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Hydrological modelling under climate change considering nonstationarity and seasonal effects

Kue Bum Kim, Hyun-Han Kwon and Dawei Han

ABSTRACT

Traditional hydrological modelling assumes that the catchment does not change with time. However, due to changes of climate and catchment conditions, this stationarity assumption may not be valid in the future. It is a challenge to make the hydrological model adaptive to the future climate and catchment conditions. In this study IHACRES, a conceptual rainfall–runoff model, is applied to a catchment in southwest England. Long observation data (1961–2008) are used and seasonal calibration (only the summer) has been done since there are significant seasonal rainfall patterns. Initially, the calibration is based on changing the model parameters with time by adapting the parameters using the step forward and backward selection schemes. However, in the validation, both models do not work well. The problem is that the regression with time is not reliable since the trend may not be in a monotonic linear relationship with time. Therefore, a new scheme is explored. Only one parameter is selected for adjustment while the other parameters are set as the fixed and the regression of one optimised parameter is made not only against time but climate condition. The result shows that this nonstationary model works well both in the calibration and validation periods.

Key words | climate change, model parameters, nonstationarity, seasonal effect

Kue Bum Kim
Dawei Han
Water and Environmental Management Research Centre, Department of Civil Engineering,
University of Bristol,
Bristol,
UK

Hyun-Han Kwon (corresponding author)
Department of Civil Engineering,
Chonbuk National University,
Jeonju-si,
Jeollabuk-do,
South Korea
E-mail: *hkwon@jbnu.ac.kr*

INTRODUCTION

The impacts of climate change are of increasing interest to water resources managers (Compagnucci *et al.* 2001; Bates *et al.* 2008). The uncertainty of the impacts of climate change may arise from numerous factors such as Global Circulation Model (GCM), downscaling method, the structure and parameters of hydrological model and emission scenarios (Wilby & Harris 2006). Numerous researches argue that GCM structure is the largest source of uncertainty and hydrological model parameterisation is almost the last (Wilby & Harris 2006; Arnell 2011; Chen *et al.* 2011; Teng *et al.* 2012). However, some studies indicate that the rank of hydrological modelling may depend on the type of hydrological model used and the study catchment (Wilby 2005; Blöschl *et al.* 2007; Blöschl & Montanari 2010) which shows that hydrological modelling should not be disregarded as insignificant in climate change impact analyses.

Generally, ensembles of these sources are used to quantify and reduce the uncertainty of the impact of climate change (Minville *et al.* 2008; Chiew *et al.* 2009; Boyer *et al.* 2010; Vaze *et al.* 2010). One assumption of these studies is that the catchment does not change with time (i.e. stationary conditions) which means the model calibrated for the historical period is valid for the future period. The premise of this assumption is that if the model is calibrated for a long time period of observation data then these calibrated parameters can be assumed to be still effective for the future climate conditions (Arnell 1994). However, in reality, due to changes of climate and catchment conditions, this stationarity assumption may not be valid in the future. Therefore, the model should be reliably calibrated under current climate conditions in order to estimate the impact of climate change on future hydrological system. However, it is a challenge to make the hydrological model adaptive to the future climate and catchment conditions that are not observable at the present time.

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The main sources of uncertainty in the hydrological modelling are model structural errors and parameterisation errors. The uncertainty of model structure errors is generally quantified by using several different models, and numerous methods are proposed regarding quantification of the uncertainty of parameterisation problem. The time varying parameters which arise from climate change and catchment change (such as land use/cover change) may be another source of uncertainty in climate change impact studies. Recently, there have been some studies about the stability of the model performances and the effect of parameter values (Xu 1999; Li *et al.* 2014; Yan & Zhang 2014; Patel & Rahman 2015). The reasons of time varying model parameters can be explained by several reasons (Merz *et al.* 2011). First, the hydrological model has structure errors and the calibrated parameters may change for different time periods in order to compensate these problems with the model structures (Wagener *et al.* 2003). Secondly, catchment characteristic change (Brown *et al.* 2005) such as land use and climate variations (Merz & Blöschl 2009) can also lead to the change of calibrated parameters. However, the correlation between parameters is complicated and may be related with catchment conditions (Wagener 2007) which make it hard to understand the reason of the parameter changes in time (Wagener *et al.* 2010).

The purpose of this study is to assess the validity of the assumption of hydrological stationarity and to improve the traditional time invariant model parameterisation for nonstationary hydrological system. Catchment change, such as land use/cover change, may be a source for the temporal change of the model parameters but it is not taken into account in this study due to difficulties in obtaining the data. We only consider the relationships between the trend of parameters and climate conditions (assuming that the climate change could be used as proxies for catchment changes such as vegetation change). Long observation data from 1961 to 2008 are used and seasonal calibration (in this study only the summer period is further explored because it is more sensitive to climate and land cover change than the other three seasons) has been done since there are significant seasonal rainfall patterns. The data are split into calibration and validation periods with the intention of using the validation period to represent the future unobserved situations. The performance of three different models, Static model, Nonstationary model and Stationary model, are compared with the calibrated model. The calibration has been conducted with the use of Nash–Sutcliffe efficiency (NSE) to minimise the difference between observed and simulated flow for the summer period and the optimised parameters have been tested in the validation period.

STUDY CATCHMENT AND DATA

Study region and data set

The Exe catchment is located in the southwest of England. The catchment area is 1530 km^2 and its average annual rainfall is 1088 mm. Four major tributaries of River Exe are River Culm, River Barle, River Clyst and River Creedy, and the river flows into the sea via the Exe Estuary on the south coast of England. The main urban areas in the Exe catchment are Exeter, Crediton, Tiverton and Cullompton. Figure 1 shows the overview of the Thorverton catchment (606 km^2) used in this study which is one of the Exe subcatchments.

Long daily time series (1961–2008) of the observed precipitation and flow data over the Thorverton catchment are provided by the UK Met Office. Daily temperature data have been downloaded from the UKCP09 gridded observation data sets. Detailed information about the data sets can be

Figure 1 | Location of the Thorverton catchment.

found at www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09. As shown in Figure 2, the hydrologic variables in this catchment have strong seasonality, i.e. there are significant seasonal rainfall and flow patterns. In general, summer is dry and warm, while winter is cold and wet. In this study only the summer period data are used since summer is more sensitive to climate and land cover change than the other three seasons.

Temporal distribution of climate variables and flow

To analyse the nonstationarity of the hydrological system, temporal distribution of climate variables and flow are estimated for the calibration period (1961–1990) by moving-averaging every 10-year value, i.e. from 1961–1970 to 1981–1990. As shown in Figure 3, the temporal trends of the summer precipitation and runoff are apparently decreasing while the air temperature tends to increase. The F-test has been done for the precipitation and temperature data. The result shows that both of those trends are statistically significant (P value = 0.0027 and P value = 0.0033 respectively). The similarity between the temporal distributions of precipitation and flow shows that the flow in this catchment is more influenced by precipitation than evapotranspiration.

