Spatial scale effects on model parameter estimation and predictive uncertainty in ungauged basins

Denis A. Hughes, Evison Kapangaziwiri and Jane Tanner

ABSTRACT

The most appropriate scale to use for hydrological modelling depends on the model structure, the purpose of the results and the resolution of available data used to quantify parameter values and provide the climatic forcing. There is little consensus amongst the community of model users on the appropriate model complexity and number of model parameters that are needed for satisfactory simulations. These issues are not independent of modelling scale, the methods used to quantify parameter values, nor the purpose of use of the simulations. This paper reports on an investigation of spatial scale effects on the application of an approach to quantify the parameter values (with uncertainty) of a rainfall-runoff model with a relatively large number of parameters. The quantification approach uses estimation equations based on physical property data and is applicable to gauged and ungauged basins. Within South Africa the physical property data are available at a finer spatial resolution than is typically used for hydrological modelling. The results suggest that reducing the model spatial scale offers some advantages. Potential disadvantages are related to the need for some subjective interpretation of the available physical property data, as well as inconsistencies in some of the parameter estimation equations.

Key words | hydrological models, parameter estimation, spatial scale, uncertainty, ungauged basins

Denis A. Hughes (corresponding author)
Jane Tanner
Institute for Water Research,
Rhodes University,
P.O. Box 94,
Grahamstown, 6140,
South Africa
E-mail: *D.Hughes@ru.ac.za*

Evison Kapangaziwiri
Council for Scientific and Industrial Research,
P.O. Box 395,
Pretoria, 0001,
South Africa

INTRODUCTION

One of the central themes throughout the history of hydrological modelling has been associated with the best type of model to use (Rogers 1978), where the choice ranges from simple to complex or conceptual to physics based (Beven 2001). Some of the discussion has been focused on the advantages and disadvantages of parsimonious versus parameter intensive models (Jakeman & Hornberger 1993; Perrin *et al.* 2001) and whether or not physics-based models can really be applied in ungauged basins without the need for some form of calibration (Beven 1989). There have been arguments and counter-arguments in support of many different types of model (Hughes 2010) and this dichotomy of experience and opinion suggests that, in the context of hydrological modelling, one size certainly does not fit all! The most appropriate model to use would therefore seem to vary with the circumstances of the application and these circumstances will be associated with the amount and quality of hydrometeorological data and basin physical property data that can be used to support the modelling exercise or to assist in the understanding of the hydrological response characteristics of the region. The choice of model may also be constrained by local experience and conventional practice and by the purpose for which the model results are intended.

One of the arguments in favour of physics-based models is that they are often applied at more detailed spatial scales than lumped or semi-distributed conceptual type models. However, the counter-argument is that there are rarely sufficient data available to quantify the parameters of physics-based models at detailed scales and the parameters, as well as the hydrological response, remain generalized at catchment scales (Beven 1989; Beven & Binley 1992; McIntyre & Al Qurashi 2009). The parameters of conceptual type models are typically designed to represent catchment

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scale processes (Wagener *et al.* 2004), but there have been few studies that have examined this design concept and its validity in detail. There remains a number of questions about spatial scale effects (Booij 2003) on the estimation of parameter values of conceptual type models.

One of the major issues with conceptual type models has always been related to equifinality (Beven & Freer 2001; Beven 2006) and the size of the parameter space, with many contributions to the literature espousing the need for parsimony and avoiding over-parameterization (Xu & Vandewiele 1995). In simple terms, equifinality is associated with models having a relatively large number of parameters and being able to generate very similar solutions with very different parameter sets. The argument is therefore that if the parameters are not identifiable, there will always be substantial doubt about which parameter sets are appropriate for a given basin and that a simpler (i.e. fewer parameters) model will be able to 'perform' equally well. The real issue revolves around how we measure the performance of a model (Clarke 2008). If the performance is measured only by our ability to calibrate a model against observed stream flow data and achieve a unique result, then certainly simpler models will frequently out-perform more complex models (Hughes 2010). If, however, the performance measures are related to the use of the model outputs to solve complex water resources management issues in both gauged and ungauged basins, the criteria for model selection become far more complex. An example is one in which the model is being used to estimate the relative contribution to low flows in rivers of near-surface runoff processes versus groundwater drainage processes. This example might be very relevant in basins where surface water and groundwater abstractions are being managed in the context of preserving low flows for the purposes of ecological sustainability. A simple model may be able to simulate the patterns of low flow response, but may not be able to distinguish between the sources of the low flows. A more complex conceptual model may include these processes in an explicit way and, therefore, has the potential to be a more valuable management tool.

While relatively complex conceptual models have the potential to be useful in practical water resources assessments, they remain plagued by the problems of equifinality, particularly if traditional approaches to their application continue to be used. In the past, there has always been a strong reliance on calibration (whether manual or automatic) in gauged basins and then some form of extrapolation of parameter sets to ungauged basins. The methods of extrapolation have varied from the identification of hydrologically similar basins (and therefore assumed similarity in parameter sets) to more quantitative estimation of parameter estimation equations using indices of physical basin properties (Duan *et al.* 2006). However, the main problem is with the calibration process itself and whether or not the approaches to dealing with equifinality have been applied consistently. While calibration guidelines can help to reduce subjectivity, there is little doubt that different users will frequently end up with different parameter sets for the same basin, using the same data and the same model. Further problems could occur in data-sparse regions where any errors in the assumptions made about the input climate signals could be translated into inappropriate parameter sets (Andreassian *et al.* 2001).

