Hydrological validation of statistical downscaling methods applied to climate model projections

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Abstract Understanding the impacts of climate change projections on the hydrological cycle is a great challenge for the hydrometeorological community. The RIWER 2030 project aims at evaluating the impacts of climate change on two French watersheds with major issues of water management. Climate change impact studies use a mixture of GCM, RCM and downscaling methods to generate local watershed climate input time-series for hydrological models to generate streamflow time-series. This modelling chain is rather complex and each step can strongly impact hydrological projections. Before using such a chain, we consider that downscaling methods must be validated on past observations. This paper aims to assess the ability of downscaling methods and hydrological models to reproduce past climate and hydrological observed series and trends. Three downscaling methods (based on analog approaches) were applied on a reanalysis of atmospheric pressure fields over the 1953–2002 period to generate climate time-series. Then, downscaled precipitation and temperatures were coupled to two hydrological models (lumped and semi-distributed) to generate streamflow time-series. Downscaling methods performances were assessed on precipitation and temperatures at different spatial and temporal scales. Hydrological model simulations were also used for a complete assessment on potential evapotranspiration, snow water equivalent and streamflows. The results show a relatively good ability of downscaling methods to reproduce climate observations and to yield good hydrological simulations. However, low flows depend strongly on downscaling methods and hydrological model performance. Downscaling methods are sometimes not able to reproduce an observed trend, which is highly questionable when used for climate change impact studies.

Key words analog methods; statistical downscaling; rainfall–runoff models; past climate validation

INTRODUCTION AND SCOPE OF THE PAPER

The RIWER 2030 project (www.lthe.fr/RIWER2030/index.html) aims to evaluate the impact of climate evolution on hydrological regimes, low flows and associated management practices, on two French catchments facing major water resources management issues (hydropower, irrigation, water supply, tourism).

Understanding the impacts of climate change on the hydrological cycle is a great challenge facing the research community helping end-users to achieve sustainable water resources management (UNESCO, 2007). Over the last couple of decades, the hydrological impacts of climate change on watersheds were the subject of studies all over the word (Gleick *et al*., 1987; Gan & Lettenmaier, 1990; Arnell, 1999; Bergström *et al.*, 2001, Evans *et al*., 2002; Shabalova *et al.*, 2003; Christensen *et al*., 2004; Chiew *et al*., 2009).

In hydrology, most of these climate change impact studies follow a similar general modelling chain (Xu, 2005). After choosing a climate change scenario from those provided by the Intergovernmental Panel on Climate Change (IPCC), a combination of GCM/RCM (Global Circulation Model/Regional Circulation Model) for large- to medium-scale climate modelling is employed and associated with a downscaling method to generate climate data (mainly precipitation, P, and temperature, T) to the scale of catchments. Then, detailed P and T scenarios are used as input data to feed a rainfall–runoff model to generate future streamflow time series. Even if the methodology is widely used, this modelling chain is rather complex and each step can strongly impact hydrological projections. Actually, some uncertainties can appear at each level of the chains and have to be evaluated against observations to avoid results as if throwing the dice (Blöshl & Montinari, 2010).

For estimating the main sources of errors, an evaluation on past climate and streamflow data can be very useful. Indeed, an estimation of the relative level of the various sources of uncertainties in past climate conditions constitutes a good indicator of their potential influence on the future projections (Prudhomme & Davis, 2009a,b).

At the upstream end of the modelling chain, the problem lies in the difficulty for GCM and RCM to represent the main characteristics of past-observed climate (geopotential pressure, humidity, air temperature). These models could be used directly (Graham, 2007) or could provide indicators to statistical downscaling methods (Maraun *et al.*, 2010). The choice of a GCM is generally considered as the main source of uncertainty, followed by the choice of the emissions scenario (Wilby & Harris, 2006; Graham *et al.*, 2007; Kay e*t al.*, 2009; Prudhomme & Davies, 2009b). Many existing studies aim to evaluate and reduce this part of uncertainty (Murphy, 2004; Stainforth *et al*., 2005; Rougier, 2007), but major improvements are still necessary (Roe & Baker, 2007).

