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Importance of soil moisture measurements for inferring parameters in hydrologic models of low-yielding ephemeral catchments

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Abstract

Low-yielding catchments with ephemeral streams provide a stern test of the capability of conceptual catchment models for predicting the hydrologic response of the natural landscape. Sustained periods of little or no flow mean that the information content of the streamflow time-series for parameter estimation is limited. During periods with no streamflow, such ephemeral catchments also offer no information on a catchment's soil moisture status. As a result, parameters estimated solely from streamflow data are often poorly identified and span a wide range of the feasible parameter space. These general observations were confirmed by an application of the conceptual VIC model in a 6 ha experimental catchment in eastern Australia. Using a Monte Carlo style assessment of parameter uncertainty, it was shown that the simple three-parameter model was ill-posed when calibrated solely to the streamflow response. Failure of the calibration procedure to distinguish unique antecedent moisture storage conditions prior to large rainfall events meant that the observed streamflow response could be replicated from a large envelope of potential parameter combinations. The inclusion of an estimated time-series index of *areal* soil moisture status into the calibration procedure, however, significantly reduced the number of feasible parameter combinations, and resulted in predictions that confirmed Bowen ratio measurements of actual evapotranspiration. Attempts to further reduce parameter uncertainty by including the measured evapotranspiration data into the joint calibration procedure were unsuccessful. The shortness of the measurement record was seen as a major factor inhibiting improvement. The results of this study highlight the critical importance of antecedent moisture conditions on streamflow yields in ephemeral catchments and point to the desirability of spatio-temporal soil moisture accounting. Future research efforts are discussed in terms of establishing the appropriate spatial and temporal resolution of soil moisture measurements needed to extend the results observed for this small experimental study to larger catchments. © 2002 Published by Elsevier Science Ltd.

Keywords: Ephemeral catchments; Conceptual catchment models; Soil moisture; Evapotranspiration; Joint calibration; Parameter uncertainty; Monte Carlo sampling

1. Introduction

Catchment models are hypotheses of the dynamic water balance at the catchment scale. The identification of such models requires validating the model hypotheses and, as part of that process, making inferences about model parameters. In this article, the issue of parameter identification is considered in the application of conceptual catchment models in low-yielding ephemeral catchments.

Conceptual models typically involve a configuration of interconnected stores with mathematical transfer functions used to direct the movement of water between stores or into the stream. Although a mass balance is enforced for each store, the flux equations defining flows into and out of the stores are typically conceptual rather than physically based (Nash and Sutcliffe, 1970). This conceptual nature means that many of the parameters, state variables, and fluxes are not directly measurable and usually represent spatially and temporally lumped catchment characteristics. Consequently, although rather parsimonious and not very data intensive, one of the distinguishing characteristics of conceptual models is that the process of parameter inference relies heavily upon calibration via inverse reasoning, typically to an observed time-series of streamflow.

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In low-yielding ephemeral catchments, parameter identification by calibration to a streamflow record is hampered by the fact that the number of non-zero data points in the streamflow time-series may be quite small, even though the length of record is large. Thus, the information content of the streamflow time-series for parameter identification is small. This presents particular problems for models that generate surface runoff through a threshold process such as a spilling bucket. During calibration the exceedence of the threshold may rarely occur and thus the bucket size is unidentifiable. This can lead to problems such as the existence of multiple optima within the feasible parameter space and the presence of high interaction or correlation between subsets of fitted model parameters (see Duan et al., 1992; Freer et al., 1996). In more humid catchments this problem is often not as severe, as the information contained in the streamflow series is likely to be rich enough to activate every model process several times during calibration (Ye et al., 1997).

A key outcome of ill-defined model parameters is that it can no longer be assumed that accurate streamflow simulation at the catchment outlet reflects accurate simulation of internal catchment states and responses. This situation arises from the large number of model parameter sets that produce virtually indistinguishable simulated streamflow time-series even though the relative contributions of the fluxes that make up the streamflow vary greatly.

One obvious and well-documented way to increase the information content available for parameter estimation is to augment streamflow data with other kinds of hydrologic information relevant to the prediction task (see for example, Mroczkowski et al., 1997; Franks et al., 1998). Examples of multiple responses include streamflow and stream chemical tracer data at different locations within a catchment and measurable internal hydrologic fluxes or states such as soil moisture, saturated areas, piezometric levels, and evapotranspiration at selected locations. Such data represent a much richer source of information about the catchment water balance dynamics than do streamflow data alone. General statements relating multiple data sources with improved parameter identification, however, have been shown to be not universal. It has been shown, for example, that augmenting streamflow with 'point' groundwater measurements does little to reduce parameter and predictive uncertainty (e.g. Seibert et al., 1997; Kuczera and Mroczkowski, 1998. *Areal* soil moisture, however, would appear to provide a valuable source of additional information, especially for ephemeral catchments during periods with no streamflow, and thus no information on catchment-average soil moisture status.

Soil moisture content is a major control on hydrological processes for both storm and interstorm periods. During storm periods it influences the partitioning of precipitation into infiltration and runoff (for saturation excess processes). For interstorm periods, soil moisture determines whether the soil column can meet the atmospheric demand for moisture; either at the surface (bare soil evaporation) or in the root zone (transpiration) and it thus affects the partitioning between latent and sensible heat fluxes. In this way, the soil moisture content is the link between the surface energy and water balances.

In most conceptual models there is some representation of soil moisture status, but validation against field data is often difficult because of at least two problems. Firstly, field measurements of soil moisture content are made at the point scale while conceptual models provide an estimate for a specified area, producing a disparity in scales. Secondly, soil moisture is highly variable in space, meaning that individual point measurements rarely if ever represent the spatial average of even small areas. This necessitates that *areal* values are estimated from many point measurements.

The hydrological literature contains few examples of catchment studies where distributed measurements of soil moisture values have been compared with values simulated by conceptual catchment models. Johnston and Pilgrim (1976) showed a comparison between soil moisture modelled with a simple conceptual model and soil moisture data obtained from field measurements, providing an independent assessment of model performance. Kuczera (1983) used soil moisture and throughfall measurements with a conceptual rainfall-runoff model. He noted that the use of data on runoff, soil moisture and interception with catchment models can yield substantial reductions in the uncertainty of model parameters. Kalma et al. (1995) described a comparison between simulated soil moisture resulting from both a *fixed* and *variable* storage conceptualisation and a soil moisture index based on point measurements to show the potential of conceptual models to make useful predictions of soil moisture status at the catchment scale. Western et al. (1999) demonstrated that simulated time-series of spatially average soil moisture storage achieved with a quasi-distributed conceptual model was consistent with the observed soil moisture characteristics. The statistical distribution of soil moisture storage assumed in the model, however, was shown to differ from that observed.

This article aims to re-examine the usefulness of conceptual models for soil moisture prediction at the catchment scale. This is done via a case study application of the conceptual variable infiltration capacity (VIC) model (Wood et al., 1992) in a 6 ha experimental catchment located in eastern Australia. The low-yielding catchment, which is representative of a large number of catchments in semiarid regions of Australia, was chosen to be a stern test of the capability of the VIC model. The VIC model uses a statistical distribution to characterise the spatial variation in soil moisture storage. For the current study, this distribution is determined explicitly by calibration against combinations of surface runoff, soil moisture and evapotranspiration data. Monte Carlo based assessment of parameter uncertainty resulting from individual and joint calibrations leads to the main contribution of the article, namely to provide insight into the value of field measured soil moisture, evapotranspiration and surface runoff data for parameter inference and hydrological prediction in low-yielding ephemeral catchments.

2. Study area

The 6 ha Nerrigundah experimental catchment is located in the Williams River catchment, approximately 11 km north-west of Dungog, New South Wales, Australia (Fig. 1). The catchment runs east to west with a relief of 27 m. Hillslopes range from 3 to 22%, with the main drainage line having an average slope of 9%. Average annual rainfall is 1000 mm and *areal* potential evapotranspiration is 1600 mm. The soil type is a moderately well drained clay-loam duplex with an *A* horizon of approximately 30–40 cm and a clay *B* horizon from 50 to over 100 cm deep. Measurement of bulk density from 19 spatially distributed soil core samples indicate that the mean porosity for the catchment is approximately 50–55% v/v, while permeameter measurements indicate that the saturated hydraulic conductivity of the *A* horizon is an order of magnitude larger than that of the *B* horizon (Walker et al., 2001).

