Impact of dynamic response characteristics on uncertain streamflow prediction

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Abstract

The influence of various dynamic watershed response characteristics as constraints on uncertain model prediction is studied. A new approach to predictions in ungauged basins is presented in this paper where dynamic response characteristics are regionalized to watershed physical characteristics. The approach therefore uses a data driven regionalization method under uncertainty rather than the standard hydrologic model driven regionalization. Uncertainty is propagated into the model predictions from ungauged basins in the form of constraints on acceptable hydrologic model behavior. This study tries to look at the impact of different response characteristics as constraints on streamflow prediction and on different parts of streamflow, driven, non driven flow and peak flows. Initial results identify key response characteristics and their importance in terms of the characteristics function of the watershed.

Key words Hydrograph indices; Prediction in ungauged basins; Predictive uncertainty; Regionalization; Reliability; Sharpness; Watershed characteristics; Watershed response;

INTRODUCTION

Predicting flows has always been a challenge in water resources. A variety of rainfall runoff models are used today that range from being computationally exhaustive to very simple lumped parsimonious models (Wagener *et al.*, 2004). The problem is accentuated further when it comes to prediction in ungauged basins. Many approaches for predictions in ungauged basins are suggested in the past but none are effective and the uncertainty factor is large. Two common approaches are using physically based models and regionalizing the model parameters to watershed characteristics. A big limitation to using physically based models is that the model parameters estimated from observable watershed characteristics do not represent the model parameters most of the times (Beven, 1989). This brings in huge uncertainties in the predictions. The limitations of regionalizing the model parameters to watershed characteristics include the model structure errors, model identification and use of an appropriate calibration strategy (Wagener and Wheater, 2005).

In this study we examine a novel approach to predictions in ungauged basins where model independent dynamic watershed response characteristics are regionalized to watershed physical characteristics. Here regression relationships with uncertainty are developed between the response characteristics and watershed physical characteristics for gauged watersheds. The uncertain prediction bands are then calculated for the ungauged watershed from this relationship. The selected model is run under Monte Carlo framework and the simulations that turn out the value of the selected response characteristic within the prediction band are classified as behavioral. In this paper we study the effect of 14 response characteristics as constraints on uncertain prediction of models. We report the initial results of the impact of 14 response characteristics computed at different temporal scales on the uncertain prediction. We also report the impact of individual response characteristics on parts of hydrograph (driven flow, peak, and non-driven flow).

CHARACTERISTICS OF DYNAMIC WATERSHED RESPONSE BEHAVIOR

Dynamic response characteristics or indices are numerical measures derived from precipitation, evapotranspiration (or temperature) and streamflow time series of the watershed. Some examples of the indices include runoff ratio, slope of the flow duration curve, limb densities, mean flow, etc. Table 1 and Fig. 1 give the description of the response characteristics used in this study. The response characteristics were calculated from the dynamic timeseries at different timescales to consider streamflow variability at these scales. For example Peak discharge precipitation ratio (Beighley and Moglen, 2002) given by equation (1) is at daily timescale, Rising limb density and declining limb density (Shamir *et al.*, 2005) are calculated from weekly timesries of streamflow, Maximum April Flow is calculated from monthly time series of flow and runoff ratio represents yearly timescales.

Since the response characteristics are independent of the model, the modeling uncertainties can be reduced if they are used judiciously in rainfall runoff modeling. It is thought that the response characteristics can be used as constraints on the model predictions.

Table 1 List of response characteristics used in this study.

Streamflow Index	Scale	Unit	Equation/ Description
Peak Discharge-Precip Ratio	Daily	-	Ratio of peak discharge to precipitation
Rising Limb Density	Weekly	week^{-1}	Number of peaks/ cumulative time of rising limbs
Declining Limb Density	Weekly	week^{-1}	Number of peaks/ cumulative time of falling limbs
Specific Runoff	Yearly	mm	Average Annual Runoff
Runoff Ratio	Yearly	-	mean annual runoff/ mean annual precipitation
Max Apr	Monthly	mm	Maximum April Flow
Max Aug	Monthly	mm	Maximum August Flow
Max Dec	Monthly	mm	Maximum December Flow
Max Neg Chg	Monthly	mm	Maximum Negative Flow Change
Max pos Chg	Monthly	mm	Maximum Positive Flow Change
Min Neg Chg	Monthly	mm	Minimum Negative Flow Change
Min Pos Chg	Monthly	mm	Minimum Positive Flow Change
FDC Sl beg	Daily	-	Slope of Flow Duration Curve (0-5% exceedance flow)
FDC Sl mid	Daily	-	Slope of Flow Duration Curve (33-66% exceedance flow)

Peak Discharge Precipitation Ratio (R(t)):

$$R(t) = \frac{Q^{a}{}_{\max}(inst) - Q^{d}{}_{\min}(avg)}{P^{2d}{}_{wt}} \tag{1}$$

Where,

Table 2 Description of terms for calculation of peak discharge precipitation ratio.

