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Regionalization of dynamic watershed response behaviour

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Abstract Approaches to ungauged basin modelling typically use observable physical characteristics of watersheds (e.g. soil data) to directly infer hydrological model parameters, or they use regionalization methods based on parsimonious hydrological models. A different approach to streamflow prediction in ungauged basins is presented here where, instead of model parameters, the model independent hydrological response behaviour is estimated in the form of streamflow indices, and then regionalized with respect to physical characteristics of watersheds. Therefore, the approach uses a data driven regionalization method (under uncertainty) rather than the common hydrological model driven regionalization method. Ensemble predictions in ungauged basins can then be constrained by limits on acceptable hydrological model behaviour. This study utilizes data from 30 watersheds in the UK. Initial results show that the predictive uncertainty of the model can be reduced considerably through this new approach.

Key words ensemble predictions; hydrograph indices; prediction in ungauged basins; predictive uncertainty; regionalization; streamflow characteristics; watershed response

INTRODUCTION

Rainfall–runoff models are standard tools for hydrological analysis. One major limitation of currently available models is the need for adjustment of the model parameters using observed watershed response data to obtain reliable predictions (e.g. Sivapalan *et al*., 2003; Wagener *et al*., 2004). The problem is accentuated further when it comes to prediction in ungauged basins, where data for parameter estimation via calibration are not available. Two common approaches to overcome this problem in ungauged situations are: (a) the use of physically based models, and (b) the regionalization of model parameters using physical characteristics of watersheds. The introduction of physically based models was based on the hope that their parameters would be equivalent (or at least strongly related) to directly observable properties. However, differences in scale, over-parameterization and model structural error, have prevented this objective from (so far) being achieved (Beven, 1989). In the regionalization approach, a (typically parsimonious) hydrological model structure is selected, and calibrated to observable watershed response for a large number of gauged watersheds. Regression equations are then developed between the model parameters and physical characteristics of watersheds. This approach also suffers from model identification difficulties, model structure errors, and difficulties in finding an appropriate calibration strategy that appropriately considers the physical meaning of the model parameters (Wagener & Wheater, 2005).

The objective of the research reported here is to achieve a continuing reduction in predictive uncertainty, while maintaining reliable predictions, leading to an increased understanding of watershed function (Wagener *et al*., 2004). In this study we introduce a new approach for improving predictions in ungauged basins that regionalizes model independent dynamic hydrological response characteristics (or indices) to physical characteristics of watersheds while considering uncertainty. The approach is applicable to any model (whether lumped or distributed) that can be run within a Monte Carlo framework, in contrast with other published approaches that can only be applied using relatively simple (identifiable) models (Wagener & Wheater, 2005). Initial results, using data from 30 watersheds in the UK, are presented here. Two of the watersheds were used for an independent evaluation of the approach.

REGIONALIZATION OF HYDROLOGICAL RESPONSE BEHAVIOUR

Dynamic response characteristics or response behaviour indices of a watershed can be derived from precipitation, evapotranspiration (or temperature) and streamflow time series of the watershed; examples include common descriptors of hydrograph shape such as runoff ratios and times to peak flow, etc. While indicators of this type are commonly used by the ecological community for the evaluation of flow regimes (e.g. Olden & Poff, 2003), they have only recently been (re)introduced in the context of hydrological model calibration (e.g. Yu & Yang, 2000; Shamir *et al*., 2004). Other examples of such indices include runoff ratios, rising and falling limb densities, mean flow, exceedence of flow percentiles, etc. (e.g. Olden & Poff, 2003; Shamir *et al*., 2004).

Our work extends these ideas by capitalizing on the information content inherent in such summary descriptors of watershed response, and by relating them to observable physical characteristics of the watersheds by means of regressive relationships. The idea of regionalizing such indices stems from the empirical observation that the amount of uncertainty involved in regionalizing hydrological model parameters can be large, particularly since it is difficult to account for the effects of model structural error during model calibration (Wagener & Wheater, 2005). Since the watershed response characteristics are not model-specific, uncertainties and confounding influences that might arise from the process of model identification are eliminated (or at least significantly reduced). Once regionalized, the behavioural information summarized by the response characteristics can be used as constraints on the model predictions, and facilitate, for example, a separation into behavioural and non-behavioural model sets using a binary classification approach. Therefore, regionalization in the context of this paper involves the development of regression relationships between watershed response characteristics and observable physical characteristics of watersheds.

