Gridded 1 x 1 km climate and hydrological projections for Norway

59
2016

REPORT

Report no. 59 – 2016

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Published by:	Norwegian Water Resources and Energy Directorate
Editor:	
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Print:	Norwegian Water Resources and Energy Directorate
Number printed:	30
Cover photo:	
ISSN:	
ISBN:	978-82-410-1512-0

Abstract: An ensemble of ten EURO-CORDEX GCM/RCM simulations, each representing two alternative emission pathways (RCP4.5 and RCP8.5), were bias-corrected using an empirical quantile mapping method. These corrected datasets covering the period 1971-2100 were then forced with a spatially distributed, gridded version of the HBV model to generate daily time series of different hydrological components. These high-resolution climate and hydrological projections, despite their limitations, represent a valuable data source for different types of climate impact studies at a national and local scale.

Key words: Gridded data, EURO-CORDEX, precipitation and temperature projections, bias-correction/bias-adjustment, empirical quantile mapping method, hydrological projections, runoff, snow water equivalent, seNorge data, Norway

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December 2016

Contents

Preface

This report gives a brief description of the high-resolution (1 x 1 km) climate and hydrological projections used in the government-commissioned report 'Klima i Norge 2100'. This report summarizes the methods used to derive these datasets. Limitations and drawbacks of the approach are also discussed. These datasets represent a valuable data source for different types of climate impact studies at a national and local scale, which also contribute to NVE's climate change adaptation plan.

Oslo, December 2016

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Summary

Outputs of global or regional climate models (GCM/RCMs) are often flawed with systematic biases despite recent progress in climate modelling. Modelling results can be very different from observations, and this can hamper their direct use in climate impact studies. Moreover, impact models often require data of higher spatial resolution than climate models usually can provide. A post-processing of GCM/RCM outputs is therefore necessary to obtain plausible time series at an appropriate scale for use in local impact studies. It is, however, important to bear in mind the drawbacks of post-processing when interpreting the results of climate impact studies based on post-processed climate data.

An empirical quantile mapping method (EQM) has been used to bias-correct and downscale precipitation and temperature projections for Norway to provide appropriate input data for an assessment of climate change effects on hydrology. An ensemble of ten EURO-CORDEX GCM/RCM simulations, each representing two alternative emission pathways (RCP4.5 and RCP8.5), were bias-corrected. The original GCM/RCM outputs with a resolution of 12.5 x 12.5 km were first re-gridded to a 1 x 1 km scale using a simple nearest neighbour method. 'seNorge' precipitation and temperature gridded data, which also have a 1 km resolution, were then used as the 'observed' data for the bias correction procedure. A transfer function based on empirical cumulative distribution functions for both observed and modelled variables in the control period was applied to correct values from the climate models quantile by quantile so that they yield a better match with the observed. Calendar-month and grid-cell-specific transfer functions were derived and they were used on daily simulated data for both control and projection periods. For precipitation, the probability of wet days was first calculated from the observational dataset on a monthly basis and modelled precipitation was modified accordingly with the same probability prior to correction.

To ensure that the bias-adjustment of future projections would not lead to unreasonably high or low values due to the extrapolation method, a quality control procedure relying on the original climate change signals was applied. The results show that the procedure is capable of removing 'hot-spots' which are evident in some of the corrected projections and rectifying the over-adjusted projections.

These precipitation and temperature datasets covering the period 1971-2100 were then forced with a spatially distributed, gridded version of the HBV precipitation-runoff model to generate daily time series of different hydrological components such as soil moisture deficit, runoff, evapotranspiration, snow water equivalent and groundwater. These high-resolution climate and hydrological datasets, despite their limitations, represent a valuable data source for different types of impact studies at a national and local scale.

1 Introduction

What will happen to water resources in Norway in a changing climate? That was one of the keys questions that the government-commissioned report 'Klima i Norge 2100' (Hanssen-Bauer et al., 2015) attempted to answer. This report gives a brief description of the high-resolution climate and hydrological projections used in 'Klima i Norge 2100' and how these datasets were derived.

Global climate models (GCMs) which are able to describe the governing processes in the atmosphere, ocean, land surface and sea ice are an important tool in assessing climate change. GCMs project future precipitation and temperature usually at a horizontal grid scale of 100 x 100 km. This resolution is considered to be too coarse to properly resolve topographic effects. Results from GCMs are hence often dynamically downscaled using regional climate models (RCMs). However, compared with actual landscape characteristics at an RCMs resolution (~12 x 12 km at best), many important details are still lacking because of the complex and highly variable topography, especially in Norway. Impact models often have to deal with processes at a finer scale and therefore require data of higher spatial resolution than the climate models normally can provide.

In addition, outputs of GCM/RCMs are often flawed with systematic biases. This is due to inadequate knowledge of key physical processes and the simplifications of the natural heterogeneity of fine-scaled climate phenomena. Figure 1 shows an example where the climate model significantly underestimates the mean monthly precipitation averaged over the whole country relative to observations for the period 1971-2000. The model also apparently underestimates the mean monthly temperature, although this may, at least in part, be due to a mismatch between the elevation of the climate model grid cell and the actual elevation of the land surface in that grid cell. In any case, these values need to be adjusted before they can be used to represent the surface temperature. Generally, the climate projections for Norway show an apparent negative bias in temperature (i.e. simulated temperatures are too cold) and substantial precipitation biases, both positive and negative. If a hydrological model is forced with these 'flawed' data, the simulated hydrological responses will inevitably be very different from what have been observed. Snowmelt will start considerably later in the snowmelt season and the timing of snowmelt floods will be delayed, often giving higher flood magnitudes (Fig. 2). Altered precipitation and temperature patterns induced by model biases can affect snow accumulation and snowmelt patterns and consequently runoff generation processes. As a result, the simulated hydrological regime and seasonal flow patterns may differ significantly from observed patterns, and this mismatch will also have an effect on the simulated hydrological response to climate change. A post-processing of GCM/RCM outputs is therefore necessary to obtain plausible time series at an appropriate scale for use in local impact studies. An example of the effects of bias-correction on estimating mean monthly precipitation and temperature are shown in Figure 1. The corrected data give a better match than uncorrected when they are compared to the observed.

The bias-correction procedure adopted in this report also includes a downscaling component, which involves transforming the climate patterns simulated at a coarse grid resolution to the finer spatial resolution of interest. The term bias-correction refers to the removal of systematic biases in simulated values relative to observed data, which, in

principle, reflect the 'true values'. Typically, this procedure is used to correct simulated data for a period in which observations are available, in this case, the control period. For the future projections periods, observations are not available, so one cannot 'correct' relative to 'true' values, but can only adjust the values based on the correction established for the control period. We, therefore, use the term 'bias-adjustment' to distinguish the procedure used for future periods with the 'bias-correction' used for the control period. Following this post-processing, a spatially distributed, gridded version of the HBV precipitation-runoff model was forced with the post-processed climate data.