$Q^{a}{}_{\max}(inst)$	Instantaneous annual maximum discharge
$Q^{d}{}_{\min}(avg)$	Minimum daily averaged discharge in the three day window prior to the peak discharge
$P^{2d}{}_{wt}$	$\sum_{j=1}^{n} P^{2d}{}_{j} * W_j$
J	Individual gages
N	Number of gages being considered =2 (pre 1948) and 3-6 (post 1948)
$P^{2d}{}_{j}$	Maximum two day precipitation in the three day window around the annual maximum discharge (t-1, t(max Q), t+1)
W_j	Weighting function determined by the mean or the inverse distance squared options

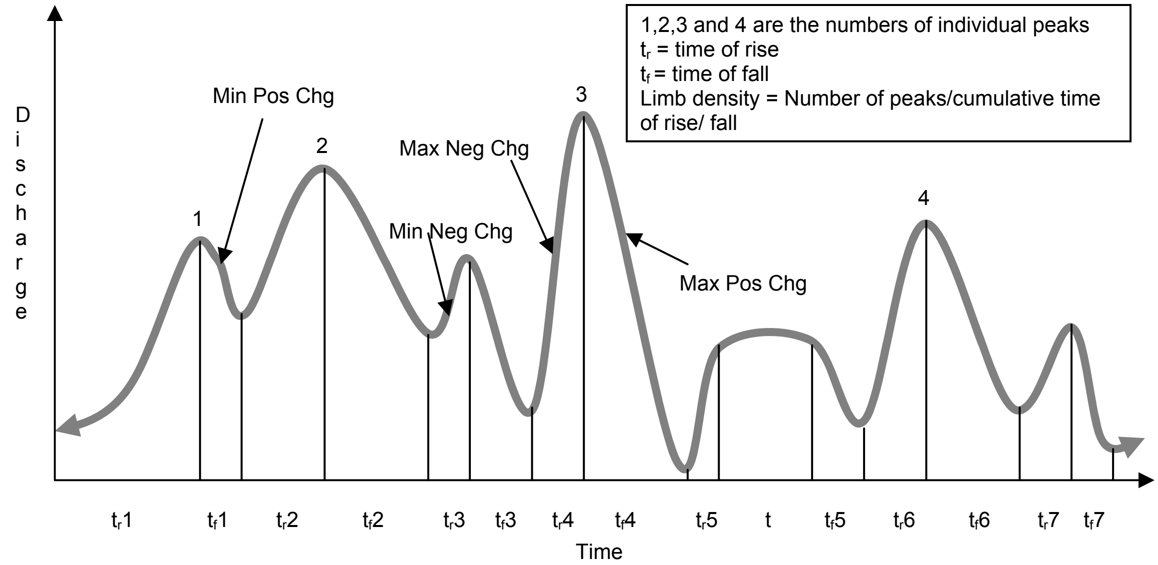

Fig. 1 Description of watershed response characteristics from Table 1.

CASE STUDY

Data

A medium sized watershed located in UK has been used for the present study. The watershed has natural flow within 10% at the 95 percentile flow. Data for the selected watershed was acquired from The 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 Center (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 but only one year (1980) of data has been used in this study to reduce the model run time.

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Method

To see the effect of various response characteristics as constraints on uncertain prediction of rainfall runoff models, 14 response characteristics were selected. The values of these characteristics were calculated for the selected watershed from the timeseries of streamflow, precipitation and evapotranspiration. Four bands of different bandwidths were calculated for each response characteristic. The bandwidths were calculated by increasing and decreasing the value of response characteristic by 25%, 50%, 75% and 100%.

