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A trading-space-for-time approach to probabilistic continuous streamflow predictions in a changing climate – accounting for changing watershed behavior

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Abstract. Projecting how future climatic change might impact streamflow is an important challenge for hydrologic science. The common approach to solve this problem is by forcing a hydrologic model, calibrated on historical data or using a priori parameter estimates, with future scenarios of precipitation and temperature. However, several recent studies suggest that the climatic regime of the calibration period is reflected in the resulting parameter estimates and model performance can be negatively impacted if the climate for which projections are made is significantly different from that during calibration. So how can we calibrate a hydrologic model for historically unobserved climatic conditions? To address this issue, we propose a new trading-space-for-time framework that utilizes the similarity between the predictions under change (PUC) and predictions in ungauged basins (PUB) problems. In this new framework we first regionalize climate dependent streamflow characteristics using 394 US watersheds. We then assume that this spatial relationship between climate and streamflow characteristics is similar to the one we would observe between climate and streamflow over long time periods at a single location. This assumption is what we refer to as trading-space-for-time. Therefore, we change the limits for extrapolation to future climatic situations from the restricted locally observed historical variability to the variability observed across all watersheds used to derive the regression relationships. A typical watershed model is subsequently calibrated (conditioned) on the predicted signatures for any future climate scenario to account for the impact of climate on model parameters within a Bayesian framework. As a result, we can obtain ensemble predictions of continuous streamflow at both gauged and ungauged locations. The new method is tested in five US watersheds located in historically different climates using synthetic climate scenarios generated by increasing mean temperature by up to 8 °C and changing mean precipitation by −30 % to +40 % from their historical values. Depending on the aridity of the watershed, streamflow projections using adjusted parameters became significantly different from those using historically calibrated parameters if precipitation change exceeded −10 % or +20 %. In general, the trading-space-for-time approach resulted in a stronger watershed response to climate change for both high and low flow conditions.

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1 Introduction

Hydrologic models are necessary to estimate how streamflow and other hydrologic variables might change under a changing climate and under changing land use at scales relevant for decision-making (Wagener et al., 2010). These models are operationally applied in risk analysis to assess how hydrologic hazard frequencies (droughts and floods) might be altered, in water management to derive strategies for the sustainable use of available resources, or to assess what ecosystem services might be available in the future (e.g. Weiskel et al., 2007; Richter et al., 1996, 2003; Poff et al., 2006, 2007; Arthington et al., 2006; Milly et al., 2008). Sustainable management of water resources and robust risk assessment will require modeling tools that provide scientifically sound and credible estimates of relevant water indicators under different scenarios (Mahmoud et al., 2009). Currently available hydrologic models have generally been found to require some degree of calibration to historical observations of the hydrologic variable of interest at the location of study to provide such robust and reliable simulations. The a priori parameterization of hydrologic models – from directly observable watershed characteristics such as soils and vegetation – is possible and widely used, but it is generally found that parameters derived from observable static characteristics of the watershed under study, are inferior to calibrated models (e.g. Duan et.al, 2006; van Werkhoven et al., 2009; Kapangaziwiri and Hughes, 2009). Calibration of the model on historical observations is therefore the most common method for identifying model parameters when sufficient streamflow data is available.

An acknowledged major problem in the use of such models is therefore the uncertainty in prediction at ungauged locations (Sivapalan et al., 2003). The regionalization of model parameters is the most widely used strategy to overcome this lack of local observations, next to the use of a priori parameter estimates. In this approach, the parameters of a hydrologic model, calibrated to many gauged watersheds, are regressed with the physical/climatic characteristics to identify a regional relationship to predict the parameters at ungauged locations. Many variants of this idea have been tried and its limitations are discussed elsewhere (e.g. Wagener and Wheater, 2006). More recently a different strategy has been promoted in which streamflow characteristics are regionalized and used to condition a hydrologic model (Bardossy, 2007; Yadav et al. 2007; Zhang et al., 2008; Bulygina et al., 2009, 2011; Wagener and Montanari, 2011). This strategy is reducing some of the problems identified in parameter regionalization such as the often-observed lack of correlation between model parameters and landscape characteristics.

We postulate that there is significant similarity between the predictions in ungauged basins problem discussed above and the task of simulating the watershed response under a potential future climate. Similar strategies might therefore be applicable to both tasks. Even if calibration on historical records provides us with reliable estimates of model parameters for current conditions, there is the potential that parameters estimated in such a manner are not reflective of the watershed behavior in a different climate (Wagener, 2007; Peel and Bloeschl, 2011). The more the potential future climate differs from the observed past, the more biased our calibrated model parameters might be.

Several recent studies have established corroborating evidence for a link between climate conditions and calibrated model parameters. Van Werkhoven et al. (2008) found that the sensitivity of the parameters of a medium complexity lumped watershed model varied with climatic conditions for different watersheds across the eastern US. Merz et al. (2011) showed that parameters of the HBV model, especially those reflecting near surface processes, varied when re-calibrating the model for data periods with different mean temperatures and precipitation. In their study, the maximum soil moisture storage parameter, FC, changed from 150 mm to 250 mm over a period of three decades which was attributed to a rise in temperature of around 2 °C. They hypothesized that this is reflecting the higher storage potential of a drier soil. Vaze et al. (2010) found that model performance declined when historically calibrated parameters were used for significantly different climatic conditions in the same watershed. They concluded that lumped conceptual runoff models calibrated over average or wet climatic periods are unsuitable for simulating runoff over dry periods of one decade when the difference in mean rainfall exceeded 15 percent. Also, they found that models calibrated over average or wet periods are suitable for simulating runoff over wet periods of one decade only when the difference in mean rainfall is less than 20 percent. A similar study by Bastola et al. (2011) shows that parameters calibrated over wet (dry) climates have a tendency to produce less (more) runoff in dry (wet) periods. Rosero et al. (2010) demonstrated that even for a physically-based model, the NOAH land surface model, behavioral parameters could be related to the climatic variability between the locations to which the model was applied.

These studies point towards the need for a new modeling strategy, one that can consider the observed relationship of parameters with climate, without which most of our predictions might be biased. One could of course argue that the uncertainty in climate change projections is so large that any uncertainty or bias in the hydrologic model and its parameters might not matter (e.g. Buytaert et al., 2009; Maurer et al., 2005; Ghosh et al., 2009). However, the question to be addressed is rather, given perfect knowledge of a future climate trajectory, could we reliably estimate streamflow (or other hydrologic variables)? Unlikely, given the evidence of the studies just described. It is also important to stress that the search for an alternative parameter estimation strategy, similar to the need to calibrate hydrologic models in the first place, is simply a reflection of the limitations of our models. Ultimately, the development of better models is the solution we should strive for, rather than a new calibration strategy (Wagener et al., 2010). Therefore, this study provides a crutch for the time being, and it might, through its results, also provide guidance how current hydrologic models could be improved.