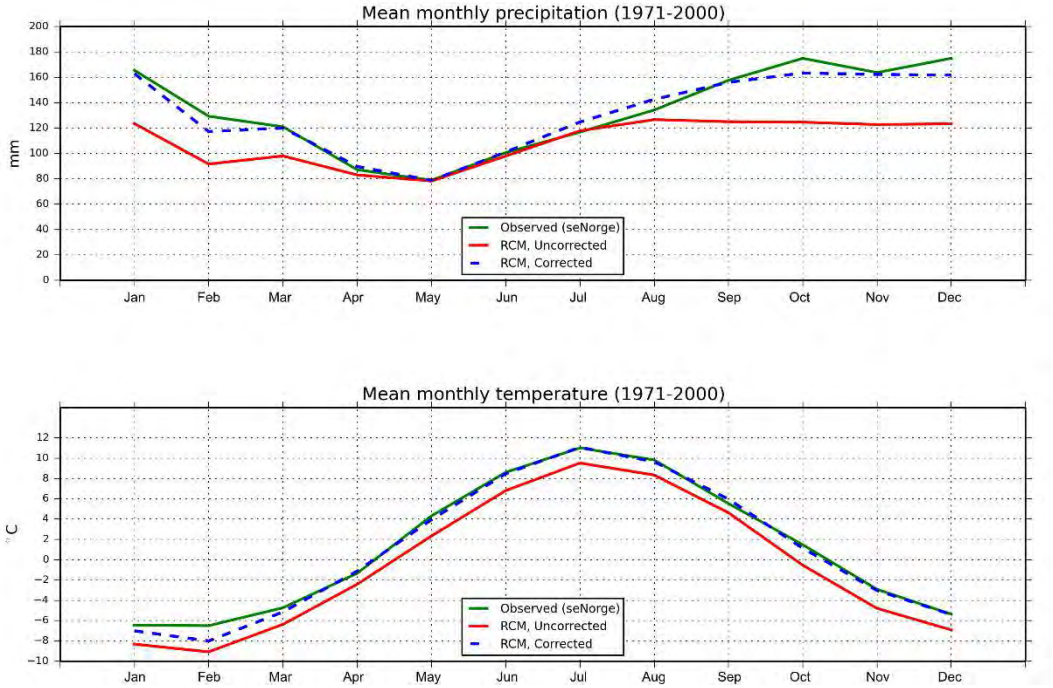

Figure 1. Mean monthly precipitation (upper panel) and mean monthly temperature (lower panel) averaged over the whole country for the period 1971-2000. The green line refers to observations based on seNorge data. The red line represents an example of original RCM outputs (uncorrected). The blue dashed line denotes the bias-corrected RCM outputs.

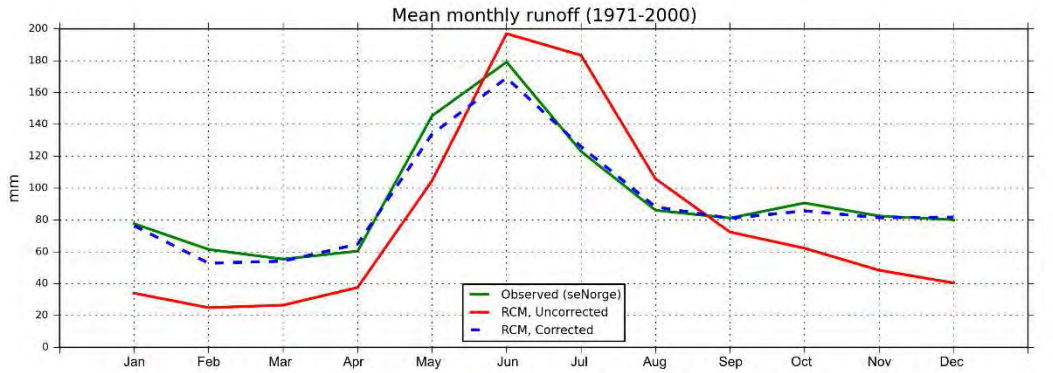

Figure 2. Mean monthly runoff averaged over the whole country for the period 1971-2000. Runoff was simulated by a distributed, gridded version of the HBV model. The green and red lines refer to runoff simulations using observed (seNorge) inputs and original (uncorrected) RCM inputs, respectively. The blue dashed line represents runoff simulations using the corrected RCM inputs.

2 Data

2.1 EURO-CORDEX climate projections

Climate impact studies rely on climate input data, and more specifically, precipitation and temperature, which are the two most important driving variables for hydrological modelling. The climate input data that have been used in 'Klima i Norge 2100' come from an ensemble of ten EURO-CORDEX runs (Jacob et al., 2014; see also http://www.euro-cordex.net/), resulting from five GCM and four RCM combinations, see Table 1.

Global climate model	Ensemble member	Regional climate model	Time period	Institution
CNRM-CERFACS-CM5	r1i1p1	CCLM4-8-17	1971-2100	Climate Limited-area Modelling Community
CNRM-CERFACS-CM5	r1i1p1	RCA4	1971-2100	Swedish Meteorological and Hydrological Institute
ICHEC-EC-EARTH	r12i1p1	CCLM4-8-17	1971-2100	Climate Limited-area Modelling Community
ICHEC-EC-EARTH	r3i1p1	HIRHAM5	1971-2100	Danish Meteorological Institute
ICHEC-EC-EARTH	r1i1p1	RACMO22E	1971-2100	Royal Netherlands Meteorological Institute
ICHEC-EC-EARTH	r12i1p1	RCA4	1971-2100	Swedish Meteorological and Hydrological Institute
MOHC-HadGEM2-ES	r12i1p1	RCA4	1971-2100	Swedish Meteorological and Hydrological Institute
IPSL-CM5A-MR	r1i1p1	RCA4	1971-2100	Swedish Meteorological and Hydrological Institute
MPI-ESM-LR	r1i1p1	CCLM4-8-17	1971-2100	Climate Limited-area Modelling Community
MPI-ESM-LR	r1i1p1	RCA4	1971-2100	Swedish Meteorological and Hydrological Institute

Table 1. Overview of GCM/RCM combinations used from EURO-CORDEX.