A simple 5-parameter lumped hydrologic model was chosen for this study (Fig. 2). It consists of a probability distributed model as the soil moisture accounting model and a combination of 3 reservoir Nash Cascade for quick flow and a single reservoir slow flow routing model. The model has five adjustable parameters, Huz, b, α, Kq and Ks (Table 3). The model was run within a Monte Carlo framework randomly sampling the parameters from a predefined uniform space.

Table 3 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

The model was run for 2000 random uniformly sampled parameter values. The simulations with the value of response characteristics within the chosen bandwidth are considered as behavioral simulation. All the behavioral simulations taken together form the uncertain prediction band of the model. The whole procedure was repeated for all the bands of the response characteristics as stated above.

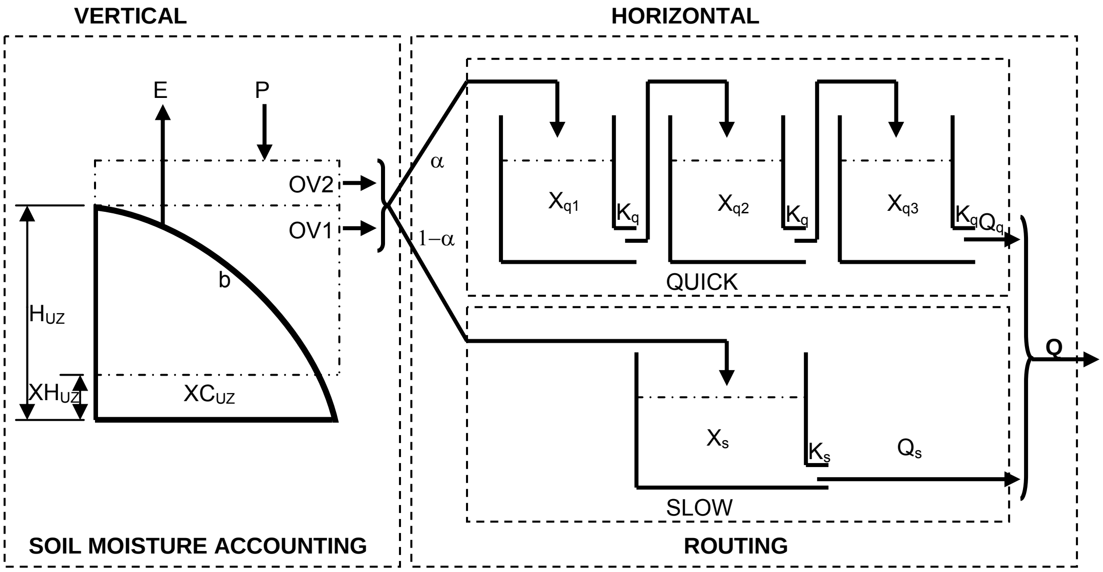

Fig. 2 Lumped 5-parameter model structure. ET and PP are potential evapotranspiration and precipitation respectively [mm]. OV1 and OV2 are model simulated effective rainfall components [mm]. X_i are states of individual buckets of the routing model. QQ is model simulated streamflow [mm]. XH_{UZ} and XC_{UZ} are Soil moisture accounting tank state contents [mm].

To see the effect of response characteristics on different parts of the hydrograph, the whole timeseries was classified into driven flow, peak flow, quick non driven flow and slow non driven flow (fig. 3). The above procedure was repeated for these parts and the results were shown in terms of Reliability and Sharpness. Reliability is the percentage of time the observed streamflow is within the prediction band of the model. Sharpness is the average measure of uncertain prediction band of streamflow in percentage. A small value of sharpness represents a large reduction in uncertainty in streamflow prediction (fig. 4).