One way to approach the problem of climate dependence of model parameters is by utilizing the similarity between extrapolation of models in space (regionalization) and the extrapolation in time, i.e. trading-space-for-time. Yadav et al. (2007) introduced a model-independent method to predict streamflow in ungauged basins by developing empirical relationships between watershed response characteristics (termed signatures) such as the runoff ratio (long term ratio of streamflow to precipitation) and climatic and physical characteristics. These signatures are regionalized in an

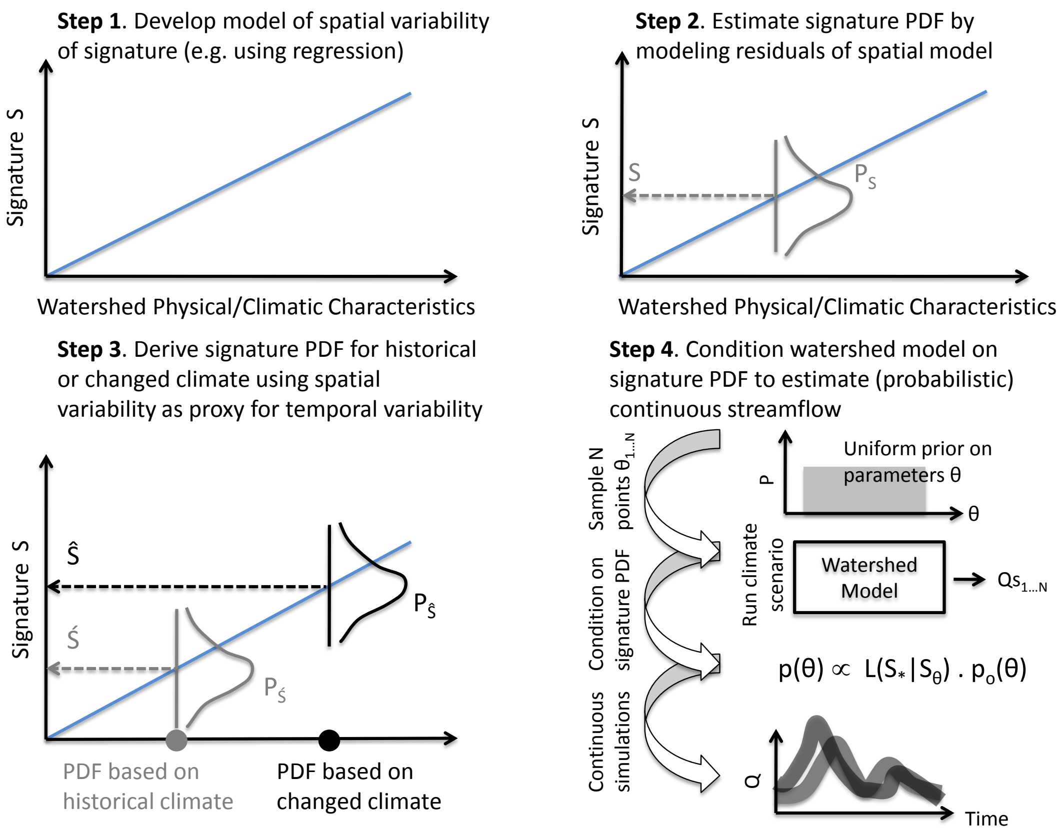

Fig. 1. The four step procedure for deriving probability distributions of streamflow for climate scenarios. In Step 2, S a signature and P_S is the probability associated with a signature value. In Step 3, $\acute{S}$ and $P_{\acute{S}}$ correspond to the distribution based on historical climate and $\hat{S}$ and $P_{\hat{S}}$ correspond to the distribution based on changed climate. In Step 4, θ represents the model parameters, $Qs_{1...N}$ represents the model simulations, S_* is the expected value of the signature derived from the regionalized relationship and S_θ is the value of the signature for the parameter θ.

uncertainty framework to predict expected streamflow signatures including their uncertainty in ungauged watersheds. These uncertain predictions can then be assimilated into any hydrologic model. A significant reduction in predictive uncertainty due to this additional source of information was observed (Yadav et al., 2007). This strategy is based on spatial gradients in signatures and it should provide useful information to be assimilated as long as the ungauged basin does not have physical or climatic characteristics outside of the range of observed characteristics used to derive the regional signature relationships. If we assume that these spatial gradients can act as a proxy for temporal gradients (Hundecha and Bardossy, 2004), then we can trade-space-for-time and use the regression relationships developed over the spatial gradient to provide a first-order estimate of signatures at (gauged and ungauged) watersheds under potential future climate regimes. Specifically, Yadav et al. (2007) found strong regional predictive capability for climate-dependent indices such as runoff ratio, which suggests that these indices can be predicted with a certain degree of reliability for potential future climate.

We propose to utilize a trading-space-for-time strategy to account for the climate dependence of behavioral parameters. In essence we are adjusting a strategy previously used to constrain hydrologic ensemble predictions at ungauged locations, i.e. those where no long-term observations of streamflow are available, to extrapolate in time. The approach accounts for uncertainty in the procedure by deriving ensemble predictions due to the uncertainty in model parameterization. This strategy is tested on five climatically different US watersheds to understand the effect of adjusting parameter sets with changing climate, i.e. whether impacts of climate change on streamflow are larger or smaller than without considering the dependence of behavioral parameters on climate.

2 Method

The basic idea propagated in this paper is that there is a significant similarity between the problems of predictions in ungauged basins (PUB) and the prediction of change (climate or land use) and this similarity can be explored (see also the discussion in Peel and Bloeschl, 2011). Here we alter a strategy for PUB so that it allows us to consider how the response of a particular watershed might change in a different climate (or potentially under altered land use). Signatures are response indices that represent the functional behavior of a watershed and can be derived from observations of hydrologic variables such as streamflow and precipitation. As mentioned earlier, Yadav et al. (2007) (also, Zhang et al., 2008) introduced a strategy in which signatures (incl. their uncertainties) are regionalized and then assimilated into a hydrological model. Uncertainty was included in this analysis by assigning prediction limits to the regionalized signature values. These limits are used to constrain the parameter space of a hydrologic model. If the simulated response for a value of a particular model parameter, θ, lies within the range predicted by the regionalization, it is accepted. A drawback of this strategy is that all accepted parameter values end up having equal probability of occurrence whether or not they are closer to the expected value of the signature, and all rejected parameters are assigned a zero probability of occurrence. Bulygina et al. (2009, 2011) overcame this limitation by using a Bayesian framework such that the posterior probability distribution for model parameters, θ, can be obtained within a regionalization framework.

In this study, we use regionalized relationships to quantify the dependence of model parameters on the climate of the watershed by assuming that spatial gradients established in the regionalized relationship will act as a proxy for temporal gradients that the watershed will undergo under climate change. A regression relationship is developed across a large spatial gradient to estimate the chosen watershed signatures as a function of the watershed physical and climatic characteristics. For a given watershed, climate indices are calculated for each future climate scenario. These indices are then used to predict climatically controlled signatures using the spatial regression equation. This is where the concept of trading-space-for-time is applied. The predicted signatures are subsequently used to condition a hydrologic model, thus considering the expected change in watershed behavior through adjusted parameter values. A similar Bayesian method to the one by Bulygina et al. (2009) is adopted to account for the uncertainty in the regionalized relationships and posterior probability distributions for model parameters are derived as a function of climate. The resulting strategy therefore addresses both the PUB and the predictions of change impacts problem, which allows it to be applied anywhere where predictions are required. The methodology is also independent of the watershed model used.

We provide a holistic approach to quantify the change in parameters with climate while estimating parameter uncertainty by following the steps described here (see Fig. 1) : (Step 1) Empirical regression relationships between signatures, S, and watershed physical/climatic characteristics are developed using spatial variability. (Step 2) The probability distribution of the signatures predicted from the regression equations is derived around their expected value, S_*, with the variance of the distribution being equal to the variance of the residuals of the predicted value. Here we assume that the residuals can be described using a normal distribution (similar to Bulygina et al., 2009, 2010). In case more than one signature is used, the joint probability density function is found by combining the probabilities from the different signature distributions. Here we assume independence of the signature so that they can be sequentially assimilated into the watershed model (Wagener and Montanari, 2011). (Step 3) In Step 2, the likelihood function for the signatures is derived as a function of the physical and climatic characteristics of the watershed, therefore, a change in climate of a watershed translates into a corresponding change in the signature and its probability density function. Substituting the spatial gradients as temporal gradients gives us two likelihood functions that can be assimilated into the model – one based on the historical climate, which is analogous to the approach of keeping model parameters fixed with climate and another based on changed climate, wherein the dependence of model parameters on climate is quantified. (Step 4) In the assimilation step, Bayes theorem is used to combine the likelihood associated with a signature with the prior information about the model parameters to estimate their posterior distribution (Liu and Gupta, 2007). The posterior distribution of a model parameter can be given as (Bulygina et al., 2009),

$$p(\theta) \propto L(S_*|S_\theta) \cdot p_o(\theta) \quad (1)$$

Where, $p_o(\theta)$ is a priori parameter distribution, a uniform distribution in this case; $L(S_*|S_\theta)$ is the likelihood of $S = S_*$ given the model estimate $S = S_\theta$. This likelihood function is derived in step 2. Using uniform random sampling, 10 000 parameter sets are generated for the hydrologic model and corresponding value of signatures is calculated. These values are used in Eq. (1) as the model estimate S_θ For every change in watershed physical/climatic characteristics, we will obtain different posterior distribution for the model parameter sets depending on how strongly the signature depends on climate. These posterior distributions of parameters are then used to predict the probability distribution of streamflow for a given climate. Thus we can predict the cumulative distribution of streamflow using the likelihood of signatures based on historical climate, termed Type H predictions or the likelihood based on changing climate, termed Type C predictions. In the case study shown below, we compare the Type H and Type C streamflow predictions for 5 study watersheds across the United States.