REGIONALIZATION CASE STUDY

Watershed data

This study uses a set of 30 small to medium sized watersheds located throughout the UK (Fig. 1), covering a wide range of soil types, topography and land uses. Most of the watersheds have natural flow within 10% at their 95 flow percentile. Data for the selected watersheds was acquired from the UK National River Flow Archive (http://www.nwl.ac.uk/ih/nrfa). The precipitation and streamflow time series was taken from "Predictions in Ungauged Basins (PUB)—UK data downloads" at http://www.nwl.ac.uk/ih/nrfa. Temperature data was obtained from The British Atmospheric Data Centre (http://badc.nerc.ac.uk/home/index.html). Potential evapotranspiration was calculated from temperature data using Hargreaves equation (Maidment, 1993). Eleven consecutive years (1980–1990) of data were available for 29 watersheds.

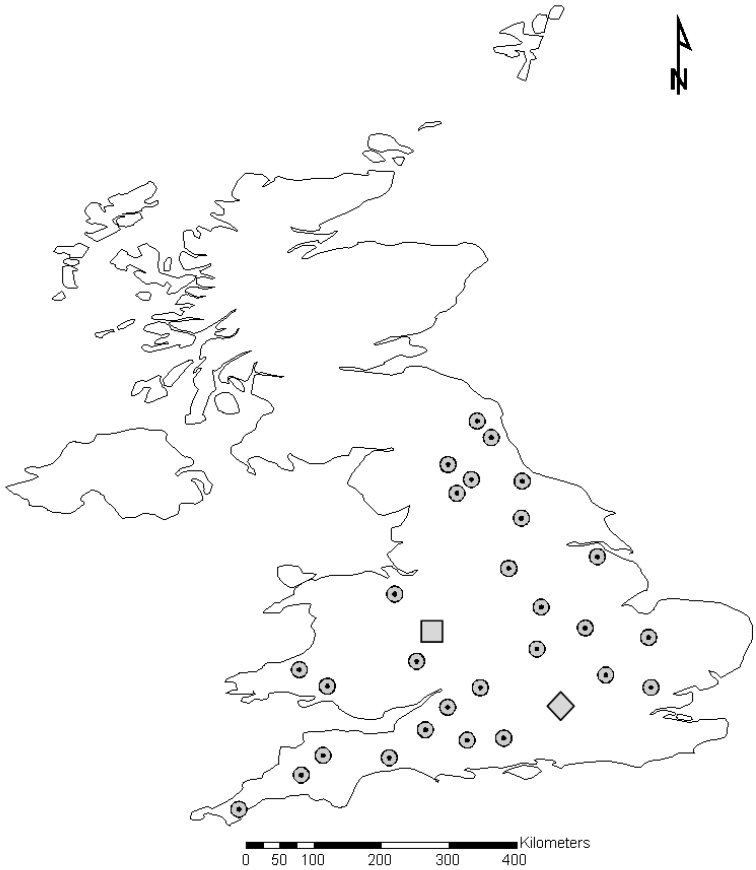

Fig. 1 Map of UK showing the location of watersheds used in this study. The square and diamond show the validation watersheds.

The time period used for the analysis was from 1 January 1983–31 December 1990; the average monthly values of rainfall, streamflow and potential evapotranspiration are plotted in Fig. 2(a–c). A normalized flow duration curve showing cumulative frequency of normalized flow values is also shown (Fig. 2(d)). The flows are normalized by the mean flow values to facilitate comparison. A steep slope in the flow duration curve indicates flashiness of the streamflow response to rainfall inputs whereas a flatter curve indicates a relatively damped response. It also represents the storage characteristics of the watersheds. Figure 2(d) shows the diversity in watersheds with respect to their hydrological response.