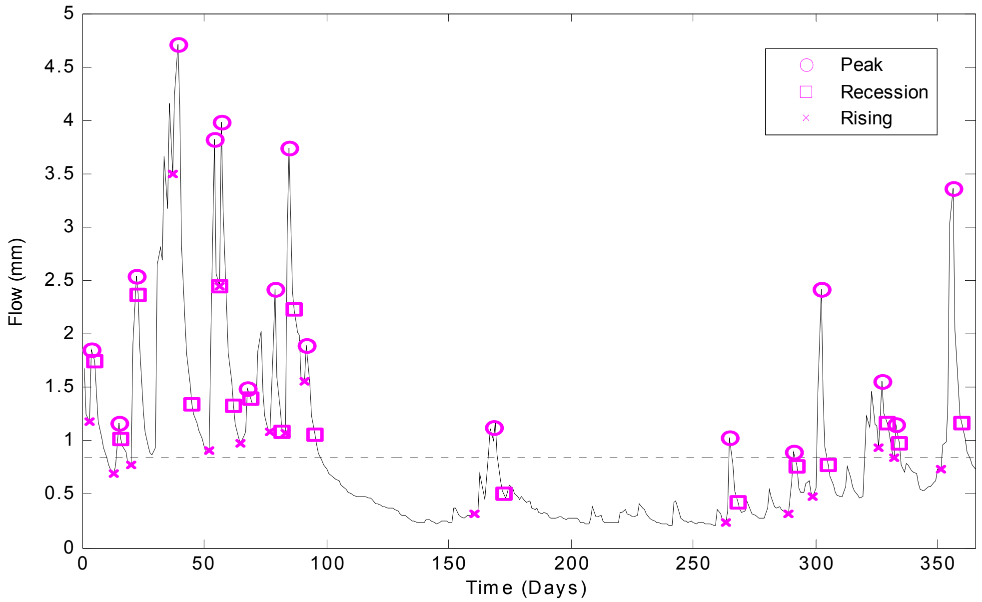

Fig. 3 The part of streamflow between cross and circle is taken as driven flow, the part between circle and square is taken as quick recession and the part between square and cross is taken as slow recession.

Results

Table 4 gives the sharpness values for the different bands of response characteristics. A lower value of sharpness (high sharpness) shows that the uncertainties in the model predictions are less. It can also be seen from Fig. 4 that the sharpness increases with the decrease in band width of the response characteristics. It is also worth noting that upon reducing the bandwidth to 25%, some part of the observed flow went out of the prediction band which shows that reliability begins to decrease as the bandwidth of the response characteristics becomes smaller. Fig. 4 shows the effect of the response characteristic, Maximum April Flow as a constraint on the uncertain prediction of the model. It can be inferred from Table 4 and Table 5 that some response characteristics constrain the model with high sharpness but show less reliability. It was observed that the reliability decreases with increasing sharpness.