Only the EUR-11 outputs were used, which have a spatial resolution of approximately 12.5 x 12.5 km. Two emission scenarios based on IPCC's Representative Concentration Pathways (RCPs) were adopted (van Vuuren et al., 2011). RCP4.5 represents a medium emission scenario in which the greenhouse gases will slowly increase until approximately 2040 and then a reduction will occur later on. RCP8.5 refers to the most severe scenario, giving a future with continuously increasing greenhouse gases. The time period simulated by the climate models in the EURO-CORDEX initiative varies, but the latest starting year is 1970. All simulations of the control or historical period, regardless of their starting year,

end in 2005. The simulated 'future' period is 2006-2100 and is designated as the projection period. Since the reference period for present climate in 'Klima i Norge 2100' is 1971-2000, and the two future periods are 2031-2060 and 2071-2100, all analyses in this report and the post-processed datasets available on the Norwegian Centre for Climate Services (NCCS) website span the period 1971 to 2100.

2.2 'seNorge' datasets

Accumulated daily precipitation and daily mean temperature observations are routinely used to produce maps of precipitation and temperature with a 1 km horizontal resolution for the whole of Norway. These gridded maps are updated on a daily basis and published on the website 'seNorge.no'. The method of triangulation and 2D-ordinary kriging are applied to spatially interpolate precipitation and temperature observations, respectively, to obtain values at the desired 1 km resolution. For further details of the interpolation procedure, see Mohr (2008). These high-resolution seNorge datasets of precipitation and temperature (version 1.1) represent the best available observational data for the whole of Norway at the time this work was undertaken. These datasets begin in 1960 and were therefore used as the observational data required to adjust the climate model biases.

3 Method

The original climate model outputs were first re-gridded to a 1 x 1 km grid using a simple nearest neighbour method. The seNorge precipitation and temperature datasets from the control period were treated as 'observed' data and used for bias-correction and bias-adjustment procedures. The precipitation projections were corrected/adjusted separately and independently from temperature projections.

3.1 Wet-day correction

Since RCM outputs tend to give more rainy days than the observed (Frei et al., 2003), wet-day correction was carried out prior to bias-correction and bias-adjustment of precipitation. In this procedure, monthly wet-day threshold values are derived for each climate model, such that the frequency of wet-days based on values above this threshold is equal to the frequency of wet-days in the observed data for a given month and a given grid cell in the dataset. Modelled precipitation values that are less than the threshold values are set to zero.

3.2 Empirical quantile mapping

Since the post-processing procedure was intended to be applied to every grid cell and to all precipitation and temperature projections, each containing over 130 years of data, it was obvious that the chosen method had to be computational efficient if the task was to be completed within a reasonable timeframe. Sorteberg et al. (2014) evaluated different distribution mapping bias-correction methods and found that no method performed better than the others in general, although all possessed some advantages and disadvantages, depending on the evaluation criterion used.

In this study, an empirical quantile mapping method (EQM) was adopted to bias-correct and bias-adjust the simulated precipitation and temperature projections (Gudmundsson et

al., 2012). This method has a computational advantage relative to theoretical distribution-based mapping methods since it does not assume a theoretical distribution, such as a Gamma distribution for precipitation. Fitting a theoretical distribution to a dataset can be very time-consuming. The EQM method instead utilizes the empirical cumulative distribution functions (ECDFs) for both observed and modelled variables. A transfer function matching the modelled ECDF in the control period with the observed ECDF was applied to adjust values from the climate projection quantile by quantile so that they yielded a better match with the observed (Fig. 3). The ECDFs were approximated using tables of empirical percentiles with fixed interval of 0.1 spanning the probability space [0, 1]. Spline interpolation was used for the values in between these percentiles and to extrapolate beyond the highest and lowest observed values. Twelve calendar-month-specific transfer functions for each grid cell were derived from 3-month windows centered on the calendar month of focus. This approach provided more robust transfer functions, which is important if they also will be used to adjust values in the projection period. The R package 'qmap' version 1.0-2 (Gudmundsson, 2014) was applied to bias-correct and bias-adjust all the datasets.

As the EQM method is applied to one variable and one location at a time and does not change the temporal structure of a climate model, the inter-variable, spatial and temporal dependencies are not corrected relative to the observations. It is important to bear in mind these drawbacks when interpreting the results of climate impact studies based on the bias-corrected/bias-adjusted climate data.

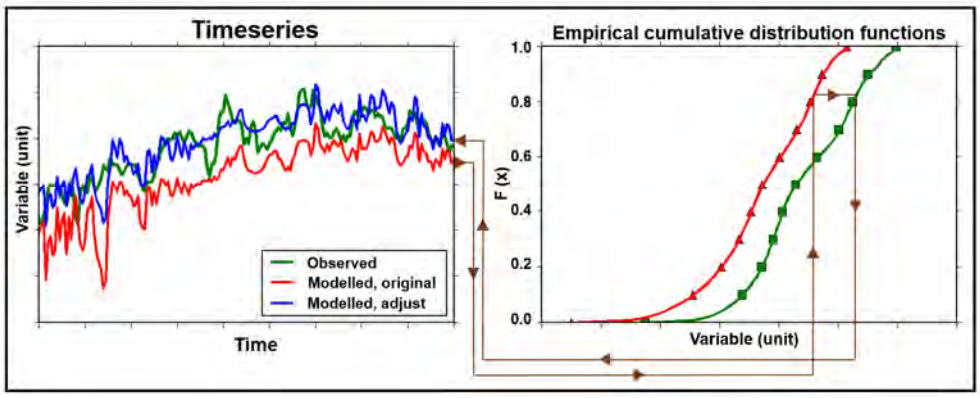

Figure 3. Synthetic example of bias-correcting modelled data using a transfer function derived from empirical cumulative distribution functions (ECDF) of observed and modelled variables. The red and green lines on the left denote the uncorrected time series and observed time series respectively. The blue line represents the bias-corrected time series. The red and green lines on the right indicate the ECDF of uncorrected data and observed data respectively.

3.3 De-trending future climate projections

The derived transfer functions from the control period were assumed to be valid for use in the projection period. However, to avoid the risk of removing/adjusting the possible long-term trend of modelled precipitation and temperature during bias-adjustment, all precipitation and temperature data in the projection period were de-trended first. Hempel et al. (2013) proposed simple mean division (dividing by the mean value) and mean subtraction (subtracting the mean value) methods to de-trend the time series for daily precipitation and temperature, respectively. The daily variability about the monthly mean remained unchanged using these procedures.

3.3.1 De-trending precipitation

The relative trend for precipitation for month *i*, ΔP_i, is defined as:

$$\Delta P_i = \frac{\overline{P}_i^{prj}}{\overline{P}_i^{ctrl}}$$

where $\overline{P}_i^{prj}$ and $\overline{P}_i^{ctrl}$ are mean monthly accumulated precipitation for month *i* for the projection and control periods, respectively. The de-trended (normalized) daily precipitation, $\hat{P}_{ij}^{prj}$, for month *i* and day number *j* in the projection period is:

$$\hat{P}_{ij}^{prj} = \frac{P_{ij}^{prj}}{\Delta P_i}$$

where P_{ij}^{prj} denotes the original daily precipitation for month *i* and day number *j* in the projection period.