More recently, the introduction of uncertainty concepts and principles into the application of hydrological models (Beven & Freer 2001; McIntyre *et al.* 2005) has offered a solution to some of the problems associated with calibration, equifinality and the selection of appropriate parameter sets. Yadav *et al.* (2007) and Zhang *et al.* (2008) report on the use of regional indices of hydrological response to constrain ensemble outputs from hydrological models. Kapangaziwiri *et al.* (2009) applied similar techniques for the widely used South African Pitman model and incorporated uncertain physics-based parameter estimation equations (Kapangaziwiri & Hughes 2008) as a way of determining prior parameter distributions to generate model output ensembles. The contributions summarized in Kapangaziwiri *et al.* (2009) represent an attempt to improve parameter estimation approaches and explicitly include uncertainty in the application of a relatively complex conceptual type model that has always suffered from problems of equifinality. The main objective of the approach is to develop parameter estimation procedures that can be applied in both gauged and ungauged basins, thus avoiding problems associated with equifinality during calibration. Such problems are almost certainly exacerbated during parameter regionalization procedures to obtain values for ungauged basins.

The uncertainty in the application of the physics-based equations of Kapangaziwiri & Hughes (2008) is largely determined by the spatial variability in the basin physical property data across the scale of the sub-basin being modelled. The previously published results of applying the parameter estimation approaches were restricted to the scale of the sub-basins (1,000–10,000 km^2) used for water resources assessments in South Africa (the so-called 'quaternary' catchments of Midgley *et al.* (1994)). Given that the basin physical property data are available at smaller scales, this study investigates the scale issues associated with the application of these parameter estimation routines and examines how spatial scale can affect the parameter value estimates and the degree of uncertainty in the resulting output ensembles.

THE MODEL AND THE PARAMETER ESTIMATION ROUTINES

The model that has been used in this study is the monthly time-step Pitman model that has been frequently used for water resources assessments in southern Africa for many years and has become a standard method used by many practitioners. It has undergone a number of developments over the years and the details of the version applied in this study are given in Hughes *et al.* (2006). The focus of the paper is on the use of the parameter estimation routines described in Kapangaziwiri & Hughes (2008) and Hughes *et al.* (2010) but applied within the uncertainty framework proposed by Kapangaziwiri *et al.* (2009). Some of the parameter estimation routines are based on earlier work by Hughes & Sami (1994) and the complete details of the approach can be found in Kapangaziwiri (2007, 2010).

The Pitman model includes explicit routines to simulate interception, infiltration excess surface runoff, soil moisture (or unsaturated zone) runoff, groundwater recharge and drainage to stream flow, as well as evaporative losses from the unsaturated zone and the groundwater storage in the vicinity of the river channel. The model therefore has a relatively large number of parameters (22 in total, but four typically have fixed values) and it is generally impossible to establish parameter sets that generate unique results through conventional calibration approaches. However, the potential advantage of the model is that the different contributions to stream flow are explicitly simulated and the model results are sensitive to changes that occur within sub-basins, given appropriate changes to parameter values. The sub-basin changes may involve climate, land use and land cover or different types of abstractions and water use. Table 1 contains a list of the main model parameters that influence volumes of runoff generation as well as a brief summary of the estimation approaches. For the purposes of this study, the vegetation cover and evapotranspiration parameters are not considered as uncertain and are therefore excluded from Table 1. Within the model, the vegetation cover parameters control the interception losses and these are not expected to make as large a contribution to the overall uncertainty as the main runoff generation parameters. The evapotranspiration parameter determines the shape of the relationships between the monthly potential evaporation input data and the level of the soil moisture store. The steeper topography parts of the sub-basins, where the majority of runoff is assumed to be generated, are dominated by a single land cover (low bush and grassland) in which the evapotranspiration parameter is not expected to vary a great deal. A further reason for excluding these parameters is that they are not part of the scale-dependent estimation process using Agricultural Geo-Referenced Information System (AGIS) data (AGIS 2007; see below).

The parameter estimation routines developed by Kapangaziwiri & Hughes (2008) are based on conceptual hydrology interpretations of the model parameters at the sub-basin scale (typically 50–1,000 km^2) and have been designed to use physical property data that are typically available at a similar, or better, resolution. Within South Africa much of this information is provided in the land type database supplied by AGIS (2007) that was originally developed for agricultural land management purposes. Further details about the basis for the development of the land types are provided in Sililo *et al.* (2001) and they are differentiated by relatively homogeneous assemblages of topography, soil types and soil depths (terrain units). The AGIS approach recognizes that topographic and soil homogeneity can occur at very small spatial scales and therefore represents a compromise between defining homogeneous areas and using a practical mapping scale.

