Journal of Hydrology 479 (2013) 200–214

Contents lists available at SciVerse ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Performance and uncertainty evaluation of empirical downscaling methods in quantifying the climate change impacts on hydrology over two North American river basins

Jie Chen [a,*], François P. Brissette [a], Diane Chaumont [b], Marco Braun [b]

[a] Department of Construction Engineering, École de technologie supérieure, Université du Québec, 1100 Notre-Dame Street West, Montreal, QC, Canada H3C 1K3
[b] Groupe Scénarios climatiques, Ouranos, 550 Sherbrooke West, West Tower, 19th Floor, Montreal, QC, Canada H3A 1B9

ARTICLE INFO

Article history:
Received 9 July 2012
Received in revised form 24 November 2012
Accepted 30 November 2012
Available online 7 December 2012
This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Martin Beniston, Associate Editor

Keywords:
Empirical downscaling
Uncertainty
Climate change
Hydrology
Model output statistics

SUMMARY

Statistical and dynamical downscaling techniques have been proposed to bridge the gaps between coarse-scale and generally biased climate model outputs and the point-scale requirements of impact model inputs. Amongst the various statistical approaches, empirical downscaling methods are the most commonly used due to their ease of implementation. Several empirical downscaling approaches have been proposed and need to be assessed as to which method contributes (or not) to the overall climate change uncertainty. Accordingly, this work aims at assessing the uncertainty of six empirical downscaling methods in quantifying the hydrological impact of climate change over two North American river basins under different climate conditions. The six empirical downscaling methods are grouped into change factor (two methods) and bias correction (four methods) approaches. The uncertainty related to the choice of an empirical downscaling method is compared to that associated with the choice of climate simulation, through the use of two Regional Climate Models (RCMs) driven by three different General Circulation Models (GCMs), totaling four RCM simulations, taken from the NARCCAP inter-comparison project. The future (2041–2065) hydrological regimes simulated with an empirical lumped hydrology model (HSAMI) are compared to the reference period (1971–1995) using a set of hydrology criteria which includes statistics of both mean and extreme values. The results show a large uncertainty envelope associated with the choice of a given empirical downscaling method, as well as for the choice of an RCM simulation. The uncertainty due to empirical downscaling and RCM simulation was more significant in projecting extreme streamflow than in projecting mean flows. Comparing the uncertainty envelope of empirical downscaling methods to the envelope resulting from four RCM simulations indicates that both are similar, even though the latter was slightly larger for some statistics. Finally, the uncertainty linked to the choice of an empirical downscaling approach (change factor vs. bias correction) was much larger than within each type. Overall, this work emphasizes the importance of using several climate projections and empirical downscaling approaches to delineate uncertainty when assessing the climate change impacts on hydrology.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC, 2007) stated that the precipitation pattern and temperature will significantly change by the end of the 21st century. The changes in precipitation and temperature will substantially affect watershed hydrology, since they are the main factors affecting the global hydrological cycle (Teutschbein and Seibert, 2010). Currently, General Circulation Models (GCMs) are the major tools used to simulate the present climate and to project the future climate change. However, the resolution of GCM outputs (usually precipitation and temperature) is too coarse and biased to be used directly by hydrological models for impact assessment.

Dynamical and statistical downscaling techniques have been used to bridge these gaps. Dynamical downscaling was developed based on dynamic formulations using the initial and time-dependent lateral boundary conditions of GCMs to drive a Regional Climate Model (RCM) to produce higher resolution outputs (Dickinson et al., 1989; Giorgi, 1990; Caya and Laprise, 1999). The spatial resolution of RCMs is much improved compared to that of GCMs (Maraun et al., 2010; Teutschbein and Seibert, 2010). RCMs provide a better description of orographic effects, land-sea contrast and land-surface characteristics (Jones et al., 1995; IPCC, 2007; Buonomo et al., 2007). Therefore, they significantly contribute added values compared to GCMs (Durman et al., 2001; Frei

* Corresponding author. Tel.: +1 5143968800x7690.
E-mail addresses: jie.chen.1@ens.etsmtl.ca, chj092413@yahoo.com.cn (J. Chen).

0022-1694/$ - see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jhydrol.2012.11.062

et al., 2006; Buonomo et al., 2007). Even though the ability of an RCM to simulate the spatial pattern and temporal characteristics of climate variables increases with model resolution, substantial biases inherited from the driving GCM or RCM still exist (Durman et al., 2001). For example, most RCMs tend to overestimate the occurrence of wet days, but underestimate the amount of heavy precipitation (Murphy, 1999; Fowler et al., 2007). In particular, RCMs show little skill at representing summer precipitation due to the difficulties in modeling convective rainfall (Maraun et al., 2010).

Statistical downscaling involves linking the states of some variables representing a large scale (predictors) to the states of some variables representing a smaller scale (predictands). Maraun et al. (2010) classified statistical downscaling into perfect prognosis (perfect prog), Model Output Statistics (MOSs) and weather generator-based methods. Perfect prog approaches involve establishing statistical relationships between variables at large-scale and local-scale (Wilby et al., 1998, 2002; Chen et al., 2012a). These approaches assume that the large-scale variables are perfectly modeled by climate models. The MOS approaches involve establishing a statistical relationship between variables simulated by the RCM (predictors) and local-scale observations (predictands) to correct RCM errors. The predictors and predictands can be on the same spatial scale (bias correction) or on a different spatial scale (both bias correction and downscaling) (Maraun et al., 2010). Statistical downscaling using weather generators is achieved through the perturbation of weather generator parameters based on changes projected by climate models between future and reference periods (Wilks, 1992, 1999; Kilsby et al., 2007; Qian et al., 2005, 2010; Chen et al., 2012b).