The regionalized signature relationships (the spatial models), which are used to derive the posteriors for model parameters are developed for the base period of 1958–1968. Streamflow predictions are derived from the framework introduced for two types of climate change scenarios: 72 synthetic climate change scenarios and for 4 test periods: 1948–1958, 1968–1978, 1978–1988, and 1988–1996. The climate of the base period serves as the historical climate, which is used to derive the likelihood that gives Type H projections. The climate in the test periods and the synthetic climate scenarios are used to derive the likelihood based on changed climate, Type C projections. Finally, Type H and Type C projections are derived and compared across the different climate scenarios. The test periods are used as a validation step in order to assess the performance of Type C and Type H projections within the observed records. Predictions for synthetic climatic scenarios are used to explore the difference between the two methods in terms of severity of streamflow response, response of streamflow indices, differences in predictive uncertainty etc.

3 Model, data, and climate change ranges analyzed

3.1 Model

The model used for demonstration of the methodology is a parsimonious lumped conceptual watershed model that is widely used (e.g. Boyle et al., 2000; Wagener et al., 2001). It is a derivative of the probability-distributed model (PDM) introduced by Moore (2007). The model is divided into three modules. The precipitation first enters a degree-day snow module that accounts for snow storage and melt (DeWalle and Rango, 2008). Following this is the soil moisture accounting module that describes the available storage in the watershed as a distribution of buckets with varying depth described by a Pareto distribution (Moore, 2007). The effective rainfall generated from the soil moisture accounting module through overflow of the buckets is routed (after splitting, using a split parameter) through a parallel routing module, which consists of a quick flow and slow flow linear reservoirs. The model has a total of 8 parameters and runs at a daily time step to account for snow accumulation and melt.

3.2 Data

A total of 394 watersheds from the MOPEX study (Duan et al., 2006) with around 50 yr of daily data were used in this study for regionalization. Other characteristics of the watersheds required for regression of signatures (such as elevation, soil types etc.) was derived from the Falcone database (Falcone et al., 2010). Watershed sizes ranged from 66.5 km^2 to 10 425 km^2. Potential evaporation is calculated from temperature using Hargreaves' equation (Shuttleworth, 1993). The baseline historical period chosen for this study was 1958-68 on the basis of data availability across all 394 watersheds, and because no significant (wide spread) trends in streamflow were detected in this period in the US (McCabe and Wolock, 2002). The five study watersheds are selected from different climatic regions (Fig. 2), i.e. from the energy-limited zone (long term precipitation, P, exceeds long-term average potential evapotranspiration, PE), the water-limited zone ($P <$PE) and the intermediate-zone where P and PE are roughly even. A detailed description of these watersheds is given in Table 1.

3.3 Climate change ranges

The International Panel on Climate Change (IPCC) provides estimates of expected changes in precipitation and temperature for the United States (Christensen et al., 2007). Guided by the expected extremes discussed in the IPCC report, we chose a matrix of temperature and precipitation change; with precipitation change steps of 10 % and temperature increase steps of 1 °C. Total ranges were −30 % to 40 % for precipitation and 0 °C to 8 °C for temperature. Time-series to drive the model for these different change scenarios were obtained by changing the mean of the precipitation and mean of the temperature for the ten-year base period of 1958–1968. We assumed that the standard deviation of precipitation and temperature remained the same, though it would be straightforward to relax this assumption. This approach to deriving synthetic climate scenarios is similar to many previous studies that assessed watershed sensitivity to climate change including those by Nash and Gleick (1991), Jones et al. (2006) or Jiang et al. (2007). The methodology proposed here could also be run with downscaled climate projections.

4 Results

4.1 Derivation of response indices

Initial tests and experience in previous studies (Yadav et al., 2007; Zhang et al., 2008) resulted in the selection of two signatures that control different aspects of watershed hydrology, runoff ratio (RR) – the long-term ratio of streamflow to precipitation - and baseflow index (BFI) – the long-term ratio of baseflow to total streamflow. Zhang et al. (2008) found that RR was an effective constraint on soil moisture accounting parameters, while BFI constrained the effective rainfall split and routing parameters. Both signatures can be calculated directly from the observed data for the baseline historical period.

Baseflow index is calculated using a one-parameter single pass digital filter method (DFM) (Arnold et al., 1995). The mean of the baseflow index for the baseline period (1958–1968) is taken as the expected value and uncertainty for the baseline period is modeled as a normal distribution for which the standard deviation is estimated from the variability in the annual values of BFI for the period 1958–1968. Spearman rank correlation values (Spearman, 1904) were calculated between the BFI estimate and available climatic catchment descriptors, including aridity index, to ensure that there is no linear or non-linear relationship between climate and baseflow index. No significant correlation between climate and BFI was found. Therefore the probability distribution of the baseflow index was not changed with climate in this study. Although baseflow index did not show strong dependence on

Table 1. Description of validation watersheds for the base period 1958–1968.

Watershed	Lochsa	Lower Androscoggin	Escambia	Meramec	Yampa
State	Idaho/Montana	Maine/New Hampshire	Alabama/Florida	Missouri	Colorado
USGS ID	13337000	1055500	2375500	7019000	9251000
Size [km^2]	3051	438	9886	9811	8832
Mean Basin Elevation [m]	1584	190	95	279	2364
Climate Regime	Energy Limited	Energy Limited	Even	Slightly Water Limited	Water Limited
Aridity Index [−]	0.64	0.86	1.04	1.37	1.81
Precipitation as Snow [%]*	56.0	29.5	0.42	7.5	48.9
Mean Annual P [mm yr^{-1}]	1314	1018	1407	905	556
Mean Annual Q [mm yr^{-1}]	911	541	525	214	132
Mean Annual PE [mm/yr]	841	878	1464	1238	1007
Monthly NSE [−]**	0.93	0.87	0.85	0.81	0.80

* This value is calculated for a threshold temperature of snow formation of 2 °C.
** Nash Sutcliffe Efficiency for base period (1958–1968).

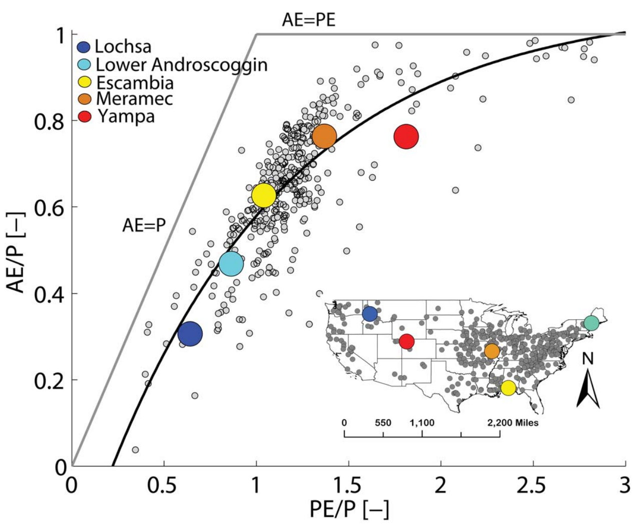

Fig. 2. The Budyo curve with the five study watersheds (394 watersheds are shown as grey dots) highlighted. The black curve shown is a fitted Schreiber model. AE, PE and P are the long term actual evapotranspiration, potential evapotranspiration, and precipitation respectively. AE/P is equal to 1-runoff ratio and PE/P is the aridity index.

climate, it was a necessary constraint on the behavioral parameter space, and hence was included as a signature.