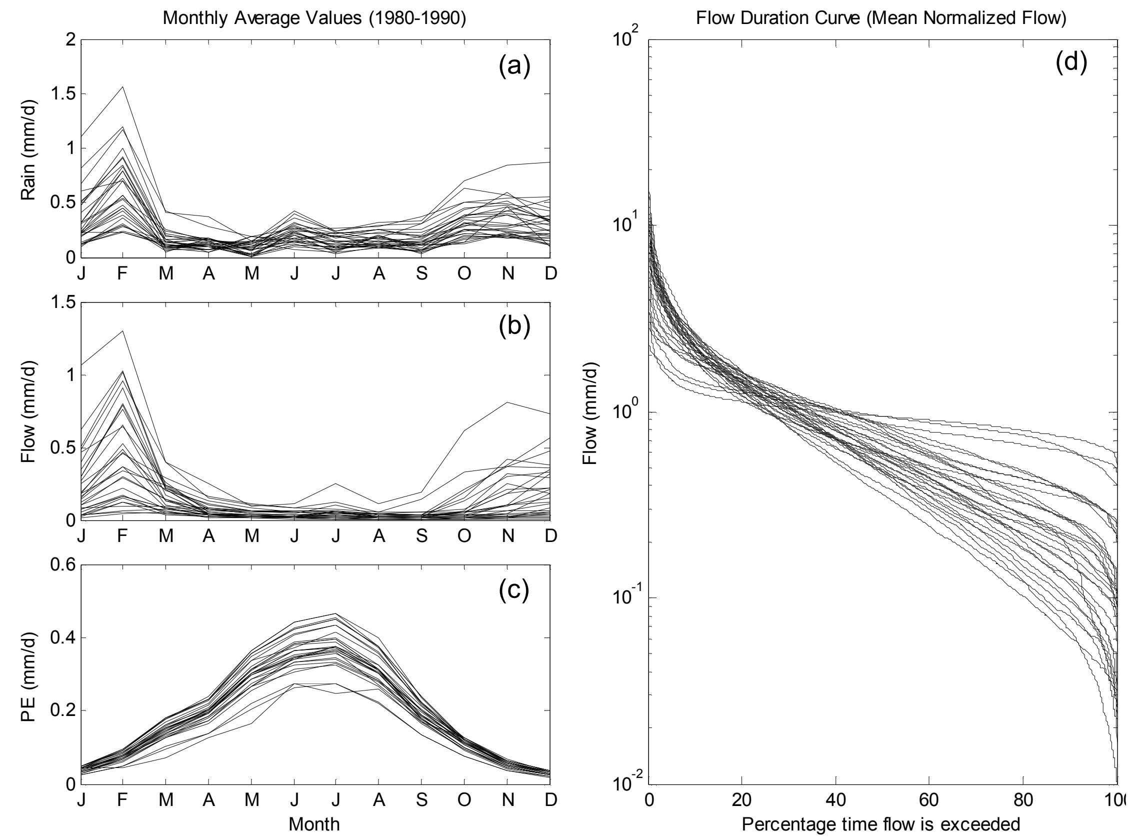

Fig. 2 Average monthly values of: (a) precipitation, (b) streamflow and (c) potential evapotranspiration for 30 UK watersheds. (d) Normalized flow duration curve.

