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Regional Climate Models for Hydrological Impact Studies at the Catchment Scale: A Review of Recent Modeling Strategies

Claudia Teutschbein[1]* and Jan Seibert[1,2]
[1]*Department of Physical Geography and Quaternary Geology, Stockholm University*
[2]*Department of Geography, University of Zurich*

Abstract

This article reviews recent applications of regional climate model (RCM) output for hydrological impact studies. Traditionally, simulations of global climate models (GCMs) have been the basis of impact studies in hydrology. Progress in regional climate modeling has recently made the use of RCM data more attractive, although the application of RCM simulations is challenging due to often considerable biases. The main modeling strategies used in recent studies can be classified into (i) very simple constructed modeling chains with a single RCM (S-RCM approach) and (ii) highly complex and computing-power intensive model systems based on RCM ensembles (E-RCM approach). In the literature many examples for S-RCM can be found, while comprehensive E-RCM studies with consideration of several sources of uncertainties such as different greenhouse gas emission scenarios, GCMs, RCMs and hydrological models are less common. Based on a case study using control-run simulations of fourteen different RCMs for five Swedish catchments, the biases of and the variability between different RCMs are demonstrated. We provide a short overview of possible bias-correction methods and show that inter-RCM variability also has substantial consequences for hydrological impact studies in addition to other sources of uncertainties in the modeling chain. We propose that due to model bias and inter-model variability, the S-RCM approach is not advised and ensembles of RCM simulations (E-RCM) should be used. The application of bias-correction methods is recommended, although one should also be aware that the need for bias corrections adds significantly to uncertainties in modeling climate change impacts.

Introduction

A changing climate and possible impacts on hydrology are currently intensely discussed issues. As the latest Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC 2007) stated, temperature, water vapor and precipitation patterns will significantly change by the end of the 21st century. With those variables being the main factors influencing the hydrologic cycle, climate change is therefore expected to have a major impact on watersheds at both global and local levels.

Since water is an essential resource, variations in the hydrologic cycle often have serious consequences. It is, thus, necessary to adjust future flood control concepts, hydropower production, agricultural irrigation, ecosystem preservation strategies and many more. To provide responsible decision makers with the best possible information, it is the scientists' job to apply reliable and accurate methods, especially in such a relatively uncertain domain as climate modeling. To drive a hydrological model, reliable information on climatological variables (e.g. temperature, precipitation, evapotranspiration, etc.) and their distribution in space and time are required.

The most commonly used tools for climate predictions are global climate models (GCMs). Because their insufficient spatial scale (grid-cell resolutions of approximately 100–250 km) is lacking detailed regional information (IPCC 2007), downscaling procedures are required in order to provide fine-resolution climate parameters for hydrological modeling. Possible downscaling methods include statistical or dynamical approaches. The former are based on statistical relationships between large-scale climate information and regional variables (Hewitson and Crane 1996; Wilby et al. 2004), whilst the latter imply the application of regional climate models (RCMs) for limited regions with boundary conditions based on GCM simulations. The advantages and drawbacks of these two fundamental downscaling approaches have been widely discussed in literature (Murphy 1998, 2000; Wilby and Wigley 1997) as have their impacts on resulting simulations (Haylock et al. 2006; Hellström et al. 2001; Schmidli et al. 2006). A comprehensive review paper on downscaling techniques for hydrological modeling is the one by Fowler et al. (2007). We focus on the use of RCMs for downscaling GCM simulations in this paper.

Most RCMs currently run at resolutions of 25–50 km. They also include representation of hydrologic components such as surface and subsurface runoff. On the catchment scale, however, their hydrological output variables are only restrictedly applicable. For that reason, hydrological variables from the RCMs are rarely used directly. Instead, their detailed climate information (e.g. temperature and precipitation) are often used to force hydrological models in order to obtain runoff simulations.

Past studies mainly focused on comparing different downscaling methods, i.e. statistical versus dynamical (Busuioc et al. 2006; Murphy 1998, 2000; Wilby and Wigley 1997), or on estimating the uncertainties either caused by the choice of climate change scenarios, GCM or by downscaling methods (Prudhomme and Davies 2009a,b). However, once decided for the dynamical downscaling approach (i.e. using RCMs), the extent of variability caused by using different RCMs has not been fully evaluated. Thus, there are no guidelines available on how to best use RCM output for further impact analyses. Some impact modelers choose to work with only one RCM; others are using multi-model approaches, so-called RCM ensembles.

The objective of this review is to provide an overview of recent modeling strategies in terms of estimating climate change effects on hydrological variables using RCM simulations as a reference for hydrologists and other scientists who are trying to assess climate change impacts on hydrology. Besides reviewing previous studies using RCM simulations for hydrological modeling studies, a case study is presented to demonstrate that RCM simulations of temperature and precipitation are subject to significant uncertainties, which limits their direct application for hydrological impact modeling. Although RCMs have been frequently used in recent years to provide hydrologists with fine-scale climate parameter for runoff predictions, this is still a relatively new field of research. Clear rules are missing, and there is no such thing as 'common practice' in terms of how to best apply RCM simulations for impact studies. With this paper we aim to highlight the need to use multi-model approaches and to apply appropriate bias-correction procedures. The paper is organized as follows: (i) introduction, (ii) a short description of regional climate modeling, (iii) an overview of bias-correction methods, (iv) examples of recent modeling strategies, (v) case study in Sweden: local validation of RCM simulations using a conceptual runoff model, (vi) discussion of the case study and previous studies and (vii) conclusion on future application of RCM output.

Regional climate modeling

Until recently, most hydrological impact studies were based on GCM simulations. However, as the resolution of these models was, and still is, much coarser than the typical catchment size, downscaling is necessary. Instead of the traditionally used statistical downscaling, the 'nested' RCM approach (Figure 1) allows a dynamic downscaling (Giorgi 2006) to capture climate processes at local scale. Such 'nested' regional modeling techniques were first applied for climate applications in the late 1980s by Dickinson et al. (1989) (Varis et al. 2004).

RCMs, also referred to as Limited-Area Models (LAMs), produce high spatial and temporal resolution climate information (Mearns et al. 2003). Coarse-grid GCM simulation output is used for initial and lateral boundary conditions, thus a one-way nesting approach is applied to retrieve high-resolution climatic variables (Mearns et al. 2003). Although the one-way mode (without feedback from RCM to GCM) is implemented in almost all RCM studies, two-way nested models (including feedback from RCM simulations to GCM) are currently under development (Lorenz and Jacob 2005). For further reading on details of the RCM technique we refer the reader to review papers on dynamical downscaling (Giorgi 2006; Mearns et al. 2003) and model intercomparisons (Déqué et al. 2007; Frei et al. 2003).

All RCMs use different techniques of discretizing equations and representing sub-grid effects (Déqué et al. 2007). Thus, a spectrum of RCMs is expected to give a variety of different simulation results, so-called ensemble predictions.

Bias correction

The resolution of RCMs typically agrees with the size of meso-scale catchments (i.e. $\sim$10–10,000 km^2), and downscaling should, thus, not be necessary. However, bias correction is usually needed as climate models often provide biased representations of observed times series due to systematic model errors caused by imperfect conceptualization, discretization and spatial averaging within grid cells. Typical biases are the occurrence of too many wet days with low-intensity rain or incorrect estimation of extreme temperature in RCM simulations (Ines and Hansen 2006). A bias in RCM-simulated variables can lead to unrealistic hydrological simulations of river runoff (Bergström et al. 2001). Thus, application of bias-correction methods is recommended (Wilby et al. 2000).

