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Regional-scale hydrological modelling using multiple-parameter landscape zones and a quasi-distributed water balance model

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Abstract

Regional-scale catchments are characterised typically by natural variability in climatic and land-surface features. This paper addresses the important question regarding the appropriate level of spatial disaggregation necessary to guarantee a hydrologically sound consideration of this variability. Using a simple hydrologic model along with physical catchment data, the problem is reconsidered as a model parameter identification problem. With this manner of thinking the subjective nature as to what to include in the disaggregation scheme is removed and the problem reconsidered in terms of what can be supported by the available data. With such an approach the relative merit of different catchment disaggregation schemes is viewed in terms of their ability to provide constrained parameterisations that can be explained in terms of the physical processes deemed active within a catchment. The outlined methodology was tested for a regional-scale catchment, located in eastern Australia, and involved using the quasi-distributed VIC catchment model to recover the characteristic responses resulting from the disaggregation of the catchment into combinations of climate, soil and vegetation characteristics. A land-surface classification based on a combination of soil depth and land cover type was found to provide the most accurate streamflow predictions during a 10-year validation period. Investigation of the uncertainty associated with the predictions due to weakly identified parameters however, revealed that a simpler classification based solely on land cover actually provided a more robust parameterisation of streamflow response. The result alludes to the hydrological importance of distinguishing between forested and non-forested land cover types at the regional-scale, and suggests that given additional information soil-depth / storage considerations may also have proved significant. Improvements to the outlined method are discussed in terms of increasing the informative content available to differentiate between competing catchment responses.

Keywords: regional-scale, spatial variability, disaggregation, hydrotype, quasi-distributed, parameterisation, uncertainty

Introduction

Regional-scale catchments are important integrators of many physiographic and climatic forces. It is well known that the spatial distribution of soil water and the production of runoff are dependent on catchment topography, soil and vegetation (or land cover) patterns. Adequately accounting for this spatial heterogeneity within catchment models has long been considered a prerequisite for improving water and energy flux predictions.

In this paper the appropriate level of spatial complexity necessary to guarantee a hydrologically sound consideration of regional heterogeneity is considered. At present there are no standard procedures for deciding what disaggregation scheme to adopt. Fully-distributed and lumped land surface representations represent contrasting modelling extremes. Lumped land-surface descriptions have been shown to be capable of reproducing the dynamics of a regional catchment hydrograph (e.g. Chiew *et al*., 1993). As a consequence of the spatial averaging however, the physical soundness of the process description is lost, and model parameters, although often well identified, behave only as “tuning variables”. At the other modelling extreme, fully-distributed land surface representations have attempted to include as much spatial detail as the model and computational demand will allow. This paradigm has gone hand-in-hand with the development of complex distributed modelling approaches that invariably require specification of numerous parameters to account explicitly for observed catchment variability. A well-documented example of this approach is the Système Hydrologique Européen (SHE) model (Abbott *et al*., 1986). Notwithstanding the considerable data and computational requirements of these fully-distributed approaches, the main difficulty that has arisen is in the calibration and validation of the model structure. At the heart of the problem is information, or rather lack of it. With streamflow, typically the only observed catchment response available for calibration, there is insufficient information to identify fully model structure and associated parameters (Beven, 1995).

Such poor parameter identification manifests itself in considerable uncertainty in hydrologic flux predictions, and perhaps more importantly, makes virtually impossible attempts to regionalise model parameters for the purpose of application to ungauged catchments, or to investigate land-use change scenarios.

The modelling dilemma that faces hydrologists can be described as follows: the simple lumped land-surface representation has parameters that are identifiable by calibration, yet their lack of physical relevance means that they cannot be relied upon to make meaningful extrapolative predictions. On the other hand the spatially detailed, distributed representations may have the potential to be used for extrapolative predictions but, because of information constraints that result in poorly identified parameters, are unable to realise it. It is clear that the need for improved understanding of the causative links between physical catchment characteristics, parameter variability and ultimately catchment response still remains.

To address this modelling dilemma, “semi-distributed” approaches have been suggested. Semi-distributed methods attempt to account implicitly for spatial variability by making use of observable patterns of organisation in terrain, soil and vegetation properties. The occurrence of these observable patterns may be identified at specific scales, and has been documented over a long period of time (e.g. Currie and Pacquin, 1987; Moore *et al*., 1993). Selective disaggregation of regional-scale catchments into distributed entities or “hydrotypes” of similar hydrological response, thus attempts to capture the hydrological dynamics of specific soil-vegetation-terrain sequences without the need to specify individual interactions or the interaction between neigbouring hydrotypes (e.g. advection effects, etc.). The difficulty lies in deciding which land-surface features have hydrological characteristics that are sufficiently distinct to warrant their being modelled separately. Although more parsimonious in comparison to fully-distributed disaggregation schemes, adequately parameterising the “dominant” response from regional hydrotypes may not be obvious, as the parameters may not be measurable directly.

This paper revisits the problem of parameter identifiability, with particular emphasis on the utility of physical catchment data (e.g. topography, soil and vegetation), and its organisation in space, in providing insight into dominant land-surface types within regional-scale catchments whose unique responses can be retrieved from a streamflow response. The issue is addressed through a regional-scale modelling methodology that links a simple hydrologic model, that contains only minimal suppositions about its structure, with regionalised “hydrotypes” that are uniform in terms of hydrological behaviour. The motivation is to develop spatial land-surface parameterisations whose characteristics are traced directly to the data.

Catchment regionalisation

“HYDROTYPE” CLASSIFICATION: PROGRESS AND PROBLEMS

The advent of improved spatial data sources and tools to handle this type of information has enabled a number of authors to suggest various combinations of land-surface characteristics that can be utilised to defined areas of similar hydrological response. Kite and Kouwen (1992) describe a catchment disaggregation approach that involves subdivision of a regional-scale catchment into a number of hydrotypes with similar land-use characteristics such as grassland, coniferous forest, etc. Liang *et al*. (1994) also describe a catchment disaggregation approach based on distinct vegetative characteristics.

Flügel (1995) incorporated additional complexity into the hydrotype delineation process by classifying areas containing unique combinations of slope, aspect, soil and land-use. High sensitivity was found for parameters describing the water-holding capacity of unsaturated storages, which were defined in terms of the rooting depth of vegetation. It was concluded that the incorporation of land-use in the hydrotype delineation process was essential in regionalising heterogeneity in regional-scale catchments.

Mitchell and DeWalle (1998) utilised elevation and land-use information for predicting streamflow in a regional-scale catchment, where snowmelt was known to dominate. To account for climatic variation with elevation the catchment was first divided into four elevation zones. The elevation zones were then further divided into forested and non-forested areas. The results indicated that the accuracy of streamflow predictions was improved with the use of combined elevation and land-use zones compared to the standard elevation zones. Jain *et al*. (1998) also divided a GCM scale catchment into a number of hydrotypes according to elevation and land cover information. Rather than having unique combinations of land cover and elevation zones, each hydrotype contained a number of different land covers. The basic requirement of the hydrotype was that the distribution of land covers and elevations were known and that the hydrotype contributed runoff to a definable stream channel.

Krysanova *et al*. (1998) applied a three-level disaggregation scheme to model streamflow and sediment transport within a mesoscale catchment. The disaggregation process involved subdividing the mesoscale catchment into regional-scale sub-catchments. Hydrotypes or elementary units were then delineated within each sub-catchment based on land-use and soil types.

Becker and Braun (1999) considered up to nine different areal disaggregation schemes based on land-use, land cover (vegetation), soil-type and slope class for a small-scale river basin. A sensitivity study of predicted streamflow showed that four hydrotypes needed to be modelled separately: (i) sealed areas; (ii) shallow ground water areas; (iii) forested areas with deep ground water tables; and (iv) arable land with deep ground water tables.