Table 1 | Main Pitman model parameters involved in the scaling exercise and a summary of the estimation methods

Parameter	Description and estimation approach
ZMIN ZAVE ZMAX	Parameters of the asymmetric triangular distribution of catchment adsorption rate (mm month^{-1}). Estimated from the infiltration characteristics of the soil based on soil texture relationships with corrections for organic content, macropore development and structure
ST	Unsaturated zone storage capacity (mm). Estimated from the soil depth and texture (translated to porosity) characteristics and including storage in the rock above the phreatic level based on fracture density and depth to groundwater
FT	Maximum unsaturated zone drainage (mm month^{-1}) when storage = ST. Estimated from topographic slope, drainage density, soil depth and texture (translated to permeability). Includes an unsaturated zone contribution based on fracture zone transmissivity and gradient
POW	Power of the relationship between unsaturated zone drainage and unsaturated zone storage. Estimated from assumptions about the spatial distribution of relative moisture contents for different levels of unsaturated zone storage using topography and soil drainage characteristics
GW	Maximum groundwater recharge rate (mm month^{-1}) when storage = ST. Difficult to estimate directly and is typically calibrated against estimates of mean annual recharge from DWAF (2005)
GPOW	Power of the relationship between groundwater recharge rate and unsaturated zone storage
Drainage density	The drainage density of the channel network expected to receive groundwater outflows
T	Transmissivity (m^2 d^{-1}) of the groundwater storage zone
S	Storativity of the groundwater storage zone
GW slope	Regional groundwater gradient used to estimate groundwater outflows to downstream sub-basins
RSF	Riparian strip factor (% of the sub-basin expected to contribute to evaporation from near-surface groundwater in the vicinity of channels)

The information required for the parameter estimation process includes soil depths for different parts of the sub-basin being modelled (hilltop, valley sides and valley bottoms), soil texture (which is then translated into soil hydraulic properties), topographic slope and sub-surface geological conditions (Kapangaziwiri & Hughes 2008). The AGIS database consists of the spatial extent of land types and within each land type the depths (as a range of values), textures and spatial extent of several soil types are defined for up to five terrain units. Associated with each terrain unit is information on the percentage area of the unit within the land type and a range of topographic slopes. The information also includes a brief description of the underlying geology, while a further database from the Department of Water Affairs and Forestry (DWAF 2005) contains additional information about variations in hydrogeological variables (transmissivity, storability, mean annual recharge, etc.) at a sub-basin scale that is equivalent to the typical scale of modelling in South Africa (the quaternary scale used in Midgley et al. (1994)).

While it is therefore possible to extract the information required for the parameter estimation routines for any single land type, the information extracted is in the form of ranges of values for several soil series across several terrain units. The approach used in the parameter estimation process is to assume that these ranges represent the extremes of the probability distribution functions of the physical property data and to use Monte Carlo sampling procedures to generate ensembles of parameter estimates. The statistical properties of these ensembles are used to define the uncertainty distributions of the model parameters (Kapangaziwiri 2010). The consequence of this approach is that the greater the diversity of topography and pedology within a land type, the greater the uncertainty in the parameter estimates. It is also quite possible for several land types to occur within individual model spatial units (sub-basins), which potentially further increases the uncertainty in the model parameter estimates.

Table 2 provides an example of some of the AGIS (2007) data input into the parameter estimation equations. Up to

Table 2 | An example of the topography and soil data input into the parameter estimation routines

Physical property	Topographic unit			Soil unit 1			Soil unit 2		
	Hill top	Mid slope	Valley bottom	Hill top	Mid slope	Valley bottom	Hill top	Mid slope	Valley bottom
% area	4	55	41				etc.		
Minimum slope (%)	0	15	0						
Maximum slope (%)	10	50	12						
% of unit				87	13	0			
Minimum depth (mm)				0					
Maximum depth (mm)				300					
Texture class				SCL					

SCL, sandy clay loam.

five different soil units can be included in the input information. The depth and texture of a soil unit are not differentiated for the different topographic units but differences occur because different soil units dominate in different topographic units. Table 3 provides an example of part of the estimation process and includes calculated variables and parameter values as well as some input data. The example provided here is based on the information used to calculate the FT parameter of the model. The appendix in Hughes *et al.* (2010) indicated that the FT parameter is made up of the sum of two estimates; FT_{soil} representing the near-surface drainage and FT_{unsat} representing the deeper unsaturated zone drainage. FT_{soil} is estimated using a combination of representative values of basin slope (BS %), soil permeability (K m d^{-1}), soil depth in the lower topographic units (LDepth mm) and assumed a contributing channel length based on drainage density (DD km km^{-2}). The contributing area (CA) per unit basin area is given by Equation (1):

Table 3 | Examples of some of the data used in the parameter estimation process for parameter FT