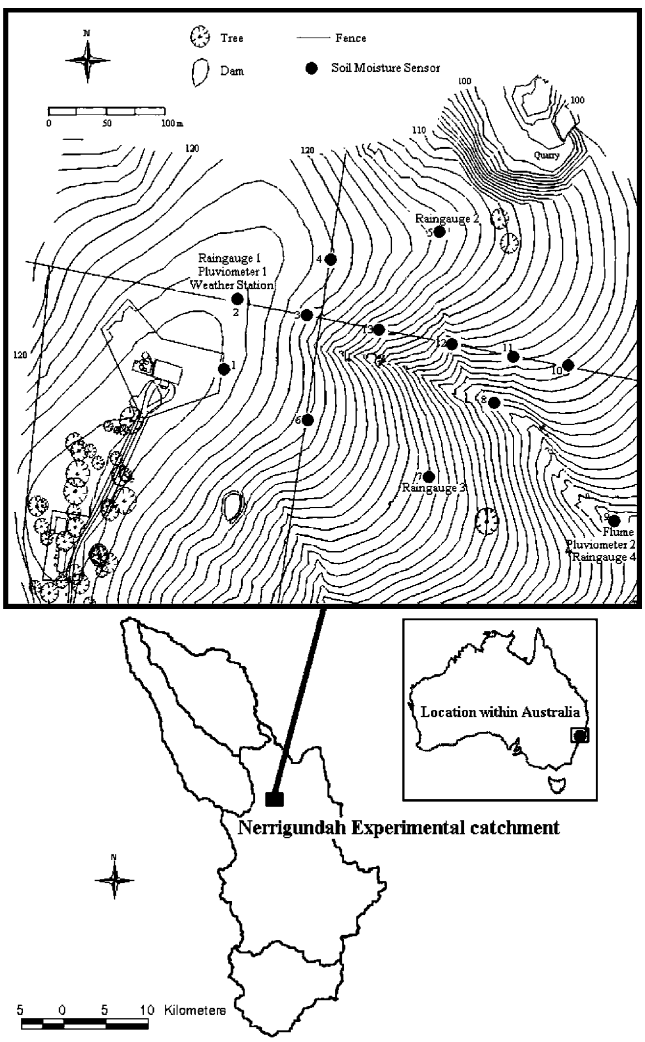

Fig. 1. The Nerrigundah experimental catchment, showing the location of the measurement sensors.

3. Measurements

For the 908-day period of investigation (28.10.1996–07.04.1999) undertaken in this study, a variety of hydrometeorological variables were measured. A weather station continuously measured net radiation, atmospheric pressure, wind speed and direction, relative humidity, air temperature, rainfall, soil heat flux and soil temperature at various depths. Apart from rainfall, all measurements were made at 1-min intervals, with the average taken every 10 min. Rainfall was recorded for each tip of the 0.2 mm tipping bucket pluviometer.

A 45 cm Parshall flume at the catchment outlet monitored surface runoff. A second pluviometer was located at the flume, and four collecting rain gauges were distributed throughout the catchment to check the spatial variability of rainfall. The additional gauges showed that rainfall at Nerrigundah was spatially uniform at both the event and seasonal scales.

The soil moisture profile was continuously monitored at 15 min increments using five Virrib soil moisture sensors (Komin, Technical Data) installed at depths of 10, 15, 20, 30 and 40 cm for an individual point in the catchment, located at the weather station. The spatial variation of soil moisture profiles was periodically monitored with time domain reflectometry (TDR) probes of various lengths up to the maximum of 1 m or bedrock at 13 sites distributed throughout the catchment. The location of these sites is displayed in Fig. 1. The spatial TDR soil moisture measurements were made on 40 days (at approximately 2-week intervals) during the experimental period.

3.1. Intensive intersampling period

For a 24-day intensive soil moisture sampling period (04.03.1999–28.03.1999), evapotranspiration measurements were made with a Campbell Scientific Bowen ratio system. The Bowen ratio system was located next to the weather station and measured sensible and latent heat fluxes over 15-min time intervals. The location of the system achieved the required fetch-to-height ratio of 1:150 (Heilman et al., 1989) for the predominant south-east wind direction. Based on spatial TDR soil moisture measurements for the top 40 cm during the intensive measurement period, it was considered that the moisture conditions at the Bowen ratio measuring site were slightly drier than the catchment-wide 'average'. It should also be noted that above average soil moisture conditions were present during the intensive sampling period relative to the entire measurement period.

Fig. 2 displays the time-series of soil moisture (% v/v), latent heat flux (W/m^2) and daily-accumulated actual evapotranspiration (mm/day) for the 24-day intensive measurement period. The period corresponded to a gradual lowering of soil moisture content from 42 to 36% v/v over the first 16 days of measurement before a 15 mm rain event on 20.03.1999 and a 30 mm rain event on the 22.03.1999 resulted in a rise in soil moisture content back to 45% v/v, with a subsequent lowering to 40% v/v over the following 6 days.

4. Soil moisture analysis

The 13 spatially distributed measurements of soil moisture were discontinuous in time (i.e. approximately one measurement every 2 weeks) while the Virrib soil moisture sensors at the weather station provided a continuous soil moisture time series for an individual point. In order to recover a continuous record of *areal* soil moisture, a merging of the two data sets was performed.

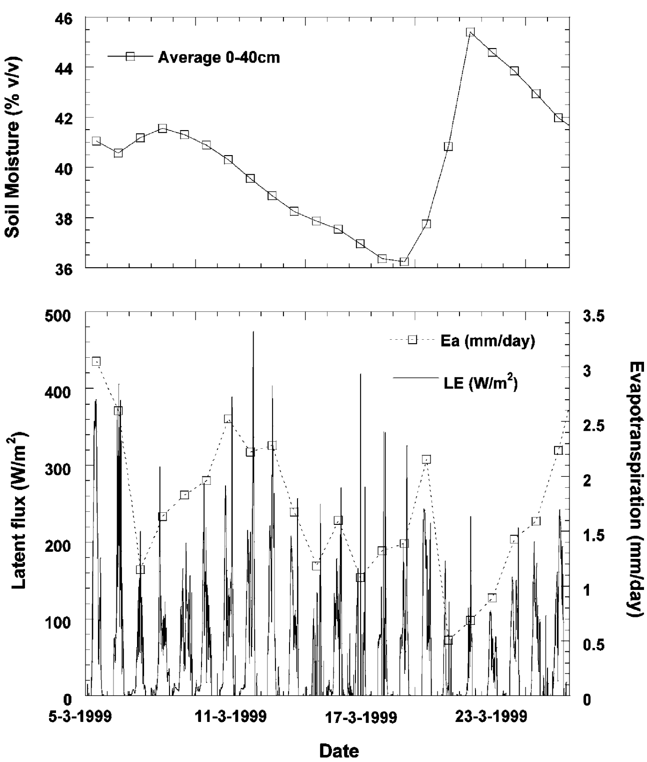

Fig. 2. Measured soil moisture (% v/v), latent heat flux (W/m^2) and daily-accumulated actual evapotranspiration (mm/day) for the 24-day intensive measurement period.

The idea was to utilise the spatial measurements to obtain instantaneous catchment average soil moisture estimates, and then to statistically regress these *areal* estimates against the corresponding point measurements. The resulting relationship would thus allow for the reconstruction of a continuous *areal* estimate from the continuous point record.

Following the methodology of Kalma et al. (1995) a soil moisture index approach was utilised in an effort to aggregate the spatial (point-scale) soil moisture measurements to a single quantity that was representative of *areal* soil moisture availability within the catchment. For each spatial location and for each day of measurement, the local value of the volumetric moisture content of the total soil profile (SM$*$, % v/v) was measured with the TDR equipment. The soil moisture index SMI$*$ at each location was then defined by

$$\mathrm{SMI}^* = (\mathrm{SM}^* - \mathrm{SM}^*_{\min})/(\mathrm{SM}^*_{\max} - \mathrm{SM}^*_{\min}) = A/B \qquad (1)$$

where $A = (\mathrm{SM}^* - \mathrm{SM}^*_{\min})$ is the removable component of total soil moisture (% v/v) and $B = (\mathrm{SM}^*_{\max} - \mathrm{SM}^*_{\min})$ represents the maximum soil moisture storage capacity (% v/v) at that point (with values obtained for the entire sampling period). SMI* values thus range between 0 and 1. Finally, with SMI$*$ estimated for each location, it was assumed that for each day of measurement, the *areal* soil moisture storage could be estimated from SMI$^{**}(\Sigma A/\Sigma B)$ based on all measurements on that day. The utility of the index approach can be seen in the comparison plots of Fig. 3a and b. Fig. 3a shows the actual measured temporal variation of the soil moisture content (% v/v) in the top 40 cm for a *dry* (Profile 2), *intermediate* (Profile 4) and *wet* (Profile 8) catchment location. Fig. 3b shows the corresponding plot using the index approach, and highlights the improved similarity between the profiles when using the index approach.