At the downstream end of the modelling chain, there is concern about the suitability of rainfall–runoff models for applications in non-stationary climate conditions. Indeed, it may depend on the model structure or on the parameters (Xu, 1999; Wilby & Harris, 2006; Kay, 2009) and has also to be taken into account as a potential source of uncertainty (Vaze *et al*., 2010; Merz, 2011). Last but not least, uncertainties also come from the ability of downscaling methods scenarios to produce satisfactory meteorological inputs for hydrological models (Salathé *et al.*, 2005; Fowler *et al.*, 2007).

The objective of the present study is to propose a hydrological validation of this part of the modelling chain directly in relation with rainfall–runoff models. The downscaled data are often evaluated against observed meteorological data (see Graham, 2007, for dynamical downscaling; Prudhomme & Davis, 2009a, and Teutshbein, 2010, for statistical downscaling), but seldom from the perspective of streamflow simulations produced by rainfall–runoff models fed with down-scaled data. Moreover, other internal state variables of rainfall–runoff models could also be used to analyse the relevance of downscaled data, such as actual evaporation and snow water equivalent.

This paper aims to assess the ability of three statistical downscaling methods and hydrological models to reproduce past climate data and streamflow characteristics. Different statistical representations are proposed to evaluate the downscaling methods in the key range of interest of observed streamflow.

METHODOLOGY, CASE STUDY AND MATERIALS

To answer these questions in the RIWER 2030 project, three statistical downscaling methods (based on analog approaches and weather types) were applied on the atmospheric pressure field re-analyses over the 1959–2002 period to generate numerous scenarios of P and T on the same period. Then, re-sampled P and T data series were input to two types of hydrological models (one lumped and one distributed) to generate streamflow time-series over the same period. Two French watersheds with contrasting hydrological regimes were used: the Durance at Serre-Ponçon and the Loire at Gien.

First, the performance of each downscaling method was directly assessed against P and T observed series and then indirectly by comparing observed streamflow data with those produced by rainfall–runoff models. For a complete performance assessment of downscaled data, some internal variables of hydrological models were also considered, such as AE and SWE. Here, due to the lack of space, results are only illustrated on streamflow simulation assessment with one down-scaled method, one hydrological model and one case study, but detailed results are available from the authors.

This assessment is based on use of deterministic and probabilistic graphical representations, to measure the skill and reliability of downscaling methods. A specific representation of low flows was also used to complete this analysis.

Selected case study

The Durance River catchment drains more than 3580 km^2 at the Serre-Ponçon multi-purpose dam. This mountainous catchment is located in the southern French Alps. The Durance hydrological

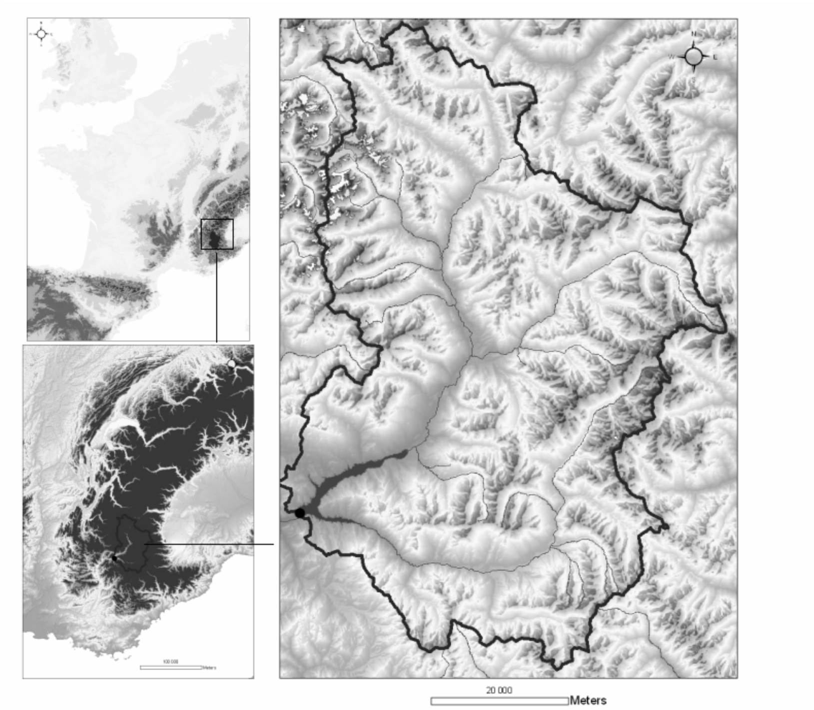

Fig. 1 Location and detailed maps of the Durance River catchment at Serre-Ponçon Dam.

regime is greatly influenced by the presence of snow on a major part of catchment during a significant period of the year. The waters stored in the Serre-Ponçon Reservoir are used for different purposes: irrigation, drinking water, hydro-electric production, sport and tourism. The area is particularly sensitive to water shortages as it is influenced by dry Mediterranean climate conditions. It is also a “hot spot” in many climate model projections, with increasing temperatures and decreasing winter precipitation (Giorgi *et al.*, 2008; Somot *et al.*, 2008).