The term 'bias correction' describes the process of scaling climate model output in order to account for systematic errors in the climate models. The basic principle is that

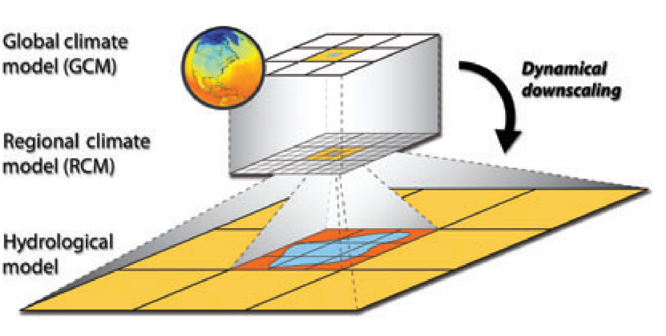

Fig. 1. Downscaling scheme from global to catchment scale.

biases between simulated climate time series and observations are identified and then used to correct both control and scenario runs. A main assumption is that the same bias correction applies to control and scenario conditions. Several techniques are available to create an interface for translating RCM output variables to hydrological models. For instance, precipitation and temperature can be bias-corrected by applying one of the following methods:

1. *Precipitation threshold*: The number of rainfall events is adjusted by applying a precipitation threshold. For instance, all days with precipitation less than 0.1 mm can be redefined to dry days (i.e. $P = 0$ mm).
2. *Scaling approach*: Monthly correction factors based on the ratio of present-day simulated values and observed values are applied so that RCM simulations have the same monthly mean values as observations (Durman et al. 2001). Usually, an additive correction is used for temperature, while a multiplicative correction is used for precipitation.
3. *Linear transformation*: Meteorological variables from the RCM are corrected with a linear transformation equation which considers changes in the mean and variance (Horton et al. 2006; Shabalova et al. 2003).
4. *Power transformation*: A non-linear correction in the form of $P' = aP^b$ is performed (Leander and Buishand 2007; Leander et al. 2008). Parameters a and b can be estimated with help of a distribution-free approach: Leander and Buishand (2007) obtained them for five-day intervals, using a 65-day window. First, they determined b iteratively by matching the coefficient of variation (CV) of the corrected daily precipitation with the CV of observed daily precipitation. Second, they obtained parameter a by matching the observed mean with the mean of the transformed daily values. Thus, a is depending on b, but not vice versa.
5. *Distribution transfer*: A transfer function is derived from historical observed and simulated cumulative distribution functions (CDFs) (Piani et al. 2009). This bias-correction method can be applied in slightly different ways, e.g. based on empirical or different theoretical distribution functions. The gamma distribution is often assumed to be suitable for rainfall-intensity distributions, but other distributions such as beta or Gaussian can also be used (Baigorria et al. 2007). Several other terms can be found in literature. Some examples are 'probability mapping' (Block et al. 2009; Ines and Hansen 2006), 'quantile–quantile mapping' (Boé et al. 2007; Déqué et al. 2007), 'statistical downscaling' (Piani et al. 2009) and 'histogram equalization' (Sennikovs and Bethers 2009).
6. *Precipitation model*: Precipitation is modeled separately with a statistical weather generator such as a random cascade precipitation model (Booij 2005). Observations are used to estimate the climate parameters of the temporal and spatial rainfall model. GCM and RCM simulations are then used for estimating changes in the parameters of the temporal and spatial model, respectively.
7. *Empirical correction*: RCM output data are tailored based on an empirical adjustment method. Engen-Skaugen (2007) introduced a correction factor based on the ratio of observed and reanalysis (ERA-15) data. Then, the precipitation is adjusted empirically including calculations of residuals, normalization of daily precipitation and tuning the standard deviation (Beldring et al. 2008; Engen-Skaugen 2007). Temperature is corrected by modifying the lapse rate and by empirical adjustments similar to precipitation.

All of these methods have certain favorable and unfavorable attributes. The simpler techniques (i.e. approaches 1–4) are less computationally demanding, but aim only at preserving monthly mean values. On the other hand, the advanced procedures (i.e. methods 5–7) are more computational demanding, but are also able to conserve standard deviation or day-to-day and seasonal variability. The general climate change signal (i.e. differences between control and scenario runs) simulated by the RCMs is usually preserved. Most bias-correction procedures are limited to regions with existing weather stations and rely on the fact that the correction procedure and its parameters are valid for larger areas. It also has to be re-emphasized that all methods are based on a stationarity assumption, which means that the applied correction procedure and parameters are assumed to remain constant over time, especially when moving from current conditions to scenario simulations. For a more detailed comparison of bias-correction methods we refer the reader to Déqué (2007) and Hashino et al. (2007).

The delta-change approach (Figure 2A) is an alternative to the direct use of RCM simulations. Here, RCM-simulated changes between control and scenario runs are superimposed upon observational precipitation and temperature time series. In contrast to the often applied scaling approach (Figure 2B), the control run corresponds to the observed climate by definition. The main disadvantage is that with this approach the temporal pattern of the climate variables will not change for the future scenario simulations. The number of rainy days, for instance, will not change with the delta-change approach. Using the delta-change approach, one also has to assume that the changes are simulated acceptably without being able to test the performance of the entire model chain for current conditions.

Recent modeling strategies for assessing impacts on catchment hydrology

In this section an overview of recent studies dealing with the impacts of climate change on hydrology is given. A critical evaluation follows in section 'Discussion'. Some recent

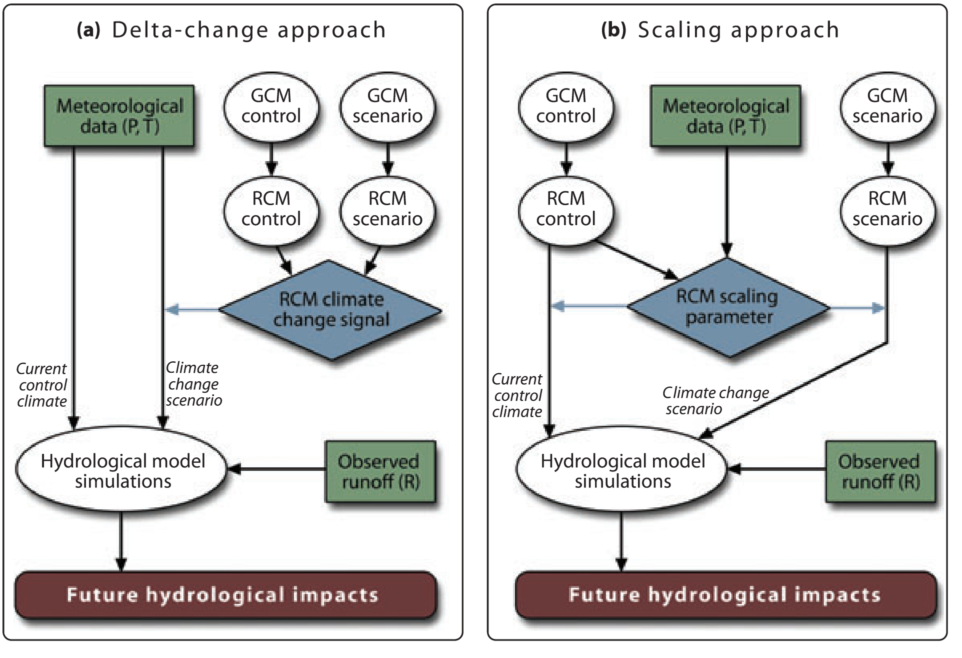

Fig. 2. RCM bias correction scheme for (a) the Delta-change approach and (b) The scaling approach.

examples are studies of the effects of climate change on runoff in general (Bergström et al. 2001), on flood frequencies (Cameron 2006), on groundwater levels (Goderniaux et al. 2009), soil moisture (Mavromatis 2009), water quality (Wilby et al. 2006) and evaporation (Kay and Davies 2008).

The modeling chains that are used for simulating climate impacts on hydrology can range from rather simple systems with only one RCM (Figure 3A) to very complex ensemble-based chains (Figure 3B). Thus, based on their degree of complexity, the majority of available papers on this subject can roughly be classified into the following two categories (Figure 3): (i) single-RCM investigations (S-RCM) and (ii) ensemble-based RCM studies (E-RCM).

A detailed overview of all studies included in this review can be found in Table 1. It gives information about the river basin analyzed and summarizes GHG emission scenarios, GCMs, RCMs and hydrological models used as well as the method of bias correction applied. Most studies have been performed for catchments in Europe or, to a somewhat lesser extent, for North-American catchments. There were only few studies found for catchments in Africa, Asia and South America (Akhtar et al. 2008; Block et al. 2009). While the list of studies included in this review is certainly not complete, these differences still indicate that there is an uneven geographic distribution of hydrological impact studies. While this might be motivated by the availability of long runoff records and other data of good quality, there is a need for hydrological impact studies based on RCM simulations in other regions of the world such as Africa and the tropics, where climate change impacts in hydrology might be different. In dry climates, for instance, the response of runoff to changes in precipitation might be enhanced.

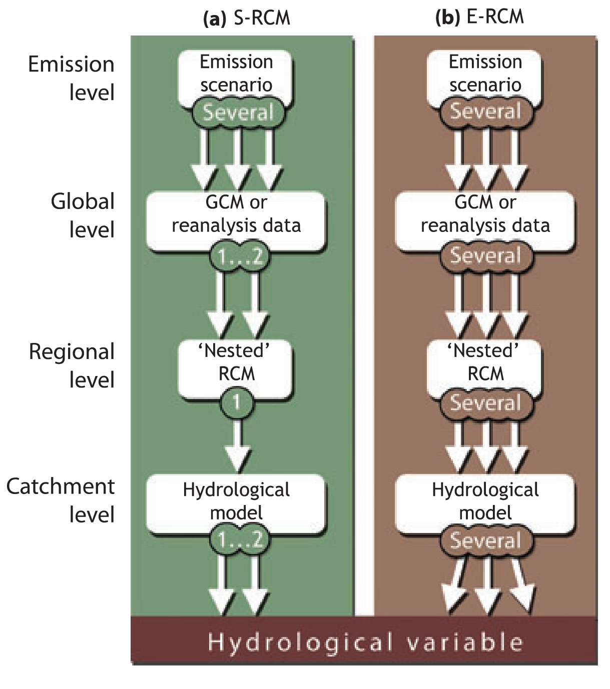

Fig. 3. Classification scheme of possible setups of modeling chains: (a) simple (S-RCM) and (b) ensemble (E-RCM) approach.