From the studies cited above it is evident that the hydrotype-disaggregation method can overcome the critical effects of averaging associated with lumped land-surface representations, as well as being more realistic in terms of data requirements and computational time as compared to the distributed modelling approach. Nummerous key questions, however, still remain unanswered. Firstly, it is not clear on which land-surface characteristics can best be used as adequate (dominant) parameters in the disaggregation process at particular scales. Secondly, concerns have been raised that by obtaining an integrated response from the aggregation of hydrotypes, the question of scale has been sidestepped by ignoring the natural heterogeneity of parameters and processes *within* the individual hydrotypes (e.g. Band and Moore, 1995; Bonta, 1998).

This paper will attempt to address both of these hydrotype-disaggregation issues. The issue of small-scale variability within individual hydrotypes is accounted for implicitly with a probability density function (PDF) methodology, while the link between dominant catchment characteristics and similarity in hydrological response is explored with a parsimonious model and qualitative reasoning. Whereas previous hydrotype disaggregation has to some extent been subjective and required *a priori* specification of model parameters, the method outlined in this paper is novel in that it allows the informative content of regional rainfall-runoff records to dictate the appropriate level of spatial complexity necessary to model regional-scale catchments.

PROBABILITY DENSITY FUNCTION (PDF) MODELLING APPROACH

As the modelling scale increases to contain a sufficient sample of the small-scale variabilities in soil, vegetation and topographic characteristics for a region, it is no longer necessary to take account of the pattern of those characteristics, but only their statistical characterisation (e.g. Moore and Clarke, 1981; Entekhabi and Eagleson, 1989; Avissar, 1992). Such statistical characterisation can be approximated by continuous analytical functions, or probability density functions (PDFs). The PDF approach considers the frequency of occurrence of variables of certain ranges without regard to the location of a particular occurrence within the area. Such an approach thus allows for the fact that the underlying variability may still be important in controlling hydrological fluxes, but that the pattern is less important.

The representative elementary area (REA) work of Wood *et al.* (1988) was an initial attempt to determine the scale, if any, at which small-scale organisation in catchment characteristics is no longer important. Using a hypothetical study of the effects of variable topography, soils and rainfall and, at least for short rainfall correlation lengths, Wood *et al.* (1988) showed that the REA for runoff generation predicted by their particular model and catchment characteristics was of the order of 1 km^2. Subsequent research has shown that it may be, for some conditions, that there is no scale at which the variance in runoff response reaches a minimum, whereas in general it should be expected that if an REA scale exists, it might vary between environments and processes (Blöschl *et al.*, 1995).

Even if it is difficult to define an REA scale unequivocally, Beven (1995) and others have suggested that it may still be possible to use an approach based on the distribution functions of variables (or parameters) to provide realistic predictions of discharge and evapotranspiration fluxes within heterogeneous terrain. What is actually required is the distribution of hydrological responses in the landscape. The problem is how to define an appropriate distribution or distributions to reflect, in a realistic way, the hydrological responses at a particular scale.

The quasi-distributed Variable Infiltration Capacity (VIC) hydrological model (Wood *et al*., 1992) was developed in an attempt to reproduce succinctly larger-scale hydrological response. The VIC model incorporates the saturation–overland flow mechanism with a continuous PDF to describe the relationship between soil moisture content and saturation, with relevant hydrological quantities determined by integration over this distribution. In essence, the distribution allows different parts of the catchment to have different significance in terms of runoff generation potential. It also takes into account that the relationship between different catchment areas may change with wetting and drying.

The advantage of the PDF modelling approach lies in its ability to reproduce catchment response with a smaller number of physically meaningful parameters than the more traditional distributed models. This reduction in parameters is in line with the principle of parsimony that requires the modeller to seek the simplest model parameterisation consistent with available evidence (Jakeman and Hornberger, 1993).

Variable infiltration capacity (VIC) model

The following section provides a summary of the quasi-distributed Variable Infiltration Capacity (VIC) hydrological model initially proposed by Wood *et al*. (1992) and subsequently modified by Kalma *et al*. (1995) and Sivapalan and Woods (1995). The VIC model adopts a statistical distribution of storage elements across the catchment to allow for the fact that small-scale variabilities of soil, vegetation and topography will cause different parts of the catchment to have different soil moisture storage. To account for this natural variation, the scaled storage capacity, *s*, is a random variable with cumulative distribution

$$F_s(s) = 1 - [(1-s)/(1-s_{\min})]^{\beta} \tag{1}$$

where s_{min} and b are model parameters. Storage capacity at any point in the catchment is defined as the maximum depth of rainfall that can infiltrate at that point. The scaled storage, *s*, is the local storage capacity divided by the largest storage capacity for any point in the catchment. If *z* is the soil depth at any point, with maximum value z_{max} and soil porosity Dq is constant throughout the catchment, then $s = (z Dq)/(z_{max} Dq)$.

The soil moisture status for the entire catchment at a particular time can be described by the scaled soil moisture variable, *v*, which represents the actual scaled soil moisture in storage at every point in the catchment (see Fig. 1). Antecedent soil moisture status is indicated by v_0, which is constant throughout the catchment. If all soil water in the catchment is assumed to be held in saturated soil, then the scaled soil moisture can be written as $v_0 = y_0/z_{max}$. This is taken to mean that the soil profile is saturated effectively to a depth y_0 (above bedrock), except in those parts of the land-surface where the depth of soil is less than y_0, in which case the land-surface is already saturated. For a given *v*, the fraction of land surface which is saturated is denoted by a, and the total soil moisture volume stored in the catchment is denoted by *w*. Given values of b and s_{min}, and any one of *v*, *w*, or a is sufficient to define the moisture status of the entire catchment (Kalma *et al.*, 1995).

The quickflow runoff generated within the VIC model is closely related to the saturation excess mechanism. Those points on the land surface with $s<v_o$ are considered to be saturated before any rain begins. If $v_o<s_{min}$, then no part of the catchment is saturated. With the addition of a scaled depth of rainfall over a specified time period *pDt* (i.e. scaled by z_{max}Dq), the level of soil moisture rises above v_o, and the saturated area expands (Da). Any rain falling on the saturated area generates immediate surface runoff (q_sDt), consistent with the saturation excess mechanism of runoff generation, while the remaining rainfall infiltrates and fills some of the available storage under the *s* curve. The subsurface (slowflow) runoff, q_bDt, is modelled as a linear function of the average value of the total soil moisture storage, *w*.

For the current study the evaporation was calculated using the method of Sivapalan and Woods (1995), in which a point-scale model of evaporation (which depends on local soil moisture conditions) is integrated over the distribution of soil moisture conditions for the whole catchment, giving a catchment-scale evaporation estimate.

Table 1 describes the five model parameters that require calibration, namely b, s_{min}, k_c, y_c and h. They can be broadly categorised into parameters that control the effective catchment storage capacity (b, s_{min}) and parameters that control the rate of removal of water from that storage (k_c, y_c, h).