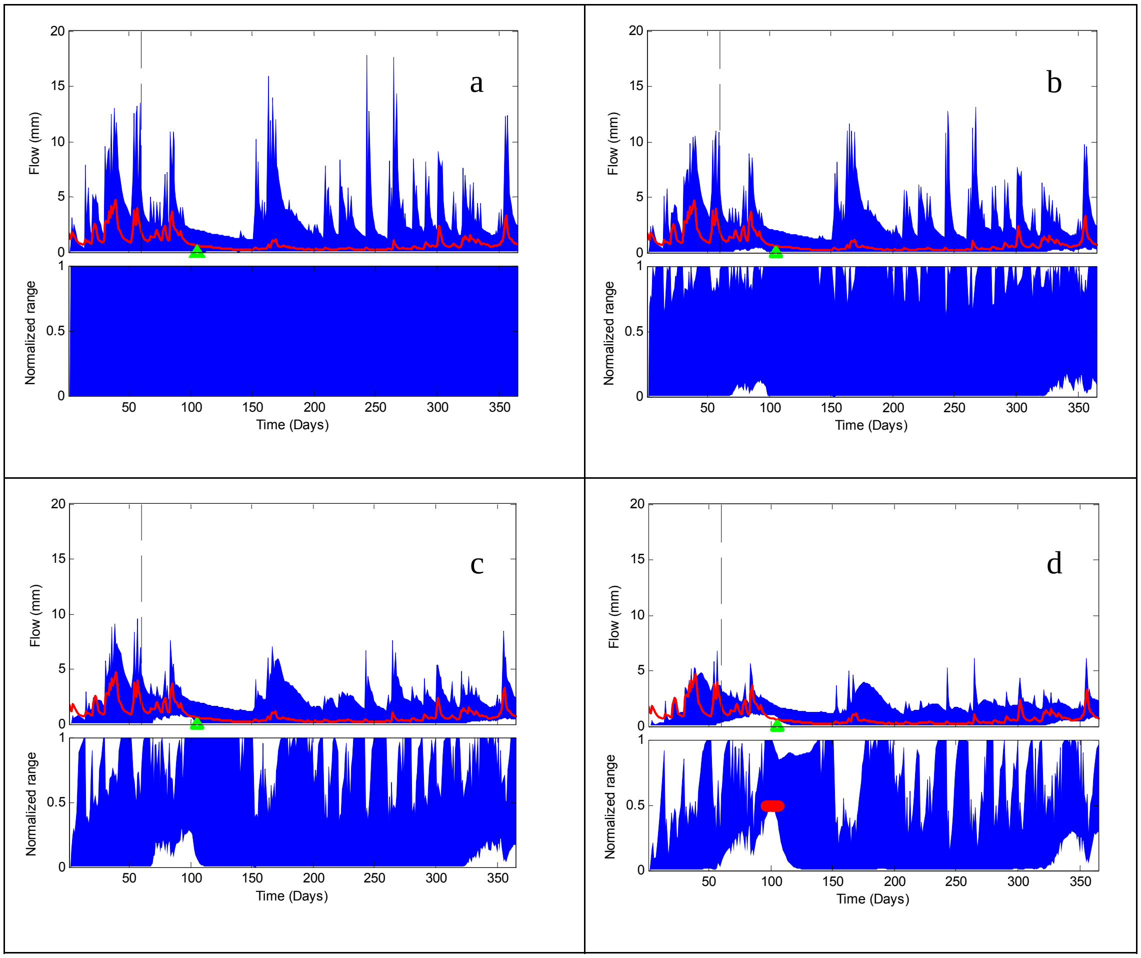

Fig. 4 Bandwidths of Maximum April Flow a) 100% b) 75% c) 50% and d) 25%. The blue area in the plot below the timeseries plot shows the values of sharpness at each time step. (d) Some part of the observed streamflow is outside the prediction band.

The blue band in the timeseries figure (Fig. 4) shows the amount of the uncertainty constrained by different bands of response characteristic.

Table 4 Average Sharpness values

	100%	75%	50%	25%
Pr_Q Ratio	98	88	84	74
RLD	100	100	99	95
DLD	100	100	99	95
Spec Runoff	76	70	62	55
Runoff Ratio	84	77	70	59
Max Apr	100	93	79	64
Max Aug	77	73	68	63
Max Dec	100	99	99	98
Max Neg Chg	100	97	93	87
Max pos Chg	86	77	74	59
Min Neg Chg	49	39	26	23
Min Pos Chg	75	66	64	50
FDC Sl beg	99	96	84	54
FDC Sl mid	97	96	89	86

Table 5 Reliability Values

	100%	75%	50%	25%
Pr_Q Ratio	100	100	100	100
RLD	100	100	100	100
DLD	100	100	100	100
Spec Runoff	100	100	100	100
Runoff Ratio	100	100	100	100
Max Apr	100	100	100	96
Max Aug	100	100	100	100
Max Dec	100	100	100	100
Max Neg Chg	100	100	100	100
Max pos Chg	100	100	100	100
Min Neg Chg	99	93	46	30
Min Pos Chg	100	100	100	98
FDC Sl beg	100	100	100	100
FDC Sl mid	100	100	100	100

DISCUSSION AND CONCLUSIONS

Sharpness for some of the response characteristics for 50% and 25% bands were high and reliability for most of them over all the bandwidths was close to 100%. The key response characteristics for the whole timeseries were, Peak discharge precipitation ratio, specific runoff, runoff ratio, maximum and minimum positive flow changes and slope of flow duration curve (0 – 5% flow). All of these characteristics are global characteristics of streamflow and these can be expected to affect the streamflow prediction significantly. The other characteristics represent the local behavior of streamflow (eg. Max April flow, Max Dec flow, etc.) and so may not play a major role in constraining the streamflows.

A look at the response characteristics that impact local parts of streamflow reveal that Limb Densities, Specific Runoff, Maximum August flow and Maximum rising limb change have significant impact on the prediction bands (high sharpness) of Driven flow, peak flow and quick recession. The slow recession part of the hydrograph was also constrained by these characteristics. In addition, the slope of flow duration curve (33%-66%) also had a notable impact on the model prediction of slow recessions. This is expected since the flow duration curve defines if the streamflow of a watershed is flashy or damped in nature.

This study sheds some light on the possible influence of various response characteristics on the uncertain streamflow predictions of any model. But these results are preliminary and hence are not conclusive since the approach has only been applied on one watershed. Validity of this novel approach can be established by applying this approach to more watersheds.

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