METHODOLOGY

Hydrological model

The model used in this paper is a conceptual rainfall-runoff model IHACRES (Jakeman & Hornberger 1993). This model has been widely applied to a variety of catchments for climate impact studies (Jakeman et al. 1993; Littlewood 1999; Letcher et al. 2001; Kim & Lee 2014). The model is composed of a non-linear module and a linear module as shown in Figure 4 and model parameters are listed in Table 1. A non-linear module converts rainfall to effective

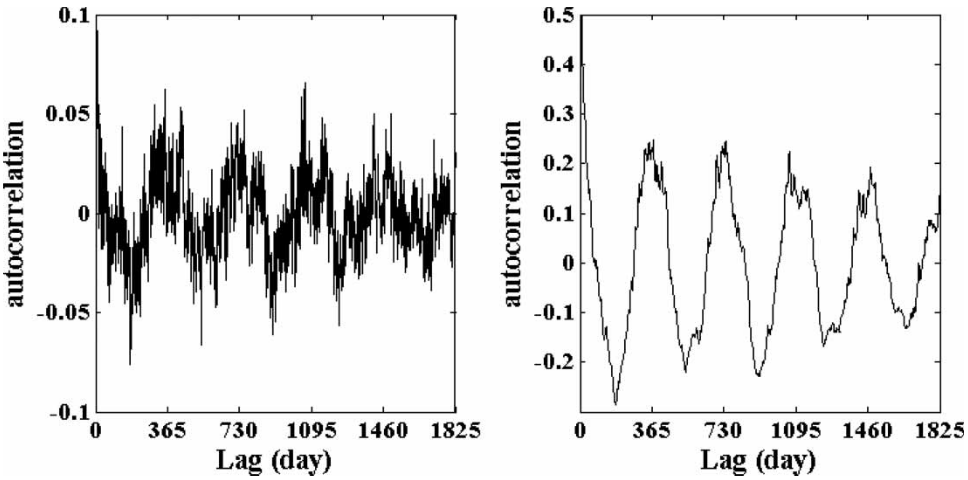

Figure 2 | The autocorrelation function for rainfall (left) and flow (right) which shows strong seasonality.

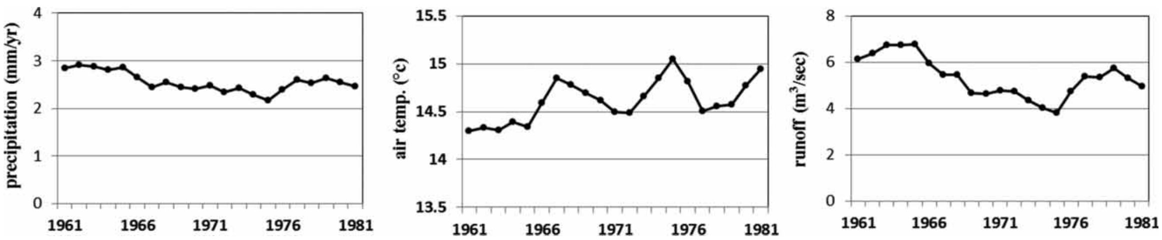

Figure 3 | Temporal distributions of climate variables and flow. Each dot is a 10-year moving average value for the summer period (i.e. the first and the last dots represent the summer mean values of 1961–1970 and 1981–1990 respectively).

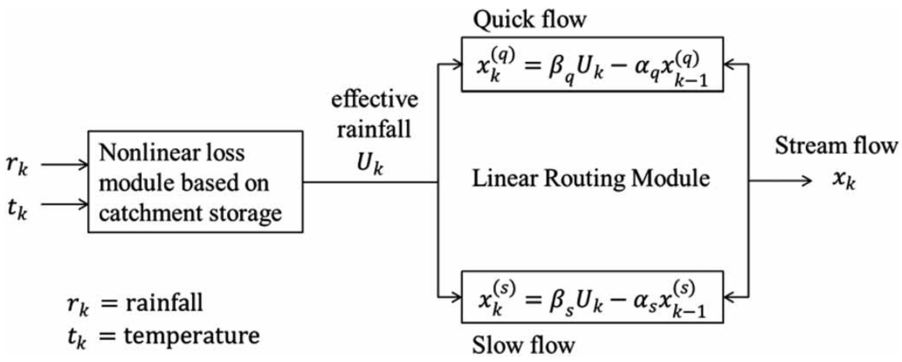

Figure 4 | Structure of the IHACRES model.

Table 1 | Parameters in the IHACRES model

Module	Parameter	Description
Non-linear	c	Mass balance
	τ_w	Reference drying rate
	f	Temperature modulation of drying rate
Linear	α_q, α_s,	Quick and slow flow recession rate
	β_q, β_s	Fractions of effective rainfall for peak response
	τ_s	Slow flow recession time constant, $\tau_s = -\Delta/\ln(-\alpha_s)$
	τ_q	Quick flow recession time constant, $\tau_q = -\Delta/\ln(-\alpha_q)$

rainfall which is calculated from the following equations.

$$U_k = [C(\varnothing_k - l)]^p r_k \tag{1}$$

where r_k is the observed rainfall, C is the mass balance, l is the soil moisture index threshold and p is the power on soil moisture respectively. The soil moisture ($\varnothing_k$) is calculated from:

$$\varnothing_k = r_k + \left(1 - \frac{1}{\tau_k}\right)\varnothing_{k-1} \tag{2}$$

where τ_k is the drying rate given by:

$$\tau_k = \tau_w \exp\left[0.062 f(t_r - t_k)\right] \tag{3}$$

where τ_w is the drying rate at reference temperature, f is the temperature modulation, t_r is the reference temperature, and t_k is the observed temperature. A linear module assumes that there is a linear relationship between the effective rainfall and flow. Two components in this module, quick flow and slow flow, can be connected in parallel or in series. In this study two parallel storages in the linear module is used and the streamflow (x_k) at time step k is defined by the following equations:

$$x_k = x_k^{(q)} + x_k^{(s)} \tag{4}$$

$$x_k^{(q)} = \beta_q U_k - \alpha_q x_{k-1}^{(q)} \tag{5}$$

$$x_k^{(s)} = \beta_s U_k - \alpha_s x_{k-1}^{(s)} \tag{6}$$

where $x_k^{(q)}$ and $x_k^{(s)}$ are quick flow and slow flow respectively and α and β are recession rate and peak response respectively. The relative volumes of quick flow and slow flow can be calculated from:

$$V_q = 1 - V_s = \frac{\beta_q}{1+\alpha_q} = 1 - \frac{\beta_s}{1+\alpha_s} \tag{7}$$

Parameterisation scheme for nonstationary hydrological system

To explore modelling of the nonstationary hydrological system we propose two nonstationary parameterisation schemes. The idea is that the model parameters are changing with time and if we can find some parameter trends against time or some meaningful correlation between parameters and weather variables, this nonstationary model performance might be better in the future than the static model assuming that the catchment does not change with time (i.e. stationary conditions). The first model is adapting the parameters using the step forward and backward selection schemes and the second model is optimising only one parameter while the other parameters are set as the fixed which are described in the following sections.

Forward and backward stepwise methods

The calibration has been done every consecutive 10-year period by moving the window one year from 1961 to 1990; hence we get 21 data points, each data representing every 10 years (i.e. the first and the last data points represent 1961–1970 and 1981–1990 respectively). Since some model parameters show trends over 30 years and some do not, the idea of a new calibration method is to constrain the model parameters one by one and calibrate the model step by step. We assumed the trend to be linear and the statistically significant level is set at 5% for detecting the trend. Here we propose the two new calibration methods, Forward Stepwise Method (FSM) and Backward Stepwise Method (BSM). FSM is to start the calibration by setting a parameter as a fixed value, whose *p*-value is the largest among the other parameters that do not show any trend (i.e. with the first 10-year value) and the rest parameters are set free during optimisation. We repeat this calibrating process step by step until all the rest of the parameters show trends in time. Next, when we encounter a situation where all the parameters show trends in mid process, we choose the parameter which has the lowest *P*-value and fix this linear regression equation followed by calibrating the rest of the free parameters for optimisation. As we have eight parameters, calibration has carried out seven times by incrementing one fixed (either constant or keeping the trend) parameter each step. Then finally we get all the parameters optimised, and with each step the parameters are optimised under previously constrained parameters.