Analog downscaling statistical methods for long-term forecasting

Over the last two decades, extensive research of downscaling methods and applications in hydrology has been carried out to adapt/derive outputs of GCM at appropriate scales for rainfall–runoff modelling (see the reviews of Xu, 1999; Fowler *et al.*, 2007; Maraun *et al.*, 2010; and the guidelines given by Wilby, 2004). These methods can be divided into two groups (Shimidlli *et al.*, 2006): dynamic downscaling with the use of RCM, and statistical methods based on relationships between large-scale climate information and regional variables. Analog methods can be classified in the second category. This method is a simple downscaling scheme widely used in the field of short-term weather forecasting, for ensemble prediction forecasting (Voisin *et al.*, 2006) and uncertainty analysis (Ramos *et al*., 2010). For a given forecast day, the method involves searching for other days in the past when the weather type and the geopotential pattern looked very similar by the predictors (the analog days). As many analogs are possible and considered equiprobable, analogy methods can produce many scenarios to reach a probabilistic framework for uncertainty assessment. Moreover, as mentioned by Koustsoyiannis (2008), a major part of the uncertainty has to be recognized and minimized by probabilistic description.

In the RIWER 2030 project, three different statistical downscaling methods based on an analog framework were used. Hereafter they will be called Analog DTG (adapted from Obled *et al.*, 2002), DDWGEN (Mezghani *et al.*, 2009) and DSCLIM (Boé *et al.*, 2006). These analog methods are based on statistical downscaling for large-scale predictors from the NCEP/NCAR reanalysis and include regional weather types (such as Garavaglia, 2010) or K-nearest neighbours for re-adjust re-sampling. For all these methods, an additional correction of temperature is applied with, for some, a multiplicative correction for rainfall.

Rainfall–runoff models and observation data

A lumped hydrological model, MORDOR (Andreassian *et al.*, 2006), and a distributed model adapted from the CEQUEAU model structure (Morin, 2002) were implemented in this study. These two rainfall–runoff models were run with the downscaled P and T data scenarios to compare the effects of calibration parameters, model structures and level of spatialization.

The MORDOR model is an operational model calibrated for short-term streamflow forecasting at EDF. The CEQUEAU model is spatially distributed in hydrological units, but uses a single offset of parameters for the entire catchment. The advantage of a distributed model is to simulate streamflow and other internal state variables (AE, SWE) in all meshes. It opens the possibility for a spatial validation inside the distributed model.

The models are fitted with a split sample test procedure on the 1959–2005 period. Calibration was performed by a multi-objective genetic algorithm, with the mean squared error criteria on hydrological regime and low flows (in accordance with the challenge of case study for climate change).

The observed data (P,T) are available from 1953 to 2005 and were provided by the 1-km^2 grid reanalyses for mountainous catchments called SPAZM (Gottardi & Gailhard, 2009). This provides a correction for the underestimation of mountainous precipitations. These P and T reanalysis/ observation data are used by the rainfall–runoff models in past climate in calibration and validation. For statistical downscaling, these data are also used as meteorological archives for re-sampling time-series.

Here, only the results from the CEQUEAU model with Analog DTG statistical downscaling methods are presented.

RESULTS FOR STREAMFLOW RECONSTITUTION

The results are based on 50 scenarios of P and T simulated between 1953 and 2002. For one scenario, each day is selected by a random sampling between the 31 analogs determined with form distance of the predictors given by NCEP-NCAR reanalysis.

Three types of streamflow time series are compared over the 1953–2002 period: (1) the 50 streamflow time series simulated by the CEQUEAU model forced with the 50 P and T time series downscaled by the Analog DTG method, (2) the streamflow series simulated by the CEQUEAU model forced with observed P and T series, and (3) the observed streamflow series. The two last series provide an evaluation of the errors produced by the rainfall–runoff model. For the study catchments, the important streamflow characteristics to consider are annual flows, hydrological regime (monthly mean flows), the snowmelt period and low-flow characteristics.