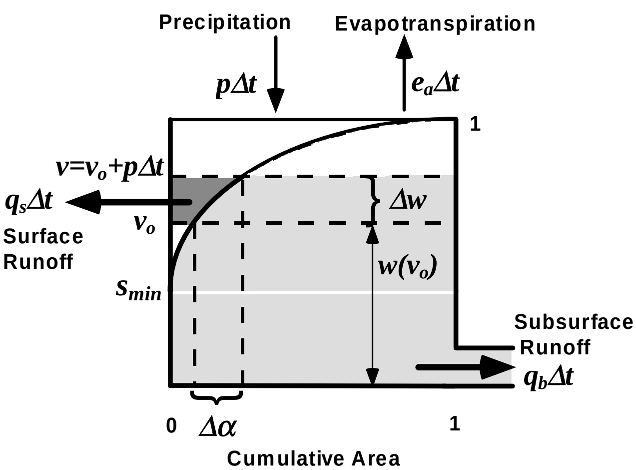


Fig. 1. *Schematic diagram of the VIC model (after Kalma* et al., *1995).*

Table 1. Description of VIC model parameters

b	Parameter controlling the curvature of the storage distribution
s_{min}	Minimum storage required for saturated area formation
h	Evaporation exponent; property of soil and vegetation types
y	Capillary fringe thickness
k_c	Baseflow recession coefficient Case study: Williams River catchment

Case study: Williams River catchment

DESCRIPTION OF THE STUDY AREA

Combination of the quasi-distributed VIC hydrological model within a regional hydrotype-disaggregation framework was tested for the 1260 km^2 Williams River catchment, located in the lower Hunter Valley Region, N.S.W., Australia (Fig. 2). The catchment is well suited to investigation of regionalisation issues, as the hydrological regime of the catchment is strongly affected by substantial heterogeneity both in land-surface characteristics and meteorological conditions.

The upper Tillegra and Chichester Dam subcatchments are characterised predominantly by steep forested slopes, rising to 1500 m (a.s.l.) in the northern-elevated areas. The lower sub-catchments draining to Glen Martin and Seaham Weir are characterised by rolling hills, with the majority of the vegetation cleared for cattle grazing.

The catchment is characterised by duplex soils that contain a sandy/silty *A* horizon on top of a heavier clay *B* horizon. The clayey *B* horizon is less permeable and gives rise to subsurface runoff at the interface between the *A* and *B* horizons. The underlying geology of the region includes both sedimentary and volcanic rocks, which allow only slow groundwater movement and small groundwater yields. The limited extent of deep subsurface flow areas within the catchment indicates that the bulk of the observed "slow flow" response in the catchment is a result of "interflow" processes.

The area has a warm, temperate climate. Orographic enhancement results in the highest rainfall totals occurring in the northern ranges where the average annual rainfall is approximately 1600 mm. The lowest annual rainfall occurs over the central part of the catchment. Further south, maritime influences reverse the rainfall gradient and annual rainfall increases to approximately 1100 mm at Seaham.

HYDRO-CLIMATIC DATA

Daily rainfall records for the period 1966-1996 were available from 28 rainfall gauges within the catchment. To account for the large spatial variability in daily rainfall, and apparent data deficiency in the northern elevated region of the catchment, an interpolation strategy was developed utilising thin plate smoothing splines and altitudinal zonation. The development of the interpolation strategy as outlined in Wooldridge *et al*. (in press) resulted in three rainfall zones for which within-zone variability of daily rainfall was negligible compared to the variability that existed between neighbouring zones. Figure 3 represents

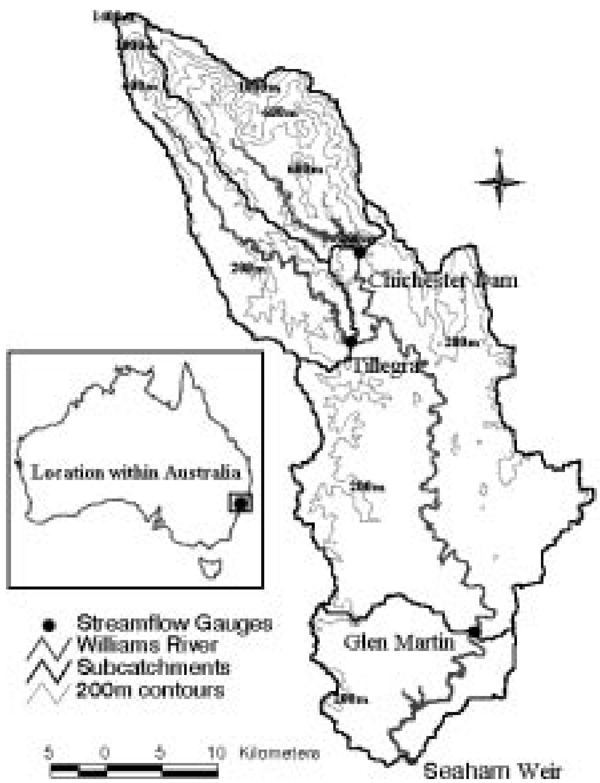


Fig. 2. *Williams River catchment above Seaham Weir indicating the four main subcatchments.*

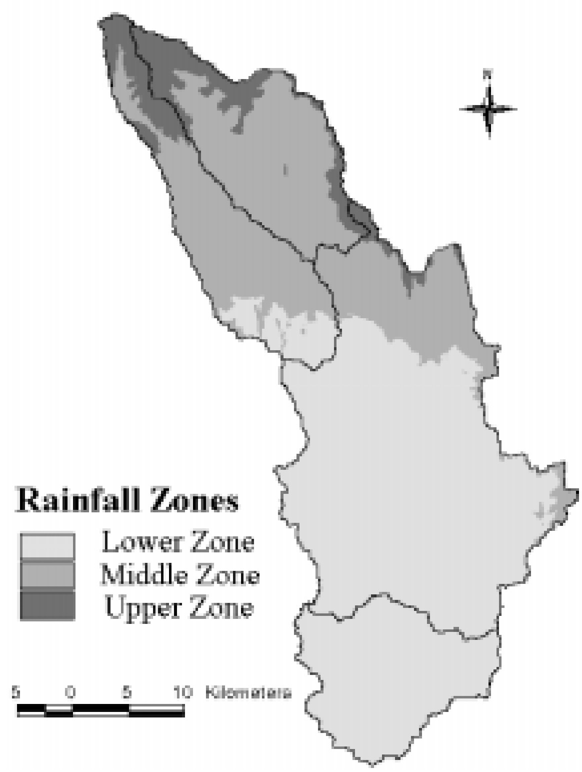


Fig. 3.*Spatial extent of the upper, lower, and middle rainfall zones*

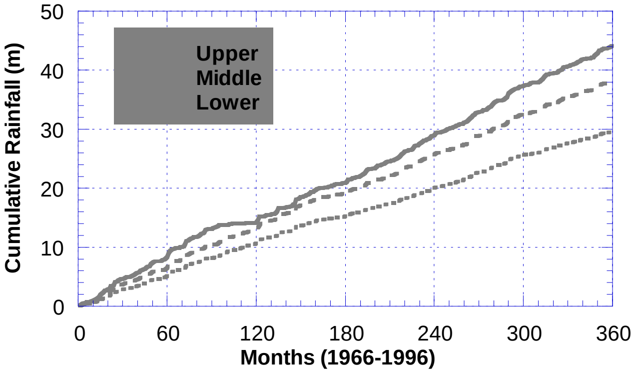


Fig. 4. *Cumulative monthly rainfall distribution (1966-1996) for each rainfall zone.*

the spatial extent of the three rainfall zones. The lower rainfall region captures the coastal influence on rainfall volumes within the catchment. The middle region represents the moderate rainfall parts of the catchment, whereas the upper region captures the higher volumes related to orographic enhancement. The different rainfall regimes for the rainfall zones are demonstrated by the cumulative monthly rainfall distributions for the period of interest (Fig. 4).

Daily potential evapotranspiration estimates within individual rainfall zones were considered uniform and derived from four climatic stations within the region using the Penman-Monteith equation (Smith *et al.*, 1990). Streamflow measurements were available at three locations within the catchment. The Tillegra and Glen Martin sub-catchments contained daily flow gauge estimates. Despite not having a flow gauge, inflow into Chichester Dam could be estimated by undertaking a water balance based on daily reservoir levels, rainfall inputs, evaporative losses and pumping abstractions. Unfortunately no streamflow measurements were available for the Seaham Weir subcatchment.