The FSM process is as follows:

1. Calibrate the model in every 10-year window from 1961–1970 to 1981–1990.
2. Test each parameter if it has a trend over the calibration period.
3. Among the parameters which do not have trends, choose the parameter that has the least trend (i.e. the largest *P*-value).
4. Fix this parameter for all the calibration periods while the other parameters are set free and do the optimisation.
5. Go to step 2 and repeat the processes until all parameters are constrained.
6. During the process when the parameters which do not show any trends are all constrained and only the parameters that have trends are left, then choose the parameter that has the strongest trend (i.e. the smallest *P*-value) and fix that trend (i.e. linear regression equation) for the calibration period, then do the calibration.
7. Repeat the processes until all parameters are constrained.

For example, Table 2 represents calibration setting and optimisation results for the FSM for the summer period from 1961 to 1990. First, the Parameter l is set as a fixed value for all the calibration period in Step 1 since l in the calibration

Table 2 | Parameter setting for calibration and optimisation results for the FSM for summer period from 1961 to 1990

	Calibration setting			Optimisation result	
	Constant (fix)	**Trend (fix)**	**Free**	**No trend**	**Trend**
Calibration			$c, \tau_w, f, \alpha_s, \alpha_q, \beta_q, l, p$	c, τ_w, β_q, l, p	f, α_s, α_q
Step 1	l	–	$c, \tau_w, f, \alpha_s, \alpha_q, \beta_q, p$	c, α_s, β	τ_w, f, α_q, p
Step 2	l, α_s	–	$c, \tau_w, f, \alpha_q, \beta_q, p$	c, τ_w, α_q, p	f, β_q
Step 3	l, α_s, α_q	–	c, τ_w, f, β_q, p	c, τ_w, β_q, p	f
Step 4	$l, \alpha_s, \alpha_q, \tau_w$	–	c, f, β_q, p	c, β_q, p	f
Step 5	$l, \alpha_s, \alpha_q, \tau_w, p$	–	c, f, β_q	–	c, f, β_q
Step 6	$l, \alpha_s, \alpha_q, \tau_w, p$	f	c, β_q	–	c, β_q
Step 7	$l, \alpha_s, \alpha_q, \tau_w, p$	f, c	β_q	–	β_q

stage has the highest *P*-value among the other parameters. The other seven parameters are set free and optimisation has been done. Next, Steps 2–5 have been carried out in the same way. In Step 5, optimisation result shows that all three optimised parameters show significant trends along time, among which f shows the lowest *P*-value. Hence, in Step 6, the trend of f along time is fixed, i.e. f value of each calibration period is calculated from a linear regression equation. Then optimisation has been done for the rest two parameters, c and β_q. Step 7 has been done in the same way. Finally, for this nonstationary model, five parameters are set as fixed values and three parameters are set to have trends along time. This nonstationary model is compared with the other models described in the following sections.

The BSM process is the same as FSM except starting to constrain the parameters that show the strongest temporal behaviour (i.e. the smallest *p*-value) instead of constraining the parameter that does not show any trend along time. Table 3 represents the calibration setting and optimisation results for the BSM for the summer period from 1961 to 1990. For this nonstationary model, two parameters are set as a fixed value and six parameters are set to have trends along time.

Adjustment of one parameter against time and climate variables

An alternative parameterisation scheme for the nonstationary system is to select only one parameter for optimisation while the other parameters are set as fixed. In other words, the stationarity assumption is valid for all parameters except one. The reason why we adopt this method is due to the issue of equifinality in modelling complex environmental system. The concept of equifinality is that many different parameters of the model may reproduce the observed behaviour of the system which are acceptable (Beven & Freer 2001). In other words, similar model performances can be achieved with different sets of parameters. Therefore, in parameterisation of a hydrological model, detecting the change of parameters with time may be a difficult problem. This is in part due to the interdependency of parameters. Since the parameters may be linked with each other to a certain degree, setting all parameters free in the optimisation process may lead to difficulty in detecting the trend of nonstationary parameters. Hence, we constrain all the parameters except one to resolve this issue. The success of this model depends on whether the optimised one parameter shows time stability or strong correlation with climate variables, given the fixed rest parameters. This is because, in this condition, the model parameter can be stably predicted with changing time and changing climate in the future. For the fixed parameter values, the first 10-year period (1961–1970) calibrated parameters are applied. The one varying parameter is selected that has a strong relationship with climate variables or shows a statistically significant linear trend along time.

Evaluation of model performance

The model performance is judged by comparing every 10-year observed flow and simulated flow in terms of the

Table 3 | Parameter settings for the calibration and optimisation result for the BSM for summer period from 1961 to 1990

	Calibration setting			Optimisation result	
	Constant (fix)	**Trend (fix)**	**Free**	**No trend**	**Trend**
Calibration			$c, \tau_w, f, \alpha_s, \alpha_q, \beta_q, l, p$	c, τ_w, β_q, l, p	f, α_s, α_q
Step 1	–	α_s	$c, \tau_w, f, \alpha_q, \beta_q, l, p$	c, τ_w, β_q, l	f, α_q, p
Step 2	–	α_s, f	$c, \tau_w, \alpha_q, \beta_q, l, p$	c, τ_w, β_q, l, p	α_q
Step 3	–	α_s, f, α_q	c, τ_w, β_q, l, p	c, τ_w, β_q	l, p
Step 4	–	α_s, f, α_q, l	c, τ_w, β_q, p	c, τ_w, β_q, p	–
Step 5	c	α_s, f, α_q, l	τ_w, β_q, p	τ_w, β_q	p
Step 6	c	$\alpha_s, f, \alpha_q, l, p$	τ_w, β_q	β_q	τ_w
Step 7	c	$\alpha_s, f, \alpha_q, l, p, \tau_w$	β_q	β_q	

NSE (Nash & Sutcliffe 1970) which is defined as:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{N}(Q_{obs,i} - \overline{Q_{obs}})^2} \tag{8}$$

where Q_{sim} and Q_{obs} are the simulated and observed runoff, respectively. $\overline{Q_{obs}}$ is the mean of the observed runoff, i is the ith day, and N is the number of days in the calibration period.