The temporal dynamics of the *areal* soil moisture index (SMI$**$) based on the 13 spatial locations was compared to the corresponding point moisture index (SMI$*$), as measured at the continuous Virrib monitoring site. As a result of soil disturbance during installation, a 10-month 'settling-in' period of the Virrib sensors was allowed in an effort to permit the soil to re-establish equilibrium conditions. The comparison was therefore not attempted until day 315 (22.08.1997) of the experimental campaign, resulting in a total of 40 point/spatial combinations.

Fig. 4 shows the plot of these 40 point/spatial soil moisture index combinations, along with a fitted cubic polynomial resulting from the regression between both quantities. The nature of the polynomial is likely to integrate the effects of a number of features, making exact physical explanation difficult. Firstly, the shape is likely to reflect the fact that the continuous soil moisture measurements were made at a comparatively dry location within the catchment. It is also likely to account

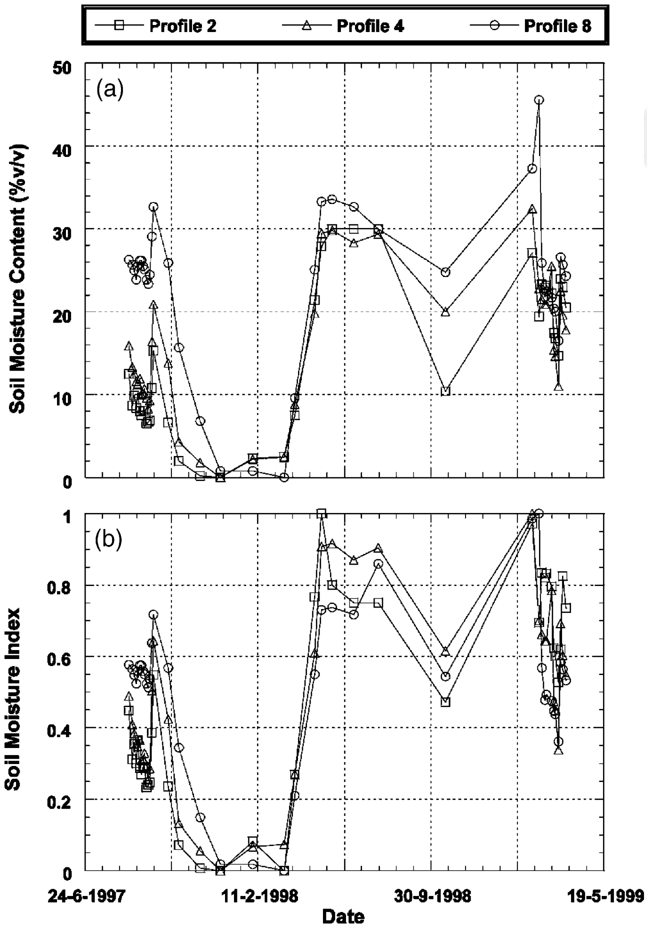

Fig. 3. (a) Measured temporal variation of the soil moisture content (% v/v) in the top 40 cm for a *dry* (Profile 2), *intermediate* (Profile 4) and *wet* (Profile 8) catchment location, and (b) the corresponding temporal variation using the soil moisture index approach.

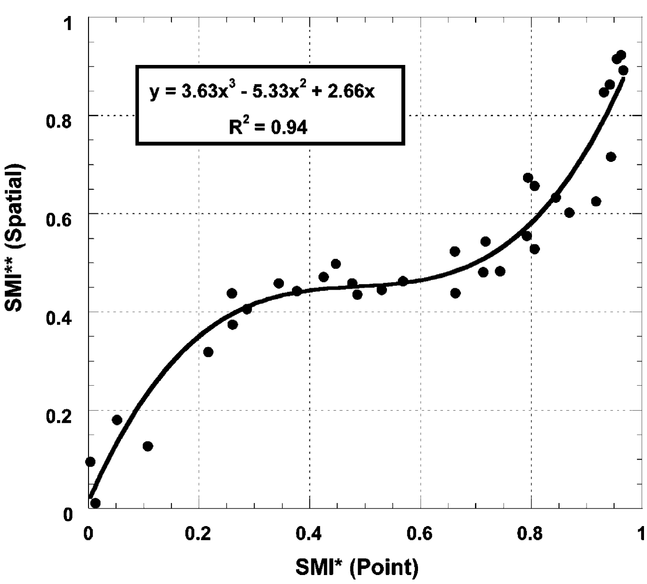

Fig. 4. Comparison between the continuous point moisture index (SMI∗) and the areal soil moisture index (SMI∗∗) for all days of spatial soil moisture measurement.

for differences in the measurement techniques. The Virrib sensors (at various depths) consist of two horizontally inserted stainless steel concentric circular rings (electrodes of diameter 28 and 20 cm), which allow soil moisture measurement by means of an electro-magnetic field generated around the two electrodes. The TDR sensors, on the other hand, measure the down and return travel time of an electro-magnetic wave for two vertically inserted stainless steel probes of known length. While both approaches make use of the dielectric properties of water, the structural differences in the approaches are likely to result in slight differences in how the measurements respond to temporal changes in soil water content.

Fig. 5 displays the result of the regression edited, continuous point moisture index (SMI∗ (point-edit)), which can subsequently be interpreted as a continuous estimate of *areal* soil moisture index. Also shown for comparison purposes is the corresponding soil moisture index (SMI∗∗) resulting from the 13 spatial profiles. It can be seen that there is good agreement between the continuous and instantaneous estimates, which engenders confidence in utilising the developed *areal* estimates for describing the catchment average soil moisture status. Potential inaccuracies induced by the largely unknown parameter uncertainty of the regression relationship should, however, be kept in mind for the modelling that is to follow.

5. Description of the VIC model

The conceptual water balance model used here is the single layer VIC model (Wood et al., 1992; Sivapalan and Woods, 1995; Kalma et al., 1995). Fig. 6a provides a schematic illustration of the soil moisture distribution approach that forms the basis of the VIC model. The VIC model assumes that scaled infiltration (i.e. storage) capacity is a random variable with its cumulative distri-

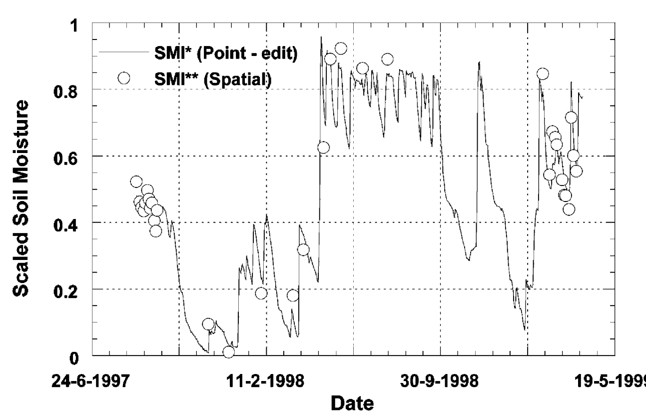

Fig. 5. Comparison of the regression edited, continuous point moisture index (SMI∗ (point-edit)), and the corresponding spatial moisture index (SMI∗∗) resulting from the 13 spatial profiles.