Methods

HYDROTYPE CLASSIFICATION

Five unique hydrotype-disaggregation strategies were investigated. Classification of the land-surface into the five hydrotypes, along with the determination of their spatial extent was facilitated within the ARC/INFO GIS software package.

Lumped catchment (Method 1)

The lumped catchment representation involved modelling the catchment as a single, lumped land surface. Catchment boundaries and the channel network were delineated from a 100 m grid cell digital elevation model (DEM) of the region using ARC/INFO hydrologic modelling functions. The depressionless DEM was prepared with the ANUDEM (Hutchinson and Dowling, 1991) package using 10 m contour intervals and drainage network information obtained from 1:25 000 scale digital topographic maps.

Land-use classification (Method 2)

A detailed land-use datalayer obtained from Landsat multispectral scanner data was available for the catchment. Inspection of the areal extent of the land cover classes showed that for hydrological considerations land cover could be appropriately reclassified into forested and non-forested areas (Fig. 5a). The forested areas are dominated by dry and wet eucalypt forests. The non-forested areas on the other hand consist mainly of grassland, with isolated areas devoted to cropping, urban settlement and mining.

Soil classification (Method 3)

A soil landscape map was available to partition the catchment into dominant soil types. Because the physical

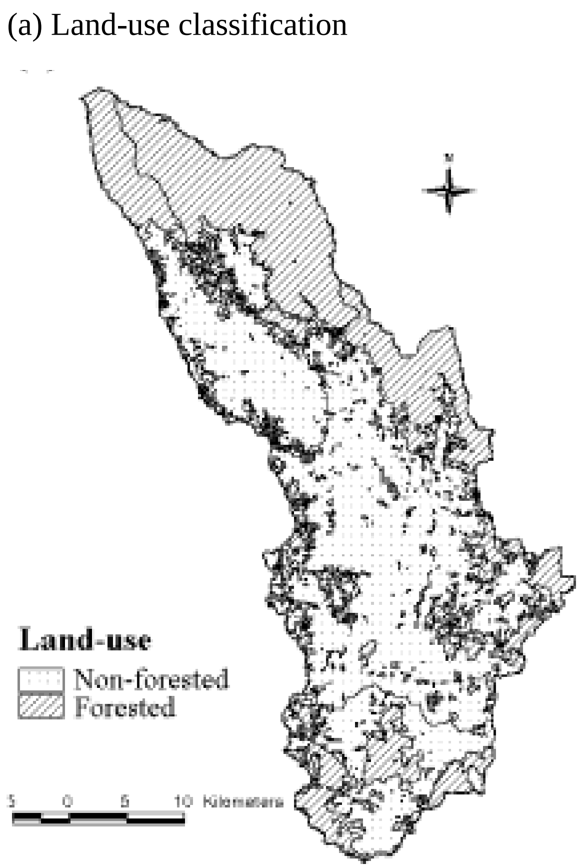


Fig. 5. *Spatial extent of the hydrotype-disaggregation strategies based on; (a) land-use, (b) soil-depth, and (c) annual soil moisture.*

composition of the soils within the region was considered reasonably similar, soil depth was chosen as surrogate for the impact of soil characteristics on hydrological response. Soils were classified as either shallow (<1.5m) or deep (>1.5m) based on soil-landscape information (Fig. 5b). A more detailed classification was not considered warranted due to the uncertainty associated with the soil depths within the different soil landscapes.

Soil / land-use classification (Method 4)

In an effort to further constrain hydrological response a combined soil / land-use disaggregation strategy was also adopted. The classification resulted in four regionalised hydrotypes based on shallow and deep soils and forested and non-forested land cover types. The four hydrotypes were denoted by; shallow_forest, deep_forest, shallow_non-forest and deep_non-forest.

Moisture regime (Method 5)

To account implicitly for possible co-occurrences of soil and land-use sequences, without the additional parameter expense of modelling the two variables separately, a disaggregation strategy based on annual moisture regime was considered. Classification based on moisture regime aimed to investigate possible synergistic evolution of soil-vegetation-topography sequences as a result of their formative climatic conditions, similar to ideas postulated by Eagleson (1982).

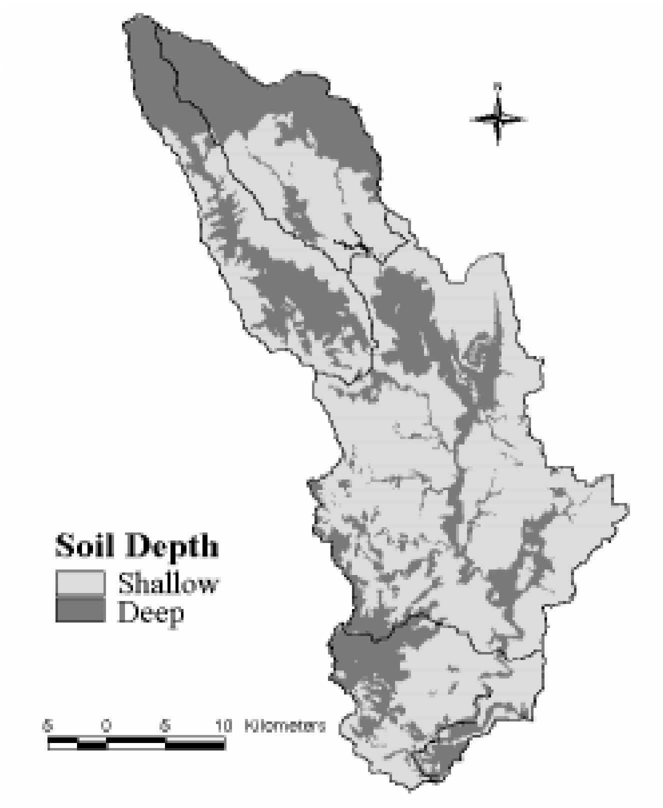
Spatial estimates of annual moisture status was provided by the Thornthwaite moisture index (I_m) (Mather, 1978), defined by:

$$I_m = 100[(P / PE) - 1] \tag{2}$$

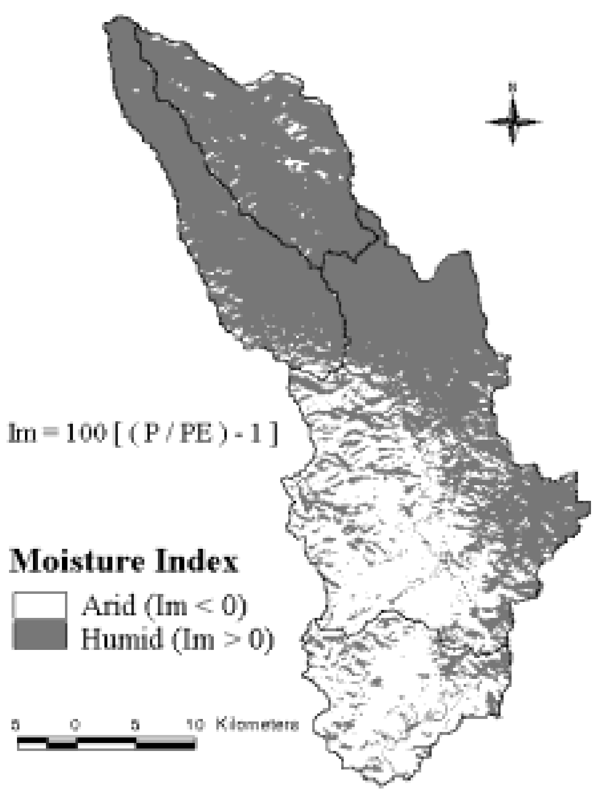
using spatial rainfall (P) and potential evapotranspiration (PE) estimates (Fig. 5c). Positive values of the index indicate a “humid” climate with a water surplus, whereas negative values indicate an “arid” climate with a water deficit. A moisture index of zero indicates that annual precipitation is just sufficient to satisfy the climatic demand for water.