Table 1. Overview of reviewed articles (red: S-RCM, blue: E-RCM).

No.	Reference	Study site	GHG emission scenarios	GCMs	RCMs	Resolution	Hydrological models	Bias correction
1	Akhtar et al. (2008)	3750–13,925 km^2 Pakistan: Hunza, Gilgit and Astore River	1 Control	2 ERA-40 reanalysis HadAM3P	1 PRECIS	50 × 50	1 HBV	Yes Scaling approach
2	Beldring et al. (2007)	505–5693 km^2 Norway: Flaksvatn, Masi, Nybergsund and Viksvatn River	3 Control A2 B2	2 ECHAM4/O-PYC3 HadAM3H	1 RegClim-HIR-HAM	50 × 50	1 HBV	Yes Empirical correction
3	Bell et al. (2007a,b)	8–9948 km^2 UK: 25 basins	2 Control A2	2 ERA-15 reanalysis HadCM3	1 HadRM3H	25 × 25	2 G2G, PDM	Not specified
4	Boé et al. (2009)	not specified France: main river basins	2 Control A1B	1 CNRM-CM3	1 CHMI-ARPE-GE/IFS	50 × 50	1 SAFRAN-ISBA-MODCOU (SIM)	Yes Distribution transfer
5	Fowler and Kilby (2007)	35–1300 km^2 UK: 8 basins	2 Control A2	1 HadCM3	1 (3) HadRM3 (3 different initial conditions)	50 × 50	1 ADM	Yes Scaling approach
6	Hay et al. (2002)	526–3626 km^2 USA: Alapaha, Animas, Carson and Cle Elum River	1 Control	1 NCEP/NCAR reanalysis	1 RegCM2	50 × 50	1 PRMS	Yes Distribution transfer
7	Jha et al. (2003)	431,000 km^2	2	2	1		1	Not specified

Table 1. (continued).

No.	Reference	Study site	GHG emission scenarios	GCMs	RCMs	Resolution	Hydrological models	Bias correction
	USA: Upper Mississippi River	Control 1% CO_2 increase per year	NCEP/NCAR reanalysis HadCM2	RegCM2	50 × 50	SWAT		
8	Kay et al. (2006a,b)	10–455 km^2 UK: 15 basins	2 Control A2	2 ERA-15 reanalysis HadCM3	1 HadRM3H	25 × 25	1 PDM	Not specified
9	Kleinn et al. (2005)	2396–24,764 km^2 Germany, Switzerland: Rhine River with 20 sub-basins	1 Control	1 ERA-15 reanalysis	1 (2) CHRM (2 resolutions)	56 × 56 14 × 14	1 WaSIM	Yes Scaling approach
10	Leander and Buishand (2007)	21,000 km^2 France, BeNeLux, Germany: Meuse River	1 Control	2 ERA-40 reanalysis HadAM3H	1 KNMI-RACMO	50 × 50	1 HBV	Yes (1) Scaling approach (2) Power transformation
11	Lee et al. (2004)	sizes not specified China, Korean Peninsula: 4 basins	1 Control	1 NCEP/NCAR reanalysis	1 SNU/RCM	50 × 50	1 simple water balance equation	Not specified
12	Payne et al. (2004)	668,000 km^2 USA: Columbia River	3 Control CO2 at 1995 levels BAU6	1 DOE/NCAR Parallel Climate Model	1 MM5	56 × 56	1 Variable Infiltration Capacity model (VIC)	Yes Distribution transfer

Table 1. (continued).

No.	Reference	Study site	GHG emission scenarios	GCMs	RCMs	Resolution	Hydrological models	Bias correction
13	Semmler et al. (2006)	2173 km^2 Ireland: Suir River	5 Control A1B A2 B1 B2	3 ERA-40 reanaly-sis ECHAM4 ECHAM5	1 RCA3	13 × 13	1 HBV	Not specified
14	Shabalova et al. (2003)	185,000 km^2 Germany, Switzerland, The Netherlands: Rhine River	1 Control 1% CO2 increase per year	1 HadCM2	1 HadRM2	50 × 50	1 RhineFlow	Yes (1) Delta approach (2) Scaling approach (3) Linear transformation
15	Steele-Dunne et al. (2008)	431–2452 km^2 Ireland: 9 basins	2 Control A1B	1 ECHAM5	1 RCA3	25 × 25	1 HBV-light (100 different parameter sets)	Yes (1) Precipitation threshold (2) Distribution transfer
16	Wood et al. (2004)	668,000 km^2 USA: Columbia River	2 Control business as usual (BAU6)	1 DOE/NCAR Parallel Climate Model	1 MM5	56 × 56	1 Variable Infiltration Capacity model (VIC)	Yes Distribution transfer
1	Block et al. (2009)	19,100 km^2 Brazil: Iguatu River (Jagua-ribe River basin)	1 Control	1 ECHAM4.5	10 NCEP RSM (10 runs)	Not specified	2 ABCD, SMAP	Yes Distribution transfer
2	Booij (2005)	21,000 km^2 France, BeNeLux, Germany: Meuse River	2 control double CO2 concentration	3 CGCM1 CSIR09 HadCM3	2 HadRM2 HIRHAM4	20 × 20	1 (3) HBV (3 different resolutions)	Yes (1) Delta approach (2) Precipitation model

Table 1. (continued).

No.	Reference	Study site	GHG emission scenarios	GCMs	RCMs	Resolution	Hydrological models	Bias correction
3	Bürger et al. (2007)	size not specified Spain: Upper Gallego catchment (Ebro)	2 control A2	4 ECHAM4/OPYC3 HadAM3H HadAM3P HadCM3	9 CNRM-ARPEGE/IFS DMI-HIRHAM ETHZ-CHRM, GKSS-CLM HC-HadRM3P KNMI-RACMO MPI-REMO SMHI-RCAO UCM-PROMES	50 × 50	2 learning machines: SVM, RVM	Not specified
4	De Wit et al. (2007)	33,000 km^2 France, BeNeLux, Germany: Meuse River	2 control A2	2 ECHAM4/OPYC3 HadAM3H	7 DMI-HIRHAM ETHZ-CHRM GKSS-CLM KNMI-RACMO MPI-REMO SMHI-RCAO UCM-PROMES	50 × 50	1 HBV	Not specified
5	Graham et al. (2007)	185,000–1.6 million km^2 Europe: Bothnian Bay, Baltic and Rhine Basin	3 control A2 B2	2 ECHAM4/OPYC3 HadAM3H	11 CNRM-ARPEGE/IFS DMI-HIRHAM ETHZ-CHRM GKSS-CLM HC-HadRM3H HC-HadRM3P ICTP-RegCM KNMI-RACMO2 MPI-REMO SMHI-RCAO UCM-PROMES	50 × 50	2 HBV, WASIM	Yes (1) Delta approach (2) Scaling approach

Table 1. (continued).

No.	Reference	Study site	GHG emission scenarios	GCMs	RCMs	Resolution	Hydrological models	Bias correction
6	Horton et al. (2006)	39–185 km^2 Switzerland: 11 mountain catchments	3 control A2 B2	3 ARPEGE/OPA ECHAM4/ OPYC3 HadCM3	9 CNRM-ARPE-GE/IFS DMI-HIRHAM ETHZ-CHRM, GKSS-CLM HC-HadRM3H KNMI-RACMO MPI-REMO SMHI-RCAO UCM-PROMES	50 × 50	1 GSM-SOCONT	yes Linear transformation
7	Leander et al. (2008)	21,000 km^2 France, BeNeLux, Germany: Meuse River	2 control A2	2 ECHAM4/ OPYC3 HadAM3H	2 KNMI-RACMO SMHI-RCAO	50 × 50	1 HBV	Yes (1) Precipitation Threshold (2) Power transformation
8	Leung et al. (2004)	668,000 km^2 USA: Columbia and Sacramento-San Joaquin River	3 control CO2 at 1995 levels business as usual (BAU6)	1 DOE/NCAR Parallel Climate Model	2 MM5 RSM	40 × 40 50 × 50	direct use	Yes Precipitation threshold
9	Moore et al. (2008)	287–3808 km^2 Sweden: Arbogaån, Hedströmmen, Köpingsån and Kollbäcsån River	3 control A2 B2	3 ECHAM4/ OPYC3 HadAM3H HadAM3P	2 HC-HadRM3P SMHI-RCAO	Not specified	1 GWLF	Yes (1) Delta approach (2) Scaling approach

SINGLE-RCM INVESTIGATIONS (S-RCM)

The simple approach of using RCM data is the application of data from only one RCM to simulate local hydrology. The modeling chain in these cases is usually very simple: (i) small number of greenhouse gas (GHG) emission scenarios, (ii) one to two GCMs, (iii) only one RCM and (iv) a small number of hydrological models (Figure 3A).