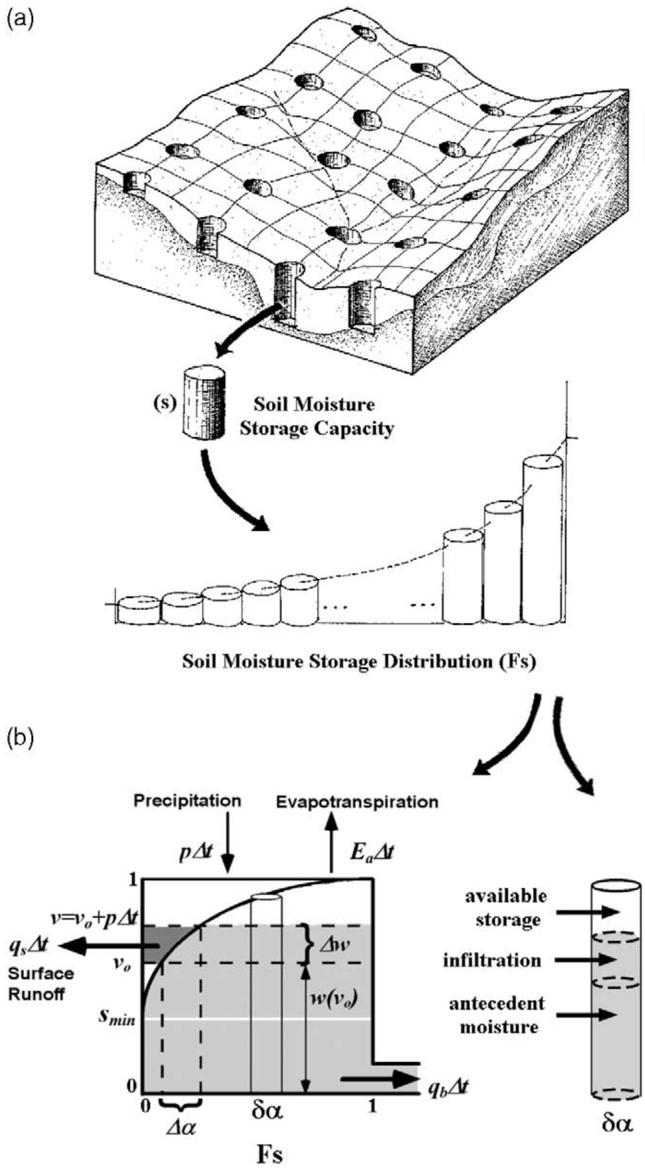

Fig. 6. (a) Distribution approach towards variability in catchment storage capacity, and (b) schematic of the VIC hydrologic model conceptualisation (after Kalma et al., 1995).

bution function given by the Xinanjiang distribution (Zhao et al., 1980). The distribution function allows for a variable bucket conceptualisation that allows runoff generation and evapotranspiration to vary within an area (e.g. lumped catchment). Here, we apply the modified distribution function (Kalma et al., 1995), which includes a minimum storage level for the initiation of surface runoff (see Fig. 6b). The cumulative distribution of the scaled (i.e. normalised) storage capacity, s, is given by

$$s = 1-(1-s_{\min})(1-\alpha)^{1/\beta} \tag{2}$$

where α represents the saturated fraction of the total catchment area, $s_{\min}$, the threshold for overland flow and β, the model parameter giving the concave-up shape for values less than 1 and convex-up for values greater than 1. Storage capacity at any point in a catchment is defined as the maximum depth of rainfall, which can infiltrate at that point. The scaled storage capacity, s, is the local storage capacity divided by the largest storage capacity at any point in the catchment.

The soil moisture status for the entire catchment can be described by the scaled soil moisture variable, v, which represents the actual scaled soil moisture in storage at every point of the catchment. Antecedent soil moisture is indicated by v_0. Those points on the land surface with $s < v_0$ are considered to be saturated, before any rain begins. If all soil water in the catchment is assumed to be held in saturated soil, then the scaled soil moisture can be written as $v_0 = y_0/z_{\max}$, where y_0 is the height of saturated soil above bedrock (for locations that are not already totally saturated) and $z_{\max}$ the maximal soil depth across the catchment (y_0 is assumed to be constant throughout the catchment). For a given v (equal to s at saturation), the fraction of land surface which is saturated is denoted by α, and the total soil moisture held in the catchment denoted by w. Given values of β and $s_{\min}$, any one of v, w or α is sufficient to define the moisture status for the entire catchment. Kalma et al. (1995) specify all of these functional relationships.

The VIC model therefore produces a time series of w, the total moisture storage for the entire catchment. If the w values are divided by w_c, the maximum possible value of w when all the soil is saturated, then the ratio w/w_c is a catchment-scale wetness index. For the modified Xinanjiang distribution (Eq. (2))

$$w_c = s_{\min} + (1-s_{\min})/(\beta + 1) \tag{3}$$

Within the current VIC formulation, catchment-scale evapotranspiration is calculated by integrating a point-scale model of evapotranspiration over the catchment-wide distribution of soil moisture conditions. The two-parameter point-scale model results in local evapotranspiration E_s being estimated as a function of local soil moisture via the following step function

$$E_s/E_p = [(v + \psi_c)/s]^{\eta} \text{for} (v + \psi_c) < sE_s/E_p \tag{4}$$
$$= 1\text{for}(v + \psi_c) \geq s$$

where E_p is the potential evapotranspiration from a uniformly wetted surface, v, the level of soil moisture (equal to s at saturation), s, the local maximum of soil moisture, ψ_c, the scaled capillary fringe thickness and η, a property of the soil and vegetation types, assumed to be constant in space. The *total* actual catchment evapotranspiration E_a may then be found (see Sivapalan and Woods (1995) by

$$E_a/E_p(v,\psi_c) = \int_0^1 E_s/E_p(s;v,\psi_c)F_s(s)\mathrm{d}s \tag{5}$$

Subsurface runoff in the VIC model is calculated as a linear function of average soil moisture storage, and surface runoff is calculated by a simple water balance.

6. Application of the VIC model

6.1. VIC simulations

For the current application of the VIC model a daily time step was used. Results are based on the 908-day period between 28.10.1996 and the 07.04.1999. Potential evapotranspiration (E_p) for the period was calculated with the Penman–Monteith model, following the methodology outlined by Smith et al. (1991). Net radiation, temperature, humidity and wind data were obtained from the Nerrigundah weather station. Daily rainfall was taken as the average of the measured volumes obtained from the two pluviometers within the catchment. Both rainfall and potential evapotranspiration were assumed to be spatially uniform.

Simulations began on 28.10.1996 with the initial condition of zero available water storage (i.e. maximum simulated saturation deficit). To allow the internal state variables to reach equilibrium, an 8-month period was allowed before any calibration of the model parameters was performed. Other parameters that were set prior to the calibration included the conceptual maximum soil depth for active soil water movement ($D_{max} = 1$ m, estimated from soil core data), the hydrologically active porosity ($\Delta\theta = \theta_{sat} - \theta_{pwp} = 0.38 m^3/m^3$), the estimated height of the capillary fringe divided by D_{max} ($\psi_c = 0.16 m/m$) and the subsurface recession constant ($k_c = 0.0$).

6.2. Parameter optimisation

Calibration of the VIC model parameters β, S_{min} and η was performed with the nonlinear regression software NLFIT (Kuczera, 1994) using a sum of squared errors objective function. The parameter search strategy employed the robust shuffled complex evolution method of Duan et al. (1992) searching over a large hypercube in parameter space; the number of complexes was set equal to the number of fitted parameters. Though not as efficient as gradient search strategies, it virtually guarantees termination close to the global optimum (Kuczera, 1997).

The VIC model was jointly calibrated to combinations of daily streamflow, soil moisture and evapotranspiration time series data from the Nerrigundah catchment. The joint calibration strategy, based on the work of Kuczera (1983), required care in its implementation. The key step was specification of a weight matrix, Ω, which determines how much weight is assigned to each fitted response. Misspecification of the weights can result in poor fits for some responses. To guard against this, it was decided to initially fit each response separately with $\sigma_i^2, i = 1,\ldots,m$, being the residual variance from m observed time series. The weight matrix was then initialised to zero except for the diagonal elements, which were set to

$$\Omega_{i,i}^{-1} = 1/\sigma_i^2 i = 1,\ldots,m \qquad (6)$$

This ensured that the joint calibration did not give undue weight to any particular response. After the first joint calibration the weight matrix was updated using the joint residual vectors.