Figure 2 presents the results at the annual time step. Two representations are shown. On the left, a classical graph where we can see the envelope produced by the 50 scenarios. This envelope has a good fit with the observed data. However, the observation is sometimes outside the envelope, especially for dry years. The right graph confirms this problem. It is a probabilistic representation showing the probability of the observation (or streamflow simulated from P and T observed) in the distribution of probability of 50 streamflows from the P, T analog as a function of the distribution probability of these 50 streamflows. This representation take inspiration from Liao & Tamea (2007) for ensemble forecasting where a good forecast calibration is on the bisector. For the high frequency up to 0.8 (forward dry year), the probability is always at 1. This can be interpreted as a bad statistical calibration. In our case, the model with downscaled data is too wet. The same representation could be also plotted for seasonal or monthly streamflow.

The left graph of Fig. 3 shows the monthly mean validation of streamflow obtained with the downscaling method. The graph represents the median (quantile 50%) and high values (quantile 10% and 90%) in the distribution for the 1952–2003 period. A good monthly mean calibration is obtained with observed data for the low flows and medium flows, except in April–May when snowmelt is over-estimated. High flows (quantile 90%) are over-estimated. Nevertheless if we compared observed streamflow modelled with P and T observed, it appears that most of the errors

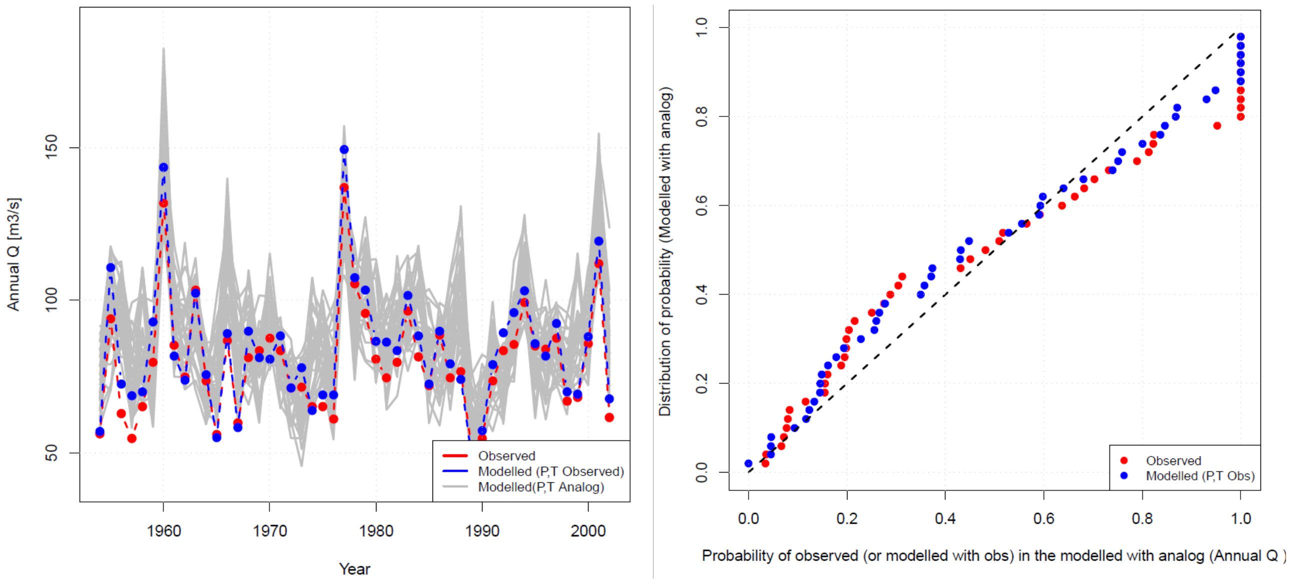

Fig. 2 Left, 1953–2002 validation of annual streamflow simulated by the CEQUEAU model for the 50 scenarios and observed streamflow data, and right, modelled streamflow data simulated by the observed P and T for the Durance catchment.