The S-RCM approach is often used in watersheds of very large size, e.g. the Yangtze River basin (Lee et al. 2004), the Upper Mississippi River basin (Jha et al. 2004), the Columbia River basin (Payne et al. 2004; Wood et al. 2004) or the Rhine River basin (Kleinn et al. 2005). Another common application of simple modeling chains is for developing or testing purposes. For example, Leander and Buishand (2007) implemented S-RCM to introduce the reader to their power transformation bias-correction method. Both Beldring et al. (2008) and Wood et al. (2004) used one GCM-driven RCM order to compare bias-correction methods. Bell et al. (2007a,b) applied one ERA40-driven RCM to test their newly developed grid-based flow routing and runoff-production model for several catchments in the UK. To analyze the impact of different RCM resolutions, Kay et al. (2006a,b) worked with one RCM at two different resolutions for flood frequency estimations in the UK. Both Boé et al. (2009) and Payne et al. (2004) applied the S-RCM approach to compare statistical with dynamical downscaling.

To assess uncertainties in the first part of the modeling chain, some papers vary emission scenarios or GCMs, but use only one RCM. Semmler et al. (2006), for instance, chose to work with four scenarios and two GCMs to force the RCA3 RCM. The RCM simulations were then used to drive the hydrological HBV model in order to obtain discharge simulations for the Suir River in Ireland. They obtained robust results for projections of future temperature and winter precipitation. However, simulations of summer precipitation varied strongly, which led to substantial variability in the simulated mean annual discharge cycle.

Other examples of studies that use an S-RCM method are the studies by Akhtar et al. (2008), Fowler and Kilsby (2007), Hay et al. (2002) and Steele-Dunne et al. (2008). Fowler and Kilsby (2007) used the same RCM with three different integrations, i.e. they applied an ensemble with members based on the same model but initiated from different points in the driving GCM. Steele-Dunne et al. (2008) emphasized that their S-RCM approach is only a first step with the future aim of using an ensemble as forcing data.

STUDIES BASED ON RCM ENSEMBLES (E-RCM)

To avoid biased modeling results and to include inter-model variability, some studies rather apply an ensemble approach (E-RCM). This can be achieved by using more than one RCM and often also a range of emission scenarios, GCMs and/or hydrological models (Figure 3B).

Examples for the application of several RCMs are relatively rare and make only one third of all reviewed studies in our paper. Booij (2005) chose one emission scenario and combined three GCMs (CGCM1, HadCM3, CSIR09) with two RCMs (HadRM2, HIRHAM4) to simulate future precipitation in the Meuse River basin. The range in HBV-simulated extreme discharges for future climate conditions was larger than for current climate. Another example is the study of Leander et al. (2008), analyzing flood quantiles of the river Meuse: three RCM–GCM configurations were set-up by combining two global models (HadAM3H and ECHAM4/OPYC3) with two regional models (RACMO and RCAO) based on emission scenario A2. They also highlight the importance of bias correction of RCM precipitation for realistic simulations of extreme floods. A different way of obtaining several RCM simulations was demonstrated by Block et al. (2009), who created a band of ten runs with the NCEP RSM–ECHAM4.5 AGCM system using observed sea-surface temperatures (SSTs), before simulating stream flow with two hydrological models (ABCD and SMAP). To explore the effects of climate change on hydrologic inputs to a Swedish lake, Moore et al. (2008) worked with three GCMs and two RCMs.

Some studies include rather complex modeling chains, producing a large range of possible outcomes. Because of the accounting for uncertainties that can be introduced at several points of the modeling chain, this usually results in the most realistic and trustworthy simulations of possible events, although it often has the largest spread. There are only a very limited number of studies available using an extensive RCM ensemble. The experimental design of Graham et al. (2007) included two emission scenarios (A2 and B2), two GCMs (HadAM3H and ECHAM4/OPY3), eleven RCMs with resolutions of 50 km and two hydrological models (HBV and WASIM). De Wit et al. (2007) used a similar model chain set-up to Graham et al. (2007), since they both derived the regional climate simulations from the PRUDENCE project (Christensen et al. 2007). Bürger et al. (2007) used the emission scenario A2, four GCMs (HadAM3H, HadCM3, HadAM3P and ECHAM4/OPYC), eight RCMs and two learning machine river flow models (SVM and RVM). However, both De Wit et al. (2007) and Bürger et al. (2007) did not specify any bias-correction method. Another even more complex modeling system is presented by Horton et al. (2006). Based on two GHG emission scenarios (A2 and B2), three different GCMs (HadCM3, ECHAM4/OPYC3 and ARPEGE/OPA), nineteen RCMs and one hydrological model (GSM-SOCONT), they assessed climate-change impacts on alpine discharge regimes.

Case study: catchment-scale test of RCM simulations

METHODS

The following multi-model case study demonstrates inter-RCM variability and the importance of using a large RCM ensemble for hydrological impact studies. We evaluated the ability of RCMs to reproduce current conditions for five Swedish catchments with areas from 147 to 293 km^2. Suitable catchments were required to be relatively small, predominantly unregulated and spatially uniform with regards to land-cover. Continuous

Table 2. Catchment characteristics.

Catchment	Abbreviation	Size (km^2)	Runoff station	Climate zone according to Köppen-Geiger classification (Kottek et al. 2006)	Annual mean temperature (°C)	Annual precipitation (mm)
Tännån	TAN	227	Tänndalen	Dfc/ET	−0.5	775
Storbäcken	STO	150	Ostvik	Dfc	2.1	617
Fyrisån	FYR	293	Vattholma	Dfb	5.2	633
Brusaån	BRU	240	Brusafors	Cfb/Dfb	5.7	632
Rönne Å	RON	147	Heåkra	Cfb	7.3	786

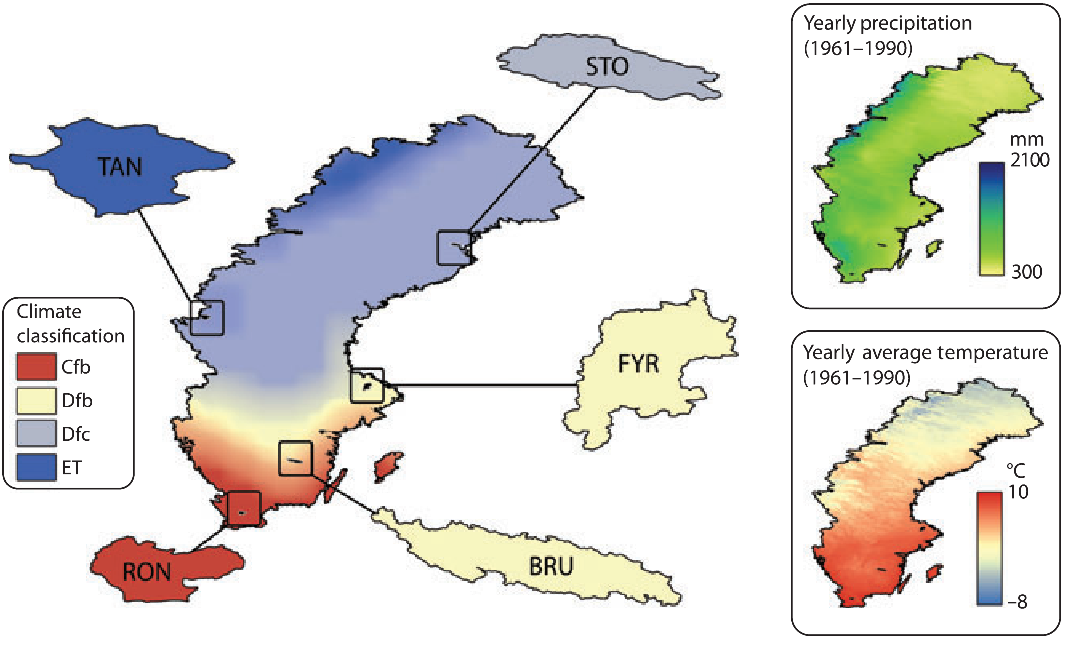

Fig. 4. Location of Swedish study sites including climate information (1961–1990).

temperature, precipitation and runoff measurements needed to be available for the period 1961–1990. The chosen catchments (Table 2) represent different climatic conditions and land-use types in Sweden (Figure 4).