EQM was applied only to the 'normalized' time series, and the trend for month *i* was then put back into the bias-adjusted normalized data for month *i* and day number *j*, $\breve{P}_{ij}^{prj}$, after the bias-adjustment procedure. The bias-adjusted precipitation for month *i* and day number *j*, $\widetilde{P}_{ij}^{prj}$, is:

$$\widetilde{P}_{ij}^{prj} = \breve{P}_{ij}^{prj} \cdot \Delta P_i$$

3.3.2 De-trending temperature

Similarly, the temperature trend for month *i*, ΔT_i, is defined as:

$$\Delta T_i = \overline{T}_i^{prj} - \overline{T}_i^{ctrl}$$

where $\overline{T}_i^{prj}$ and $\overline{T}_i^{ctrl}$ refer to mean monthly temperature for month *i* for the projection and control periods, respectively. The de-trended (residual) daily temperature, $\hat{T}_{ij}^{prj}$, for month *i* and day number *j* in the projection period is:

$$\hat{T}_{ij}^{prj} = T_{ij}^{prj} - \Delta T_i$$

and T_{ij}^{prj} represents the original daily temperature for month *i* and day number *j* in the projection period.

The EQM method was then applied to the 'residual' time series. After bias-adjustment, the trend for month *i* was re-introduced to the bias-adjusted residual data for month *i* and day number *j*, $\breve{T}_{ij}^{prj}$. The bias-adjusted temperature for month *i* and day number *j*, $\widetilde{T}_{ij}^{prj}$, is:

$$\widetilde{T}_{ij}^{prj} = \breve{T}_{ij}^{prj} + \Delta T_i$$

3.4 Quality control of the bias-adjusted data

As the EQM method does not assume any theoretical distributions, and no upper or lower limits were set on the transfer functions, extrapolation beyond the maximum or minimum values of the transfer functions in the projection period using spline method can lead to unreasonably high or low values of precipitation and temperature. These artefacts or 'hot-spots' had to be removed before the data were passed on to the hydrological model. As a result, all bias-adjusted data were subjected to a simple quality control to ensure that the bias-adjustment procedure did not alter the original climate change signal significantly. Empirical cumulative distribution functions (ECDFs) for original climate data and bias-adjusted data were examined for both control and projection periods. Original climate change signals and the change signals based on the bias-adjusted data for specific percentiles were calculated and compared. The criteria listed below were used to determine whether over-adjustment had occurred and a new re-adjustment was necessary.

3.4.1 Precipitation

The original precipitation change signal (relative change) for percentile q, $RC_q^{original}$, between the control and projection periods can be defined as:

$$RC_q^{original} = \frac{\left(P_q^{prj} - P_q^{ctrl}\right)}{P_q^{ctrl}}$$

where P_q^{prj} and P_q^{ctrl} are the original precipitation data equivalent to percentile q of ECDF of original dataset in the projection and control periods respectively.

Similarly, the relative precipitation change of the bias-adjusted precipitation from the control to the projection period for the q percentile is:

$$RC_q^{adjust} = \frac{\left(\widetilde{P}_q^{prj} - \widetilde{P}_q^{ctrl}\right)}{\widetilde{P}_q^{ctrl}}$$

where $\widetilde{P}_q^{prj}$ and $\widetilde{P}_q^{ctrl}$ denote the bias-adjusted precipitation in the projection and control periods.

The absolute difference between RC_q^{adjust} and $RC_q^{original}$ is given as:

$$diffP_q = \left| RC_q^{adjust} - RC_q^{original} \right|$$

and if $diffP_q$ is larger than 0.05, a new re-adjustment is carried out. $RC_q^{original}$ simply replaces RC_q^{adjust} in the calculation of a new estimate for precipitation adjustment $\hat{\widetilde{P}}_q^{prj}$:

$$\hat{\widetilde{P}}_q^{prj} = (RC_q^{original} \cdot \widetilde{P}_q^{ctrl}) + \widetilde{P}_q^{ctrl}$$

3.4.2 Temperature

For temperature, the absolute change was considered instead. The original temperature change signal for percentile q, $AC_q^{original}$, between the control and projection periods is:

$$AC_q^{original} = T_q^{prj} - T_q^{ctrl}$$

where T_q^{prj} and T_q^{ctrl} are equal to the q percentile of ECDF of the original temperature data in the projection and control periods respectively. The temperature change signal based on the bias-adjusted data is defined as:

$$AC_q^{adjust} = \widetilde{T}_q^{prj} - \widetilde{T}_q^{ctrl}$$

where $\widetilde{T}_q^{prj}$ and $\widetilde{T}_q^{ctrl}$ refer to the q percentile bias-adjusted temperature data in the projection and control periods.

If $diffT_q$ is larger than 3, where $diffT_q = \left| AC_q^{adjust} - AC_q^{original} \right|$, a new estimate for temperature, $\hat{\widetilde{T}}_q^{prj}$, is given as:

$$\hat{\widetilde{T}}_q^{prj} = AC_q^{original} + \widetilde{T}_q^{ctrl}$$

Figure 4 illustrates how the over-adjusted temperature data were modified so that a better match to the original temperature change signals was obtained.

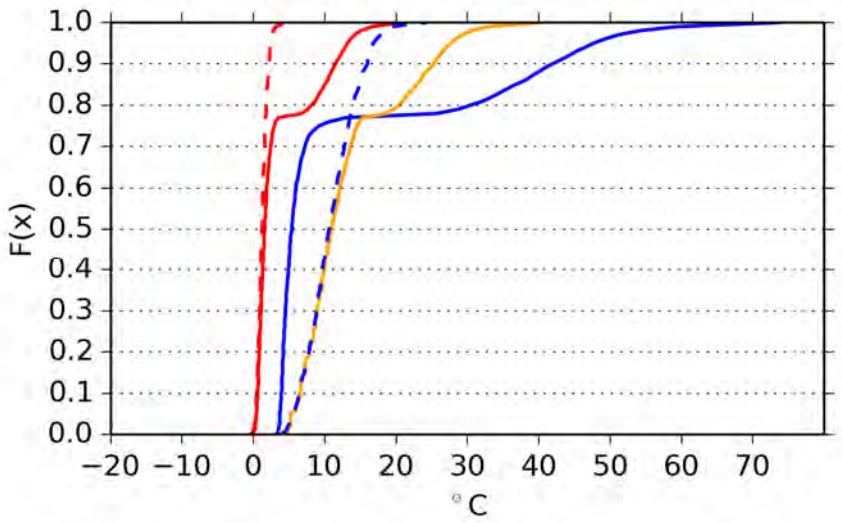

Figure 4. Synthetic example of the quality check procedure. The dashed and solid red lines represent the empirical cumulative distribution function (ECDF) of original modelled temperature for the control and projection periods respectively. Similarly, the dashed and solid blue lines denote the ECDF of bias-corrected temperature for control period and bias-adjusted temperature for projection period. The solid orange line indicates the re-adjusted temperature for the projection period after the quality check procedure.