To evaluate the performance of the nonstationary model, four different models are compared as illustrated in Figure 5. The calibrated model is the model of which the parameters are optimised for each time period hence it shows the best performance for the whole calibration period from 1961–1970 to 1999–2008. The static model is adopted to evaluate whether the conventional stationarity assumption is valid for the climate change impact study. This model uses parameters calibrated for the first 10-year period (1961–1970) and these parameters are applied for the rest periods to see whether the model performance is kept or decreases along time. The nonstationary model is adjusting parameters against time while the stationary model is similar to the static model except for using the first 10-year period parameters of the nonstationary model. Therefore, when we compare the model performance along time, the calibrated model and the static model start at the same R^2 value, and the nonstationary model and the stationary model start at the same R^2 value. For the static and stationary models, the calibration period is the first 10 years (1961–1970) and the validation periods are from the second 10 years (1962–1971) to the last 10 years (1999–2008) while for the nonstationary model the calibration periods are from 1961–1970 to 1981–1990 and the validation periods are the following periods from 1982–1991

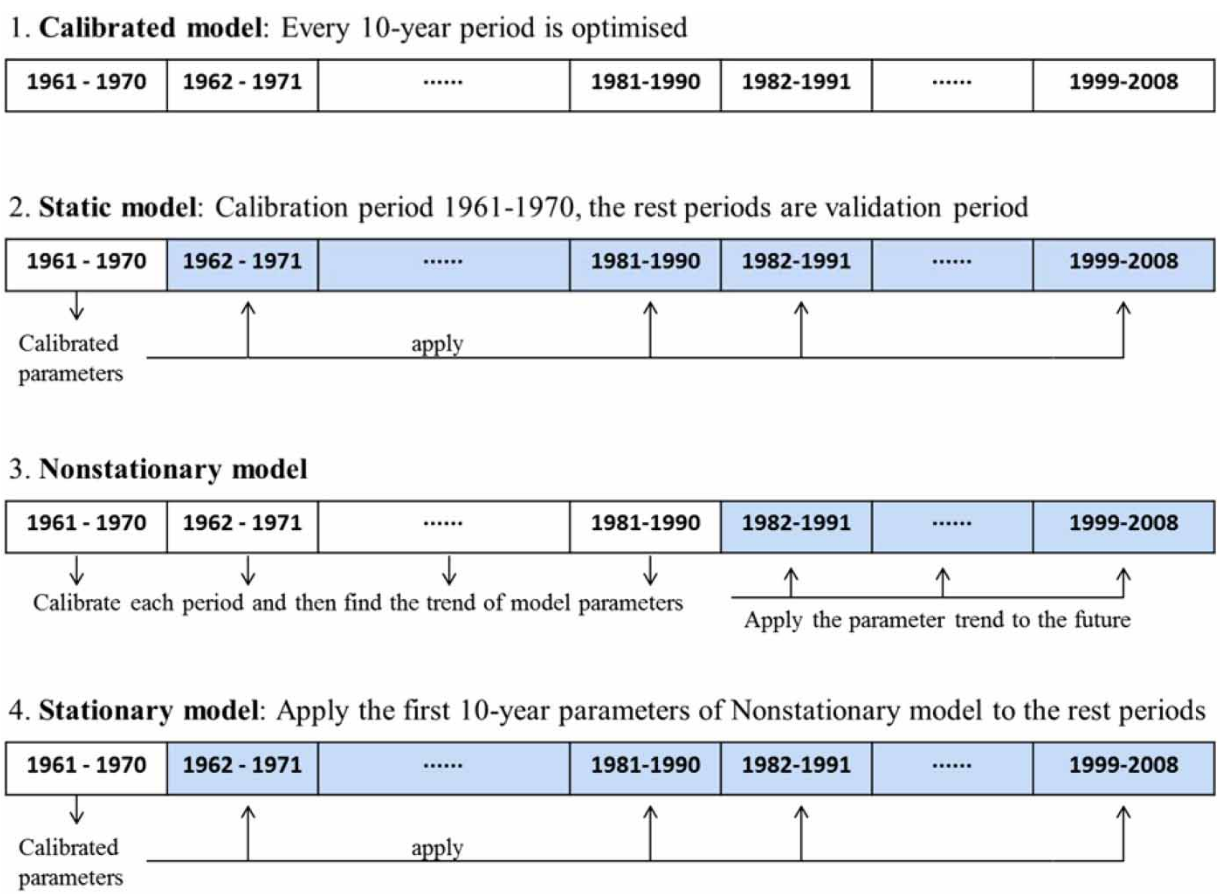

Figure 5 | Illustration of four different models. The shaded areas are the validation period.

to 1999–2008. The nonstationary models have been validated in two ways. First, the trend of model parameters along time is assumed to be linear for the calibration period and this linear equation is extrapolated to the validation period. Second, multiple linear regression analysis has been carried out between each model parameter and climate variables. The climate variables used for multiple regressions are rainfall (average, maximum, variance and kurtosis), temperature (average, maximum, variance and kurtosis), number of wet days, potential evapotranspiration. The parameters for the validation periods are calculated from this multiple regression equation by inputting the climate variables of each validation period.

RESULTS

Temporal behaviour of model parameters

In Figure 6, the model parameters are plotted against the period from 1961 to 1990 to analyse the temporal behaviour. Each dot is the optimised parameter for every 10-year period. The mass balance *c* and quick flow recession time constant τ_q do not show any significant temporal trends. However, there are some parameters that show statistically significant temporal trends. The reference drying rate τ_w decreases with time. This is plausible since if the reference drying rate decreases, the soil tends to be drier (Equations (2) and (3)) which is due to the increase of temperature (Figure 3). The slow flow recession time constant τ_s and the relative volume of slow flow to total flow v_s show an increasing trend and a decreasing trend respectively. These parameters are related to converting effective rainfall to flow which is more related to the catchment characteristics than the climate conditions.

The temperature modulation of drying rate *f* shows an interesting temporal behaviour. The parameter *f* controls the sensitivity of drying rate τ_k to changes in temperature. It decreases until the end of the 1970s but from the beginning of the 1980s, on the contrary, it starts to increase. We could not find any correlation between this parameter and climate variables (precipitation, temperature, potential evapotranspiration, etc.). However, as shown in Figure 7, we find a positive correlation between *f* and Palmer Drought Severity Index (PDSI) (Alley 1984). The PDSI for this catchment has been calculated by using the MATLAB tool (Jacobi *et al.* 2013). The zero PDSI means normal state and drought is expressed in negative values, i.e. the smaller the value is the more severe the drought it is. A possible interpretation of this trend is that large *f* means that τ_k is sensitive to