The annual rainfall surface was created by spatial interpolation of long-term rainfall records for the 28 rainfall stations within the study region. The spatial interpolation was achieved using tri-variate thin plate smoothing splines

(b) Soil depth classification



(c) Annual moisture classification



of latitude, longitude and elevation as implemented in the ANUSPLIN package (Hutchinson, 1995). The annual potential evapotranspiration surface required a two-step process. Firstly, a net radiation surface was created using the grid-based solar radiation modelling program SRAD (Mckenney *et al*., 1999). The net radiation surface created by SRAD was then combined with spatial temperature data to create potential evapotranspiration surfaces using the Priestley-Taylor equation (Priestley and Taylor, 1972). Several simplifying assumptions were needed to apply the equation. A uniform 10% reduction in net radiation was applied to account for losses to subsurface heat flow. A spatially uniform value of 1.26 was also utilised for the Priestley-Taylor empirical coefficient. Further details of the application of SRAD and the development of spatial potential evapotranspiration estimates within the Williams River catchment are being prepared for publication.

HYDROTYPE - MODEL INTEGRATION

Disaggregation of the catchment into three rainfall regions, along with hydrotype-disaggregation (1-4 regions) required that VIC daily water balance calculations be undertaken concurrently for up to 12 possible rainfall-hydrotype combinations. To achieve this, it was necessary to determine the fractional coverage of each hydrotype within each rainfall region. Outlet streamflow for the internal subcatchments or the entire catchment could then be obtained as the areal weighted accumulation of individual rainfall-hydrotype combinations. Because variations in precipitation input result in different soil moisture status, it was also necessary to account for variations in antecedent moisture conditions within each rainfall-hydrotype class at the start of each model run.

Despite the fact that up to 12 rainfall-hydrotype combinations were required to obtain an accumulated streamflow output, only parameter variations due to the hydrotype classification were modelled, such that the end result was a unique parameter set for each hydrotype class. Using the forested and non-forested land cover classification as an example, these considerations can be formalised. For a time step, *t*, with number of rainfall zones, *n*, the catchment model can be described by the multiresponse regression model

$$q_t = \sum^{n} \left[f\left(x_{(t,n)}, \theta_{Forested}\right) + f\left(x_{(t,n)}, \theta_{Non-Forested}\right)\right] + \varepsilon_t \quad (3)$$

where q_t is the combined runoff total at a particular point; *f*(   ) represents the VIC model conceptualisation; $x_{(t,n)}$ is the vector of measured rainfall zone inputs; $q_{Forested}$ represents the parameter vector for the forested response; $q_{Non-forested}$ represents the parameter vector for the non-forested response; and e_t is a random error. The random error represents the effects of measurement error in q_t and $x_{(t,n)}$ as well as model error.

MODEL CALIBRATION AND TESTING

Optimisation of VIC parameters

Investigation of the soil landscape map for the Williams River catchment suggested appropriate values of 2.5 m and 0.35 m^3 m^{-3} for z_{max} and *Dq* respectively. Without further information both parameters were fixed at those values prior to calibration and were considered spatially uniform for the entire catchment, except when applying the soil-depth classification, when a shallow depth criterion of 1.5 m was also utilised.

The optimisation strategy adopted to identify the five VIC model parameters for the different hydrotype-disaggregation strategies involved running the model for the entire daily rainfall and potential evapotranspiration record, and then optimising parameters based on weekly aggregated streamflows totals using the nonlinear regression software NLFIT (Kuczera, 1994). Previous calibration to forested and non-forested land cover types has shown that optimisation at the weekly time-scale is capable of constraining VIC model parameters that control the dynamics of predicted runoff (Wooldridge *et al*. in press). Optimisation at the weekly time-scale also eliminates the need for overland or within stream routing.

The parameter search strategy employed by NLFIT is the robust shuffled complex evolution (SCE) method of Duan *et al*. (1992). With the current calibration the number of complexes was set equal to the number of fitted parameters. A warm-up period of five months was used to minimise the effects of the initial moisture store contents on the parameter estimates. Optimisation of parameters was then based on minimising the objective function defined by:

$$\psi(\beta) = \sum_{t=6}^{n} \left[\left(Q_t^{\lambda} - \hat{Q}_t^{\lambda}\right) - \phi\left(Q_{t-1}^{\lambda} - \hat{Q}_{t-1}^{\lambda}\right)\right]^2 \quad (4)$$

where Q_t and $\hat{Q}_t$ denote observed and computed weekly runoff at time *t*, *l* is a transformation constant (Box and Cox, 1964), and *f* denotes the parameter of a first-order autoregressive process. Fixed values of *f* = 1, and *l* = 0.5 were utilised for all optimisations. The Box-Cox lambda value of 0.5 results in a square root transformation, and accounts for the observed growth in residual variance with increasing runoff.

The three measured streamflow records available within the Williams River catchment were utilised to provide multiple conditioning of optimised parameters, following previous work within the catchment by Wooldridge *et al*.

(in press). The joint calibration strategy was performed within the NLFIT modelling framework, and incorporated the assumption that the random error for each response were cross-correlated with the random errors of the other responses following the work by Kuczera (1983).

In the calibration the two parameters controlling water removal via catchment evapotranspiration, namely, ψ_c and η, displayed strong correlation, which is indicative of an evapotranspiration routine that is ill-posed with respect to streamflow data. The calibration strategy therefore involved fixing the scaled capillary fringe thickness ψ_c (scaled by $z_{max}\Delta\theta$), to a value of 0.005 m m^{-1} based on information from Sivapalan and Woods (1995) and then optimising η based on the rainfall-runoff data.

Hydrotype evaluation

The classical split-sample strategy was adopted to evaluate the performance of the different hydrotype-disaggregation schemes. The first 20 years of the streamflow record (1966–1986) were employed for hydrotype-parameter optimisation, and the remaining ten-year period (1986-1996) reserved for an independent check of streamflow predictive ability.

The accuracy of streamflow predictions in both calibration and validation was tested using two performance statistics; the coefficient of efficiency (E^2), and the residual mass coefficient (M). The E^2 error criteria of Nash and Sutcliffe (1970) is given by

$$E^2 = \frac{\Sigma\left(Q_{obs} - \overline{Q}_{obs}\right)^2 - \Sigma\left(Q_{obs} - Q_{pred}\right)^2}{\Sigma\left(Q_{obs} - \overline{Q}_{obs}\right)^2} \tag{5}$$

where Q_{obs} is the observed discharge, $\overline{Q}_{obs}$ is the mean of the observed discharge, and Q_{pred} is the predicted discharge. The coefficient of efficiency (E^2) compares both the shape and size of the hydrographs. The efficiency E^2 varies from $-\infty$ to 1. The efficiency value of 1 indicates perfect agreement. The efficiency value of zero means that the error model is as good (or bad) as setting the simulated value constantly to the mean runoff.

The residual mass coefficient (M) is given by

$$\boldsymbol{M} = \frac{\Sigma\left(\boldsymbol{D} - \overline{\boldsymbol{D}}\right)^2 - \Sigma\left(\boldsymbol{D} - \hat{\boldsymbol{D}}\right)^2}{\Sigma\left(\boldsymbol{D} - \overline{\boldsymbol{D}}\right)^2} \tag{6}$$

where D, $\overline{D}$ and $\hat{D}$ are the departure and the mean departure from the mean observed residual mass curve, and the departure from the mean for the estimated residual mass curve, respectively. If a flow sequence contains systematic errors then the M statistic should indicate their presence. Systematic errors occur when the sign of the error tends to persist over a series of time intervals (Aitken, 1973). A value of M equal to 1 indicates perfect agreement.