3.5 Results

3.5.1 Precipitation

The spread in the bias-adjusted and quality-controlled RCM projections are presented in median (50th percentile), low (10th percentile) and high (90th percentile) values. When comparing far future (2071-2100) and present (1971-2000) climates, the median annual precipitation change for Norway as a whole is approximately a 10% increase for RCP4.5 and a 20% increase for RCP8.5 (Fig. 5). For RCP4.5, the 10th and 90th percentiles vary from practically no change to an increase of 16%. For RCP8.5, an increase between 10 to 28% is projected.

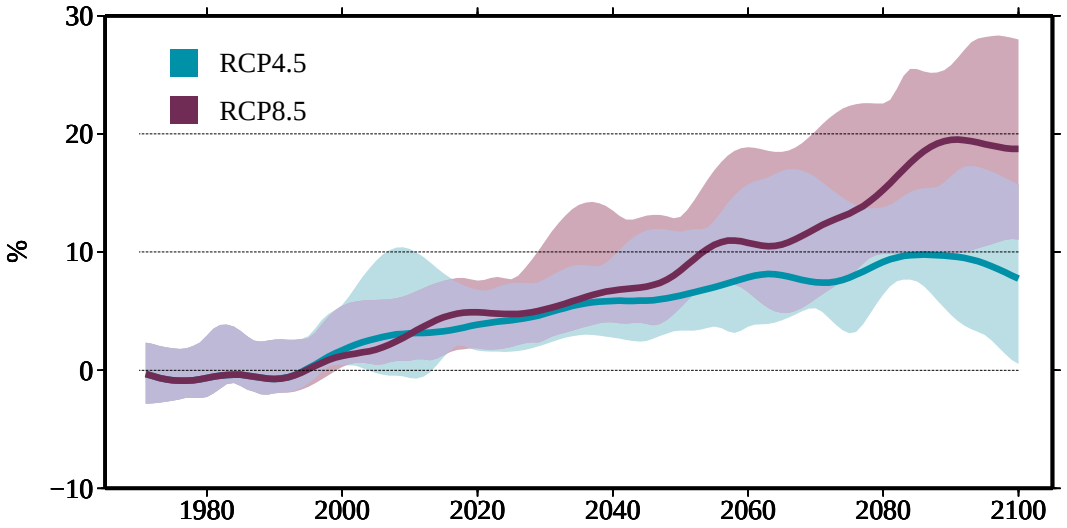

Figure 5. Percentage change in annual precipitation for Norway relative to the reference period (1971-2000). The blue and red lines show the median values for the ensemble of 10 RCM runs for RCP4.5 and RCP8.5. To remove short-term variability, both curves are smoothed using a 30-year Gaussian filter. Shaded areas surrounding the precipitation curves indicate the spread of the RCM results (10th and 90th percentiles).

Figure 6 illustrates the regional pattern of the median percentage changes in annual precipitation for RCP4.5, whereas Figure 7 shows the median changes for RCP8.5. The increases are considerably larger for RCP8.5

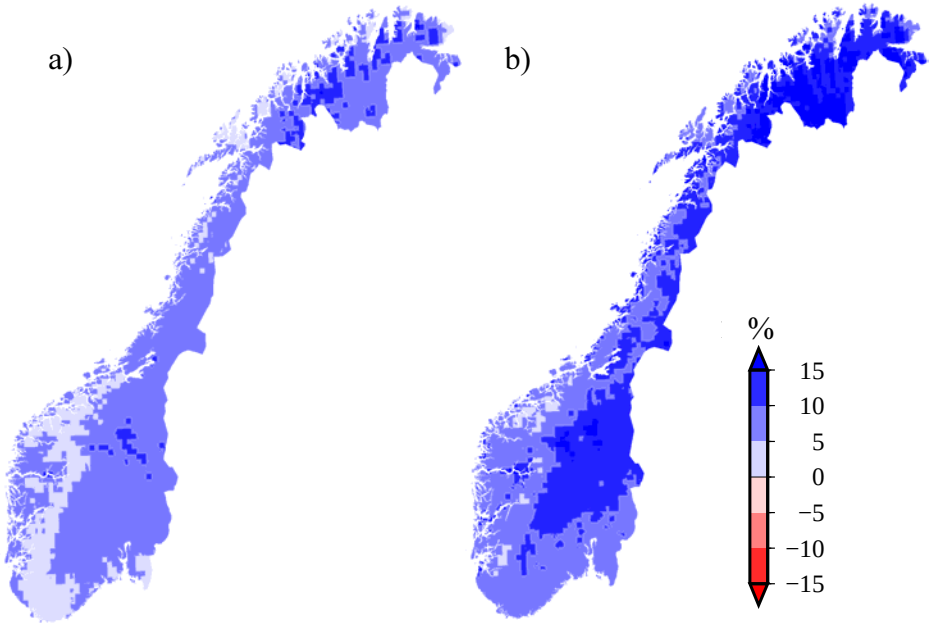

Figure 6. Median percentage change in annual precipitation based on 10 RCM runs for RCP4.5 between the reference period (1971-2000) and the projection periods a) 2031-2060 and b) 2071-2100, respectively.

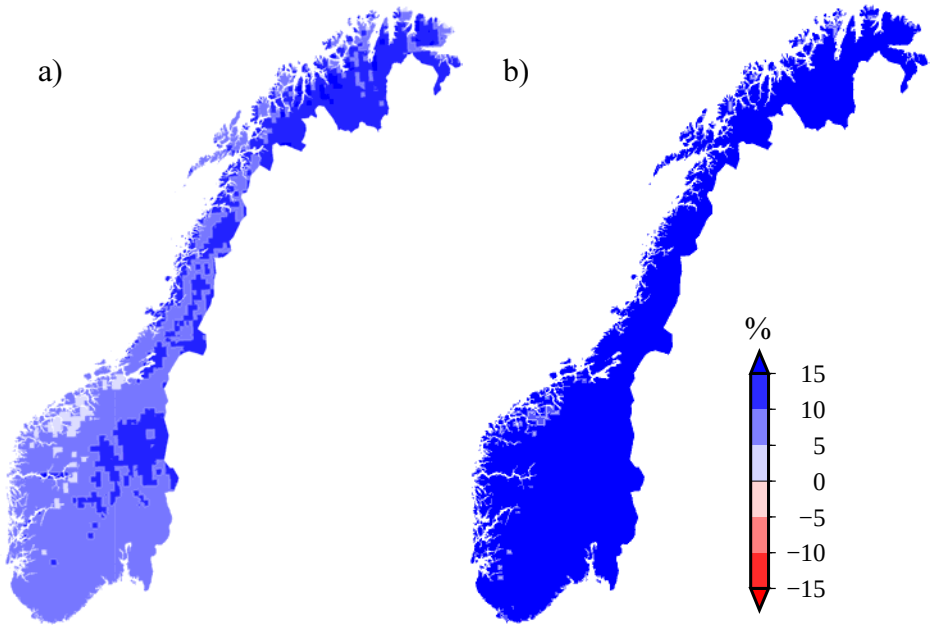

Figure 7. Median percentage change in annual precipitation based on 10 RCM runs for RCP8.5 between the reference period (1971-2000) and the projection periods a) 2031-2060 and b) 2071-2100, respectively.