To assess the worth of the different data sources in terms of parameter identification, a thorough uncertainty analysis was undertaken for the optimal parameter sets. This was achieved by directly computing the posterior probability distribution of each parameter. The posterior probability distribution represents what is known about a parameter given the available data. All things being equal, the more a posterior distribution concentrates its probability mass about a particular value the more precise (or certain) the knowledge of that parameter will be.

Monte Carlo-based methods provide a useful tool for sampling from the posterior distribution. Two generic Monte-Carlo sampling approaches exist: namely importance sampling and Markov chain sampling. Kuczera and Parent (1998), provide a complete description of both approaches, and emphasize that Markov chain sampling is a more efficient method as it adapts to the true shape of the posterior distribution via a random walk process. For the present application, the Markov chain sampling methodology of Kuczera and Parent (1998) was adopted, resulting in the implementation of the Metropolis algorithm (Metropolis et al., 1953). The algorithm was used to generate five parallel sequences, each with 2500 samples. Each sequence was started at the most probable parameter value. The first 500 samples in each sequence are discarded, leaving a total of 10,000 samples. The parameter covariance and Metropolis scaling were updated after every 500 samples. An acceptable R statistic (Gelman et al., 1997) indicated approximate convergence.

7. Results and discussion

7.1. Calibration to streamflow

In a general sense, calibration of the VIC model to streamflow involved optimising the model parameters to ensure that the minimum soil moisture deficit ($s_{min} - \nu$) following a prolonged dry period would generate the correct amount of streamflow for the next large rainfall event. This could be achieved by adjusting either the threshold depth to overland flow, s_{min}, or the evaporation parameter, β (which would then change v). Table 1a presents the Metropolis-sampled posterior mean and standard deviation of the three fitted VIC parameters obtained from calibration against the observed streamflow record. Fig. 7a presents the corresponding plot of the observed and predicted streamflow responses. The good agreement between responses as indicated by the relatively high Nash and Sutcliffe (1970) coefficient of efficiency (i.e. $E^2 = 0.90$), implies that the VIC model was able to successfully capture the streamflow response of the catchment to precipitation and other climatic inputs. The large standard deviations associated with the posterior means of the fitted parameters, however, suggest a high degree of uncertainty associated with the optimal parameter estimates. This high degree of uncertainty is demonstrated by the plot of the posterior density distribution of the 10,000 Metropolis samples for the β and $s_{\min}$ (Fig. 8a) and, β and η (Fig. 8b) parameters. Both plots indicate a high degree of parameter interaction, and suggest that an equally acceptable streamflow prediction could occur from over a wide range of the feasible parameter space. Presumably this parameter interaction is a result of the previously mentioned fact, that for adequate runoff prediction with the VIC model following dry periods (a common occurrence in ephemeral catchments), it is not strictly necessary that the actual level of soil moisture in storage (i.e. v) needs to be predicted correctly, only that the minimum soil moisture deficit

$$(s_{\min} - v)$$

is correct. Subsequently, there are many ways in which

Table 1
Metropolis sampled, posterior mean and standard deviation of the three fitted VIC parameters resulting from calibration to (a) streamflow data, (b) joint streamflow and soil moisture data (c) joint streamflow and evapotranspiration data and, (d) joint streamflow, soil moisture and evapotranspiration data

Parameter	Mean	Standard deviation
(a) Calibration to streamflow data		
β	2.32	1.065
$s_{\min}$	0.19	0.016
η	1.08	0.146
(b) Calibration to streamflow + soil moisture data		
β	2.91	0.170
$s_{\min}$	0.33	0.008
η	2.02	0.054
(c) Calibration to streamflow + evapotranspiration data		
β	0.865	0.063
$s_{\min}$	0.463	0.049
η	4.41	0.347
(d) Calibration to streamflow + soil moisture + evapotranspiration data		
β	2.68	0.168
$s_{\min}$	0.31	0.010
η	2.19	0.082

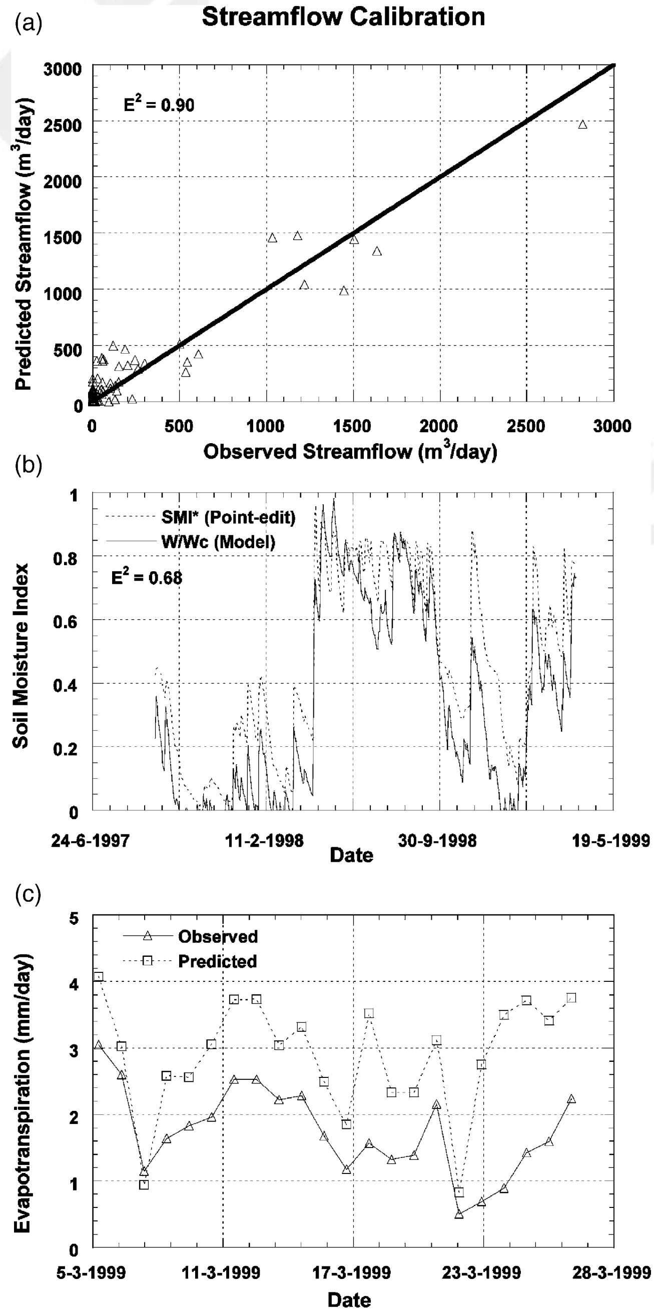

Fig. 7. *Streamflow calibration*. Comparison of observed and model predicted (a) streamflow, (b) *areal* soil moisture status and (c) evapotranspiration.

β, $s_{\min}$ and η can interact to ensure that the correct volume of runoff is achieved.

As an independent check of the usefulness of the streamflow calibrated VIC model as a predictor of the dynamic catchment water balance, a comparison was made between model predicted soil moisture status and actual evapotranspiration, and the equivalent quantities as obtained by field measurement. Fig. 7b displays the comparison of the *areal* wetness index obtained from the merged point and spatial field analysis (SMI∗ (point-

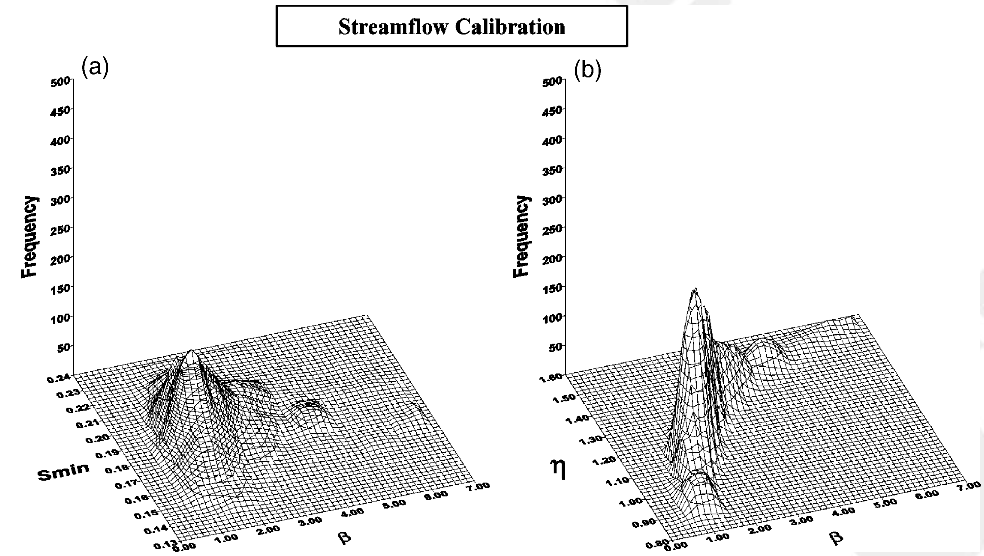

Fig. 8. A plot of the posterior probability surface for the VIC model parameters; (a) β and $s_{\min}$ and (b) β and η resulting from calibration solely to *streamflow* data. Each plot is based on 10,000 samples as generated by the Metropolis algorithm.