The diagnostic output of NLFIT provides estimates of the E^2 and M statistics. The output summary also provides approximations of the mean and standard deviation of fitted parameters along with an indication of parameter interactions. The estimated standard deviation (s) divided by the mean of a fitted parameter ($\bar{x}$) can be used to determine its coefficient of variation, CV.

$$CV = \frac{s}{\bar{x}} \tag{7}$$

The CV is a dimensionless measure of parameter uncertainty. The lower the CV, the more precise the value determined by the optimisation, and hence the lower the uncertainty. As a guide, a CV value of 0.25 or less indicates "sensitive" parameters (Mein and Brown, 1978).

Results and discussion

Table 2 summarizes the most probable parameter values along with their approximate coefficient of variation (CV) obtained for the 20-year calibration period for the five hydrotype-disaggregation strategies. Table 3(a) lists the E^2 and M performance statistics for each strategy for the three independent streamflow observations employed during the calibration period. Table 3(b) displays the corresponding statistics for the different hydrotype-disaggregation strategies using the parameters from Table 1 for the ten-year validation period.

LUMPED PARAMETER APPROACH (METHOD 1)

The lumped parameter approach provided parameter estimates that are well constrained from the streamflow record. Despite providing constrained parameter values the inferior predictive statistics within the validation period, compared to the spatial hydrotype approaches, emphasizes the limitation of lumped parameter models in predicting catchment response in periods outside the calibration conditions.

The fact that the identified value of a number of the parameters for the lumped land-surface description are approximately the average of those obtained for several of the alternative spatial hydrotype strategies, alludes to the main reason for the relatively poor predictive capability of the lumped hydrotype (i.e. that a lumped response is forced to compromise or average hydrological extremes). The inferior values of the M statistic confirms this fact and

Table 2. Most probable parameter estimates, along with approximate coefficient of variation (*CV*) for the five hydrotype-disaggregation strategies.

Method 1: Lumped				
Parameter	Most probable	*CV*		
b	3.542	0.048	………..	………..
s_{min}	0.072	0.052	………..	………..
k_c	0.005	0.038	………..	………..
h	0.961	0.041	………..	………..
Method 2: Land-use classification				
	Forested	***Non-forested***		
Parameter	Most probable	*CV*	Most probable	*CV*
b	2.421	0.075	5.204	0.078
s_{min}	0.114	0.053	0.061	0.055
k_c	0.010	0.041	0.002	0.073
h	1.500	0.055	0.485	0.081
Method 3: Soil-depth classification				
	Deep Soil (>1.5m)	***Shallow Soil (<1.5m)***		
Parameter	Most probable	*CV*	Most probable	*CV*
b	1.331	0.072	4.921	0.094
s_{min}	0.064	0.081	0.058	0.081
k_c	0.008	0.058	0.005	0.074
h	0.672	0.042	0.046	0.092
Method 4: Soil/Land-use classification				
	Deep_Forest	***Shallow_Forest***		
Parameter	Most probable	*CV*	Most probable	*CV*
b	1.686	0.139	1.338	0.228
s_{min}	0.130	0.198	0.143	0.239
k_c	0.015	0.138	0.007	0.167
h	1.044	0.149	2.081	0.239
	Deep_Non-forest	***Shallow_Non-forest***		
	Most probable	*CV*	Most probable	*CV*
b	4.521	0.128	5.821	0.155
s_{min}	0.090	0.156	0.067	0.219
k_c	0.005	0.111	0.003	0.173
h	0.523	0.232	1.112	0.268
Method 5: Moisture regime				
	Humid	***Arid***		
Parameter	Most probable	*CV*	Most probable	*CV*
b	2.921	0.081	3.423	0.091
s_{min}	0.105	0.092	0.053	0.088
k_c	0.007	0.088	0.003	0.084
h	1.232	0.125	0.863	0.101

suggests that the lumped representation systematically under- and over-predicts the streamflow response.

LAND-USE CLASSIFICATION (METHOD 2)

Distinct parameterisations were achieved for forested and non-forested hydrotypes within the catchment, highlighting that the characteristic response for each land cover type was detectable from the regional-streamflow records. On the whole the *CV*s for the fitted parameters were marginally inferior to those achieved for the lumped representation,

Table 3. Streamflow predictive statistics (E^2 and M) for, (a) the calibration period (1966-1986) and (b) the validation period (1986-1996), at the Tillegra, Chichester and Glen Martin streamflow gauges.

Catchment	*Simulation Statistic*	*Lumped*	*HYDROTYPE-DISAGGREGATION* *Land-use*	*Soil*	*Soil/land-use*	*Moisture*
(a) Calibration Period (1966-1986)						
Tillegra	E^2	0.86	0.87	0.87	0.87	0.87
	M	0.32	0.82	0.72	0.79	0.59
Chichester	E^2	0.79	0.82	0.81	0.82	0.79
	M	0.42	0.73	0.65	0.67	0.59
Glen Martin	E^2	0.83	0.84	0.84	0.85	0.84
	M	0.63	0.87	0.81	0.92	0.80
(b) Validation Period (1986-1996)						
Tillegra	E^2	0.75	0.83	0.79	0.84	0.77
	M	0.27	0.86	0.71	0.75	0.46
Chichester	E^2	0.71	0.75	0.73	0.76	0.73
	M	0.35	0.74	0.67	0.71	0.57
Glen Martin	E^2	0.74	0.84	0.83	0.85	0.80
	M	0.57	0.83	0.76	0.85	0.69

and can be attributed to the additional parameter complexity. Investigation of the E^2 and M statistics for both the calibration and validation period however, highlights the superior predictive ability of the forested and non-forested land-surface representation as compared to the lumped representation.

The relative improvement of the dual land-use representation over the lumped land-surface representation is best illustrated by comparing the uncertainty prediction limits associated with the simulated streamflow response for each case. Prediction limits represent the predictive uncertainty in simulated response arising from both parameter uncertainty and the inherent noise in the data and model. For the present application the prediction limits were generated using a Monte Carlo scheme that utilised the Metropolis algorithm (Metropolis *et al.*, 1953). Figure 5(a) represents an observed streamflow sequence obtained during the calibration period along with the 90% prediction limits associated with the lumped and dual land-use representations. It can be seen that the 90% prediction limits are considerably more constrained for the land-use representation, especially for the peaks, which show a reduction in predictive uncertainty in the order of 25%. The result highlights the fact that although the increased parametric complexity of the land-use distinction results in less well identified parameters, the ability to distinguish between the dual responses actually reduces the uncertainty in model predictions.

The parameterisations associated with the forest and non-forest regions are explainable in terms of the physical processes deemed active in the Williams River catchment. The larger value of s_{min} and smaller value of b for the forested regions compared to the non-forested regions confirm that the forest areas are associated with larger water storage, and produce a much less "peaky" runoff response, with reduced surface runoff or "quick-flow" contributions. The larger value of the recession constant, k_c, for the forested areas is also consistent with greater contributions to the "slow-flow" runoff component, resulting from increased lateral water movement due to forest litter and soils loosened by tree roots. The smaller value of s_{min} and larger value of b for the non-forest areas are linked with less water storage and a more "all-or-nothing" response to runoff, with dynamic formation and depletion of zones of saturation. The relative values of the evapotranspiration parameter (h) also suggest that for a given catchment wetness, greater evapotranspiration will occur from the forested areas. The simplicity of the evapotranspiration routine makes it difficult to draw conclusions about the exact nature of the evapotranspiration variation (e.g. rooting depth, canopy effects, etc.). The addition of a more physically based yet parsimonious evapotranspiration routine is the subject of on-going research.