3.5.2 Temperature

The median mean temperature increase for Norway by the end of the century is approximately 3 ℃ for RCP4.5 and 5 ℃ for RCP8.5 (Fig. 8). Most of the projections (10th and 90th percentiles) show an increase between 2.5 ℃ and 4 ℃ for RCP4.5 and 3.5 ℃ and 6 ℃ for RCP8.5, respectively.

The largest changes in annual mean temperature are expected in northern Norway for both emission scenarios and future periods (Fig. 9 and 10). For western Norway, the temperature increase is lower than for northern and eastern Norway for RCP8.5 (Fig. 10). Generally, the increases are significantly larger for RCP8.5.

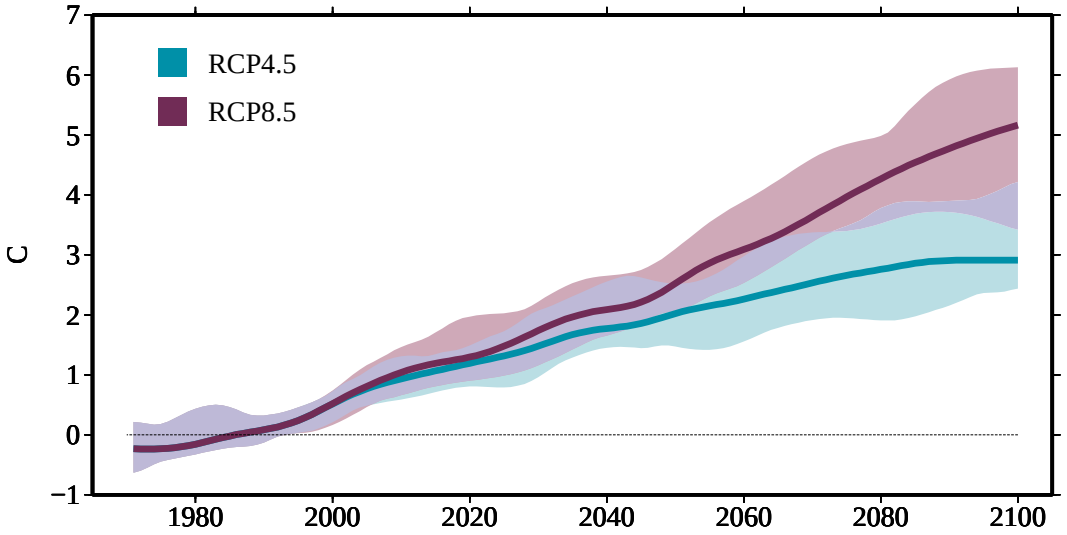

Figure 8. Change in annual mean temperature for Norway relative to the reference period (1971-2000). The blue and red lines show the median values for the ensemble of 10 RCM runs for RCP4.5 and RCP8.5. To remove short-term variability, both curves are smoothed using a 30-year Gaussian filter. Shaded areas surrounding the temperature curves indicate the spread of the RCM results (10th and 90th percentiles).

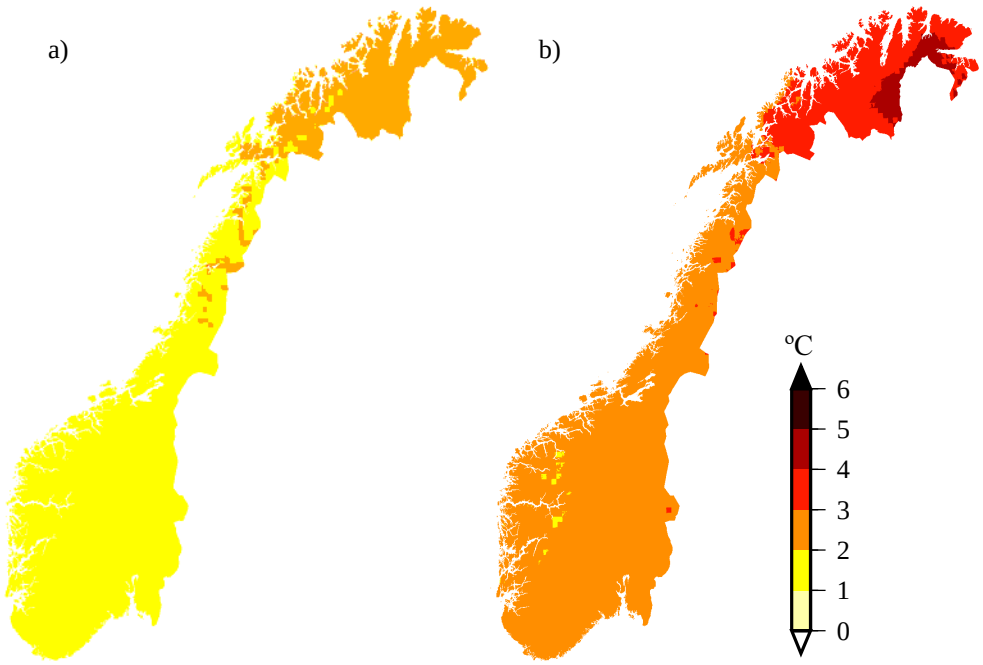

Figure 9. Median change in annual mean temperature based on 10 RCM runs for RCP4.5 between the reference period (1971-2000) and the projection periods a) 2031-2060 and b) 2071-2100.