Most RCM simulations include hydrological variables such as surface and subsurface runoff. While it has been stated that RCM simulated surface runoff might not agree well with observations (Evans 2003), there are only a few studies which actually compared RCM streamflow with observed streamflow. These few studies indicated that runoff is not reliably simulated by RCMs (Giorgi et al. 1994; Hagemann et al. 2004). Large errors occur in the runoff generation, which is partly because the RCM-simulated correlation between runoff and anomalies in the difference of total precipitation and evaporation is too strong (van den Hurk et al. 2005). For this reason, instead of using hydrological variables from the RCMs directly, it is rather common to use their detailed climate information to force hydrological models to simulate river runoff in offline-mode.

As a first test we compared RCM simulations directly to observations. The RCM runoff was evaluated against measured streamflow for those seven RCM where runoff simulations were available. Given the size of the RCM grid cells, subsurface runoff from one cell is negligible compared to surface runoff. We performed then a direct RCM evaluation based on their ability to reproduce average and extreme values of observed temperature and precipitation series for the time period 1961–1990. Our examination included fourteen ERA40-driven RCM simulations (Table 3) with resolutions of 25 km, which were downloaded from the ENSEMBLES EU project webpage (http://www.ensembles-eu.org). The studied catchments were relatively small and captured by approximately one grid cell in the RCMs. For comparison, we applied (i) only the center cell that covered the catchment and (ii) values averaged over the central grid cell and its eight neighboring cells. Data from a 4-km-gridded database were used as observed meteorological data; these data were derived from the Swedish Meteorological and Hydrological

Table 3. ERA40-driven RCM experiments.

Institute	Model	Acronym	Country of origin
C4I	RCA3	C4IRCA3	Ireland
CHMI	Aladin	CHMIALADIN	Czech Republic
CNRM	Aladin	CNRM-RM4.5	France
DMI	HIRHAM	DMI-HIRHAM	Denmark
ETHZ	CLM	ETHZ-CLM	Switzerland
HC	HadRM3Q0	METO-HC_HadRM3Q0	UK
ICTP	RegCM	ICTP-REGCM3	Italy
KNMI	RACMO	KNMI-RACMO2	The Netherlands
Met.no	HIRHAM	METNOHIRHAM	Norway
MPI	REMO	MPI-M-REMO	Germany
SMHI	RCA	SMHIRCA	Sweden
UCLM	PROMES	UCLM-PROMES	Spain
OURANOS	CRCM	OURANOSMRCC4.2.3	Canada
EC	GEMLAM	RPN_GEMLAM	Canada

Institute (SMHI) using spatial interpolation based on the national observation network data and topographic information (Johansson 2002).

Since the objective was to demonstrate the consequences of applying direct RCM output, no bias-correction was applied. Initial tests, however, indicated large effects of biases in the RCM temperature. Therefore, a simple seasonal bias correction for temperature was performed to eliminate this source of bias in the hydrological modeling and to allow assessment of the RCM precipitation simulations. The temperature data were bias-corrected by scaling the RCM-simulated monthly means to match observations using twelve correction constants which were added to the RCM-simulated temperature series.

While simulated temperature and precipitation series can be compared directly to observations, we were also interested in the combined effect on runoff simulations. Thus, we simulated the runoff with help of the HBV-light model (Seibert 2003), which was first calibrated against observed runoff series (available from SMHI) using measured series for temperature and precipitation. To consider parameter uncertainty, the model was calibrated 100 times for each catchment using a genetic algorithm which, due to its stochastic components, can result in different calibrated parameter sets (Seibert 2000). These parameter sets were then used to simulate runoff using the RCM simulations as input. In the further analyses, the ensemble mean of simulations using these 100 parameter sets was used. The HBV-simulated runoff was compared to measured time series in terms of long-term seasonal averages and the frequency distribution of annual maximum flows (separated seasonally into spring and autumn floods).

Results

Comparing RCM-simulated runoff with observations confirms earlier findings that for meso-scale catchments, the hydrological RCM output variables are often error-prone. The comparison with observed runoff shows significant deviations of RCM-simulated surface runoff (Figure 5). The RCMs are generally not able to reproduce observed long-term seasonal surface runoff in a satisfactory way: simulated spring flood events are either poorly timed or occur with incorrect orders of magnitude. While there is some variation in the amount of the deviations, it is worth noting that the results are poor for all RCMs.

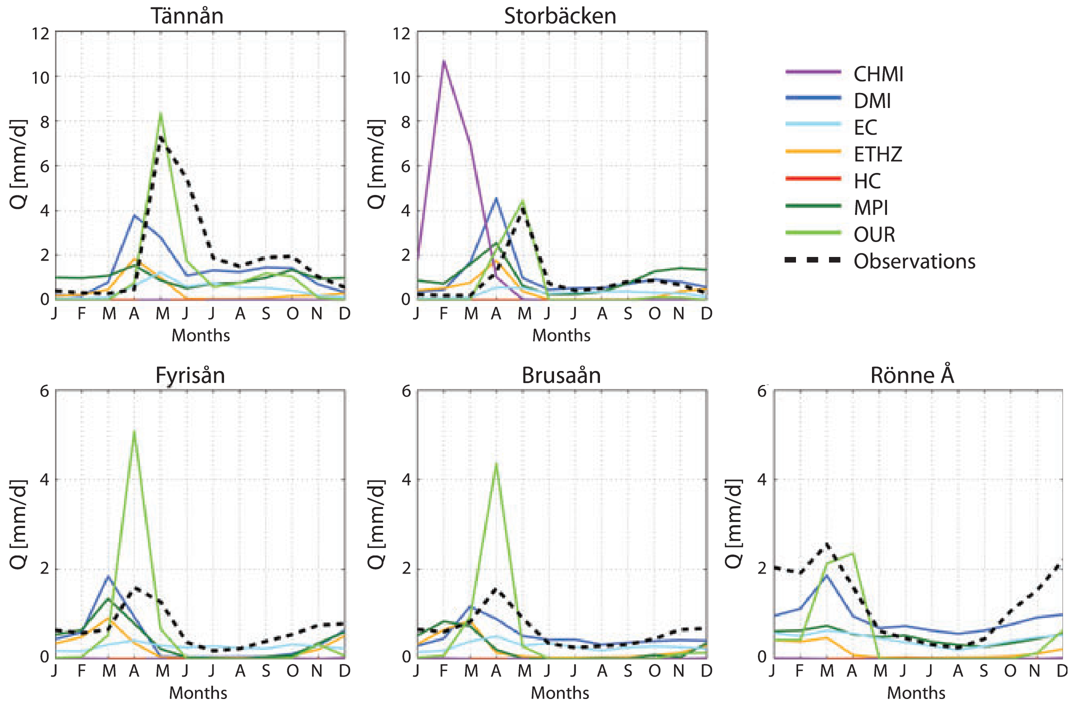

Fig. 5. Seasonal surface runoff average (1961–1990) simulated directly by a set of RCMs, in comparision with observation. In the ENSEMBLES database the surface runoff field was only available for download for seven out of the 14 suitable RCMs. Note the different scales in each row of the diagram.

The plots and objective functions show significant differences in the ability of RCMs to reproduce temperature and precipitation data under current climate conditions. Performances of the applied RCMs depend largely on the investigated climate variable and the catchment location. All RCMs are able to reproduce the long-term seasonal changes for temperature and precipitation to a certain degree. For monthly mean temperature (Figure 6), the ensemble mean fits the observations well, especially for the three southernmost watersheds (FYR, BRU and RON). In the two northernmost catchments (TAN and STO), the RCMs tend to overestimate winter temperatures and underestimate summer temperatures. The spread around the observations is relatively small. This gives us a robust signal, although the predictions are more variable in the northern catchments. In comparison, simulations of monthly long-term precipitation (Figure 7) are much more variable. There is a strong tendency of all RCMs to simulate too many low-intensity rain events. The ensemble means are prone to overestimate spring precipitation and underestimate summer/autumn precipitation.