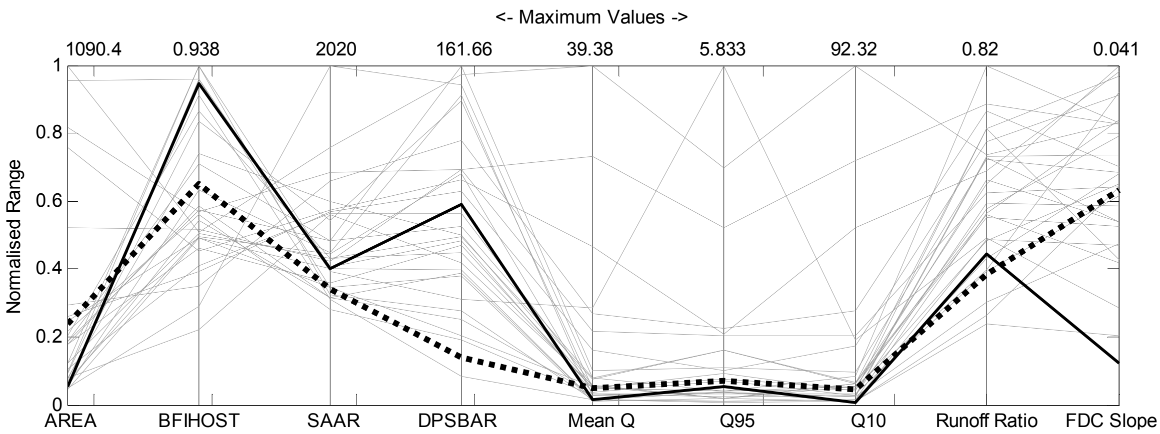

Fig. 3 Parallel coordinate plot showing the variation of response and physical characteristics among 30 UK watersheds. Maximum values for each characteristic are shown on the top axis. SAAR is the standard average annual runoff for the period 1961–1990. Validation watersheds are shown as black lines.

A comprehensive list of physical characteristics for all the watersheds was compiled from the National River Flow Archive (http://www.nwl.ac.uk/ih/nrfa) and the data CD accompanying the Flood Estimation Handbook (FEH, 1999). The main features of these watersheds are presented in a parallel coordinates plot in Fig. 3. The plot shows that most of the watersheds tend to have small area, small mean flow, small ten- and ninety-five percentile flow exceedence values. The two watersheds to be treated as “ungauged” in the study are shown by the continuous and dotted black lines and have very different characteristics from each other.

METHOD

The physical characteristics used in this study were BFIHOST and DPSBAR. BFIHOST (–) is the long-term average fraction of flow that occurs as baseflow—regionalized for the UK—and DPSBAR (m km^{-1}) is an index of watershed steepness (Boorman *et al*., 1995). BFIHOST is estimated from a regression equation where BFIHOST is the independent variable and the HOST classifications (combining soils and geological information in the Hydrology Of Soil Types) are the dependent variables. The equation takes the form:

$$BFIHOST = a_1 * HOST_1 + a_2 * HOST_2 + ... + a_{29} * HOST_{29} \tag{1}$$

where $HOST_1 ... HOST_{29}$ are the proportions of each of the HOST classes, and $a_1 ... a_{29}$ are the regression coefficients (Boorman *et al*., 1995).

Only two response characteristics were used in this study, runoff ratio and slope of the FDC. Runoff ratio is the ratio of mean annual streamflow, normalized by watershed area, to mean annual precipitation. The slope of the FDC was calculated by taking the part of curve between the 33% and 66% flow exceedence values of streamflow normalized by their means. Linear regression equations between individual response characteristics and physical characteristics for the 28 UK watersheds were developed based on an equation of the following form (Kottegoda & Rosso, 1997):

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{p-1} x_{p-1} + \varepsilon \tag{2}$$

where Y is the response characteristic of interest, $x_1, x_2, ..., x_{p-1}$ are p–1 physical characteristics with p regression coefficients (β_0, β_1, … , β_{p-1}) and ε is an error term. Figure 4 shows the regression relationships between BFIHOST and FDC slope (Fig. 4(a)), and DPSBAR *vs* runoff ratio (Fig. 4(b)) under uncertainty. The coefficients of determination (R^2) were 0.69 and 0.58, respectively. The regression includes the estimation of prediction and confidence intervals; the confidence interval is a measure of the certainty (or uncertainty) of predicting the true (expected) value of the variable while the prediction interval is a measure of the certainty of predicting some future (possible) value of the variable. Since the uncertainty in prediction intervals includes the uncertainty in the regression parameters (β_0, β_1, …, β_{p-1}) and any new measurement (Y), this interval is wider than the confidence interval, which considers uncertainty in regression parameters only, while the measurements are assumed to be random variables. Figure 4 also shows the watersheds sorted by drainage area (black corresponds to the smallest area and white corresponds to the largest area). The Roden River at Rodington, shown in square markers (dotted line in Fig. 3), and the Tillingbourne River at Shalford, shown in diamond markers (solid black in Fig. 3) are the two watersheds not used for developing the regression equations. These two watersheds were chosen intentionally to test the strength of the approach such that one