The unique characteristics of each downscaling method lead to different future climate scenarios, implying that the downscaling approaches add uncertainty in climate projections. The uncertainty related to climate scenarios may be amplified when taking into account the choice of impact models, such as hydrological models. Many studies have focused on the uncertainty related to GCMs and greenhouse gas emission scenarios (GGESs), and have consistently found that GCMs were the largest uncertainty contributors (Jenkins and Lowe, 2003; Rowell, 2006; Wilby and Harris, 2006; Deque et al., 2007; Prudhomme and Davies, 2009; Kay et al., 2009; Chen et al., 2011a). However, the studies of Horton et al. (2006), Chen et al. (2011b), and Teutschbein et al. (2011) all highlighted that downscaling approaches are also a large uncertainty contributor, up to the level of GCMs for some hydrological statistics. The importance of downscaling uncertainty has been given more attention in recent years. Mpelasoka and Chiew (2009) compared the impact of three empirical downscaling methods (constant scaling – also known as the delta change method, daily scaling and daily translation) on the construction of runoff projections across Australia. The daily scaling method displayed advantages over constant scaling in projecting the changes of runoff, especially in projecting extreme runoff. The uncertainty associated with the choice of a downscaling method was found to be much smaller than that related to GCMs. Themeßl et al. (2010) compared an ensemble of seven statistical and bias correction approaches in downscaling RCM daily precipitation over the historical data period in the Alps region. The results showed that the bias correction approaches such as quantile mapping and local intensity scaling, and the nonlinear analogue method yielded systematic improvements in daily precipitation statistics, while multiple linear regression methods exhibited significant drawbacks in modeling daily precipitation, because there may not be a linear relationship between predictors and local daily precipitation. The quantile mapping method showed the best performance comparing to other six methods, particularly in the downscaling of precipitation extremes. Chen et al. (2011b) investigated the uncertainty related to six dynamical and statistical downscaling methods in quantifying the impacts of climate change on the hydrology of a Canadian river basin. A large uncertainty was found to be associated with the choice of downscaling methods, even comparable to GCM uncertainty for some hydrological statistics. Teutschbein et al. (2011) assessed the uncertainty by using three statistical downscaling methods (an analog method, a multi-objective fuzzy-rule-based classification and the statistical downscaling model (SDSM)) to downscale precipitation from two GCMs under two GGESs. They quantified the variability of seasonal streamflow and peak flood in Sweden and found that the uncertainty was large enough to render the determination of future trends impossible. The choice of a GCM dominated the uncertainty envelope, but the choice of downscaled precipitation series had a substantial impact on the streamflow projection.

Amongst the various statistical approaches reported in literatures (Wilks, 1992; von Storch et al., 1993; Wilby et al., 2002; Mpelasoka and Chiew, 2009; Themeßl et al., 2010, 2011; Chen et al., 2011b, 2012a, 2012b), empirical downscaling methods are very commonly used due to the ease of their implementation. They are MOS approaches that seek to use information from biased model outputs. The commonly-used empirical downscaling methods can be grouped into change factor and bias correction approaches (Ho et al., 2012). Change factor approaches assume that the climate change signal (CCS) is reasonably projected by climate models, even though the models are biased. Alternatively, bias correction approaches suppose that the model biases stay constant over time. In other words, bias correction approaches assume that the relationship between the distributions of observed and modeled variables for the reference period is the same as that for the future period. A study by Ho et al. (2012) showed that these two downscaling approaches give substantial differences in spatial warming patterns over Europe.

Even though there are several studies assessing the uncertainty related to the choice of a downscaling method, only a few take into account the uncertainty associated with the choice of an empirical downscaling approach, and even fewer involve evaluating the uncertainty of empirical downscaling on climate change impacts. For climate change impact studies, downscaling of climate model outputs (e.g. precipitation and temperature) is not an end in itself since the ultimate goal is to provide inputs to impact models. Thus, it is necessary to know to what extent the choice of an empirical downscaling approach contributes to the overall uncertainty in climate change impacts.

This work assesses the uncertainty of six empirical downscaling methods in quantifying the hydrological impact of climate change over two North American river basins under different climate conditions. The six empirical downscaling methods are grouped into change factor (two methods) and bias correction (four methods) approaches. The uncertainty linked to the choice of an empirical downscaling method is further compared to that associated with the choice of a climate simulation, through the use of four climate simulations from the combination of two RCMs and three GCMs, taken from the North American Regional Climate Change Assessment Program (NARCCAP) inter-comparison project (Mearns et al., 2007, 2009). This work mostly deals with the uncertainty linked to the empirical downscaling methods in a changing climate and is less concerned with the evaluation of the individual method performance in the reference period.

2. Study area and data sources

2.1. Study area

Two North American river basins (Manicouagan 5 basin in the Province of Quebec and Chickasawhay basin in the state of Missis-