SOIL CLASSIFICATION (METHOD 3)

The hydrotype-disaggregation strategy based on a shallow

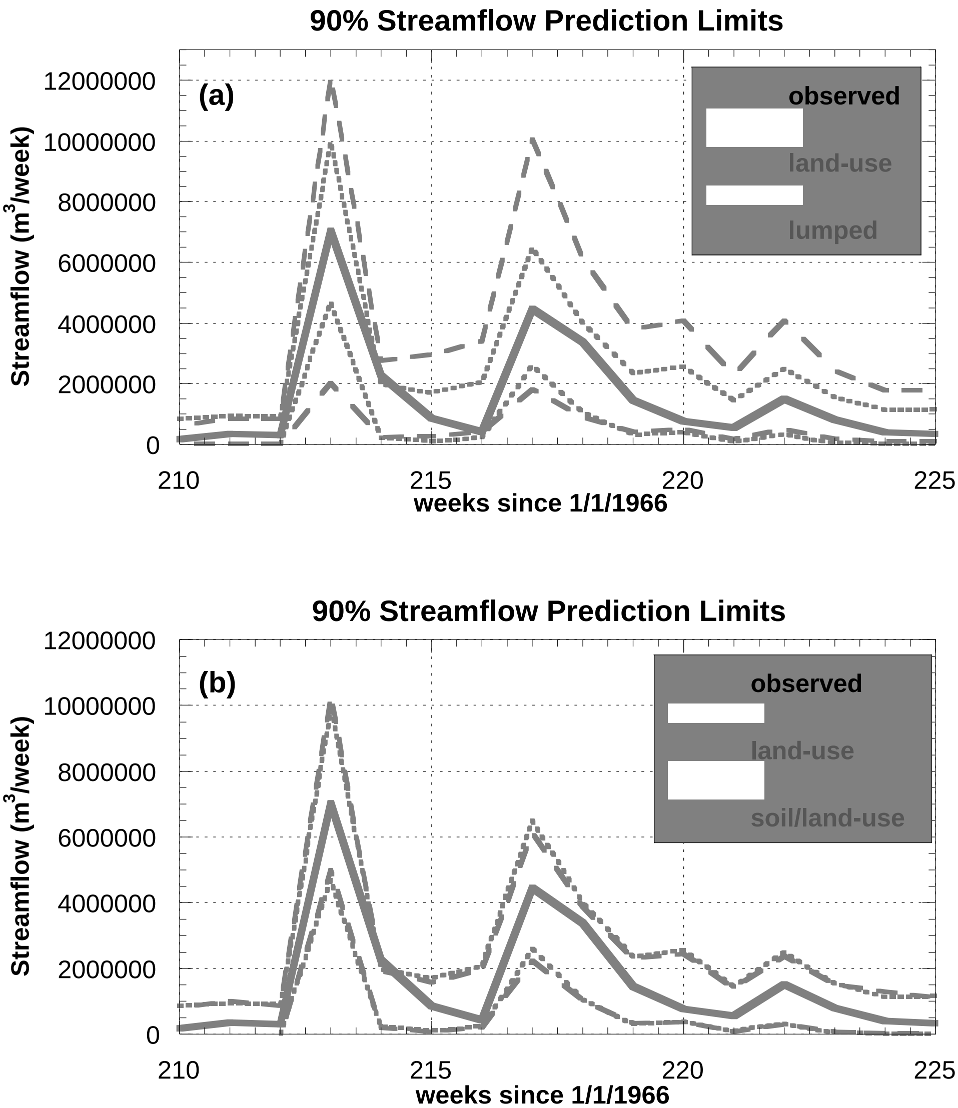


Fig. 6. *Comparison of 90% streamflow prediction limits resulting from (a) land-use and lumped hydrotypes, and (b) land-use and combined soil/land-use hydrotypes.*

and deep soil classification resulted in a parameterisation that displayed similar predictive ability to the land-use strategy during calibration, but which was slightly inferior during validation. Comparison of the soil derived parameters with equivalent parameters identified for the land-use and lumped land-surface representation reveal some interesting features resulting from the soil depth classification. The distinguishing feature is that the only parameter that shows a significant difference between the shallow and deep classification is b. The relative values of b indicate the expected physical variation in response associated with shallow and deep soil. The shallow soil with presumably lower storage capacity has a higher value of b indicating a much quicker and more dynamic runoff response. In contrast the deeper soil has a lower value of b reflecting the increased storage capacity. It is interesting to note that the values identified for b in both the soil and land-use classifications are very similar, which begs the question as to the extent to which the parameter is influenced by soil or land-use (vegetation type). The fact that there is a correlation of deep soil with forested land surface types makes answering the question difficult given the available information. Comparison of the other calibrated model parameters s_{min}, k_c, and h, shows that there is little distinction made between the deep and shallow derived values. The result suggests that these model parameters are relatively insensitive to soil depth, or at least the classification scheme utilised for this exercise. Comparison of the most probable value of s_{min}, k_c, and h for the two soil depths along with the equivalent values identified for the lumped classification confirm this suggestion as they all have similar values. This suggests that the soil classification is in effect only extracting the equivalent lumped value to represent: (i) surface runoff initiation; (ii) subsurface recession; (iii) evapotranspiration response. The result reaffirms the importance of the distinction between forest and non-forest vegetation types in constraining regional hydrological response.

SOIL/LAND-USE CLASSIFICATION (METHOD 4)

The combined soil and land-use hydrotypes required the identification of 16 model parameters from the regional-streamflow records. The *CV* statistic for all parameters was below the 0.25 criterion of Mein and Brown (1978). On average however the model parameters for this method were associated with higher uncertainty than the other methods.

Despite the associated parameter uncertainty, in terms of predictive ability during the validation period as described by the E^2 statistic the combined soil/land-use hydrotypes were the superior disaggregation strategy. The question must be asked however, whether the improvement in prediction simply results from the increased degrees of modelling freedom associated with the method. Calculation of the 90% prediction limits resulting from the combined soil/land-use hydrotypes and comparing them to the land-use hydrotypes (Fig. 5b) show that the predictive uncertainty for both methods is similar. This result is likely to be attributed to the fact that the uncertainty associated with the parameters for the soil/land-use hydrotypes offsets the improvement in predictive ability resulting from the constraining of the distinct hydrological responses. In terms of robust parameterisations therefore, the sole use of the land-use parameterisation would most likely be advocated. This is not to say that soil-depth is not important in constraining hydrological predictions, only that the information content of the data is such that the soil-depth induced response cannot be distinguished significantly from that of the land-use response. It is extremely likely that the land-use classification actually incorporates implicitly soil-depth information due to correlation between the two variables.

Despite the uncertainty, inspection of the most probable parameters is insightful in alluding to links between model parameters and physical catchment characteristics. It is evident that, irrespective of the soil depth, forested and non-forested areas are associated with unique values of b. This suggests that within the Williams River catchment land cover characteristics act as a conceptual surrogate for catchment storage, and the resulting partitioning of rainfall into its quick and slow flow components. The s_{min} parameter controlling the initiation of surface runoff also seems to be most strongly influenced by land cover type, with more water required to initiate surface runoff for the forested areas. This alludes to the possibility that the s_{min} parameter is accounting for interception storage. The slow-flow recession parameter, k_c, also shows a tendency to be most affected by land cover type, with higher values for the forested areas, highlighting the increased slow-flow contributions for this land cover type. The h evapotranspiration parameter is interesting. Consistent with the land cover hydrotypes, for a given catchment wetness a quicker rate of evaporation results from the forested areas. Surprisingly however, a quicker rate of evapotranspiration is expected for the shallow areas as opposed to deep. This result can be rationalised, however, upon consideration of the assumptions within the evaporation routine of the VIC model. Because a uniform wetness depth is assumed, and actual evapotranspiration is calculated as a function of the residual between this wetness level and the variable soil surface (as described by Eqn. 1), then it is clear that a shallower soil will have smaller residuals and therefore higher evaporative rates. The failure of the evaporation routine to account explicitly for the ability of forest vegetation to extract deep soil water via its root system is seen as an area in which the model can be improved.