The RCMs are to a certain extent only able to provide sufficient data for the HBV runoff simulations. Although the general curve progression of the HBV-simulated runoff fits well with observations in terms of spring and autumn flood timing (Figure 8), the magnitude differs significantly up to ±100% deviation for several model chains (Figure 9). Simulations of extreme floods in spring and autumn also show a large RCM variability (Figure 10). Autumn floods tend to be underestimated. This is partly due to the poor HBV performance in this season because the model is trained for higher flow events. The RCM/HBV performance is also largely affected by the catchment location. Certain

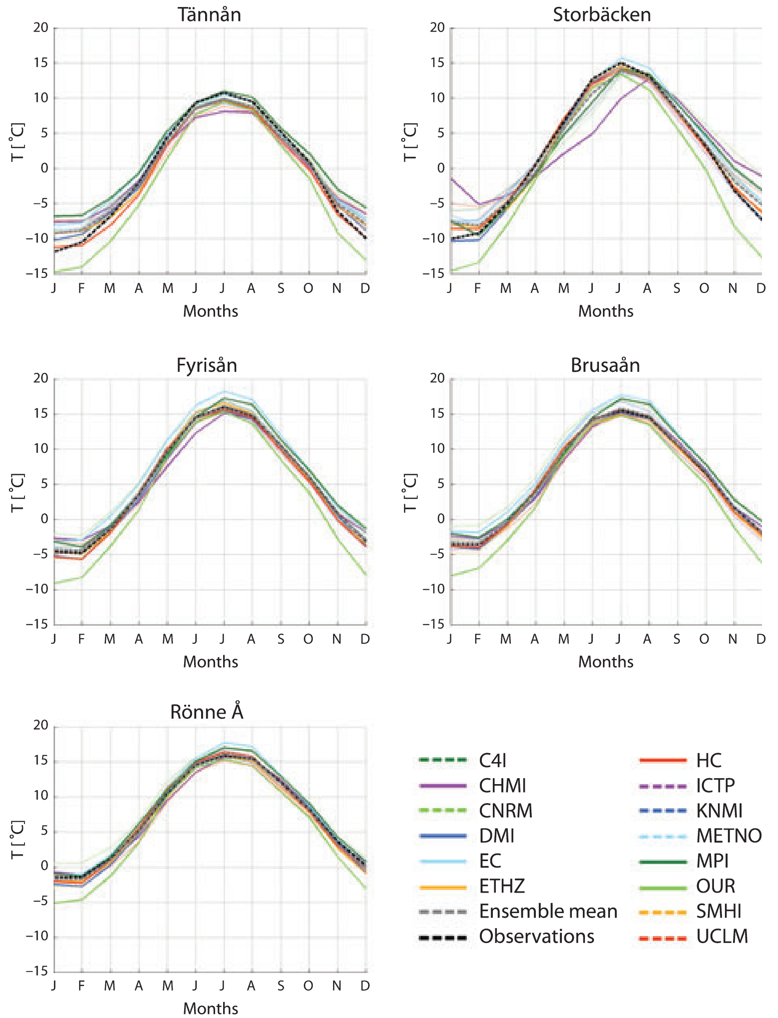

Fig. 6. Long-term (30 yr) average monthly temperature as simulated by the different RCM for current conditions compared to observations (1961-1990).

models are rather suitable for the southernmost catchments (e.g. ICTP, UCLM and CHMI) whereas others fit the northernmost catchments better (e.g. EC, MPI, SMHI and DMI). It is, however, challenging to pick one model that works best for all locations, all seasons and both mean as well as extreme runoff.

Due to their relatively small size, the study catchments were approximately captured by only one grid cell in the RCMs. One might argue that using simulations from only one RCM grid cell could be the cause for biases in precipitation as it might be doubtful to what extend RCMs are able to accurately simulate local climate information. To address this issue, the values for observed temperature and precipitation were also compared to the values averaged over the central grid cell and its eight neighboring cells. However, using precipitation and temperature values averaged over nine grid cells instead of applying only the center cell did not result in significantly different results.

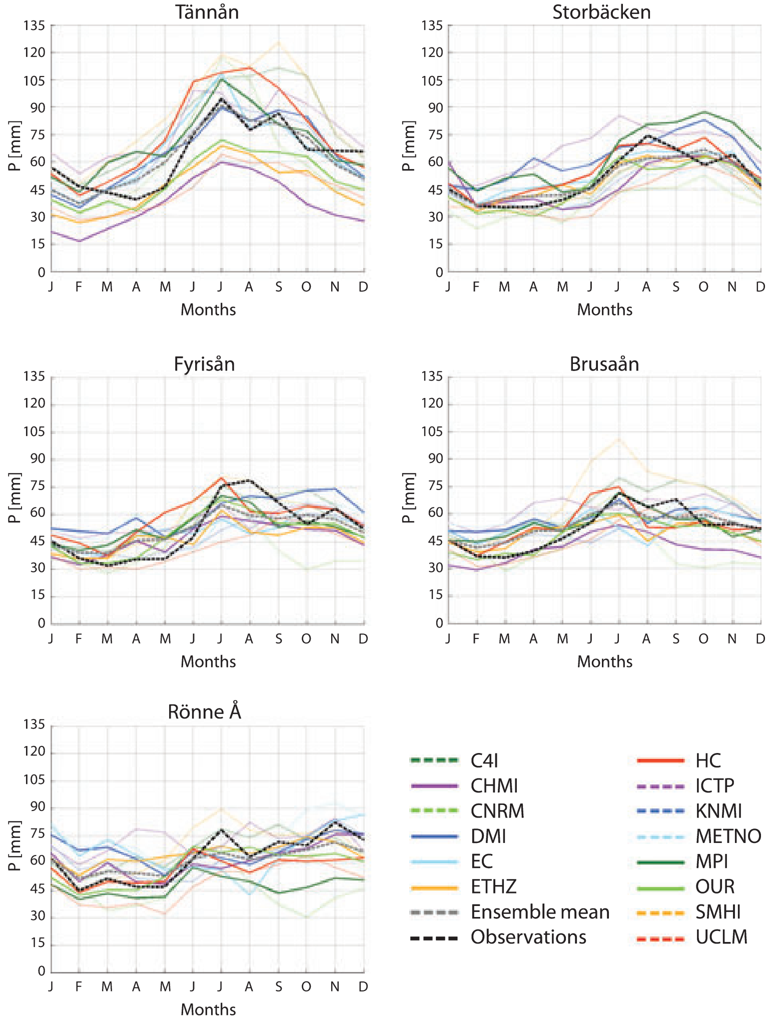

Fig. 7. Long-term (30 yr) average monthly precipitation as simulated by the different RCM for current conditions compared to observations (1961-1990).

Discussion

The quality of RCM output is still a much debated subject amongst climate modelers and depends very much on the model applied, its set-up (initial and boundary conditions) and the model domain. Opinions about the application for further impact modeling diverge considerably and range from the direct use of RCM-simulated hydrologic variables to complex multi-model approaches (E-RCM) with bias correction. Although RCMs simulate surface runoff in addition to climate variables, they are unable to realistically simulate surface runoff, as demonstrated in this paper using the example of the Swedish catchments. Although this is partly due to the fact that RCM runoff schemes are not necessarily designed to simulate discharge accurately, they do respond to general tendencies in the water balance (van den Hurk et al. 2005). Thus, the hydrological output variables from RCMs are not directly useful for hydrological impact studies. The coupling of RCM climate output and hydrological modeling is also subject to challenging

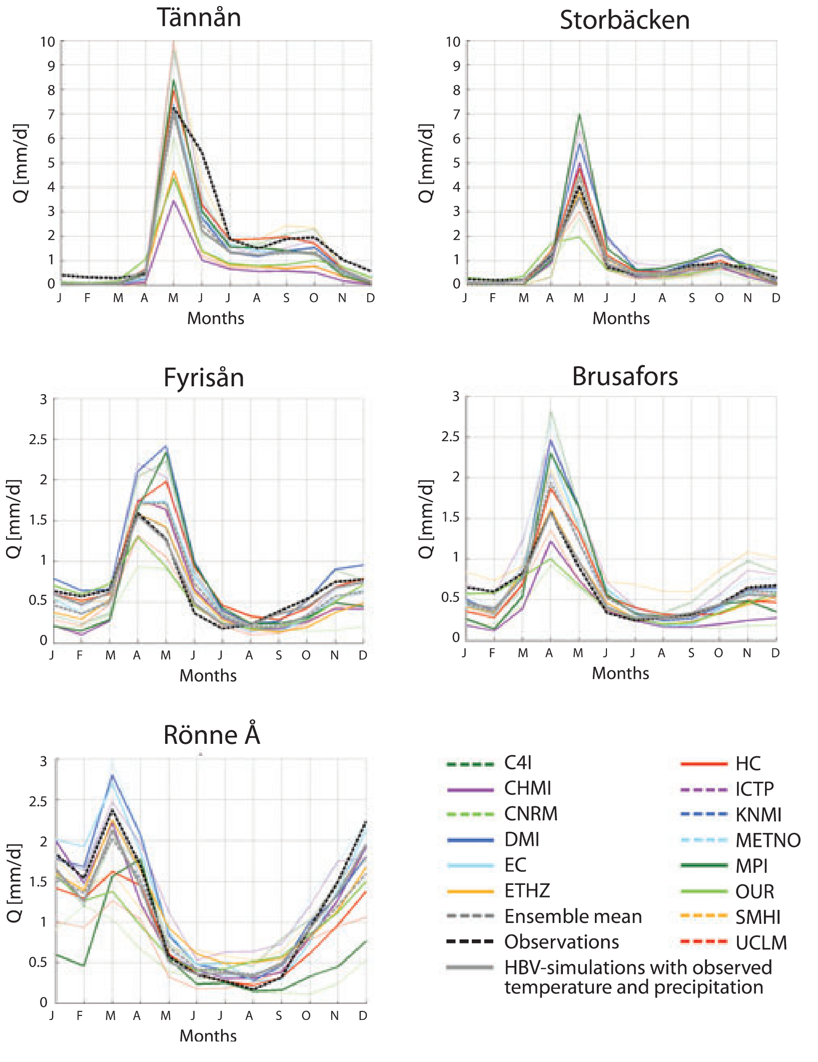

Fig. 8. Mean HBV-simulated runoff from an RCM ensemble (30 yr averages). Note the different scale for the two northernmost catchments (upper row).