RR on the other hand is to a very large extent climate controlled (e.g. Sankarasubramanian and Vogel, 2003). RR is therefore regionalized utilizing its correlation with climatic gradients. Budyko (1974) was the first to empirically derive a relationship between aridity index (ratio between long-term mean potential evapotranspiration and mean precipitation) and evaporative index (ratio between long-term mean actual evapotranspiration and precipitation, which is equal to 1-RR). Several empirical relationships between the two ratios have been developed since, out of which we tested the Schreiber relationship, the Ol'dekop relationship and the Turc-Pike relationship (Dooge, 1992) for the baseline period 1958–1968. The best regression relationship was obtained using Schreiber's equation, resulting in an R^2 value of 0.69:

$$\frac{\mathrm{AE}}{P} = 1.07 - 1.34 \cdot \exp\left(-\frac{\mathrm{PE}}{P}\right) \qquad (2)$$

where, AE is the actual evapotranspiration, PE is the potential evapotranspiration and P is the precipitation, AE/P is the evaporative index, and PE/P is the aridity index for the period 1958–1968. The uncertainty in the runoff ratio was modeled based on an assumed normal distribution with standard deviation equal to that of the residuals of the regressed relationship. We used this relationship developed over the spatial gradient across 394 watersheds in US to trade space-for-time and predict the future runoff ratio distribution for the 5 study watersheds for changing climate scenarios.

The combination of the two probability distributions, regionalized RR and local BFI, results in a joint PDF that represents the likelihood equivalent that can now be assimilated into any hydrologic model (Eq. 1). The expected value of RR and its probability distribution will change with a changing climate, and so will the joint PDF. It was assumed that RR and BFI are uncorrelated and the two distributions were combined sequentially.

4.2 Validation analysis on test periods

Figure 3 shows a comparison of Type H and Type C streamflow projections. Using the cumulative distribution of the predicted streamflow, the most probable flow and the 90 % prediction limits for Type H and Type C predictions were derived and plotted for the 4 test periods in each of the 5 watersheds, resulting in 20 possible data points for assessment. Along with the projections, the actual observed flow values are also plotted for comparison. All flows are shown as a ratio of the flow in the base period.

Across the 5 watersheds, precipitation varied from −10 % to 23 %, mean temperature varied from −0.86 °C to 0.86 °C, and total potential evapotranspiration varied from −5 % to 2 % of the base period value. Figure 3 compares the two types of predictions for changes in streamflow but does not assess their performance with changing climate directly. However, we found that the change in climate of validation period from base period is related to a corresponding change in streamflow. The linear correlation between the change in the climate of a watershed, measured as change in aridity index, and the change in the observed streamflow was found to be −0.76 across all watersheds, implying that the change in streamflow can be used as a proxy for change in the climate. The negative value of the correlation indicates that an increase in aridity index leads to a decrease in the streamflow and vice versa. Figure 3 shows that Type C predictions are closer to the observed values as the percentage change in streamflow increases. The mean distance of the most probable flow to the observed flow for Type C and Type H is 0.122 and 0.128 respectively implying that for the test periods, both methods perform equally well in general. However, when the change in flow is within 25 % of the base period flow, the distance for Type H and Type C predictions are 0.127 (H) and 0.136 (C); for 25 %–50 % they are 0.091 (H) and 0.076 (C) and for 50 % change they are 0.187 (H) and 0.070 (C), respectively. This suggests that historical calibration will be better if the climate change is small, but changed parameters will improve performance if change is above 25 %.

The 90 % prediction limits for Type H and Type C are smaller and similar to each other for the first three watersheds. But as we move towards drier watersheds, the limits become wider and different from each other. This indicates that for dry watersheds, the difference between the two types is more evident even for historical climate variability.

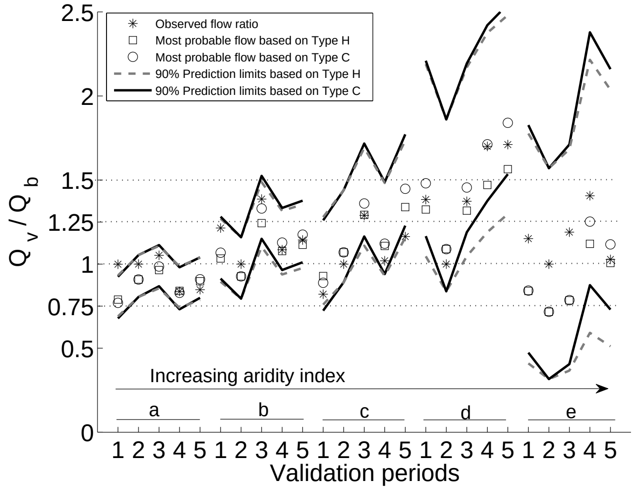

Fig. 3. Validation plot showing the ratio of validation period streamflow (Q_v) to base period streamflow (Q_b) for the 5 study watersheds sorted by increasing aridity index (PE/P) (**(a)** Lochsa, **(b)** Lower Androscoggin, **(c)** Escambia, **(d)** Meramec, **(e)** Yampa). Validation periods are 1: 1948–1958, 2: 1958–1968 (base period), 3: 1968–1978, 4: 1978–1988, 5: 1988–1996. Dashed and continuous lines show the 90 % prediction limits for historical conditioning and conditioning based on changing climate respectively.

4.3 Predictions for synthetic climate scenarios

Streamflow projections were calculated for the synthetic climatic scenarios discussed in Sect. 3. A total of 72 combinations of different climate scenarios that resulted from changing precipitation and temperature from base period (historical) time series were modeled to derive Type H (historical) and Type C (changed) projections. Figure 4 compares the projections from these two methodologies. The figure shows colored contours generated from the most probable estimates of flow for the synthetic climate scenarios for Type H and Type C predictions as a function of change in precipitation and temperature for the 5 study watersheds. Additional information on uncertainty resulting from the projected streamflow ranges using the watershed model is included in the background grey contours. Prediction uncertainty is calculated for every climate scenario as the difference between the 90 % lower and upper prediction limits. All values are normalized with respect to the values during the base period (the 0-0 coordinate) climate and the watersheds are arranged in order of increasing aridity index.

First, the colored contours of most probable flow are discussed followed by the discussion on grey background contours. In case of colored contours, for any particular contour plot, as we move from left to right, the effect of increasing precipitation is seen in the most probable flow estimates as parallel contours with increasing values. Along the y-axis, as the temperature increases, the contours bend away to the right due to decrease in predicted flow as a result of both increase in temperature and potential evapotranspiration. The angle of the contour lines for most of the plots is greater than 45°, indicating that the streamflow is more sensitive to changes in precipitation than to changes in temperature. Comparing the contours across all the watersheds for Type H and Type C projections, the main observation is that Type C projections are more sensitive to changes in climate. The contour lines are closer to each other for Type C implying higher sensitivity to precipitation and the angle that the contour lines make with the x-axis is greater for Type C predictions implying higher sensitivity to temperature. The further the future scenarios depart from the historical period (the 0-0 coordinate, which results in a Q_c/Q_h ratio of 1), the greater is the difference between the two projections.