edited)) and that produced by the VIC model (w/w_c). It can be seen that while the temporal trace of relative catchment wetness shows good agreement, the absolute values are rarely consistent. On average, over the entire period of investigation, the model simulates the catchment as being drier than reality. Although only a relatively short record, comparison of observed and predicted actual evapotranspiration for the 24-day Bowen ratio measurement campaign (Fig. 7c) suggests that a possible reason for the drier prediction of soil moisture status could be due to the fact that the model parameterisation results in an over-prediction of actual evapotranspiration for relatively wet conditions. The essence of the evapotranspiration scheme utilised by the VIC (as described by Eq. (4)) is that the actual evaporation from bare-soil and vegetated surfaces is a fraction κ of the energy-limited (potential) rate, $E_a = \kappa E_p$, where κ is non-linearly related to soil moisture availability. The performance of this type of evapotranspiration scheme has traditionally been shown to become less satisfactory as the modelling time-scale is reduced, leading to an overestimation of evaporation during wet periods, and under-estimation during dry periods (Chen et al., 1996). Because there are significant no-flow periods in the calibration record, within which there is no information available to infer the correct temporal evolution of soil moisture status, it is likely that the evapotranspiration rates resulting from such a scheme are not sufficiently constrained by the streamflow response alone.

7.2. *Joint calibration involving streamflow and soil moisture*

Table 1b presents the Metropolis sampled, posterior mean and standard deviation of the three fitted VIC model parameters obtained from joint calibration to the observed streamflow and *areal* soil moisture data. The corresponding plots of observed and predicted streamflow (Fig. 9a) and *areal* soil moisture status (Fig. 9b) resulting from the two optimised time-series, show that while streamflow predictability is similar in comparison to the single streamflow calibrated model, soil moisture prediction is considerably more consistent with the jointly calibrated model. Weiss and Smith (1998) explain that it is common for the fit of each individual data set based on a joint calibration to be worse than the fit of each data set using the estimates from that data set. The improvement in the prediction of the internal soil moisture state variable also corresponds with a significant reduction in the standard deviations associated with the mean posterior parameter values of the optimal parameter set (Table 1b). This reduction in parameter uncertainty is reflected in the constrained posterior density distributions for the β and $s_{\min}$ (Fig. 10a) and, β and η (Fig. 10b) parameters.

From Fig. 9 it is clear that the inclusion of the soil moisture data in the calibration process has provided additional information with which to accept or reject competing model parameterisations. This additional information can be reconciled with the fact that by forcing the model to reproduce the time-series of soil moisture status, the acceptable range of the evaporation parameter η is necessarily reduced. Because of the competing interaction of $s_{\min}$ and β, the constraining of β must similarly constrain the acceptable range of $s_{\min}$.

As an independent check of the value of the reduced parameter uncertainty, Fig. 9c shows the 24-day time-series of observed and predicted actual evapotranspiration resulting from the joint streamflow and soil moisture calibrated model. Comparison of the plot to the cor-

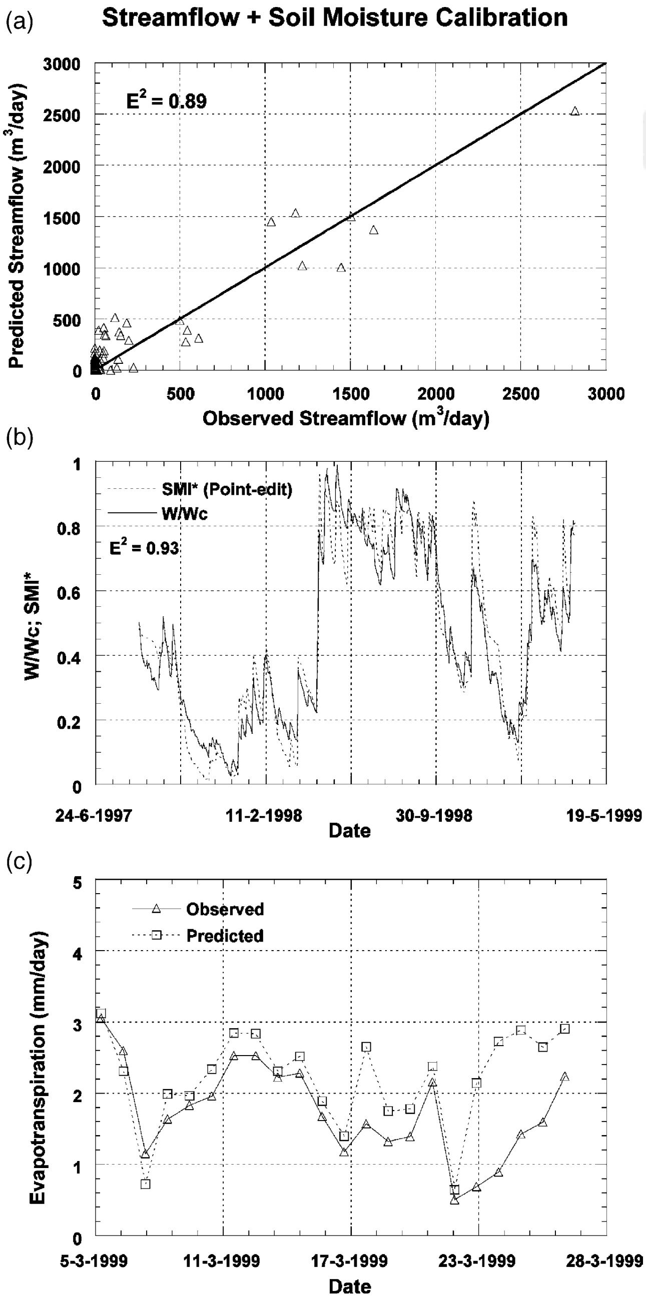

Fig. 9. *Joint streamflow and soil moisture calibration*. Comparison of observed and model predicted (a) streamflow, (b) *areal* soil moisture status and (c) evapotranspiration.

responding predictions resulting from the streamflow calibrated model (Fig. 7c) shows that the jointly calibrated model results in considerably improved prediction of evapotranspiration, with predictions being surprisingly accurate given the conceptual simplicity of the evapotranspiration routine. The improvement in evapotranspiration prediction highlights the importance of accurate soil moisture accounting when evapotranspiration routines based on $E_a = \kappa E_p$ relationships are applied at the small-catchment scale. The comparatively poor evapotranspiration estimates from the 23.03.1999 to 26.03.1999 could possibly be related to measurement error, as rain fell during this period and could have interfered with the measurement sensors of the Bowen ratio system. Assuming the data to be true could, however, allude to the above-mentioned deficiency with this style of evapotranspiration routine that results in over-estimation of evapotranspiration for the wet conditions.

A question that deserves to be asked about the joint soil moisture calibration is, 'Would the same constraining of the parameters occur for a humid, energy limited catchment as opposed to a water limited ephemeral catchment?' While the answer to this question obviously lies in a repeat application, initial reasoning would tend to suggest not. For the humid catchment with abundant water supply, the VIC model conceptualisation would consistently result in the local soil moisture storage level, v, being above $s_{\min}$. The correct simulation of evaporation and runoff would therefore only require that the changes in soil moisture be correct and not necessarily require the absolute values of soil moisture to be correct. Specifying soil moisture correctly may therefore not provide improved simulation of fluxes such as evapotranspiration and streamflow for humid catchments. In such situations it may prove more beneficial to investigate the integrated value of soil moisture status (i.e. saturated area fraction).