Physical property	Mean	Standard deviation
Basin slope (%) obtained from area weighted samples of the slope values in Table 2	18.0	4.1
Permeability (m d^{-1}) obtained from area weighted samples of the soil textures in the five soil units and using relationships from Cosby *et al.* (1984)	32.5	12.1
Valley bottom soil depth (mm) from weighted samples of soil depth from the five soil units	646.0	59.3
Drainage density (km km^{-2}) – user input	1.8	0.18
Groundwater drainage vector slope (%) from assumed values for different geological configurations	3.0	0.0
Fracture zone transmissivity (m^2 d^{-1}) from geological information	2.5	0.5
FT_{soil} (mm $month^{-1}$) – parameter estimate (see text)	5.7	3.7
FT_{unsat} (mm $month^{-1}$) – parameter estimate (see text)	8.4	1.9
FT (mm $month^{-1}$) – parameter estimate (see text)	14.5	3.8

$$\mathrm{CA}(\mathrm{m}^2\,\mathrm{km}^{-2}) = 2 \times \mathrm{DD} \times \mathrm{LDepth} \tag{1}$$

and Equation (2):

$$\mathrm{FT}_{\mathrm{soil}}(\mathrm{mm\,month}^{-1}) = \mathrm{CA} \times K \times 30 \times \mathrm{BS}/100{,}000 \tag{2}$$

where 30 represents the number of days in a month and 100,000 is used to correct the length units to mm. FT_{unsat} is based on the same principles as FT_{soil} but using the vector slope of the fracture zone (VS %) and the transmissivity (T m^2 d^{-1}) in Equation (3):

$$\mathrm{FT}_{\mathrm{unsat}}(\mathrm{mm\,month}^{-1}) = 2 \times \mathrm{DD} \times T \times 30 \times \mathrm{VS}/100 \tag{3}$$

The use of a fixed 30 day period introduces a slight bias in the equation, but this is negligible compared with the other uncertainties inherent in the estimation equation.

The first part of the uncertainty approach assumes that the ranges of the primary input data (slopes, soil depths and texture related soil hydraulic properties; Table 2) represent 5 and 95% points on a normal cumulative probability distribution function and 5,000 area weighted Monte Carlo samples are used with the estimation equations given in Kapangaziwiri & Hughes (2008) to generate the statistical properties (means and standard deviations of normal or log-normal distributions) of secondary variables (e.g. basin slope, permeability and soil depth). Uncertainty in the parameter estimates is based on independent Monte Carlo samples (5,000) of the secondary variables that are used in Equations (1)–(3). The final estimate of the mean and standard deviation of FT is based on 5,000 samples from the FT_{soil} and FT_{unsat} distributions (Table 3). The use of normal or log-normal distributions is based on the assumption that the bounds of the soil depth, slope or other data represent extremes that are less likely than values within the range. Haan *et al.* (1998) noted that the means, variances and ranges have more influence on the uncertainty outputs than the type of distribution. The use of 5,000 samples was relatively arbitrary but some initial tests using a larger number did not appear to affect the results. The dependency between model parameters (e.g. between moisture storage and some of the runoff parameters) is taken care of by the fact that they use some common physical property variables.

AN EXAMPLE APPLICATION

Tests of the parameter estimation routines and the effects of spatial scale have been made in several basins within South Africa (Kapangaziwiri 2010). This paper reports on one of these tests in detail and summarizes several others. The detailed assessment is based on three sub-basins (H10A to C) in the headwaters of the Breede River located in the Western Cape Province of South Africa (Figure 1). A stream flow gauging station is located at the