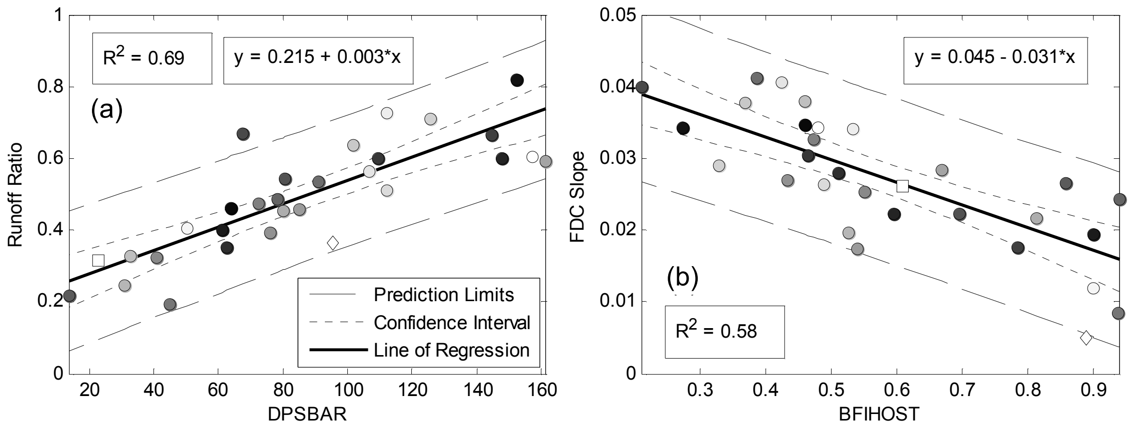

Fig. 4 Linear regression between response and physical characteristics for 28 UK watersheds. The square and diamond show the validation watersheds.

of them was close to the regression line and the other far away from it. The known values of DPSBAR and BFIHOST were used to calculate the confidence and prediction limits of runoff ratio and flow duration curve slopes from the regression equations for the two validation watersheds.

The simple lumped hydrological model (e.g. Wagener *et al.*, 2001) chosen for this study (Fig. 5) has five adjustable parameters, *Huz*, *b*, α, *Kq* and *Ks* (Table 1). It consists of a probability-distributed model as the soil moisture accounting model and a combination of a three-reservoir Nash Cascade for quick flow and a single reservoir slow flow routing model. The model was run within a Monte Carlo framework by randomly sampling 10 000 parameter sets so as to uniformly cover a predefined feasible space. For performance evaluation, the Nash-Sutcliffe Efficiency measure (NSE) (equation. (3)) and the Root Mean Squared Error measure (RMSE*) (equation (4)) were used, the latter computed using a Box Cox transformation applied to the observed and simulated flows:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(q_i - \hat{q}_i)^2}{\sum_{i=1}^{N}(q_i - \frac{1}{N}\sum_{i=1}^{n} q_i)^2} \tag{3}$$

$$RMSE^* = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(q_i^* - \hat{q}_i^*)^2} \tag{4}$$

$$q_i^* = \left(q_i^{\lambda} - 1\right)/\lambda \tag{5}$$

where q_i is mean daily streamflow (mm), $\hat{q}_i$ is the model simulated daily streamflow (mm), N is the length of time series of flow, q_i^* and $\hat{q}_i^*$ are Box Cox transformed values of daily observed and simulated streamflows, respectively (5), with a value of 0.3 for the transformation parameter λ. The two measures were selected because of their emphasis on fitting different parts of the time series of flow (i.e. peak flows and low flows, respectively).