As we move from wet to dry watersheds, the contours for both types become more closely spaced indicating the increased sensitivity of the dry watersheds. Not only this, the sensitivity to temperature is higher for the two driest watersheds, Meramec and Yampa, as indicated by the increased

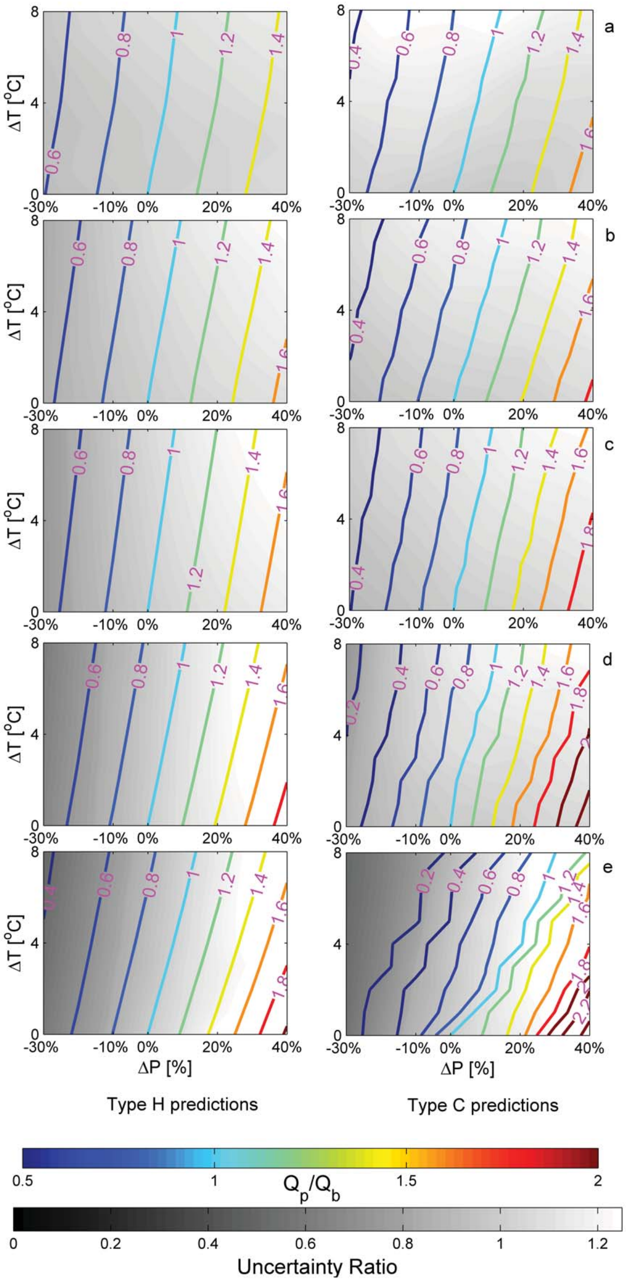

Fig. 4. . Contours of most probable streamflow (Q_p) in colored lines normalized by the most probable flow for the historical or base period (Q_b). The background grey variation shows the uncertainty in the predictions normalized with respect to the uncertainty predicted for historical flows for: **(a)** Lochsa, **(b)** Lower Androscoggin, **(c)** Escambia, **(d)** Meramec, **(e)** Yampa. Watersheds are arranged in order of increasing aridity index.

angle of the contour lines with the x-axis. This change is not seen in the three wetter watersheds – Lochsa, Lower Androscoggin and Escambia, where the sensitivity to temperature remains more or less constant across all three watersheds. Another important feature of the plots is that the Type H contours are a linear function of climate whereas increasingly non-linear behavior is observed in the Type C contours as the watersheds get drier. This is a direct consequence of varying the posterior distribution of the parameters with climate. In case of Type H predictions the posterior signature distributions (runoff ratios) for the climate remain the same and only the input to the model changes in a linear manner, leading to the linear behavior of the contours. For Type C predictions however, the model is forced to reproduce the expected distribution in the signature for the changed climate leading to a more non-linearity in the contours. From these observations, it can be concluded that drier watersheds are more sensitive to climate change and also, that the impact of changing parameters with climate will be higher on these. Note that these results are valid for the most probable flow only which is modeled after the expected value of the runoff ratio.

We now examine the impact of changing parameters with climate on the difference between 90 % predicted upper and lower ranges of streamflow, which is assumed to be a typical uncertainty range for projections. The background grey contours show that in Type H predictions, the uncertainty is higher in wet and hot regimes than for wet to intermediate watersheds, whereas, for dry watersheds, it is highest in wet regimes irrespective of temperature increase. For Type C predictions, the uncertainty is highest in hot regimes for the wettest watershed while it shows no sensitivity to precipitation change. As we move to watersheds with higher aridity index, the impact of precipitation on the uncertainty grows to an extent where, for the driest watershed, uncertainty is highest for the greatest changes in precipitation and does not show much dependence on temperature. This trend is because wetter catchments are more likely to be energy limited ($PE/P < 1$) and drier catchments are more likely to be moisture limited ($PE/P > 1$). Therefore it is likely that changes to the limiting variable for these catchments will have a larger impact on the simulation than if the non-limiting variable is changed. Across both Type H and Type C predictions, uncertainty is lower for the drier catchments if precipitation decreases and higher in the drier catchments if precipitation increases.

In order to assess the difference in the projected hydrographs in more detail, Fig. 5a shows 90 % prediction limits for monthly time series of predicted flow for a climate change scenario of decrease in precipitation of 20 % and increase in temperature of 2 °C for the Escambia watershed as an example. The flow has been log transformed to accentuate the difference between low flows since the predictions are for a scenario with drier climate. One can see that the lower limits of projections for Type C are in general below Type H. On the other hand, the upper limits of the flow estimates are similar to each other, being different only in their extremes, with Type H being higher than Type C. This result suggests that it will be important to test the new approach proposed here for the estimation of flood and low flow frequencies in

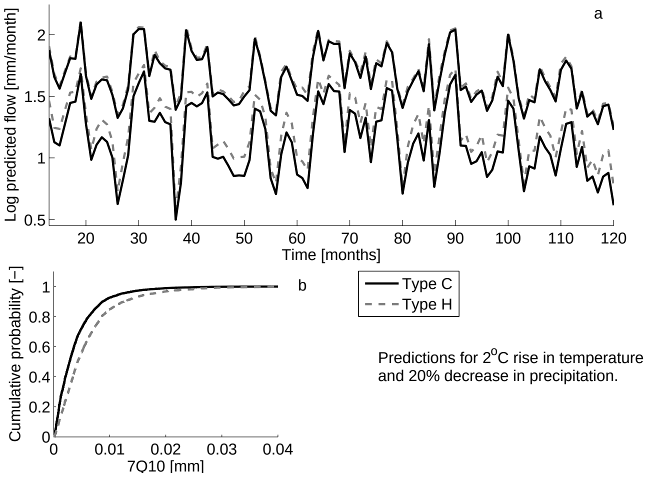

Fig. 5. (a) Monthly time series of predicted flow for a climate scenario of 20 % decrease in precipitation and 2 °C increase in temperature for the Escambia watershed. Dashed and continuous lines show the 90 % prediction limits for Type H and Type C respectively. The flow has been log transformed to accentuate the difference between low flows. The first year of simulated flows is the warm up period and is not plotted. **(b)** Cumulative probability of 7 day low flow with a return period of 10 yr (7Q10) calculated for the Escambia watershed for identical climate scenario for Type H and Type C predictions.

a changing climate. It was also found that in case of wetter climates Type C prediction are higher than Type H.

These continuous time streamflow projections can now be used to derive any streamflow-based indicator of interest. This is very relevant since many ecological and water resources indicators are of great interest for a wide range of applications (e.g. Weiskel et al. 2007; Richter et al., 1996, 2003; Poff et al. 2006, 2007; Arthington et al., 2006; Milly et al., 2008; Wagener et al., 2011). One such index that is calculated in this study just as an example is the 7-day low flow with a return period of 10 yr (7Q10) (Chapra, 1997). The index is calculated using both Type H and Type C projections for the above climate scenario (which is at the lower end of climate change strength) and its cumulative probability for Escambia watershed is plotted in Fig. 5b. It is observed that values of 7Q10 based on Type C predictions are always lower than Type H predictions. It reinforces the fact that using parameters that are fixed with climate (Type H) can lead to underestimation of droughts.