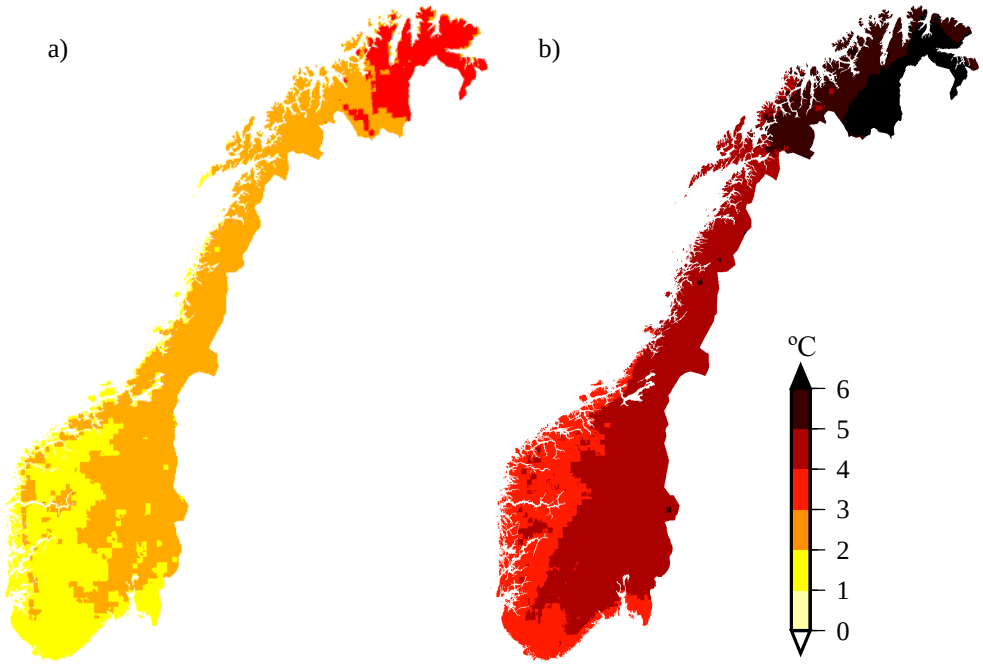

Figure 10. Median change in annual mean temperature based on 10 RCM runs for RCP8.5 between the reference period (1971-2000) and the projection periods a) 2031-2060 and b) 2071-2100.

4 Hydrological modelling

A spatially distributed version of the HBV precipitation and runoff model was used to assess the hydrological responses to climate change (Beldring et al., 2003; Beldring, 2008). The model calculates the water balance for 1 x 1 km grid cells characterized by their elevation and land use. Each grid cell can be divided into two land use zones with different vegetation types, a lake area and a glacier area. The model was run using a daily time step, with precipitation and temperature data as input. It has components for accumulation, sub-grid scale distribution and ablation of snow, interception storage, sub-grid scale distribution of soil moisture storage, evapotranspiration, groundwater storage and runoff response, lake evaporation and glacier mass balance. Potential evapotranspiration is a function of temperature and seasonally varying vegetation characteristics. Further description of model structure and algorithms can be found in Bergström (1995).

Due to the absence of directly measured catchment characteristics, to natural variability and to the non-linearity of the processes involved, calibration is necessary to adjust the model parameters to improve the model's ability to reproduce the observed hydrological data. A regional set of parameters for each land use class were determined using a multi-criteria calibration approach, where the residuals between simulated and observed daily streamflow from 121 Norwegian catchments located in areas with different hydrological regimes and landscape characteristics were considered simultaneously. This calibration procedure rests on the hypothesis that model elements with identical landscape characteristics have similar hydrological behaviour and should, therefore, be assigned the same parameter values. The grid cells should represent the significant and systematic variations of land surface properties, and representative (typical) parameter values should be applied for different classes of soil and vegetation types, lakes and glaciers (Gottschalk et al., 2001). The period 1991-2000 was chosen as the calibration period. For model calibration daily precipitation and temperature grids at 1 x 1 km spatial resolution from the Norwegian Meteorological Institute (Tveito et al., 2005) were used.

Model simulations produced gridded daily time series of soil moisture deficit, runoff, evapotranspiration, snow water equivalent and groundwater for each 1 x 1 km grid cell. The model was run continuously for the period 1970-2100, and the first year was considered a spin-up year such that the results were not included in the further analyses. Runoff and evapotranspiration are flux variables representing average values over each grid cell in mm/day. The other variables are state variables, which describe the average condition of the hydrological components in a grid cell with unit mm (or $m^3/1000\ m^2$).

4.1 Results

Only example results are presented in this report. For more comprehensive results, see 'Klima i Norge 2100'.

4.1.1 Runoff

Figure 11 shows the percentage changes in annual runoff for Norway when compared to the reference period (1971-2000). Relatively small changes are projected for the next 50 years based on the median values of the ten projections considered. Towards the end of the century, the median projection indicates a slight increase, 3% for RCP4.5 and 7% for RCP8.5. However, the spread in RCM results is rather large, as indicated by the 10th and

90th percentiles. This can be attributed to the differences in projected precipitation and temperature from the RCMs.

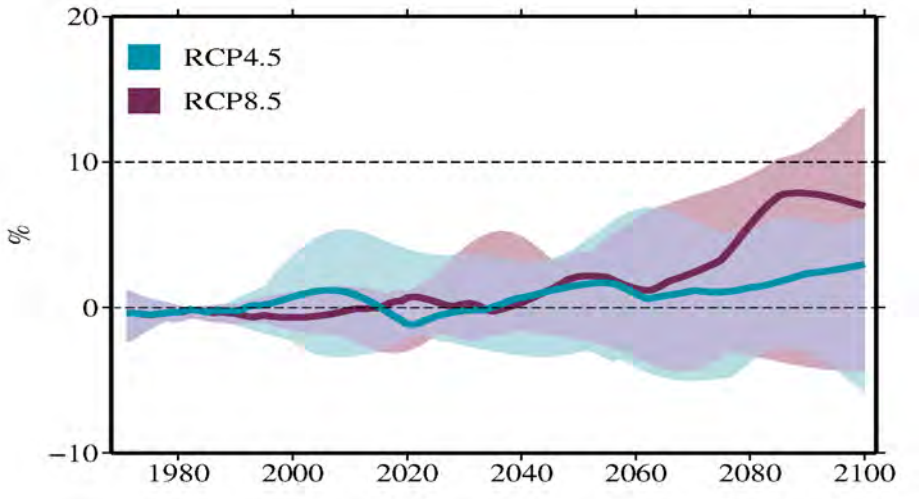

Figure 11. Percentage change in annual runoff for Norway relative to the reference period (1971-2000). The blue and red lines show the median values for the ensemble of 10 RCM runs for RCP4.5 and RCP8.5. Shaded areas surrounding the runoff curves indicate the spread of the RCM results (10th and 90th percentiles). To remove short-term variability, all curves are smoothed using a 30-year Gaussian filter.