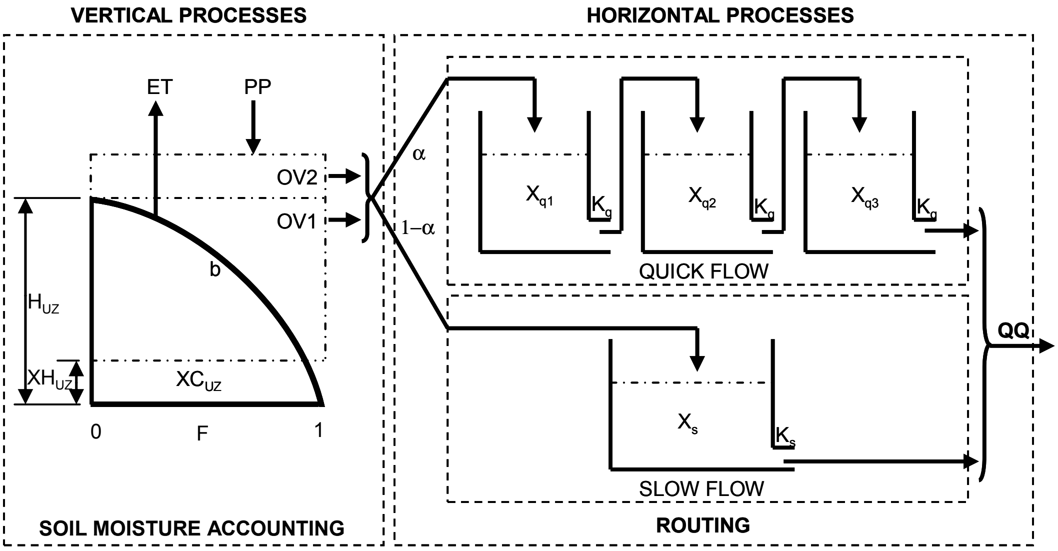

Fig. 5 Lumped 5-parameter model structure. ET and PP are potential evapotranspiration and precipitation respectively (mm). OV1 and OV2 are model simulated effective rainfall components (mm). X_i are states of individual buckets of the routing model. QQ is model simulated streamflow (mm). XH_{UZ} and XC_{UZ} are soil moisture accounting tank state contents (mm).

Table 1 Description of model parameters.

Parameter	Description	Unit	Min	Max
H_{UZ}	Maximum storage capacity of watershed	mm	1	300
b	Index describing spatial soil moisture distribution	–	0	2
α	Flow distribution coefficient	–	0	1
K_q	Residence time of quick flow reservoir	s^{-1}	0	1
K_s	Residence time of slow flow reservoir	s^{-1}	0	1

For selection of parameter sets giving acceptable simulations, those having response indices (runoff ratio or FDC slope) that lie within the confidence and prediction limits were considered behavioural, i.e. acceptable representation of the watershed. The method was first applied separately for each of the regression equations individually and then using the combination of both. The maximum and minimum simulated flows generated by the behavioural parameter sets (i.e. lying within the confidence and prediction intervals) were determined for each time step, and used to form the predictive ranges for the simulations.

RESULTS

The method described above was tested using the two "verification" watersheds as stated before. For reasons of brevity, only the results from the Roden River at Rodington (dotted line in Fig. 3, square in Fig. 4) are presented in detail here. The results obtained by using only one regression equation (runoff ratio *vs* DPSBAR) are shown in Fig. 6(a)–(c). The confidence and prediction intervals derived from the regression analysis have clearly constrained the parameter space in terms of the performance evaluation criterion used. Figure 6(c) shows the maximum and minimum simulated flows for these intervals and for the complete range of simulations. The 50-day period before the dashed vertical line was used as a model warm-up period. The observed streamflow is seen to lie fully inside the prediction intervals after the warm-up period. The number of behavioural simulations when flow is constrained by the prediction limits of the runoff ratio was 5764 (58%), and the corresponding number was 1857 (19%) for flow constrained by confidence limits of the runoff ratio.

The number of behavioural simulations decreased further when the constraints imposed by both regression equations were applied simultaneously (see Fig. 7(c)) resulting in a further narrowing of the confidence and prediction bands (compare with Fig. 6(c)). Again, the observed flow and best simulations lie within the predicted range. The confidence and prediction limits for this case are shown in Fig. 7(a) and (b). When the flow was constrained by the wider ranges (prediction limits) of both response characteristics the number of behavioural simulations was 1114 (11%), reducing to only 42 (0.4%) when the flow was constrained by the narrower confidence limits.