7.3. *Joint calibration involving streamflow and evapotranspiration*

The measured 24-day evapotranspiration record was utilised to investigate the ability of a joint calibration based on streamflow and evapotranspiration to aid in parameter identification and thereby constrain parameter uncertainty. Theoretically, if the evapotranspiration record could be considered representative of the *areal* estimate, and if it was of a sufficient length to contain the dynamics of both the wetting and drying of the soil profile for a variety of catchment wetness conditions, then one would expect it to be a rich source of information with which to condition the internal dynamics of the model.

Table 1c presents the Metropolis-sampled posterior mean and standard deviation of the three fitted VIC parameters obtained from joint calibration to the observed streamflow and evapotranspiration data. Examination of the parameter values for the optimal parameter set reveals a considerably smaller value of β and larger values of $s_{\min}$ and η compared to the previous parameter combinations. The result of these parameter changes in terms of changes in model function can be reconciled as follows. The smaller value of β will result in lower levels of saturation over all soil moisture levels and lead to reduced surface runoff for a given rainfall input. The larger value of $s_{\min}$ means a greater level of antecedent wetness needs to be exceeded before the initiation of

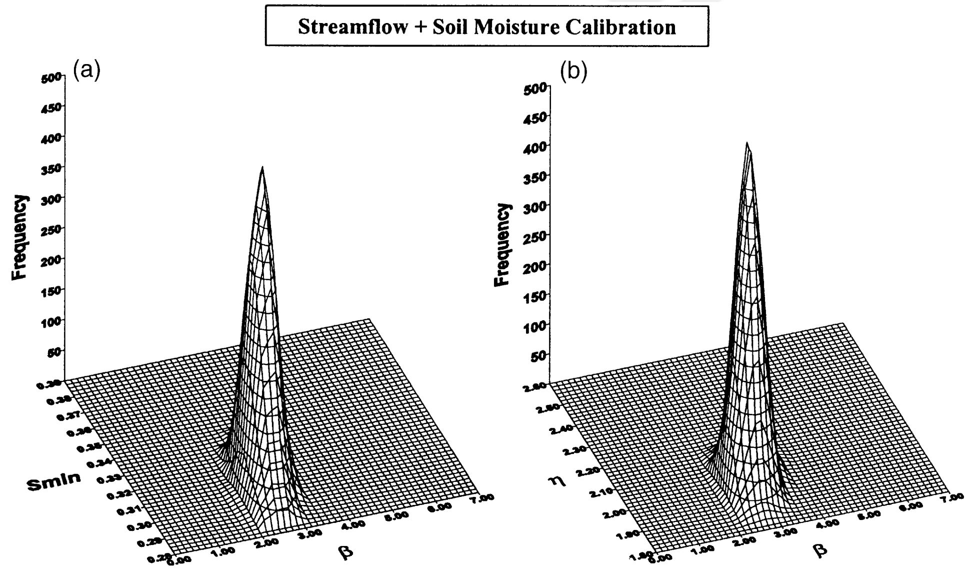

Fig. 10. A plot of the posterior probability surface for the VIC model parameters; (a) β and $s_{\min}$ and (b)β and η resulting from joint calibration to streamflow + soil moisture data. Each plot is based on 10,000 samples as generated by the Metropolis algorithm.

surface runoff. Finally, the larger value of η means a reduced rate of evapotranspiration, although this will be offset to some extent by higher average soil moisture levels. A consequence of these parameter changes is a less dynamic catchment in terms of runoff and evaporative fluxes, meaning that more water is held in storage.

The result of this parameterisation in terms of predicted streamflow, soil moisture and evapotranspiration can be seen in Fig. 11. Due to the joint conditioning, the parameterisation results in good predictions of the streamflow and evapotranspiration responses. The predicted soil moisture response, however, shows a poor correlation with the observed equivalent, with a more constant (i.e. less dynamic) soil moisture variation. Clearly, the evapotranspiration and streamflow fluxes have been achieved at the expense of non-realistic soil moisture conditions. By maintaining the catchment in a 'wet' state, the streamflow and evapotranspiration volumes have been simulated with lower rates of evapotranspiration and streamflow per unit surface area in unit time.

The poorly constrained posterior probability density distributions for the β and $s_{\min}$ (Fig. 12a), and β and η (Fig. 12b) parameters, confirm the uncertainty associated with the model parameterisation. It should be noted that the y-axis scale describing the variation of $s_{\min}$ (Fig. 12a) and η (Fig. 12b) is different from the earlier equivalent plots and those which are to follow. In the case of $s_{\min}$ (Fig. 12a), the y-axis scale is threefold larger, and for η (Fig. 12b), the y-axis scale is eightfold larger. In a comparative sense therefore, there is considerably more variation in the $s_{\min}$ and η parameters for the case when optimisation is based on the joint streamflow and evapotranspiration record.

The inability of the evapotranspiration data to provide constrained, physically realistic, parameter estimates is a possible consequence of the Bowen ratio measurements not being representative of the 'averaged' evapotranspiration behaviour of the catchment (e.g. due to soil moisture and atmospheric boundary layer variability etc.). Given the reasonably homogeneous nature of the catchment, a more likely reason is that the evapotranspiration record was too short to capture the full spectrum of soil moisture/evapotranspiration conditions experienced within the catchment. Because the measuring period only corresponded with the catchment being in a relatively wet state, the parameterisation was not forced to be representative of the total dynamics experienced by the catchment.

This result has a number of implications. Firstly, it would appear that multiple discontinuous measurement periods for a range of soil moisture conditions may prove to be more beneficial than a long continuous measurement record obtained under similar moisture conditions. Secondly, and in a related fashion, when undertaking joint calibrations with variables of different measurement periods, a method of weighting each response variable that takes into consideration the range of 'realised' responses during the conditioning period relative the 'potential' range (over all conditions) may be beneficial. While the current study re-confirms the inability of streamflow (especially for ephemeral conditions) to strongly constrain model behaviour, it would appear that too much weight was given to the period for which evapotranspiration measurements were undertaken.

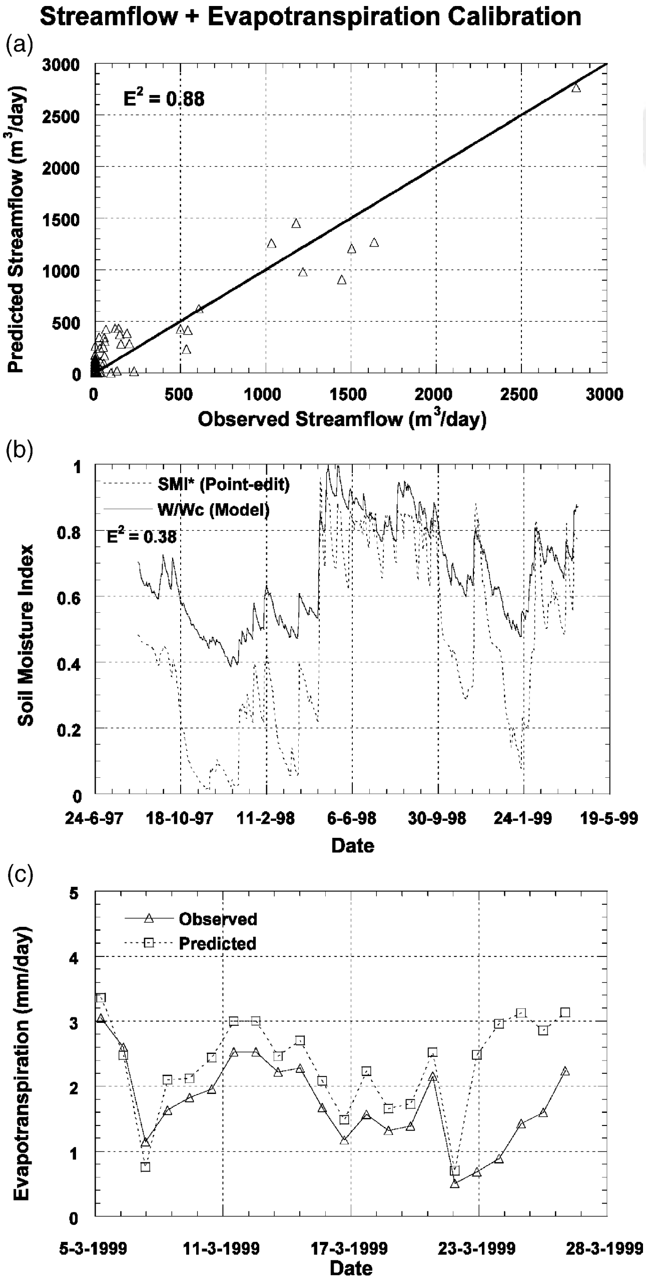

Fig. 11. *Joint streamflow and evapotranspiration calibration*. Comparison of observed and model predicted (a) streamflow, (b) *areal* soil moisture status and (c) evapotranspiration.