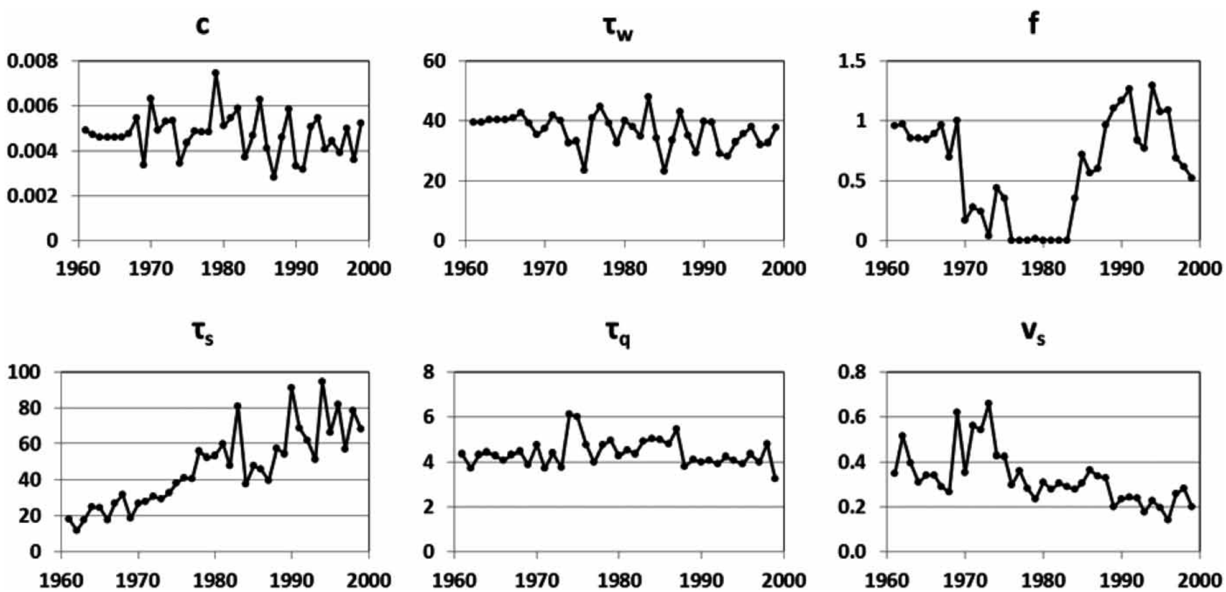

Figure 6 | Model parameters calibrated every moving 10-year period from 1961 to 1999 (mass balance *c*, reference drying rate τ_w, temperature modulation of drying rate *f*, slow flow recession time constant τ_s, quick flow recession time constant τ_q, relative volume of slow flow to total flow v_s).

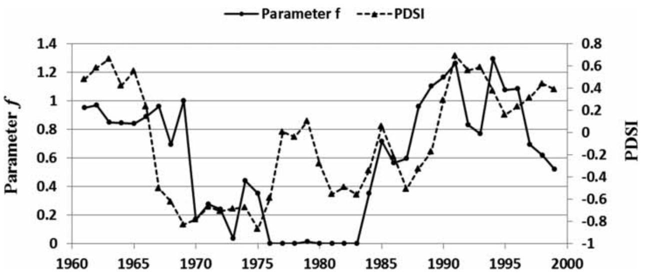

Figure 7 | Temporal distribution of drying rate f and Palmer Drought Severity Index (PDSI).

temperature change and this large τ_k results in small evapotranspiration, i.e. high PDSI. On the other hand, small f means τ_k is non-sensitive to temperature change and this small τ_k results in large evapotranspiration, i.e. low PDSI. Therefore, parameters f and PDSI are positively correlated.

Comparison of the model performance

To evaluate the nonstationary model, four different model performances are analysed in Figure 8. Understandably, the calibrated model shows the best performance for the whole calibration period since the parameters are optimised for each time period. The overall trends of both the static and stationary model performances are getting worse as time goes by. This is a plausible result since in reality the climatic conditions change with time, but in the static and stationary model the temporal change of the model parameters is not considered which brings about error along time. This implies that the stationarity assumption is not valid in the future for this catchment in summer. However, the nonstationary models, both FSM and BSM, work well for the calibration period. The NSE of the nonstationary model is a little less than the calibrated model.

However, in the validation period both the forward and backward multiple parameter changing models fail. The validation has been carried out in two ways, according to how to estimate the parameters in the validation period, as mentioned above under 'Evaluation of model performance' and here only the validated result of FSM is represented in Figure 9 (the performance of BSM for validation period is worse than that of FSM). The nonstationary model performance in the left panel of Figure 9 is estimated by extrapolating the parameters trend based on time. On the other hand, multiple regression analysis has been done between parameters and climate variables for the extrapolation of parameters during the validation period in the right panel of Figure 9. We can see that the performance of the FSM nonstationary model (the dashed-dotted line) is still better than that of the static model (black dashed line), but the difference between the calibrated model (black line) is quite large.

The poor performance of the nonstationary model in the validation period means that both the regression of parameters with time and weather variables is not reliable since the trend of parameters in the calibration period may not be in a monotonic linear relationship. In other words, the relationship that expresses the trend of parameter in the calibration period cannot capture the relationship between the parameter and time or parameter and climate variables in the validation period for this catchment and

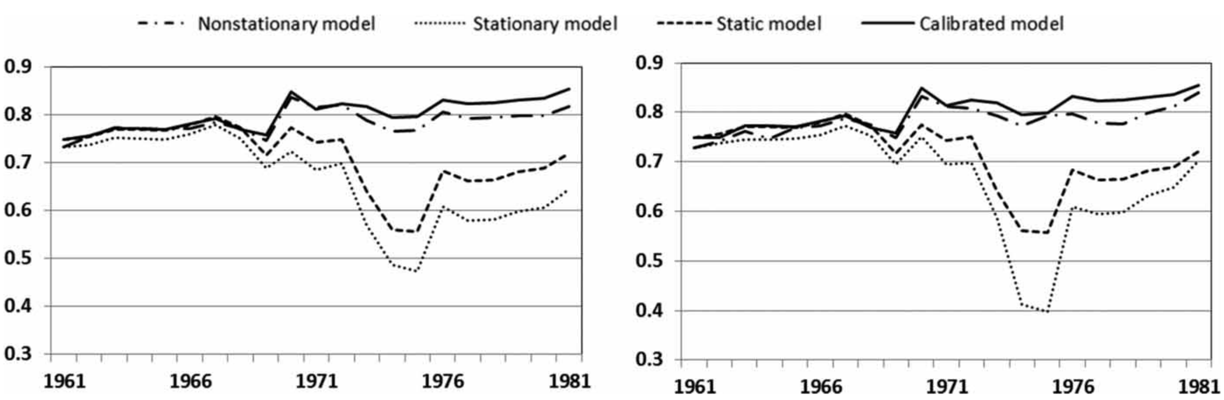

Figure 8 | Model performances (NSE) for every 10-year period from 1961–1970 to 1981–1990. Left: forward stepwise method. Right: backward stepwise method.

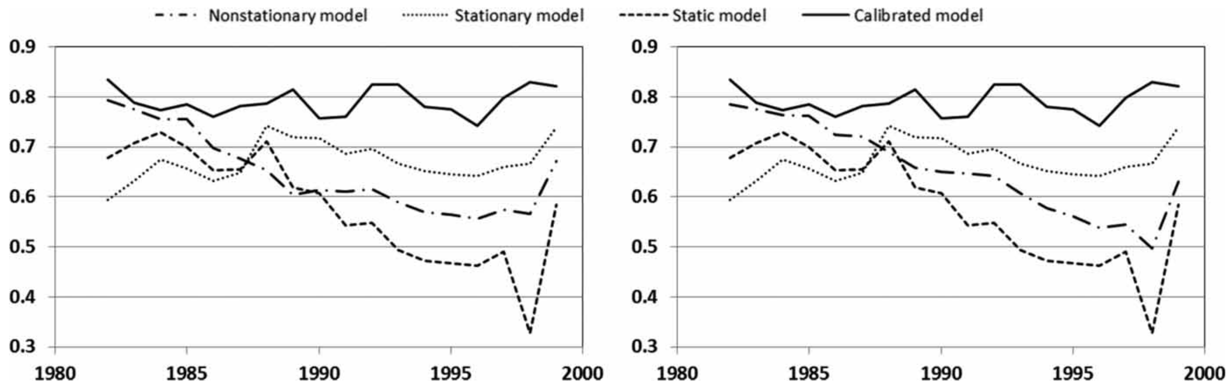

Figure 9 | Model performances (NSE) for the validation period. Left: the extrapolation of parameter trends is based on time. Right: multiple regression analysis has been done between parameters and climate variables for the extrapolation of parameters during the validation period.

input data. For example, the temporal distribution of the temperature modulation of drying rate f shows quite a linear relationship during the calibration period (the data point from 1961 to 1981 in Figure 6); however, the trend tends to be opposite afterwards. Another issue is that changing multiple parameters may not make every parameter optimised since they are interdependent and may be unnecessarily correlated with each other (e.g. their effects could offset each other which result in equifinality).