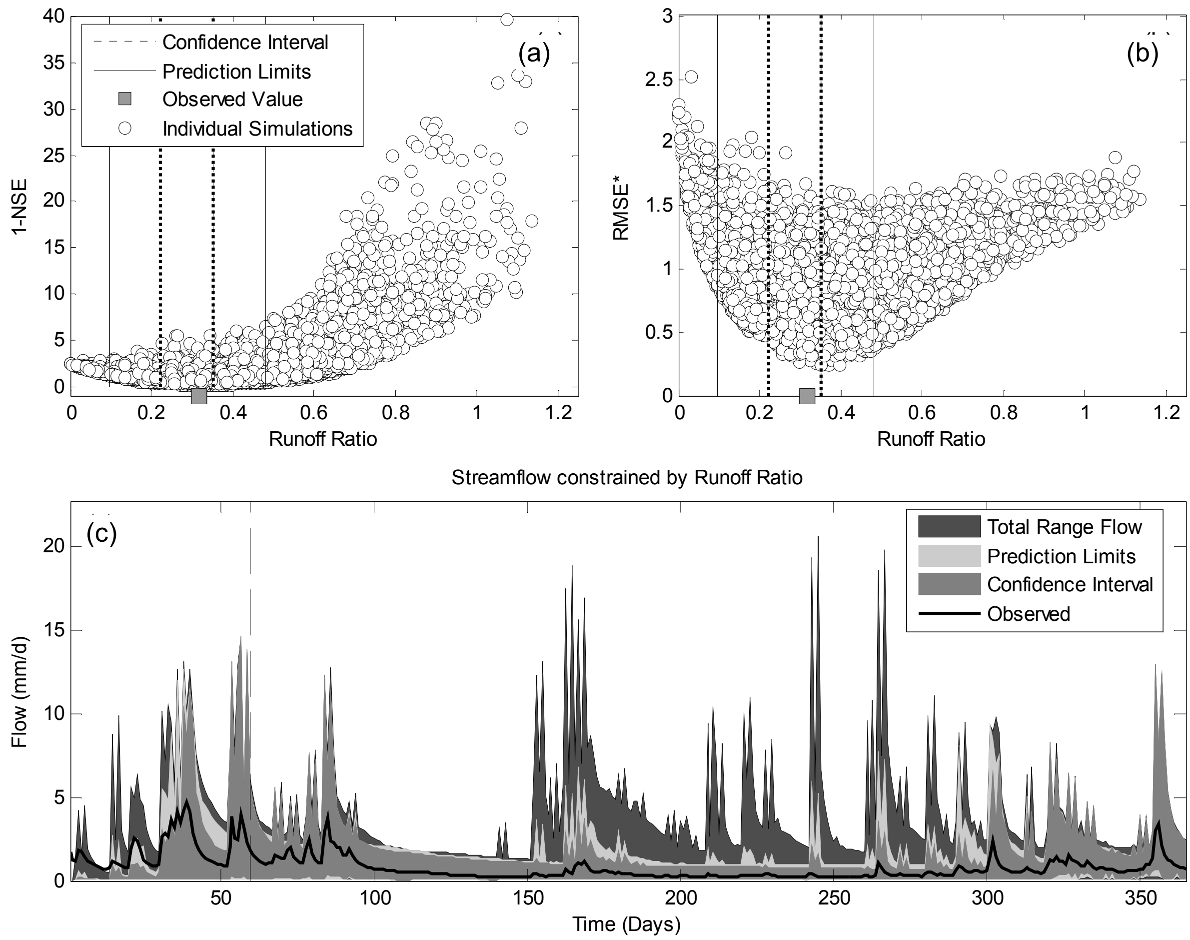

Fig. 6 Dotty plots of simulated runoff ratio *vs* (a) 1-NSE and (b) RMSE*. (c) Observed and (constraint) predicted streamflow ranges.