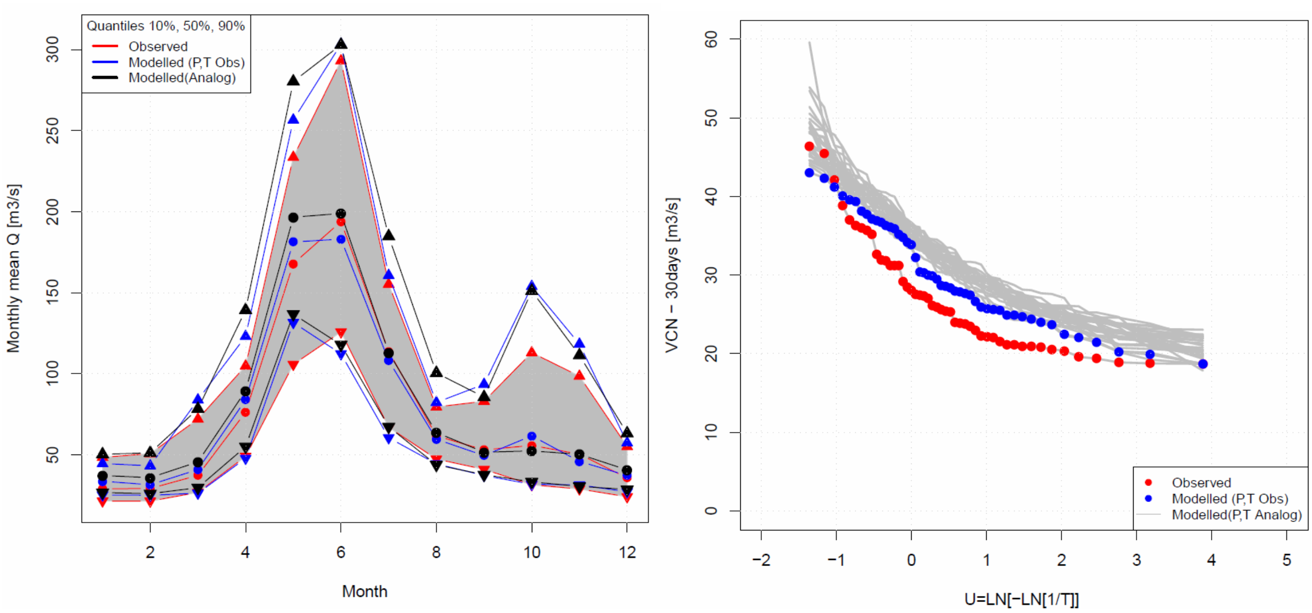

Fig. 3 Left: 1953–2002 validation of quantiles (0.1, 0.5 and 0.9) of monthly mean streamflow (hydrological regime) simulated by the CEQUEAU model. Right: statistical adjustment distribution of on a 49 years period. (1953–2002) of VCN30 values (minimum annual mean flow over a period of 30 consecutive days).

come from the hydrological model. In the right graph, the ability to simulate the distribution of low flow with analog data is shown with the VCN30 norm (minimum annual mean flow over a period of 30 consecutive days) indicator. Although the hydrological model is not perfect (difference between the red and blue curves), the low-flow statistical distributions simulated with downscaled data are really over-estimated.

Finally, the streamflow modelled from downscaled data provide good estimation for the medium range. But, they are too wet for the dry periods at all time steps (annual, monthly means and low flow statistics). Nevertheless, a part of the error comes from the hydrological model.

CONCLUSION AND PERSPECTIVES

For the case study presented (CEQUEAU model, Durance catchment and Analog DTG methods), the results show a relatively good ability of downscaling methods to reproduce hydrological observations at different spatio-temporal scales. Some good results on snowmelt periods indicate a good coherence in the P and T re-sampling time-series (the interest of analog days). However, it appears that the simulation of some key variables of interest for water resources management, such as low flows, depends strongly on the selected downscaling method and the hydrological model performance. Downscaling methods are sometimes not able to reproduce observed trends, which is highly questionable when they are used in climate change impact studies. Moreover, given that downscaling methods and hydrological models will be used in non-stationary climate conditions, it is also important to check that downscaled data can reproduce some trends in observations.

These representations should allow a benchmarking of three downscaling methods and two rainfall–runoff models on two contrasted catchments within the RIWER project. The benchmarking makes it possible to determine the failures of each part (and consequently helps to correct and improve them). This step should be carried out before using the downscaled data with the outputs of GCM as predictors, which will certainly reveal new errors.

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