Model performance of adjusting one parameter against time and climate variable

Although, the performances of both the FSM and BSM nonstationary models are good in the calibration period, they are not satisfactory in the validation period. Therefore, we evaluated the other nonstationary model which is calibrated by optimising only one parameter while the other parameters are fixed. The catchment drying rate τ_w has been selected as an adaptive parameter due to its time stability and link with temperature as shown in Figure 10. The parameter is optimised with the rest of the parameters fixed. It is apparent that the trend is gradually decreasing while the air temperature is increasing over the whole period.

We cannot assume that the trend of parameter τ_w in Figure 10 may appear in the far future as well. However, it can be justified to extrapolate the trend to the future since the observation data are quite long (1961–2008, 47 years) and the trend is stable.

Figure 11 compares the performances of four different models: calibrated model, static model and two nonstationary models. We do not consider the stationary model here.

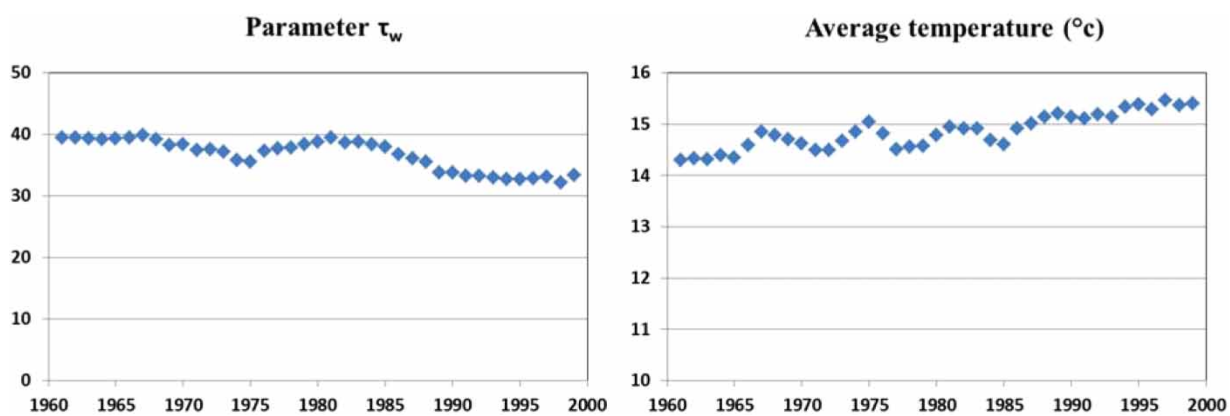

Figure 10 | Temporal distribution of the catchment drying rate (τ_w) and average temperature in summer.

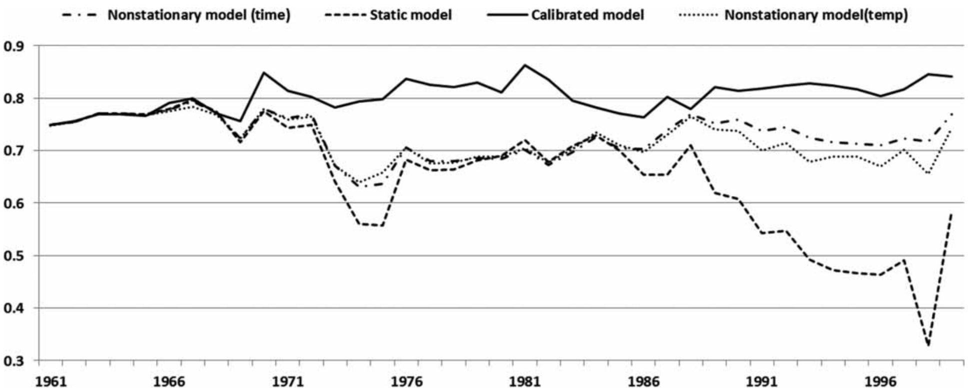

Figure 11 | Model performances (NSE) for every 10-year period from 1961–1970 to 1999–2008.

The result shows that this nonstationary model works well both in the calibration and validation period compared with the static model. For this nonstationary model, two different models have been made according to how to build a regression equation to calculate the parameter for the validation period. The parameter of the first model has been estimated by using linear regression analysis along time for the calibration period and this relationship is assumed to be valid for the validation period. On the other hand, for the second model, linear regression analysis has been carried out between parameter τ_w and air temperature. Likewise linear extrapolation is applied. In Figure 11, the performance of the first nonstationary model is slightly better than the second one. However, the weakness of estimating the parameter by using a monotonic linear relationship with time may not be reliable if the future is too distant since this may result in an unreasonable parameter value. Therefore, the nonstationary model which estimates the future parameter based on the relationship with climate variable might be more plausible.

DISCUSSION AND CONCLUSIONS

In this study, the trend of the hydrological model parameters are found and extrapolated in order to adapt to the future unobserved situations by functionally relating them with time or climate variables. However, the obstacle of this approach is that different parameter sets can produce a similar model performance which is known as parameter equifinality and this may result in large uncertainty in prediction (Beven 1993; Niel *et al.* 2003; Wilby 2005; Minville *et al.* 2008). These diverse sets of possible parameters may lead to different results when they are applied to assess the impacts of climate change on flow (Uhlenbrook *et al.* 1999) and make it difficult to find the trend of parameters. This may be one likely reason for unsatisfactory performance of the stepwise calibrated models in the validation period. Another reason can be when the parameters are extrapolated just in time or in functionally related climate variables, the estimated parameter set may not be an optimised one since there are complex correlations among them. It is not straightforward to understand the temporal change of model parameters (Wagener *et al.* 2010). Therefore, we propose a calibrating scheme that optimises only one parameter which shows an apparent trend and has strong correlation with climate variables.

To further validate the approach of adjusting only one parameter we have added another catchment. The East Dart River at Bellever (21.5 km^2) is used, which is located in the southwest of England. Figure 12 compares the performances of four different models which are previously mentioned under 'Model performance of adjusting one parameter against time and climate variable'. The performance of the nonstationary model is better than the static model, which is similar to the Thorverton catchment result. This supports the conclusion that the adaptive parameter approach is effective.