5 Discussion

This study showed again that dry watersheds are more sensitive to climate change than wet watersheds, and also, that the impact of using changing parameters was more pronounced in them. Dooge (1992) showed that all empirical (spatial) models agree on watershed runoff being more sensitive to variation in average precipitation and average potential evapotranspiration for more arid environments ($\mathrm{PE}/P > 1$). The fact that drier watersheds also yield greater difference between the Type H and Type C projections can be related to the use of Schreiber's model for which the sensitivity of long-term runoff to changes in long-term precipitation and long-term potential evapotranspiration is derived (Dooge, 1992):

$$\Psi = 1 + \mathrm{PE}/P \tag{3}$$

where, Ψ is the sensitivity of the long-term runoff and PE/P is the long-term aridity index. According to this equation, the sensitivity of runoff ratio increases as the aridity index increases. Since the posteriors for Type C predictions are modeled after Schreiber's equation in this study, similar effects are seen in the result obtained. There is of course a question about whether behavior of the watershed as it is simulated is the long-term behavior after the transition period or is a transition behavior and how long a new climate regime would have to be there for a watershed to respond differently. Sankarasubramanian and Vogel (2003), found that arid and semi-arid basins exhibit greater precipitation elasticity than humid basins in the US. They also find that the relationship between precipitation and runoff is generally non-linear due to the influence of storage processes within the basins. Using both Type H and Type C predictions yielded non-linear relationship between precipitation and runoff indicating that these projections are realistic. Furthermore, Type C predictions displayed increasing non-linearity in their response as the watersheds became drier.

Determining the range of climate change within which a watershed performs satisfactorily on historically conditioned parameters is important for assessing the reliability of projections derived through different strategies. We calculated these thresholds for the watersheds in this study and found interesting results. The thresholds of temperature and precipitation change after which the two methods, Type H and Type C, became significantly different were found to vary across watersheds (Fig. 6). In case of predictions for the most probable flow, the threshold values are smaller for watersheds with high aridity index ($\mathrm{PE}/P > 1$). In addition, for Yampa, a dry and snow dominated watershed, the two methods differ by 25 % in their predictions of most probable flow (calculated as a percentage of the most probable flow predicted for historical period) for a decrease in precipitation as low as -10 % of the historical precipitation, whereas they differ by less than 5 % in their predictions of most probable flow for precipitation change up to +20 % of the historical value. Thus, Yampa shows greater difference between the two methods in dry climates. For watersheds with low and intermediate aridity index ($\mathrm{PE}/P < \sim 1$), a precipitation change of $\pm$ 20 % leads to a 5 %–10 % difference in predictions. The temperature thresholds also vary across the watersheds. In snow dominated watersheds (a, b, e), the two methods perform differently for Type H and Type C distributions even with slight increase in temperature. On the other hand,

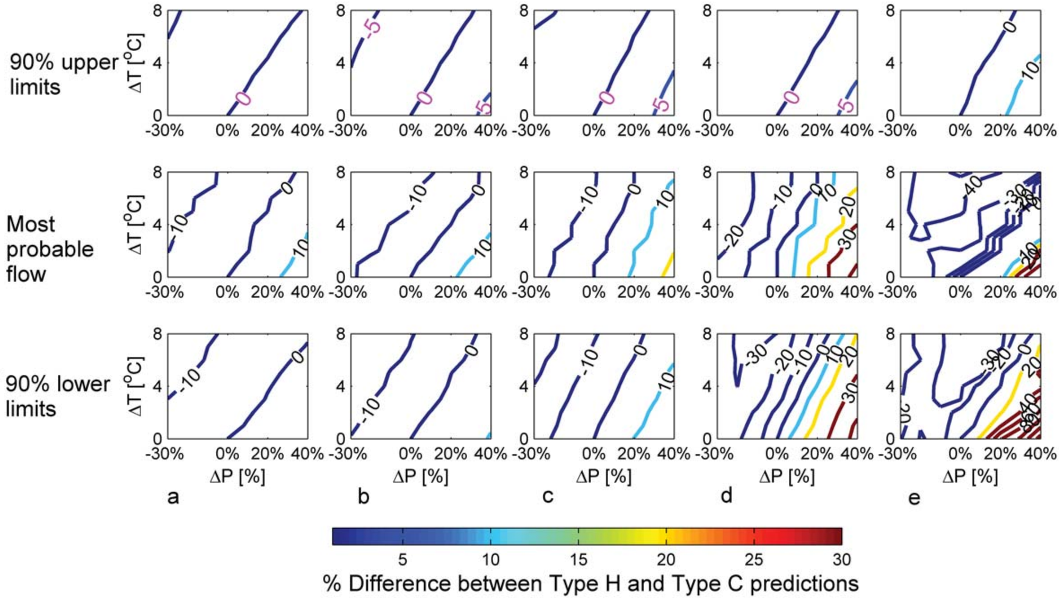

Fig. 6. Contour plots to illustrate the difference in Type H and Type C predictions. The difference between the 90 % upper limits, most probable flow, and the 90 % lower limits is calculated as a percentage of the prediction for the historical climate for: **(a)** Lochsa, **(b)** Lower Androscoggin, **(c)** Escambia, **(d)** Meramec, **(e)** Yampa.

non-snow dominated watersheds (c and d) show similar predictions for flow when temperature increases up to 2 °C for constant precipitation. While comparing the 90 % prediction limits, it was found that for watersheds with high aridity index, the 90 % lower limits of the flow also become significantly different. The 90 % upper limits are not significantly different using the two methods across all the watersheds. Therefore uncertainty limits for Type H and Type C projections deviate from each other as the watershed gets drier. The fact that the uncertainty ranges are relatively constant for humid watersheds demonstrates the robustness GLUE method (Beven and Freer, 2001) for the uncertainty estimation for humid watersheds but as we move towards drier watersheds, the results will become increasingly different.

Vaze et al. (2010) found that the hydrologic model parameters calibrated on historical streamflow regimes proved to be inferior (to parameters calibrated on new climatic conditions) if changes from historical conditions exceeded $\pm 2°$ change in temperature and ± 20 % change in precipitation. In this study we found that these ranges are a function of the watershed itself, i.e. of its historical climatic regime. Also, any attempt to validate the framework developed here on actual observations requires a significant degree of change in the climate of the watershed within the available data set. Analysis of the study watersheds showed, that the historical decadal variability allowed for some points of validation for the new methodology. The greater the change in flow from the base period, the more reliable was the method of conditioning on changed climate as was discussed with respect to Fig. 3.

Risbey and Entekhabi (1996) produced contour plots of the watershed streamflow response to changes in precipitation and temperature for the Sacramento River basin using the PRMS model. They found that the streamflow has a much higher sensitivity to precipitation change than to temperature change. This result is similar to the one found here, where changes in precipitation generally cause a stronger streamflow response than changes in temperature. However, the impact of temperature becomes more significant for Type C predictions.

As mentioned earlier, Merz et al. (2010) show that some parameters of their model change with climate. They found that the degree day factor decreased by about 0.2 mm °C day^{-1}, the snow correction factor decreased by 0.2, the maximum soil moisture storage, FC, increased from 150 mm to 250 mm, and the non-linearity parameter for runoff generation (B) changed from 3 to 5, over a period of 1976–2006, which was marked by a temperature increase of around 2 °C while precipitation has slightly increased over the three decades. They attribute the increase of storage to the higher capacity of soils to store moisture due to continuous evaporation of incoming moisture. The model used by Merz et al. (2010) is the HBV model, which is similar to the model used in this study though a bit more complex. We found that the storage calculated from the parameters of the soil moisture accounting module (cmax and b) in our study was higher for drier and hotter climates. 90 % upper and lower limits of storage along with the most probable values were calculated and spearman rank correlation analysis was carried out with the aridity index for the 72 climate scenarios across all 5 watersheds. The spearman rank correlation values (Spearman, 1904) for upper limits across all the watersheds for all climate scenarios was of the order of 0.99, for lower limits it varied between 0.62–0.99 and for the most probable storage the range was 0.25–0.82. Thus showing that the storage parameter values increase with increasing dryness. This result corroborates Merz et al.'s (2010) finding, which was similar for historical climate change.