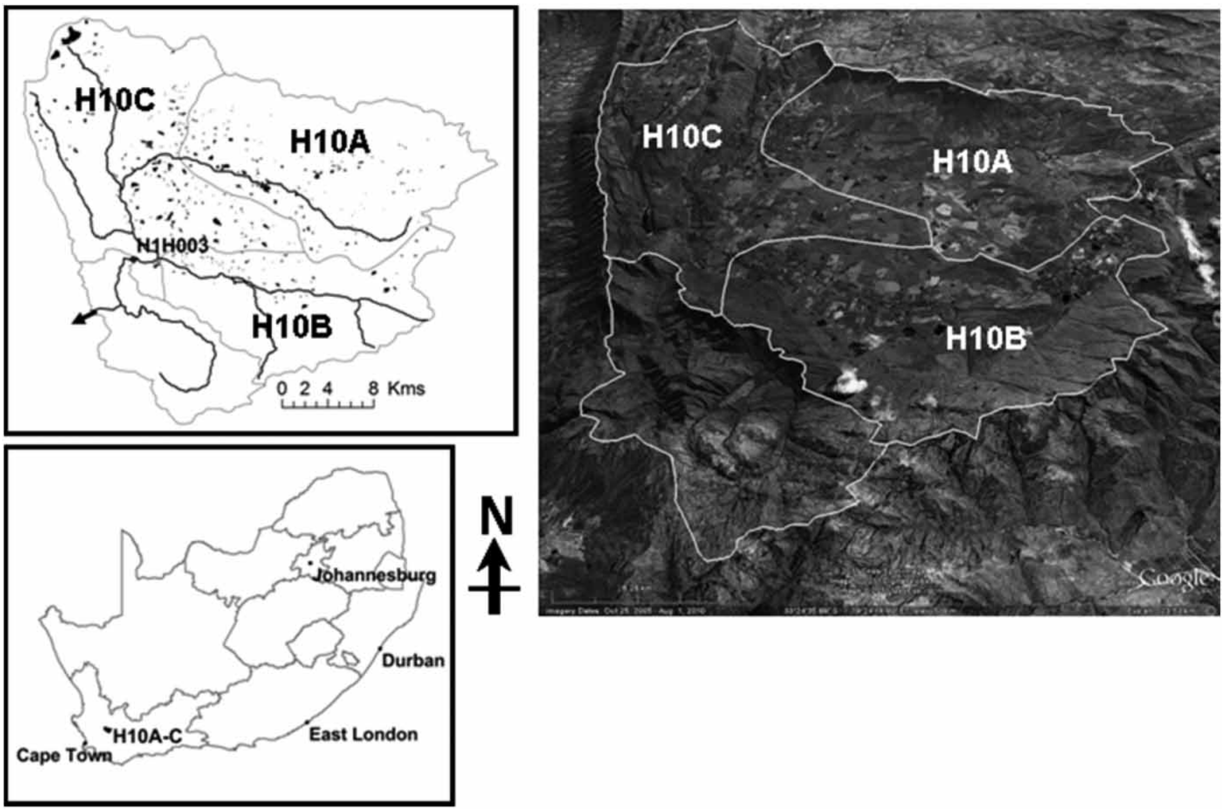

Figure 1 | Headwater sub-basins of the Breede River H10A to C (including a tilted Google Earth image).

outlet of sub-basin H10C; however, the observed stream flows are substantially impacted by both surface (from farm dams) and groundwater abstractions for irrigated agriculture (Hughes & Mantel 2010). Assessments of the performance of the parameter estimation routines are therefore partly based on previous model simulations (Midgley *et al.* 1994) that were calibrated against estimates of the naturalized observed flows. Figure 1 illustrates that the catchment is made up of steep mountain topography surrounding a much flatter valley floor. This results in not only a relatively large number of land types covering the whole area (13 for H10A to C), but also substantial variations in topography, soil depth and soil texture across the different land types. There are also differences in the geology of the main mountain ranges with some dominated by quartzitic sandstone with high recharge potential and others by interbedded shales and sandstones with lower recharge.

The three sub-basins H10A to C have been further subdivided on the basis of the variability in the land type characteristics. Table 4 summarizes the catchment areas and number of land types in the original sub-areas and the sub-divisions, which have been based on the variability that exists between the individual land types. H10A-1 is defined as the ridge on the northern boundary of H10A, H10A-2 represents the valley floor, while H10A-3 represents the hills and mountain tops on the eastern boundary of H10A. H10B and H10C have been sub-divided into two areas each, the first ones (B-1 and C-1) representing the mountain ridges with steep topography and shallow soils and the second ones (B-2 and C-2) representing the flatter valley floors with deeper soils. Table 4 also includes information about the adjustments made to the rainfall inputs for the sub-divisions relative to the original sub-basins. These adjustments are based on gridded ($1' \times 1'$) data for the whole country (Dent *et al.* 1989)

Table 5 presents the results of the parameter estimation process for sub-basin H10A and the three sub-divisions. While some of the values are a direct consequence of the application of the parameter estimation equations of Kapangaziwiri & Hughes (2008), others (notably the groundwater parameters) are based on several assumptions about the differences between the sub-divisions:

- The differences in the surface runoff parameter ZMIN mean values are generally consistent with the authors' expectations, based on conceptual understanding. However, the overall uncertainty appears to have increased across the three sub-divisions.
- The high ZMAX mean value and low uncertainty were not expected. However, the generally high values for ZMAX suggest that the surface runoff component of the model is unlikely to play a major role in simulating total runoff.
- The variations in ST are as expected, but the uncertainty does not seem to have been reduced. Part of the reason for this is a relatively high variability in soil depth within the valley bottom land types.
- The FT parameter estimation equation integrates the physical properties before applying the final equation and the high H10A estimate is a reflection of the combination of deep soils and steep slopes across all of the land

Table 4 | Catchment areas, mean annual rainfall (MAP) and number of different land types for the original sub-basins and the smaller sub-divisions

	Sub-basin or sub-division						
	H10A			**H10B**		**H10C**	
Area	233.7			162.5		259.6	
No. of land types	5			6		6	
MAP (mm)	510.2			704.7		670.7	
	A-1	**A-2**	**A-3**	**B-1**	**B-2**	**C-1**	**C-2**
Area (km^2)	28.0	119.2	86.5	92.6	69.9	116.8	142.8
No. of land types	2	2	1	3	3	4	2
MAP (mm)	887.7	421.5	510.2	875.2	478.5	849.8	524.2

Table 5 | Uncertain estimates of the model parameters for H10A and A-1, A-2 and A-3. The values given are the means and standard deviations (in parenthesis) of normal probability distributions