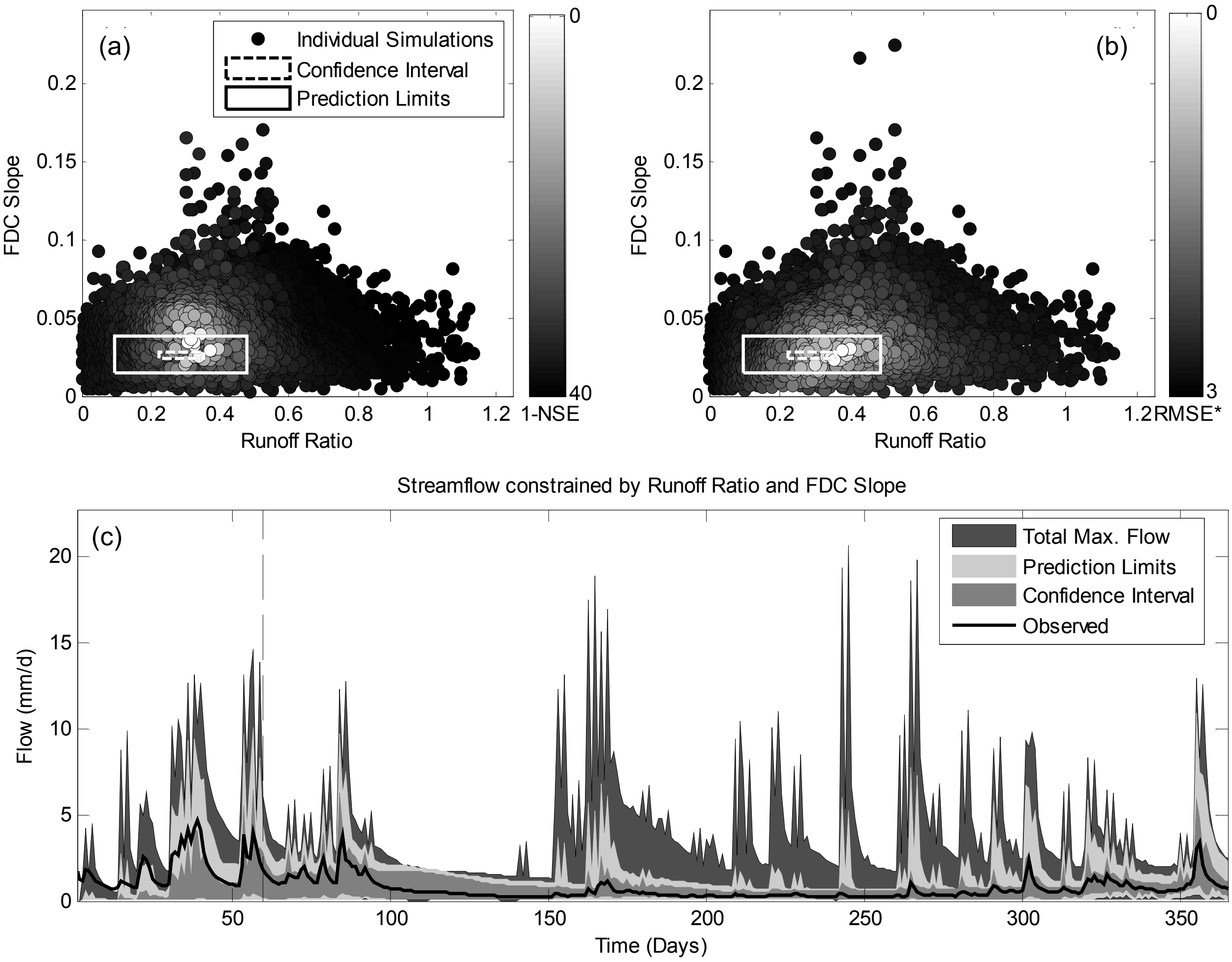

Fig. 7 Dotty Plots of runoff ratio *vs* slope of flow duration curve for: (a) 1-NSE and (b) RMSE*. (c) Observed and (constraint) predicted streamflow ranges.

DISCUSSION AND CONCLUSIONS

This paper presents an approach to reduce the uncertainty on predictions in ungauged basins through the regionalization of watershed characteristics using a framework that properly exploits the "uncertainty" information contained in the regionalization regression relationships. The initial results presented here illustrate the efficiency and ability of the approach in providing suitably constrained model-based hydrological predictions. More thorough testing will include the use of a larger set of informative indices and alternative hydrological models. Further, results with more statistical robustness can be obtained by a bootstrapping-type approach in which watersheds within the data set are treated in turn as ungauged. These results will be reported in due course. As always, we invite discussion and correspondence on this and related topics.

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