7.4. Joint calibration involving streamflow, soil moisture and evapotranspiration

The final component of this study investigated the potential of observed streamflow, *areal* soil moisture and evapotranspiration data to provide improved constraint of parameter estimates. Table 1 presents the Metropolis-sampled posterior mean and standard deviation of the three fitted VIC parameters obtained from the joint calibration. It can be seen that the optimal parameter set is very similar to that determined using only the streamflow and soil moisture data. However, comparison of the associated standard deviations for the model parameters indicates a slight deterioration with the inclusion of the evapotranspiration data. This is confirmed by the slightly less constrained posterior probability density distributions for the β and $s_{\min}$ (Fig. 13a), and β and η (Fig. 13b) parameters. Such a result would appear to suggest that the additional information in the evapotranspiration record (above that contained by the streamflow and soil moisture data) is limited. This is likely a consequence of the limitations of the evapotranspiration data outlined in the previous section. Although not shown, investigation of the fitted streamflow, *areal* soil moisture status and evapotranspiration time-series also showed that the slight improvement gained in predicting the evapotranspiration response (in comparison to the joint streamflow and soil moisture parameterisation) was at the expense of the soil moisture response.

8. Conclusions and recommendations

This study has illustrated how a simple three-parameter version of the conceptual VIC model is ill-posed when calibrated to the streamflow time-series for a 6 ha *ephemeral* catchment. The fact that a streamflow response is an integrated result of both quick-flow and slow-flow processes, combined with the fact that extended periods with no streamflow offer no information on the catchment's soil moisture status, makes the process of inferring the compartmentalisation of storage within the catchment largely unachievable. As a consequence, the internal soil moisture state and evapotranspiration flux of the model, while being able to provide a trace of the temporal dynamics, have only limited correspondence in terms of the correct absolute values.

The inclusion of an additional measure of *areal* soil moisture status was shown to provide significant constraint of the feasible parameter space, by providing additional information regarding the correct compartmentalisation of storage. This result confirms suggestions by Jakeman and Hornberger (1993) who concluded with regard to the robust application of conceptual models that "information on the flow needs to be obtained from time-series data on the inputs and outputs of about every second storage that is separately parameterised". If, for example, with three or more connected storages, one has flow data only into the first and out of the last storage, then the uncertainties of estimating the characteristic hydrological properties of all these storages will be extremely high.

For the present study, the availability of spatially distributed measurements of soil moisture was a key factor in defining a meaningful catchment-scale soil moisture index. While these measurements were obtained using only modest equipment, for larger catchments it would

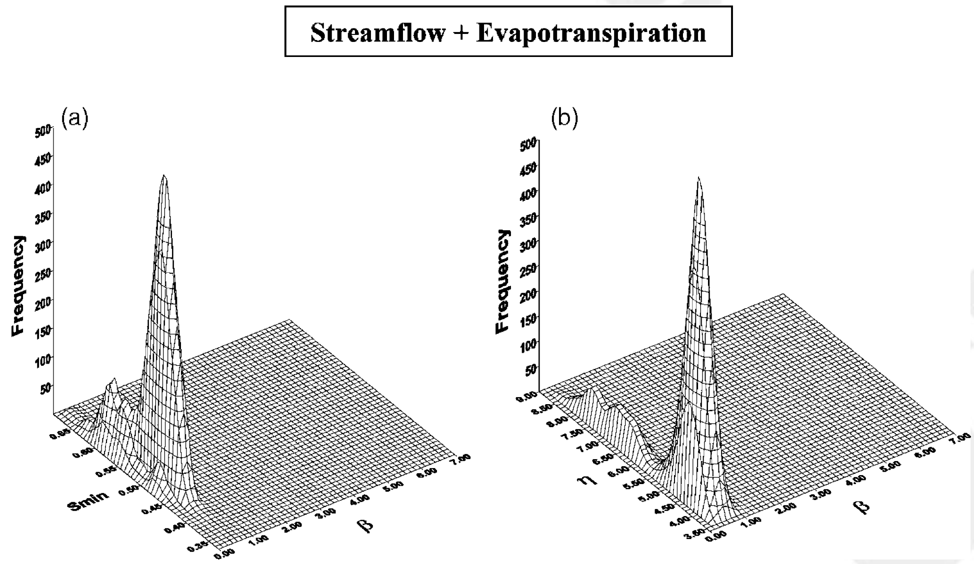

Fig. 12. A plot of the posterior probability surface for the VIC model parameters; (a) β and s_{min} and (b) β and η resulting from joint calibration to streamflow + evapotranspiration data. Each plot is based on 10,000 samples as generated by the Metropolis algorithm.

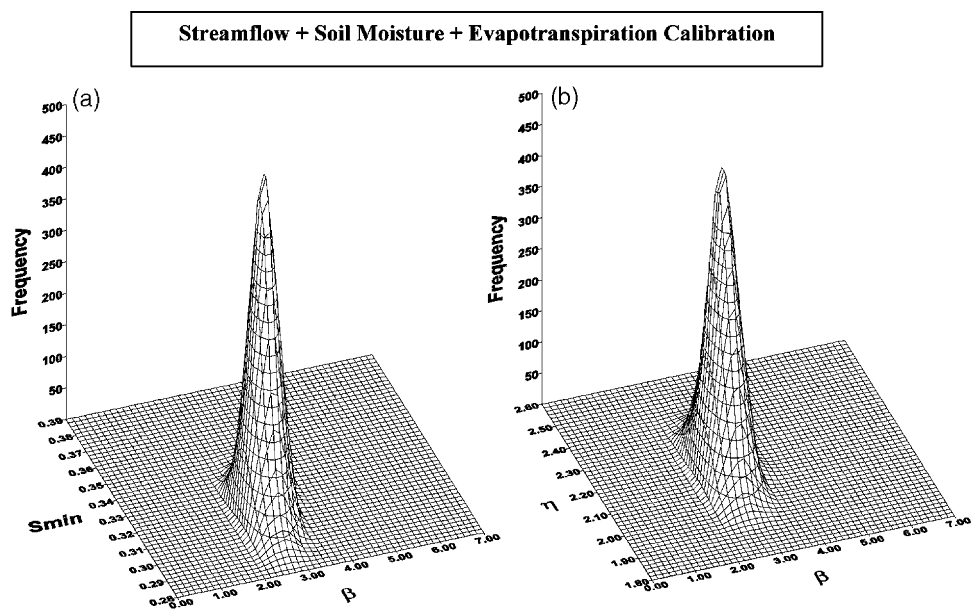

Fig. 13. A plot of the posterior probability surface for the VIC model parameters; (a) β and s_{min} and (b) β and η resulting from joint calibration to streamflow + soil moisture + evapotranspiration data. Each plot is based on 10,000 samples as generated by the Metropolis algorithm.

become increasingly difficult to maintain such a sampling density. This raises an important question. If some form of 'internal' moisture measurement is required to provide confidence in the application of conceptual models for use in catchment management studies and other applications, 'To what level of detail should these measurements be made, both spatially and temporally?' Recent studies indicate that it might be possible to obtain reliable *areal* estimates of soil moisture from a limited number of point measurements, if the locations of these measurements are chosen thoughtfully (Grayson and Western, 1998). Our work with the VIC model within the Nerrigundah catchment also suggests that the most important time to optimise the model in terms of the correct soil moisture storage (i.e. antecedent conditions) is the dry period prior to a significant runoff event. While predicting the onset of significant runoff events is problematic, historical/seasonal rainfall-runoff information may provide clues for suggesting appropriate sampling times. It may be therefore that it is not necessary to have extravagantly detailed spatial and temporal soil moisture patterns to provide significant parameter constraint within land surface models. The utility of such suggestions will be the focus of additional research efforts.

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