Parameter	Sub-basin or sub-division			
	H10A	A-1	A-2	A-3
ZMIN	64.4 (10.5)	45.0 (0.0)	60.8 (10.1)	37.3 (10.7)
ZAVE[a]	179.2 (0.0)	82.8 (0.0)	252.1 (0.0)	122.4 (0.0)
ZMAX	1,195.6 (26.4)	800.0 (0.0)	884.6 (25.7)	726.0 (13.8)
ST	167.6 (23.1)	109.7 (18.2)	206.7 (34.8)	141.2 (21.8)
FT	14.5 (3.8)	7.9 (1.4)	5.0 (2.2)	6.0 (1.2)
POW	2.0 (0.5)	2.5 (0.2)	2.1 (0.2)	2.2 (0.2)
GW[b]	10.0 (1.8)	29.0 (2.5)	2.0 (0.6)	15.0 (2.0)
GPOW	3.0 (0.0)	3.0 (0.0)	3.0 (0.0)	3.0 (0.0)
Drainage density	0.4 (0.0)	0.1 (0.0)	0.4 (0.0)	0.2 (0.0)
T	50.0 (10.0)	50.0 (10.0)	50.0 (10.0)	50.0 (10.0)
S	0.001 (0.0)	0.001 (0.0)	0.001 (0.0)	0.001 (0.0)
GW slope	0.01 (0.0)	0.075 (0.0)	0.01 (0.0)	0.05 (0.0)
RSF	0.2 (0.02)	0.1 (0.01)	0.25 (0.03)	0.15 (0.02)

[a]ZAVE is not estimated with uncertainty but during the parameter sampling routine within the model it retains its relative position between ZMIN and ZMAX.
[b]The GW parameter values are calibrated against the range of recharge values expected based on data given in DWAF (2005).

types. All of the sub-division estimates are lower reflecting the more realistic combinations of low slopes and deep soils or steep slopes and thin soils.

- The uncertainty values for the GW parameter have been established by trial and error to ensure that the range of mean annual recharge in the output ensembles is consistent with the range given in DWAF (2005). The values used for the sub-divisions have been set to generate the same overall range of recharge for the total sub-basin and have been based on the assumption that A-1 will experience the majority of the recharge and A-2 very little, with A-3 being intermediate.
- The other groundwater parameter values have been quantified on the basis of assumptions about the differences in the sub-divisions. The sub-basin values have been retained when differences are not expected. The DD of channels receiving groundwater drainage is expected to be higher in the valley floor, as is the riparian strip factor. The GW slope parameter differences have been set to reflect the assumption that recharge in the topographically steep areas will drain to the valley floor zone, but that drainage out of the sub-basin as a whole will be limited by low gradients. There is no allowance in the model for groundwater drainage directions that are different to the topographic drainage, while there is the possibility that this process plays a role in this area.

The pattern of differences in the sub-basin parameters and those quantified for the sub-divisions in H10B and C are very similar to those listed in Table 5 for H10A. Specifically, the pattern of FT values with lower means and uncertainty for the sub-divisions are much the same and this is expected to have a dominant effect on the ensemble results.

Figure 2 compares the range of the ensemble flow duration curves (FDCs) for the original sub-basin distribution system with the earlier simulations of natural flows (WR90 – taken from Midgley *et al.* (1994)). The uncertain parameter estimation procedures for the sub-basin scale simulations have clearly generated results that are consistent with the existing simulations except in the region of extreme low flows (% exceedence >90%). However, the observed FDC suggests that there could be additional uncertainty about the characteristics of the natural flow regime. The impacts in this area are dominated by irrigation abstractions

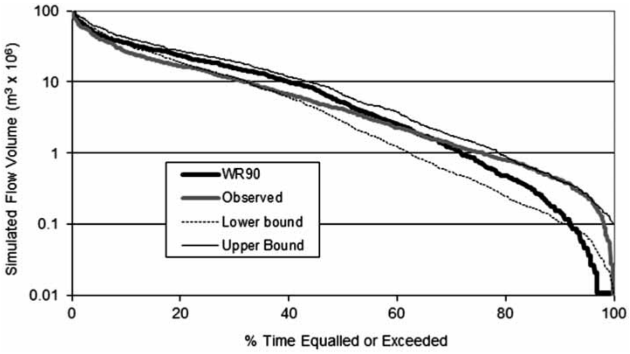

Figure 2 | Flow duration curves of the previous simulation of natural flow (WR90), the bounds of the sub-basin uncertainty ensembles and the naturalized observed flow data at the outlet of H10C.

from small farm dams (Hughes & Mantel 2010) with some groundwater abstraction and the possibility of some minor return flows from the town of Ceres located near the catchment outlet. The expectation is that the observed record would reflect reductions in moderate to low flows relative to the natural flow regime. The sub-basin scale simulations would therefore appear to be reasonably behavioural at moderate to high flows, but less so at low flows.