MOISTURE REGIME (METHOD 5)

The calibration or retrieval of model parameters for arid and humid regions resulted in a parameterisation that was not significantly different between the two classes. It is evident that there is a deterioration of the parameter *CV* for b compared to land-use and soil classifications and as well as a deterioration of h compared to the land-use classification. A reduction in predictive ability compared to methods 2 and 4, especially for the validation period is also evident. A likely conclusion from these observations is that the link between soil-depth and vegetation is not sufficiently *ordered* to be useful for retrieval of distinct hydrological responses. A possible reason for this conclusion is the fact that significant anthropogenic clearing of the catchment has occurred, especially within the Tillegra subcatchment. Inspection of the spatial moisture classification (Fig. 5c) shows that, in terms of similar soil (Fig. 5b) and land-use (Fig. 5a) combinations, it is really only the Tillegra subcatchment that fails to follow the general pattern of humid areas being associated with forested land cover and deep soils, and arid areas being associated with non-forested land cover and shallow soils. Using logic gained from previous parameterisations, it can be understood that loss of forested areas from the lower parts of the Tillegra subcatchment is likely to cause a smoothing of the b and h

parameters between the arid and humid classification, and lead to values that approximate the lumped parameterisation.

Conclusions and future work

Regional-scale catchments are characterised typically by natural variability in climatic and land-surface features. In this paper, the important question regarding the appropriate level of spatial disaggregation necessary to guarantee a hydrologically sound consideration of this variability has been addressed. Examination of previous attempts to answer this question, reveal the common trend of subjectively grouping land-surface features into quasi-homogeneous "hydrotypes", assigning *a priori* "averaged" parameters, and then evaluating model performance against some arbitrary "goodness-of-fit" measure. Such an approach however sidesteps the question of scale by ignoring the natural heterogeneity of parameters and processes within the individual hydrotypes. An implicit assumption is also made that large-scale response can be obtained from the aggregation of essentially point processes.

In this paper, determination of what types of land-surface features need to be modelled separately to constrain hydrological prediction was considered as a model parameter identification problem. This manner of thinking meant the subjective nature as to the appropriate level of spatial complexity was removed and the problem reposed in terms of what could be supported by the available data. This shift in thinking meant that instead of assigning *a priori* parameters for selected hydrotypes, parameters were required to be retrieved from rainfall-runoff records. The extracted parameterisations therefore permit an attempt to represent large-scale process controls, as opposed to the aggregation of small-scale responses. The merit of different hydrotype-disaggregation schemes could thus be viewed in terms of their ability to provide constrained parameterisations that could be explained in terms of large-scale processes deemed to be active.

The methodology outlined was tested within the 1260 km^2 Williams River catchment, and involved using the quasi-distributed VIC catchment model to provide the characteristic responses for individual hydrotypes. The selection of the model was in line with the mentality of seeking the simplest model parameterisation consistent with the available evidence, and utilised the minimum possible suppositions about its structure. The model is based on a simple quick-flow and slow-flow conceptualisation, but utilises a distribution approach to account for *within* hydrotype variability in hydrological response associated with natural small-scale variabilities of topography, soils and vegetation. Accounting for this natural variability is seen as a positive step in addressing the scale issue associated with the hydrotype-disaggregation approach. Intuitively, the model assumptions regarding runoff formation (i.e. uniform antecedent wetness level) are strengthened when applied to areas of similar hydrological regime. To account for this a regional partitioning of climatic inputs was implemented. By constraining the likely variance in runoff response resulting from contrasting hydrological regimes, the ability to extract the influence of land-surface features was strengthened.

Four hydrotype-disaggregation strategies based on soil-depth, land-use, combined soil-depth and land-use, and a moisture index were investigated and compared to the lumped land-surface representation. For the catchment features investigated, it was found that land-use, based on a forested/non-forested classification, was the most dominant feature influencing hydrological response. Parameterisation of both forest and non-forest areas resulted in significant constraining of predictive uncertainty as compared to the lumped representation as well as providing parameter estimates that were well identified from the regional streamflow records, and that were consistent with the physical processes deemed active. Combining land-use with soil depth information resulted in the most accurate streamflow predictive tool during a ten-year validation period. The increased number of parameters necessary to describe the combined influences of soil-depth and land-use however resulted in parameter estimates that were associated with increased uncertainty. This parameter uncertainty when propagated through to an estimate of streamflow predictive uncertainty showed that the combined soil/land-use hydrotypes were no more useful as a predictive tool than the land-use hydrotypes alone. This is not to say that soil-depth is not important in constraining hydrological predictions, only that the information content of the data was such that soil-depth induced response could not be significantly distinguished above that of the land-use response. A contributing factor to this result is the fact that the land-use classification actually incorporates implicitly soil-depth information due to correlation between the two variables. Attempts to utilise these correlations with an annual moisture classification were largely unsuccessful when compared to the land-use classification. Anthropogenic forest clearing, resulting in a disturbance in the soil-vegetation-topographic sequence was seen as a possible contribution to this result.

The results of this study have highlighted the limitation of streamflow, being an integrated value, to identify spatial parameter distributions. Distinguishing between contrasting hydrological responses resulting from forested and non-forested areas successfully allowed eight model parameters to be identified. Efforts to incorporate additional parameters to include the soil-depth description were hampered by reduced parameter identification. The apparent improvement in the number of parameters that could be defined from the streamflow record above that previously reported (i.e. 4–5 according to Jakeman and Hornberger, 1993) was considered to be a combined result of: (i) the improved representation of the functioning of the catchment resulting from the disaggregation process; (ii) the additional informative content available to constrain parameters resulting from the multiple streamflow gauges used in calibration. The improved informative content from the streamflow records is unlikely to be related solely to the number of gauges, but rather to the fact that each gauge was measuring the integrated response resulting from unique combinations of the various hydrotypes.

It is evident that further refinement of the outlined modelling strategy, through the addition of a greater number of modelled hydrotypes or additional model complexity, can only proceed with the incorporation of additional data sources. For regional-scale catchments, the use of localised time-series of evapotranspiration and groundwater measurements, is unlikely to provide significant improvement in the information content available to identify model parameters and structure (Seibert, 1997; Kuczera and Mroczkowski, 1998). What is required are commensurate estimates of the key modelled variables (e.g. soil moisture, regional evapotranspiration and saturated areas). Saturated area estimates in particular would seemingly provide a very rich data source, as they reflect the integrated response of a number of catchment processes, and have the advantage of a very high *space* resolution as opposed to a very high *time* resolution of time series such as hydrographs. By conditioning to saturated areas, the ability to constrain the gross internal functioning of the model between the two competing runoff formation processes (i.e. baseflow and overland flow) should be improved. Research in the microwave remote sensing domain has offered some promise of delivering distributed data sets of moisture data, but to date the accuracy of retrieved estimates has been complicated by a number of factors (for a brief summary see, Van Oevelen *et al*., 1996). Recent findings by Franks *et al*. (1998) suggest that even where accurate quantitative data of catchment-scale saturated areas are unavailable, uncertain estimates of an expected saturated area from partial field knowledge may be utilised to improve the conditioning afforded by discharge time series alone. Future research with the outlined methodology will attempt to focus on the utility of such suggestions.

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