issues. The results of the multi-RCM approach for runoff simulations of meso-scale catchments in Sweden clearly demonstrate the inter-model variability of RCMs. Considering the spread in the resulting discharge curves it is remarkable that most of the studies reviewed in this paper are based on simulations of a single RCM to make a projection of future climate change impacts. There are reasons for S-RCM approaches, such as limited computing power in older studies, very large catchment sizes or developing and testing of new methods, but in general it is difficult to justify the S-RCM approach.

If the catchment extends over a couple of climate model grid cells, further scaling is, in most cases, not applied: e.g. the Yangtze River basin (Lee et al. 2004), the Upper Mississippi River basin (Jha et al. 2004), the Columbia River basin (Payne et al. 2004; Wood et al. 2004) or the Rhine river basin (Kleinn et al. 2005). This means, that the large scale justifies the S-RCM approach, because the deviations of RCM-simulated climate data from observations are mostly averaged out at larger spatial scales, leading to

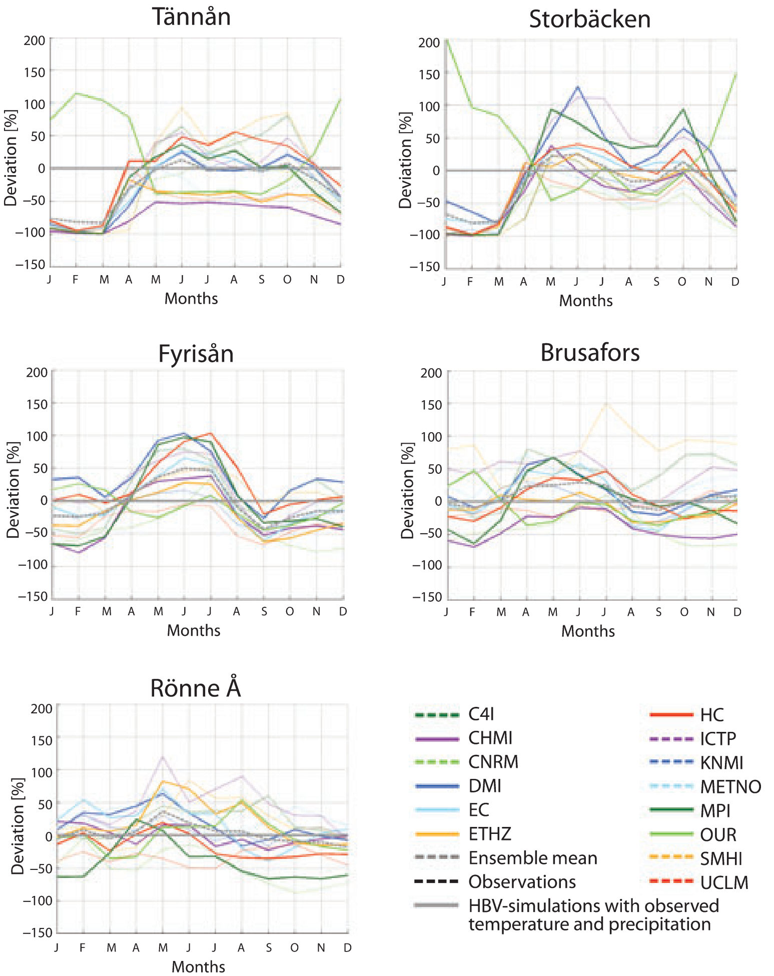

Fig. 9. Percentage deviation of the mean HBV-simulated runoff (driven with an RCM ensemble) from HBVsimulated runoff forced with observed precipitation and temperature (30 yr averages).

similar performances of the hydrological model (Dankers et al. 2007). However, even in larger catchments, RCM outcomes can vary from model to model. For example, Graham et al. (2007) demonstrated that RCM simulations of the average seasonal precipitation over the Bothnian Bay have a large spread, whereas temperature simulations are more evenly distributed. Resulting discharge simulations showed partly delayed peak flows and varying magnitudes.

Using the S-RCM approach for developing or testing purposes as Beldring et al. (2008), Wood et al. (2004), Bell et al. (2007a,b), Leander and Buishand (2007) and Kay et al. (2006a,b) did, can be useful to reduce the labor and computing power demand of ensemble simulations. For these purposes, such a simple modeling chain might be suitable for a start. Nevertheless, these methods should also be tested on a modeling chain with additional RCMs. Kay et al. (2006a,b), for instance, remind the reader that their 'results should not be treated as predictions of what will happen [...] in the future, as they rely only on a single run of a single RCM/GCM combination for a single emission scenario'.

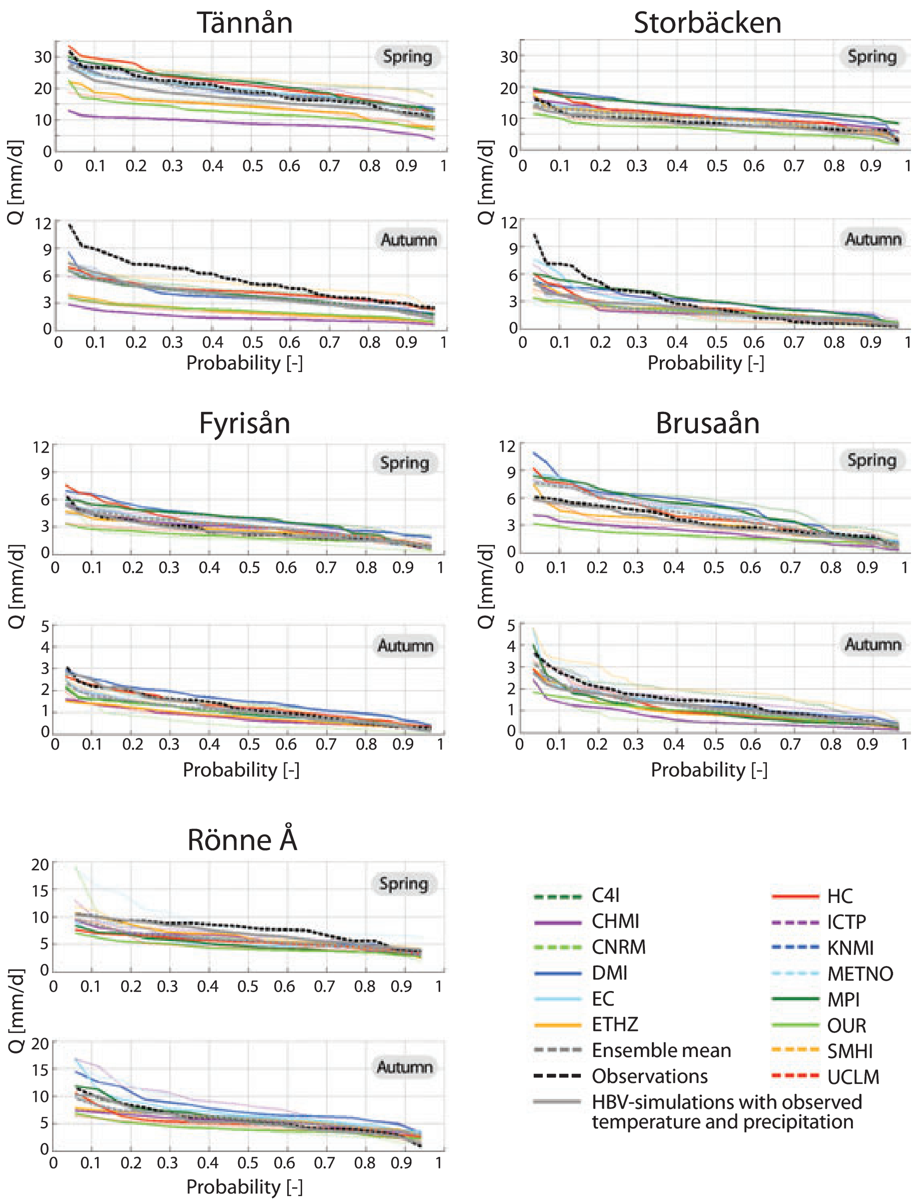

Fig. 10. HBV-simulated runoff for spring (top) and autumn (bottom) flood events from an RCM ensemble. Note the different scales in each row of the figure.