Another important aspect of this study was the impact of the sampling method used on the results. While constraining for climate change, the number of parameter sets within the 90 % prediction intervals decreased substantially from around 8000 (out of 10 000 initially sampled) to as low as 1000 for extremely dry climates with high aridity index. There can be (at least) two possible explanations for this behavior – either the model used is not sufficient for simulating the processes in highly arid climates since fewer parameter combinations are able to capture the expected signature dynamics, or, the method of uniform random sampling being used in this study is not able to generate parameter sets in the feasible space. Zhang et al. (2008) used a multi-objective optimization algorithm to determine the feasible solutions that satisfied the regionalization constraints. They found that using a multi-objective evolutionary algorithm increased the number of solutions found as compared to the uniform random sampling. The future scope of this work will include the introduction of a more efficient algorithm to search the parameter space.

6 Conclusions

In this paper, we develop a novel probabilistic uncertainty framework based on a trading-space-for-time idea to account for the problem that behavioral parameter will change with changing climate. We show how this approach can be used to derive probabilistic streamflow predictions under different climatic scenarios from which a wide range of streamflow indicators can be derived. The approach is independent of the particular watershed model used and can be applied to both gauged and ungauged basins. Results for five test watersheds indicate that the performance of predictions based on changing parameter with climate become more reliable as the climate deviates significantly from historical observations when comparing simulations within historical variability. This implies that while validation of the strategy is difficult given the limited climatic variability over the available data period, results suggest an improvement of projections if changing parameters are considered. It was found that the thresholds of temperature and precipitation change after which the conditioning on historical climate differs significantly from the conditioning on changing climate vary with the climate in which the watershed is initially located. Some general observations were that for dry watersheds, in the case of decreasing precipitation, the two methods' results were significantly different even for small changes in precipitation. Also, predictions for snow dominated watersheds differ significantly even for small changes in temperature. For non-snow dominated watersheds, the performance of Type H and Type C predictions is similar for a temperature increase up to 2 °C. In wet to intermediate watersheds the two methods give similar predictions for a precipitation change up to ± 20 %, which means that calibration on historical observations will be a good strategy within a certain range of climatic variability.

There are of course several simplifications in this study that in the future should be improved. One of the limitations of this study is that the model used for deriving the Budyko curve is the simple, two-parameter, Schreiber model. Other studies have explored the relationship between aridity index and evaporation ratio (Milly, 1994; Sankarasubramanian and Vogel, 2003) and tried to develop a theoretical relationship for the two indices by considering storage variability between watersheds. Using a more sophisticated approach in modeling the relationship between aridity index and evaporation ratio might reduce the scatter of the model residuals. Another limitation is that only two signatures have been used in this study for constraining the hydrologic model. The use of more signatures is likely to capture more characteristics of the streamflow and therefore improving the accuracy of the predictions by reducing the uncertainty ranges (e.g. Yadav et al., 2007). Thirdly, guided sampling techniques such as multi-objective evolutionary algorithms can improve the efficiency and effectiveness of finding behavioral parameter sets in the parameters space (Zhang et al., 2008).

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References

Arnold, J. G., Allen, P. M., Muttiah, R., and Bernhardt, G.: Automated base flow separation and recession analysis techniques, Ground Water, 33, 1010–1018, doi:10.1111/j.1745-6584.1995.tb00046, 1995.

Arthington, A. H., Bunn, S. E., Poff, N. L., and Naiman, R. J.: The challenge of providing environmental environmental flow rules to sustain river ecosystems, Ecol. Appl., 16, 1311–1318, 2006.

Bárdossy, A.: Calibration of hydrological model parameters for ungauged catchments, Hydrol. Earth Syst. Sci., 11, 703–710, doi:10.5194/hess-11-703-2007, 2007.

Bastola, S., Murphy, C., and Sweeney, J.: Evaluation of the transferability of hydrological model parameters for simulations under changed climatic conditions, Hydrol. Earth Syst. Sci. Discuss., 8, 5891–5915, doi:10.5194/hessd-8-5891-2011, 2011.

Beven, K. and Freer, J.: Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology, J. Hydrol., 249, 11–29, doi:10.1016/S0022-1694(01)00421-8, 2001.

Boyle, D. P., Gupta, H. V., and Sorooshian S.: Toward improved calibration of hydrologic models: Combining the strengths of manual and automatic methods, Water Resour. Res., 36, 3663–3674, doi:10.1029/2000WR900207, 2000

Budyko, M. I.: Climate and Life, Academic Press, New York, 1974.

Bulygina, N., McIntyre, N., and Wheater, H.: Conditioning rainfall-runoff model parameters for ungauged catchments and land management impacts analysis, Hydrol. Earth Syst. Sci., 13, 893–904, doi:10.5194/hess-13-893-2009, 2009.

Bulygina, N., McIntyre, N., and Wheater, H.: Bayesian conditioning of a rainfall-runoff model for predicting flows in ungauged catchments and under land use changes, Water Resour. Res., 47, W02503, doi:10.1029/2010WR009240, 2011

Buytaert, W., Célleri, R., and Timbe, L.: Predicting climate change impacts on water resources in the tropical Andes: Effects of GCM uncertainty, Geophys. Res. Lett., 36, L07406, doi:10.1029/2008GL037048, 2009.

Chapra, S. C.: Rivers and Streams, in: Surface Water-Quality Modeling, pp. 243–244, Waveland Press, Inc., Long Grove, Illinois, 1997.

Christensen, J. H., Hewitson, B., Busuioc, A., Chen, A., Gao, X., Held, I., Jones, R., Kolli, R. K., Kwon, W.-T., Laprise, R., Magaña Rueda, V., Mearns, L., Menéndez, C. G., Räisänen, J., Rinke, A., Sarr, A., and Whetton, P.: Regional Climate Projections, in: Climate Change 2007: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., Cambridge University Press, Cambridge, UK and New York, USA, 2007.

De Walle, D. R. and Rango, A.: Principles of Snow Hydrology, Cambridge University Press, Cambridge, UK, 2008.

Dooge, J.: Sensitivity of runoff to climate change: A Hortonian approach, B. Am. Meteorol. Soc., 73, 2013–2024, doi:10.1175/1520-0477(1992)073, 1992.

Duan, Q., Schaake, J., Andreassian, V., Franks, S., Gupta, H. V., Gusev, Y. M., Habets, F., Hall, A., Hay, L., Hogue, T. S., Huang, M., Leavesley, G., Liang, X., Nasonova, O. N., Noilhan, J., Oudin, L., Sorooshian, S., Wagener, T., and Wood, E. F.: The Model Parameter Estimation Experiment (MOPEX): An overview of science strategy and major results from the second and third workshops, J. Hydrol., 320, 3–17, doi:10.1016/j.jhydrol. 2005.07.031, 2006.

Falcone, J. A., Carlisle, D.M., Wolock, D. M., and Meador, M. R.: GAGES: A stream gage database for evaluating natural and altered flow conditions in the conterminous United States, Ecology, 91, 62, 2010.

Ghosh, S. and Mujumdar, P. P.: Climate change impact assessment: Uncertainty modeling with imprecise probability, J. Geophys. Res., 114, D18113, doi:10.1029/2008JD011648, 2009.

Hundecha, Y. und Bárdossy, A.: Modeling of the effect of land use changes on the runoff generation of a river basin through parameter regionalization of a watershed model, J. Hydrol., 292, 281–295, doi:10.1016/j.jhydrol.2004.01.002, 2004.

Jiang, T., Chen, Y. D., Chong-yu, X., Chen, X., Chen, X., and Singh, V. P.: Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China, J. Hydrol., 336, 316–333, doi:10.1016/j.jhydrol.2007.01.010, 2007.