To make the approach more solid, we tried other parameters as the adaptive one. Only the non-linear module

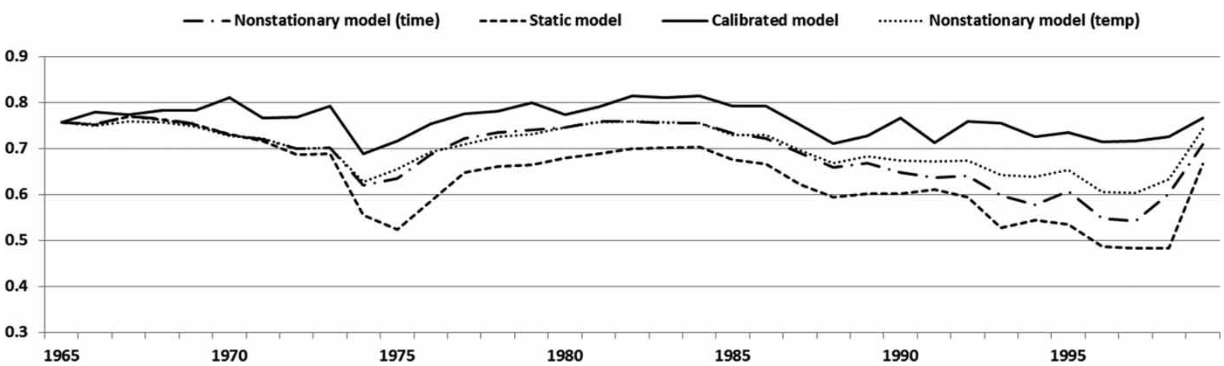

Figure 12 | Model performances (NSE) for every 10-year period from 1965–1974 to 1999–2008 for the Bellever catchment.

parameters are examined since these are more related to the weather variables than the linear module parameters. Among non-linear module parameters, f, the temperature modulation is excluded because the temporal distribution of this parameter does not show any consistent trend. A comparison of the nonstationary model performances among different adaptive parameters is shown along with the calibrated and the static model in Figure 13. As expected, adjusting the drying rate τ_w shows the best performance and the mass balance C has a good performance as well. On the other hand, adjusting the soil moisture index threshold l and the power on soil moisture p are not as good as τ_w and C but are still better than the static model. Figure 14 shows the result for the Bellever catchment. Although the difference between the performances of the adaptive parameters is less than those with the Thorverton catchment, adjusting the drying rate τ_w shows the best performance. Since adjusting other parameters also has a good performance (i.e. better than the static model), this adaptive parameter approach can be a useful method in climate change studies.

There are some possible research areas to be explored further. First, although the proposed methodology, which is adjusting one parameter against time and weather variable, works well for this catchment it does not assure the same result for different catchments and different climate conditions. Therefore, further research is needed to explore the proposed scheme in different catchments in order to find out whether the trend of model parameters and climate variables show consistent spatial correlations which may add credibility to our proposed method. Second, in this study, the catchment conditions are not considered. However, the parameter trends in time may be related to the changes of catchment characteristics and should be explored further. A possible approach to this issue could be based on the Normalized Difference Vegetation Index (NDVI). Third, for decision making regarding the impact of climate change on water resources, water allocation model should be used to see the

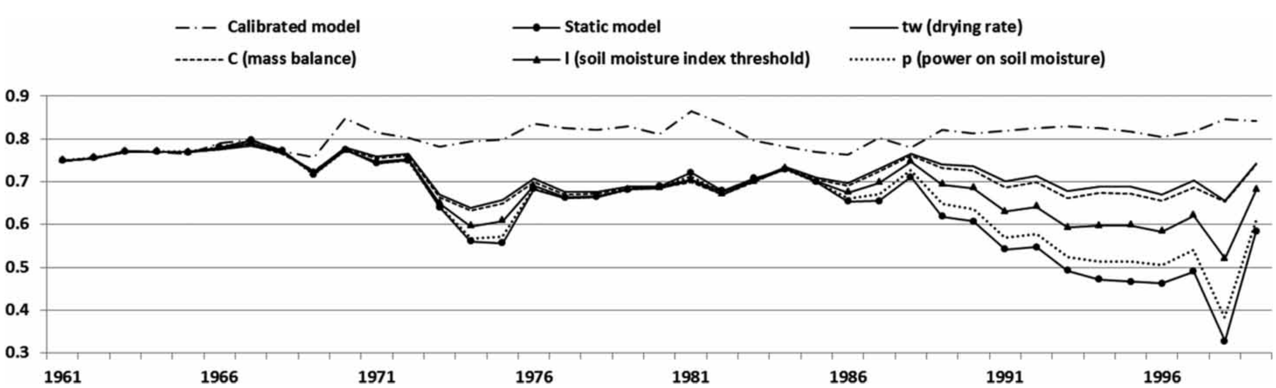

Figure 13 | Comparison of model performances (NSE) among different adaptive parameters for the Thorverton catchment.

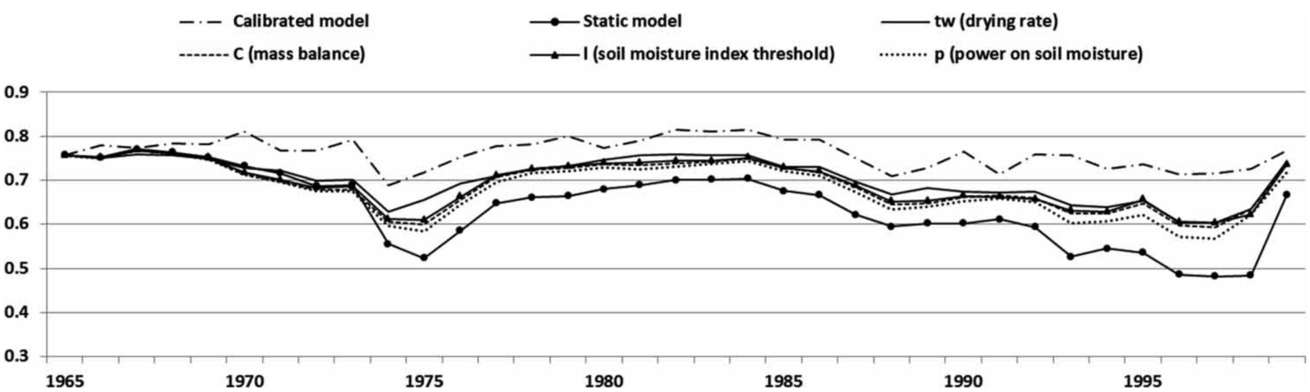

Figure 14 | Comparison of model performances (NSE) among different adaptive parameters for the Bellever catchment.

difference of various adaptation options (e.g. how much larger the reservoir volume should be expanded?).

The main findings of this paper are as follows: The temporal trends of summer precipitation and runoff are apparently decreasing while the air temperature tends to increase. Some model parameters such as the reference drying rate τ_w, the slow flow recession time constant τ_s and the relative volume of slow flow to total flow v_s show clear trends in time when calibrated every 10-year period from 1961–1970 to 1999–2008 for this catchment. We have proposed two parameterisation schemes when conceptual hydrological model is used to assess the impact of climate change. The first method is to adapt the parameters using the step forward and backward selection schemes. However, in the validation period, both the forward and backward multiple parameter changing models do not show much improvement compared with the model which uses time invariant parameters (i.e. static model). One problem is that the regression with time is not reliable since the trend may not be in a monotonic linear relationship with time. The second issue is that changing multiple parameters makes the selection process complex which is time consuming and not effective in the validation period. As a result, a new scheme is explored: only one parameter is selected for adjustment while the other parameters are fixed and regressions of parameters are made against climate conditions and time. It has been found that such a new approach is effective and this nonstationary model works well both in the calibration and validation periods. Although the catchment is specific in southwest England and the data are for the summer period only, the methodology proposed in this study is general and applicable to other catchments. We hope this study will stimulate the hydrological community to explore a variety of sites so that valuable experiences and knowledge could be gained to improve our understanding of such a complex modelling issue in climate change impact assessment.

