, and constant values have been applied across the three catchments considered. Overall, the hydrologic response of each catchment can be seen to be represented well, with the timing of peak flows simulated accurately across the three catchments, and the best overall performance obtained for the largest catchment considered.

For ungauged catchments, flow records from nearby catchments may be required to determine the groundwater parameters, however only a short period of runoff events is required to estimate the values, compared to a long streamflow record that would be required to calibrate all SMA parameters. Two parameters were determined from a prior calibration study, and further work should investigate the physical basis and sensitivity of the model to these parameters.

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