Jones, R. N., Francis, H. S. C., Boughton, W. C., and Zhang, L.: Estimating the sensitivity of mean annual runoff to climate change using selected hydrological models, Adv. Water Resour., 29, 1419–1429, doi:10.1016/j.advwatres.2005.11.001, 2006.

Kapangaziwiri, E. and Hughes, D. A.: Assessing uncertainty in the generation of natural hydrology scenarios using the Pitman monthly model, Paper presented at the 14th SANCIAHS Symposium, Pietermaritzburg, KwaZuluNatal, South Africa, 2009.

Liu, Y. and Gupta, H. V.: Uncertainty in hydrologic modeling: Toward an integrated data assimilation framework, Water Resour. Res., 43, W07401, doi:10.1029/2006WR005756, 2007.

Mahmoud, M., Liu, Y., Hartmann, H., Stewart, S., Wagener, T., Semmens, D., Stewart, R., Gupta, H. V., Dominguezm, D., Dominguez, F., Hulse, D., Letcher, R., Rashleigh, B., Smith, C., Street, R., Ticehurst, J., Twery, M., van Delden, H., Waldick, R., White, D., and Winter, L.: A formal framework for scenario development to support environmental decision making, Environmental Modeling and Software, 24, 798–808, doi:10.1016/j.ensoft.2008.11.010, 2009.

Maurer, E. P. and Duffy, P. B.: Uncertainty in projections of streamflow changes due to climate change in California, Geophys. Res. Lett., 32, L03704, doi:10.1029/2004GL021462, 2005.

McCabe, G. J. and Wolock , D. M.: A step increase in streamflow in the conterminous United States, Geophys. Res. Lett., 29, 2185, doi:10.1029/2002GL015999, 2002.

Merz, R., Parajka, J., and Blöschl, G.: Time stability of catchment model parameters: Implications for climate impact analyses, Water Resour. Res., 47, W02531, doi:10.1029/2010WR009505, 2010.

Milly, P. C. D.: Climate, soil water storage, and the average annual water balance, Water Resour. Res., 30, 2143–2156, doi:10.1029/94WR00586, 1994.

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaierand, D. P., Stouffer, R. J.: Stationarity Is Dead: Whither Water Management?, Science, 319-, 573–574, doi:10.1126/science.1151915, 2008.

Moore, R. J.: The PDM rainfall-runoff model, Hydrol. Earth Syst. Sci., 11, 483–499, doi:10.5194/hess-11-483-2007, 2007.

Nash, L. L. and Gleick, P. H.: Sensitivity of stream?ow in the Colorado basin to climatic changes, J. Hydrol., 125, 221–241, doi:10.1016/0022-1694(91)90030-L, 1991.

Peel, M. C. and Bloeschl, G.: Hydrological modeling in a changing world, Prog. Phys. Geog., 35, 249–261, 2011.

Poff, N. L., Bledsoe, B. D., and Cuhaciyan, C. O.: Hydrologic variation with land use across the contiguous United States: geomorphic and ecological consequences for stream ecosystems, Geomorphology, 79, 264–285, 2006.

Poff, N. L., Olden, J. D., Merritt, D., and Pepin, D.: Homogenization of regional river dynamics by dams and global biodiversity implications, Proceedings of the National Academcy of Sciences, 104, 5732–5737, 2007.

Richter, B. D., Baumgartner, J. V., Powell, J., and Braun, D. P.: A method for assessing hydrologic alteration within ecosystems, Conserv. Biol., 10, 1–12, 1996.

Richter, B. D., Matthews, R., Harrison, D. L., and Wigington, R.: Ecologically sustainable water management: managing river flows for river integrity, Ecol. Appl., 13, 206–224, 2003.

Risbey, J. S. and Entekhabi, D.: Observed Sacramento Basin stream-flow response to precipitation and temperature changes and its relevance to climate impacts studies, J. Hydrol., 184, 209–223, doi:10.1016/0022-1694(95)02984-2, 1996.

Rosero, E., Yang, Z.-L., Wagener, T., Gulden, L. E., Yatheendradas, S., and Niu, G.-Y.: Quantifying parameter sensitivity, interaction, and transferability in hydrologically enhanced versions of the Noah land surface model over transition zones during the warm season, J. Geophys. Res., 115, D03106, doi:10.1029/2009JD012035, 2010.

Sankarasubramanian, A. and Vogel , R. M.: Hydroclimatology of the continental United States, Geophys. Res. Lett., 30, 1363, doi:10.1029/2002GL015937, 2003.

Shuttleworth, W. J.: Evaporation, in: Handbook of Hydrology, edited by: Maidment, D. R., 4 pp., 18, Mcgraw-Hill, 1993

Spearman, C.: The proof and measurement of association between two things, Am. J. Psychol., 15, 72–101, 1904.

Sivapalan, M., Takeuchi, K., Franks, S. W., Gupta, V. K., Karambiri, H., Lakshmi, V., Liang, X., McDonnell, J. J., Mendiondo, E. M., O'Connell, P. E., Oki, T., Pomeroy, J. W., Schertzer, D., Uhlenbrook, S., and Zehe, E.: IAHS Decade on Predictions in Ungauged Basins (PUB), 2003–2012: Shaping an exciting future for the hydrological sciences, Hydrolog. Sci. J., 48, 857–880, 2003.

Van Werkhoven, K., Wagener, T., Reed, P., and Tang, Y.: Characterization of watershed model behavior across a hydroclimatic gradient, Water Resour. Res., 44, W01429, doi:10.1029/2007WR006271, 2008.

Van Werkhoven, K., Wagener, T., Reed, P., and Tang, Y.: Sensitivity-guided reduction of parametric dimensionality for multi-objective calibration of watershed models, Adv. Water Resour., 32, 1154–1169, 2009.

Vaze, J., Post, D., Chiew, F., Perraud, J.-M, Viney, N., and Teng, J.:Climate non-stationarity - Validity of calibrated rainfall-runoff models for use in climate change studies, J. Hydrol., 394, 447–457, doi:10.1016/j.jhydrol.2010.09.018, 2010.

Wagener, T.: Can we model the hydrologic implications of environmental change?, Hydrol. Process., 21, 3233–3236. doi:10.1002/hyp.6873, 2007.

Wagener, T. and Wheater, H. S.: Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty, J. Hydrol., 320, 132–154, 2006.

Wagener, T. and Montanari, A.: Convergence of approaches toward reducing uncertainty in predictions in ungauged basins, Water Resour. Res., 47, W06301, doi:10.1029/2010WR009469, 2011.

Wagener, T., Boyle, D. P., Lees, M. J., Wheater, H. S., Gupta, H. V., and Sorooshian, S.: A framework for development and application of hydrological models, Hydrol. Earth Syst. Sci., 5, 13–26, doi:10.5194/hess-5-13-2001, 2001.

Wagener, T., Sivapalan, M., Troch, P. A., McGlynn, B. L., Harman, C. J., Gupta, H. V., Kumar, P., Rao, P. S. C., Basu, N. B., and Wilson, J. S.: The future of hydrology: An evolving science for a changing world, Water Resour. Res., 46, W05301, doi:10.1029/2009WR008906, 2010.

Weiskel, P. K., Vogel, R. M., Steeves, P. A., Zarriello, P. J., DeSimone, L. A., and Ries III, K. G.: Water use regimes: Characterizing direct human interaction with hydrologic systems, Water Resour. Res.,43, W04402, doi:10.1029/2006WR005062, 2007.

Yadav, M., Wagenerm, T., and Gupta, H.: Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins, Adv. Water Resour., 30, 1756–1774, doi:10.1016/j.advwatres.2007.01.005, 2007.

Zhang, Z., Wagener, T., Reed, P., and Bushan, R.: Ensemble streamflow predictions in ungauged basins combining hydrologic indices regionalization and multiobjective optimization, Water Resour. Res., 44, W00B04, doi:10.1029/2008WR006833, 2008.