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REFERENCES

Alley, W. M. 1984 The Palmer drought severity index: limitations and assumptions. *J. Clim. Appl. Meteorol.* **23** (7), 1100–1109.

Arnell, N. 1994 9: Hydrology and climate change. In: *The Rivers Handbook*, Vol. 2 (P. Calow & G. E. Petts, eds). Blackwell, Oxford, UK, pp. 173–185.

Arnell, N. 2011 Uncertainty in the relationship between climate forcing and hydrological response in UK catchments. *Hydrol. Earth Syst. Sci.* **15**, 897–912.

Bates, B., Kundzewicz, Z. W., Wu, S. & Palutikof, J. 2008 *Climate change and water*. Intergovernmental Panel on Climate Change (IPCC), Secretariat, Geneva.

Beven, K. 1993 Prophecy, reality and uncertainty in distributed hydrological modelling. *Adv. Water Resour.* **16** (1), 41–51.

Beven, K. & Freer, J. 2001 Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *J. Hydrol*. **249** (1), 11–29.

Blöschl, G. & Montanari, A. 2010 Climate change impacts – throwing the dice? *Hydrol. Process*. **24** (3), 374–381.

Blöschl, G., Ardoin-Bardin, S., Bonell, M., Dorninger, M., Goodrich, D., Gutknecht, D., Matamoros, D., Merz, B., Shand, P. & Szolgay, J. 2007 At what scales do climate variability and land cover change impact on flooding and low flows? *Hydrol. Process*. **21** (9), 1241–1247.

Boyer, C., Chaumont, D., Chartier, I. & Roy, A. G. 2010 Impact of climate change on the hydrology of St. Lawrence tributaries. *J. Hydrol*. **384** (1), 65–83.

Brown, A. E., Zhang, L., McMahon, T. A., Western, A. W. & Vertessy, R. A. 2005 A review of paired catchment studies for determining changes in water yield resulting from alterations in vegetation. *J. Hydrol*. **310** (1), 28–61.

Chen, J., Brissette, F. P., Poulin, A. & Leconte, R. 2011 Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed. *Water Resour. Res*. **47** (12), W12509.

Chiew, F. H. S., Teng, J., Vaze, J., Post, D. A., Perraud, J. M., Kirono, D. G. C. & Viney, N. R. 2009 Estimating climate change impact on runoff across southeast Australia: Method, results, and implications of the modeling method. *Water Resour. Res*. **45** (10), W10414.

Compagnucci, R., Da Cunha, L., Hanaki, K., Howe, C., Mailu, G., Shiklomanov, I., Stakhiv, E. & Döll, P. 2001 Hydrology and water resources. *Clim. Change* **2001**, 191–233.

Jacobi, J., Perrone, D., Duncan, L. L. & Hornberger, G. 2013 A tool for calculating the Palmer drought indices. *Water Resour. Res*. **49** (9), 6086–6089.

Jakeman, A. & Hornberger, G. 1993 How much complexity is warranted in a rainfall-runoff model? *Water Resour. Res*. **29** (8), 2637–2649.

Jakeman, A., Littlewood, I. & Whitehead, P. 1993 An assessment of the dynamic response characteristics of streamflow in the Balquhidder catchments. *J. Hydrol*. **145** (3), 337–355.

Kim, H. & Lee, S. 2014 Assessment of a seasonal calibration technique using multiple objectives in rainfall–runoff analysis. *Hydrol. Process*. **28** (4), 2159–2173.

Letcher, R., Schreider, S. Y., Jakeman, A., Neal, B. & Nathan, R. 2001 Methods for the analysis of trends in streamflow response due to changes in catchment condition. *Environmetrics* **12** (7), 613–630.

Li, H., Beldring, S. & Xu, C.-Y. 2014 Stability of model performance and parameter values on two catchments facing changes in climatic conditions. *Hydrol. Sci. J*. **60** (7–8), 1–14.

Littlewood, I. 1999 Improved unit hydrograph characterisation of the daily flow regime (including low flows) for the River Teifi, Wales: towards better rainfall-streamflow models for regionalisation. *Hydrol. Earth Syst. Sci*. **6** (5), 899–911.

Merz, R. & Blöschl, G. 2009 A regional analysis of event runoff coefficients with respect to climate and catchment characteristics in Austria. *Water Resour. Res*. **45** (1), W01405.

Merz, R., Parajka, J. & Blöschl, G. 2011 Time stability of catchment model parameters: Implications for climate impact analyses. *Water Resour. Res*. **47** (2), W02531.

Minville, M., Brissette, F. & Leconte, R. 2008 Uncertainty of the impact of climate change on the hydrology of a Nordic watershed. *J. Hydrol*. **358** (1), 70–83.

Nash, J. & Sutcliffe, J. 1970 River flow forecasting through conceptual models part I – A discussion of principles. *J. Hydrol*. **10** (3), 282–290.

Niel, H., Paturel, J.-E. & Servat, E. 2003 Study of parameter stability of a lumped hydrologic model in a context of climatic variability. *J. Hydrol*. **278** (1), 213–230.

Patel, H. & Rahman, A. 2015 Probabilistic nature of storage delay parameter of the hydrologic model RORB: a case study for the Cooper's Creek catchment in Australia. *Hydrol. Res*. **46** (3), 400–410.

Teng, J., Vaze, J., Chiew, F. H., Wang, B. & Perraud, J.-M. 2012 Estimating the relative uncertainties sourced from GCMs and hydrological models in modeling climate change impact on runoff. *J. Hydrometeorol*. **13** (1), 122–139.

Uhlenbrook, S., Seibert, J., Leibundgut, C. & Rodhe, A. 1999 Prediction uncertainty of conceptual rainfall-runoff models caused by problems in identifying model parameters and structure. *Hydrol. Sci. J*. **44** (5), 779–797.

Vaze, J., Post, D. A., Chiew, F. H. S., Perraud, J. M., Viney, N. R. & Teng, J. 2010 Climate non-stationarity–validity of calibrated rainfall–runoff models for use in climate change studies. *J. Hydrol*. **394** (3), 447–457.

Wagener, T. 2007 Can we model the hydrological impacts of environmental change? *Hydrol. Process*. **21** (23), 3233–3236.

Wagener, T., McIntyre, N., Lees, M., Wheater, H. & Gupta, H. 2003 Towards reduced uncertainty in conceptual rainfall-runoff modelling: Dynamic identifiability analysis. *Hydrol. Process*. **17** (2), 455–476.

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. & Wilson, J. S. 2010 The future of hydrology: an evolving science for a changing world. *Water Resour. Res*. **46** (5), W0531.

Wilby, R. L. 2005 Uncertainty in water resource model parameters used for climate change impact assessment. *Hydrol. Process*. **19** (16), 3201–3219.

Wilby, R. L. & Harris, I. 2006 A framework for assessing uncertainties in climate change impacts: low-flow scenarios for the River Thames, UK. *Water Resour. Res*. **42** (2), W02419.

Xu, C.-Y. 1999 Operational testing of a water balance model for predicting climate change impacts. *Agricult. Forest Meteorol*. **98**, 295–304.

Yan, C. & Zhang, W. 2014 Effects of model segmentation approach on the performance and parameters of the Hydrological Simulation Program–Fortran (HSPF) models. *Hydrol. Res*. **45** (6), 893–907.

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