Figure 3 illustrates the results of the simulations based on the spatial sub-divisions. The immediate impression is that the overall uncertainty has been reduced. The range of the sub-basin uncertainty, expressed as the difference in the extremes of mean monthly runoff as a percentage of the median, is 31.1%, while this reduces to 18.3% for the sub-division uncertainty. However, there has also been a general decrease in the simulated runoff of approximately 17%, based on the mean monthly runoff volumes of the

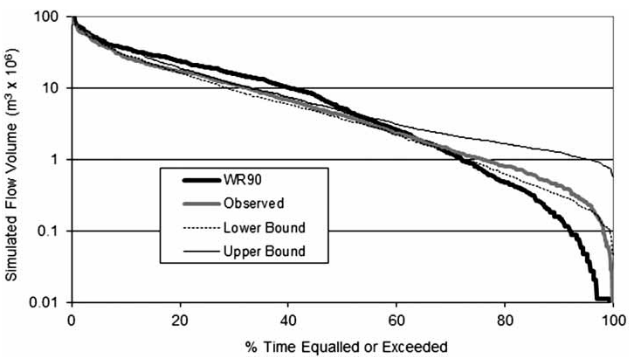

Figure 3 | Flow duration curves of the previous simulation of natural flow (WR90), the bounds of the sub-division uncertainty ensembles and the naturalized observed flow data at the outlet of H10C-2.

median ensembles. Comparison of Figures 2 and 3 indicates that this results from lower simulations of moderate flows, while the low flows simulated by the sub-division approach have increased. Based on the assumptions already referred to about the observed flows, the sub-division uncertainty ranges are more behavioural at low flows, but less so at moderate to higher flows, compared with the sub-basin simulations.

DISCUSSION

Table 6 summarizes the results of applying the parameter estimation equations to 30 gauged sub-basins in South Africa and 41 in other countries of southern Africa (Kapangaziwiri 2007). These results were based on the use of the equations without uncertainty, which is equivalent to using the mean values of the uncertain parameter estimates. The AGIS (2007) data are not available for the southern Africa examples and the estimates of appropriate physical property values relied on more subjective interpretations of the available information. The results clearly indicate the potential of the parameter estimation equations compared with the use of existing parameter sets based on regionalization (the 'WR90 parameters' in Table 6 taken from Midgley *et al.* (1994)). The regional WR90 parameters were based on relatively subjective assessments of sub-basin similarity and extrapolation from calibrated parameter sets for the limited number of gauged catchments within South Africa.

Table 6 | Comparison of simulation results for gauged catchments in South Africa and southern Africa (taken from Kapangaziwiri (2007))

	South Africa		
Objective function	**Parameter estimation equations**	**WR90 parameters**	**Southern Africa**
% with CE $\geq$0.6	63	53	85
% with CE(ln) $\geq$0.6	83	47	68
% with Bias $\leq$10%	70	27	95
% with Bias(ln) $\leq$10%	50	33	85

CE and CE(ln) are the Nash–Sutcliffe coefficients of efficiency based on untransformed and natural log transformed values.
Bias and Bias(ln) are % errors in mean monthly flow based on untransformed and natural log transformed values.
WR90 parameters refer to simulations using the regional parameters of Midgley *et al.* (1994).

The application of the sub-division approach to five other regions in South Africa with similar, but less extreme, degrees of variability in terms of topography and soil characteristics produced mixed results. However, these results have not been examined in as much detail as the H10 group of sub-basins and were mainly evaluated on the basis of the reduction in uncertainty in mean monthly runoff and whether the reduction in scale of parameter estimation produced biased results compared to the sub-basin scale estimates. There was substantial variability in the degree of uncertainty produced by the application of the parameter estimation approach at the sub-basin scale and the sub-division approach reduced the uncertainty in more than 50% of the examples. In the other cases, the uncertainty remained largely unchanged and there were no cases in which the scale reduction introduced any bias compared with the sub-basin results.

The detailed assessment of the results for H10 suggests that some improvements in parameter estimation can be gained through a reduction in scale, but has also revealed some potential weaknesses in the parameter estimation procedures. Table 5 indicates that the parameter estimation equations have generated values for the surface runoff parameters (ZMIN and ZMAX) without uncertainty for sub-division H10A-1 and this result is repeated for the other mountain sub-divisions (H10B-1 and H10C-1). This result is mainly a consequence of no variation in the soil texture information, as the AGIS (2007) database suggests that the dominant soils are all of the same texture class (loamy sands). This statement is unrealistic and results from the use of fixed infiltration variables for a given texture class and therefore the same values for the ZMIN, ZAVE and ZMAX parameters. However, model spatial units that have the same texture class would still be expected to have variations in their infiltration characteristics and a future revision of the parameter estimation equations needs to take this factor into account. It is also worth noting that it is very difficult to include areas of very steep slopes and bare rock into the parameter estimation equations. It is therefore not unreasonable to suggest that the surface runoff contribution from the mountain sub-divisions has been under-estimated.

While there remains some uncertainty about the real patterns of natural flows, there is evidence to suggest that the reduction in spatial scale has improved the low flow simulations, but has had little impact on the uncertainty in the lower part of the FDC. The estimation equations for some of the parameters that determine low flows are based on several of the physical property variables and therefore will never be estimated without uncertainty as can occur with ZMIN and ZMAX. The values for the FT parameter given in Table 5 illustrate that the range of physical properties across the sub-basin scale can lead to high values and high uncertainty. This situation is a consequence of independently sampling from the different physical properties, specifically soil depth and topographic gradient in the case of FT. In reality, deep soils and high slopes (giving high FT values) will not occur together and the lower estimates of FT for A-1 to A-3 (Table 5) indicate that such combinations do not occur within the three sub-divisions. While some combinations of deep soils and high slopes are excluded in the parameter estimation process (by rejecting samples that have assumed unrealistic combinations and re-sampling), the results suggest that some unrealistic combinations can still be generated.