As Kay et al. (2006a,b) concluded, the mean of several RCM-ensemble members would give a better representation of current and future conditions and, thus, ensemble runs would be necessary to reduce errors.

The S-RCM approach should be limited to these pilot studies and should not be used when one wants to make statements about climate change impacts. Still, such statements can be found in literature. Some examples are the papers of Hay et al. (2002), Fowler and Kilsby (2007), Steele-Dunne et al. (2008) and Akhtar et al. (2008). Despite the very simple modeling chain in the study of Hay et al. (2002), they used the rather advanced probability-mapping bias correction. Their conclusion was that RCM output can be made appropriate with help of bias correction. Akhtar et al. (2008) suggested that RCMs could be used as input to hydrological models in regions with lacking climate data records. Steele-Dunne et al. (2008) stated that the generation of ensemble climate simulations will be necessary in the future.

There are uncertainties in the simulation of regional climate changes and in the translation from RCMs to catchment scale (Arnell 1999). Different downscaling techniques (including different RCMs) have diverse outcomes, even if they are forced with the same coarse-resolution GCM. A few good examples can be found in the literature comprising a complex and extensive modeling chain accounting for these uncertainties. Booij (2005), for instance, chose two RCMs to simulate future precipitation in the Meuse River basin. The range in HBV-simulated extreme discharges for future climate conditions was larger than for current climate and he stated that this range is amongst others the result of the differences between the applied climate models. Other excellent examples are the studies of Leander et al. (2008), Block et al. (2009) and Moore et al. (2008). They all adopted the E-RCM approach but employed different procedures to correct for biases in RCM output. Leander et al. (2008) used three RCM–GCM configurations and applied the precipitation threshold approach as well as a power transformation to correct for precipitation bias. Block et al. (2009) worked with a band of ten RCM runs and bias-corrected precipitation with the distribution transfer method. Moore et al. (2008) combined three GCMs with two RCMs and used the scaling technique to correct the RCM-simulated precipitation.

Due to the consideration of uncertainties at any points of the modeling chain, complex E-RCMs as used by Bürger et al. (2007), De Wit et al. (2007), Graham et al. (2007) and Horton et al. (2006) usually result in the largest spread and, thus, higher reliability of the forecast. It must be noted that both Bürger et al. (2007) and De Wit et al. (2007) did not specify any bias correction. According to Durman et al. (2001), uncorrected RCMs have a general tendency to produce inaccurate probabilities of extreme precipitation events. Therefore, studies without accounting for RCM biases lead to less reliable results.

One conclusion of Graham et al. (2007) was that the selection of GCMs for forcing the RCMs has larger effects on hydrological simulations than either using different RCMs with the same GCM forcing or the choice of emission scenario. Déqué et al. (2007) came to the same conclusions that the uncertainty caused by the selection of the GCM accounts generally for the largest portion. However, for summer precipitation the selection of the RCM is of the same importance as the choice of GCM regarding the source of uncertainties. De Wit et al. (2007) stated that different RCMs forced by the same GCM generate different mean seasonal precipitation and evaporation patterns. Horton et al. (2006) – using the modeling system with most model combinations of all reviewed papers – found out that the simulated discharges are highly variable for a given emissions scenario and that this variability was induced by both, the driving GCM and the inter-RCM variability. Their study demonstrated that the application of an RCM ensemble with the same forcing GCM can generate variability of the same magnitude as the variability produced by using the same RCM driven by different GCMs. A similar spread of results was obtained for our test study using fourteen RCM forced with the same initial and boundary conditions. Thus, both previous studies and the analyses presented here highlight that inter-RCM variability cannot be neglected.

Weigel et al. (2009) compared single-model versus multi-model combinations. They discussed the fact that multi-model ensembles widen the ensemble spread and entail a reduction in the root-mean-squared error (RMSE) of the ensemble mean as well as an improved forecast reliability (Weigel et al. 2009). It needs to be considered that ensemble forecasts depend on the number of available models, the inter-model independency, the expenses for several climate model runs and the occurrence of systematic biases (Weigel et al. 2009). One could argue that models which perform well for current conditions should be given more consideration when using the different models for ensemble predictions. In other words, the performance of an individual model (or model chain) for current conditions could be a basis for weighing factors when computing the ensemble mean and spread. This issue has been a basis for sensitivity and uncertainty studies. Often, however, there is no basis for absolute rejection of a certain hypothesis, i.e. a certain RCM (Spear and Hornberger 1980). In fact, it is not clear if the best-performing RCMs actually reproduce current conditions for the correct reasons. While such a weighting approach would certainly be reasonable, the selection and weighing of different GCMs did not make a significant difference for the predicted runoff impacts in southeast Australia (Chiew et al. 2009). Weighting of RCMs is a relatively new topic within the field of regional climate modeling and weighting procedures have been introduced to the modeling chain just recently (Casanova and Ahrens 2009; Fowler and Ekström 2009; Kug et al. 2008). From these studies it can be concluded that (i) a performance-based weighting procedure is able to improve the simulation results (Casanova and Ahrens 2009), (ii) a simple skill-based weighting is often more effective than more sophisticated weighting methods (Casanova and Ahrens 2009), (iii) weighting methods work most effectively for ensembles with a large number of models (Kug et al. 2008) and (iv) due to a lack of inter-model independency the differences between weighted and unweighted ensembles can be rather small (Fowler and Ekström 2009).

Conclusion

A variety of RCMs is available with significant differences in their performance under current and future climate conditions. The inevitable question arises of whether this opportunity has been fully utilized. Many studies still apply only a very limited number of RCMs and ignore possible biases. This might be acceptable in studies where the focus is on methodological developments rather than on actually drawing conclusions on hydrological impacts. However, there are numerous studies with the latter focus, where an S-RCM setup has been used. With progressive advances in computer technology, computation power should not be a limiting factor any longer. Furthermore, the number of publicly available archives containing RCM-simulation ensembles (e.g. from European projects, such as PRUDENCE and ENSEMBLES) is rising. Thus, for future studies the availability of RCM output variables over certain domains (e.g. Europe and North America) cannot be considered as an excuse for not applying an E-RCM approach.

Research in regional climate modeling has developed substantially within recent years. RCMs are now considered to perform satisfactorily in order to be used for hydrological impact studies. Nonetheless, there is a substantial contribution of the RCMs to the total variability at the end of the modeling chain that cannot be neglected. Thus, we believe that using an S-RCM approach and ignoring this inter-RCM variability can turn hydrological impact studies into gambling 'just like throwing a dice' (Blöschl and Montanari 2010). For five meso-scale catchments in Sweden used in the test case here, the ensemble-mean runoff fits the observations better than the individual models. This indicates that multi-model approaches are useful for climate change impact assessments for two reasons:

the ensemble mean may provide better runoff simulation results and the spread of the ensemble members allows the evaluation of uncertainties. Our and previous results also demonstrate that due to the significant systematic errors in the RCMs and uncertainties in their transformation to local scales, bias correction is still needed when using RCM output for hydrological modeling. The question to which degree the same bias corrections are valid for scenario simulations still remains open, but one should be aware that the need for bias corrections adds significantly to uncertainties in modeling climate change impacts.

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Short Biographies

Claudia Teutschbein is currently a PhD candidate in Physical Geography at Stockholm University, Sweden. She was educated at the Dresden University of Technology in Germany and at Uppsala University in Sweden. With experience in civil engineering, water management and hydrology, she holds a master's degree is soil science from the Swedish University of Agricultural Sciences. Focus of her ongoing PhD studies is on hydrological modeling for climate-change impact assessment. Her interest in projections of future changes in hydrological regimes has led her to work on regional climate modeling techniques with focus on combined uncertainties of the simulation of catchment-scale impacts.

Jan Seibert is a professor at the University of Zurich, where he is heading the ''Hydrology and climate'' unit. After receiving his PhD from Uppsala University he has been employed by Oregon State University, the Swedish University for Agricultural Sciences and Stockholm University. His main research interest is hydrological modeling at different scales in combination with experimental studies. Research topics include the use of catchment models for land-use and climate change impact studies, the further development of catchment models, model calibration, validation and uncertainty analysis, and the relations between topography and hydrological processes.

Note

* Correspondence address: Claudia Teutschbein, Department of Physical Geography and Quaternary Geology, Stockholm University, S-10691 Stockholm, Sweden. E-mail: claudia.teutschbein@natgeo.su.se.

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