Part of the process of reducing the scale of modelling involved subjective changes to some of the parameter values rather than the application of estimation equations. These subjective changes apply to the groundwater parameters and specifically to the main recharge parameter, GW. The groundwater parameter values are mainly based on the Groundwater Resource Assessment II (GRAII) database (DWAF 2005), which provides information at the sub-basin scale (i.e. averaged values for H10A to C). Modifying these data for the sub-divisions relies upon a conceptual interpretation of the differences that occur at smaller scales. While it is not unrealistic to expect that sound conceptual assumptions can be developed in most situations on the basis of hydrological process understanding, translating these assumptions into appropriate parameter value changes will remain a challenge. For example, higher volumes of recharge will be expected in the mountain areas that have higher rainfall and thinner soils. It is also expected that the gradient of the local water table will be relatively high in the mountain areas, suggesting a dominance of groundwater transfers to the next downstream area rather than re-emergence as river flow within the sub-division. While these are sound conceptual principles, it is more difficult to be confident that they translate into the parameter value differences between H10A-1 and H10A-2, for example (Table 5). There can be no doubt that some of the differences in the results illustrated in Figures 2 and 3 are associated with the translation of conceptual principles to quantitative values. However, some tests to assess the effects of changing the parameter values within ranges that still conform to the conceptual principles referred to above suggested that the results presented in Figures 2 and 3 would not change substantially.

With respect to the effort involved in setting up the model and applying the parameter estimation routines, there is very little to choose between the two scales. By far the greatest effort is expended in the extraction of the details contained within the land type data, which are available in a text format that does not readily allow automatic processing. There is a degree of subjectivity in the extraction process.

CONCLUSIONS

Previous assessments of the parameter estimation procedures, based on results for gauged catchments (Table 6), suggest that they can be applied successfully. The assumption is therefore that they are applicable in ungauged catchments and will be at least as good as other methods used for setting parameter values. The further advantages are that they can explicitly include uncertainty and that they are less subjective than some of the existing regional parameter estimation approaches (Midgley *et al.* 1994). Hughes & Mantel (2010) investigated the contribution of parameter uncertainty compared to uncertainties in climate forcing data (rainfall) and water use data in the simulation of present day stream flows. They found that the contributions can be very different depending on the available information and the specific situation. Within the H10 sub-basins used in this study, rainfall uncertainties associated with a lack of gauges in the mountain areas contribute a greater degree of uncertainty than the model parameters for high flows, while parameter uncertainty dominated in the low flow simulations. In another region of South Africa, with far less topographic variation, the contribution of rainfall uncertainty was small, while the contributions of water use and parameter uncertainty were very similar at low flows due to the lack of reliable water use data. Model structural uncertainty is not considered in this study as it focuses on a single model that is used frequently for practical water resources assessment.

While the results of this study have suggested that there are potential advantages to reducing the scale of modelling and therefore of parameter estimation, there remain some unresolved issues about the overall benefits. One of the reasons that these issues are unresolved is that the data available to test various parts of the process are not generally available. In the example used, an accurate assessment of which of the three simulation results (the previously available results, the sub-basin ensembles and the sub-division ensembles) are the most behavioural is not possible, despite the fact that the basin is gauged at the outlet. The gauged records reflect anthropogenic changes to the flow regime which are not very well documented or quantified (Hughes & Mantel 2010), a situation that is common to almost all of the observed stream flow records in South Africa. Even where stream flow gauges exist, the natural flow regime is therefore effectively ungauged. While Midgley *et al.* (1994) and other sources of information in the country include 'naturalized' time series of gauged records, there clearly remains a great deal of unquantified uncertainty in these results. If the previously calibrated simulation results for the outlet of H10C (the 'WR90' line in Figures 2 and 3) are an indication, there are likely to be situations in South Africa in which the conventional wisdom related to natural flow estimates could be very different to reality.

There are two clear advantages in the reduction of spatial scale. The first is the ability to more explicitly represent spatial climate variations in areas where there are steep topographically controlled gradients in rainfall and evapotranspiration demand (although the latter has not been addressed in this study). The second is that unrealistic combinations of physical property variables (deep soils and steep slopes) are less likely to occur within the parameter estimation equations, leading to more realistic parameter uncertainty ranges. One disadvantage is related to an increase in the level of subjectivity required to establish the reduced scale simulations, given that the existing database used for the groundwater parameter estimates is based on the coarser scale. A further problem is that this study has revealed some potential inconsistencies in at least one of the parameter estimation approaches (the surface runoff parameters controlling the catchment absorption component of the model). Fortunately both of these disadvantages can be addressed through further research, the latter through a re-examination of the principles used to interpret the land type information and quantify the probability distributions of the physical property data. The problems with the subjectivity in the groundwater parameter estimations can be addressed through further research into the conceptual understanding of surface-groundwater processes at appropriate spatial scales within regions representing different combinations of hydro-geological and topographic characteristics.

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