The projected relative changes in seasonal runoff are considerably larger than for annual runoff (Fig. 12), and this is caused by seasonal changes in precipitation and temperature characteristics. The largest relative increases are expected in the winter due to increased precipitation and to more precipitation in the form of rain, rather than snow, leading directly to runoff. Summer seasons are projected to have the largest relative decreases due to higher evapotranspiration losses and reduced runoff resulting from earlier snowmelt. Both emission scenarios show similar patterns, although changes in RCP8.5 are more pronounced.

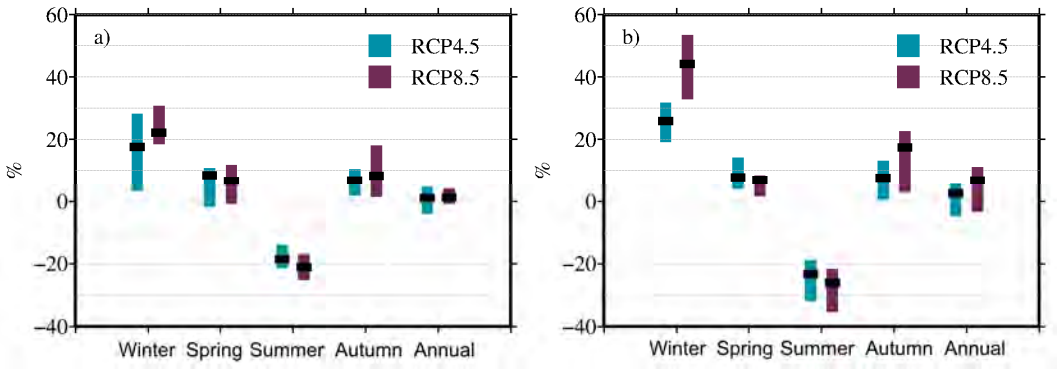

Figure 12. Relative percentage changes in seasonal and annual runoff for Norway from 1971-2000 to a) 2031-2060 and b) 2071-2100 for RCP4.5 (blue) and RCP8.5 (red). Median projections are marked as a black solid line, while low (10th percentile) and high (90th percentile) projections are marked by the lower and upper ends of the boxes.

Regional differences in changes in annual runoff are shown in Figure 13. The median projection indicates a slight increase in runoff for both emission scenarios and future periods (2031-2060 and 2071-2100) in Østlandet, Vestlandet and Nordland regions. However, a slight decrease is projected for Trøndelag. For Sørlandet, Troms and Finnmark regions, only minor changes in annual runoff are expected.

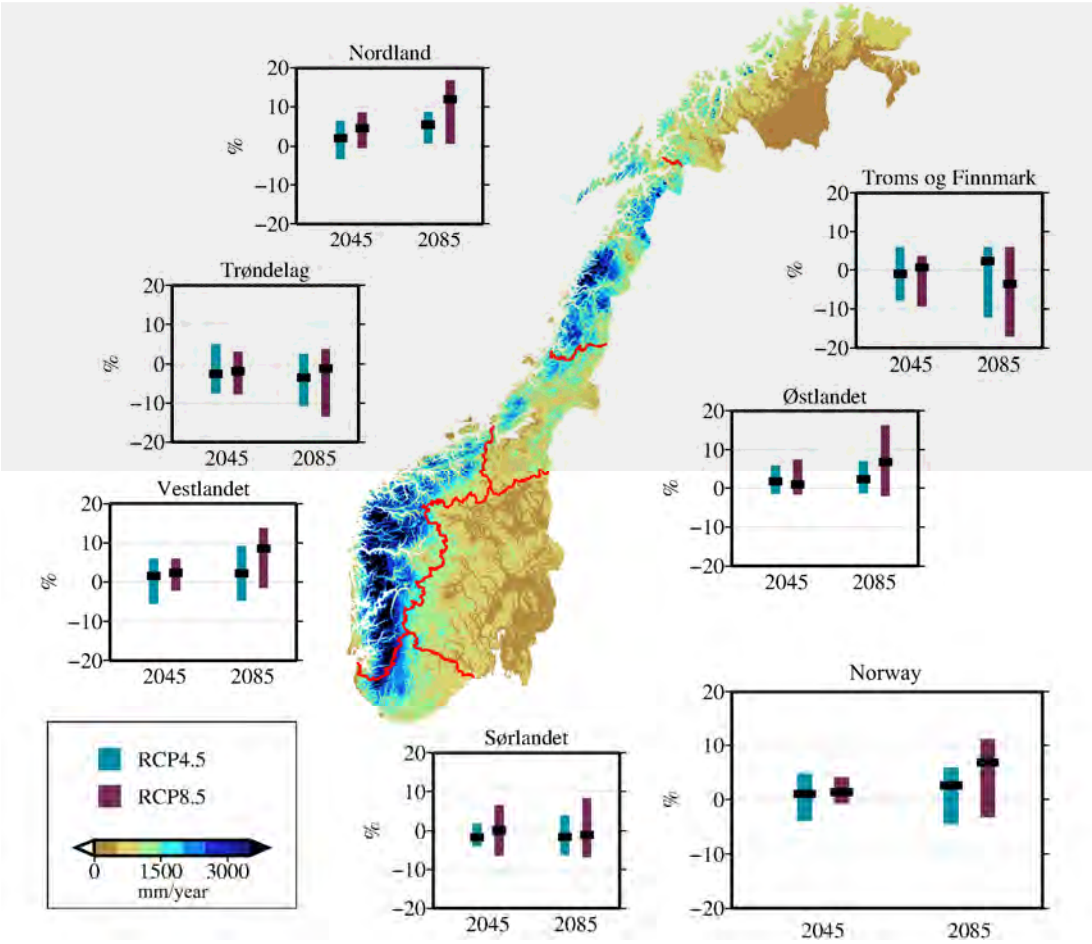

Figure 13. Relative percentage changes in annual runoff for different regions of Norway from 1971-2000 to 2031-2060 (2045) and 2071-2100 (2085) for RCP4.5 (blue) and RCP8.5 (red). Median projections are marked as a black solid line, while low (10th percentile) and high (90th percentile) projections are marked by the lower and upper ends of the boxes. The map in the middle shows the annual runoff (1971-2000) and the red lines indicate the regional boundaries.

Although precipitation and temperature are bias-corrected in the reference period, the runoff simulations averaged over the whole country using the corrected climate model inputs do not perfectly match the simulation results using observed (seNorge) inputs (Fig. 14). The observation-based runoff simulations are often larger than the simulations with bias-corrected inputs in the summer months, whereas the opposite effect (i.e. observed values are lower than simulated) is seen in the spring months. For autumn and winter, no significant differences are evident. This can be an indication that the day-to-day variability is not sufficiently represented in the corrected datasets relative to the observed 'true' values. Another contributing factor can be the existence of temporal and spatial biases in the climate model inputs. The highly non-linear nature of the hydrological processes further enhances these differences.

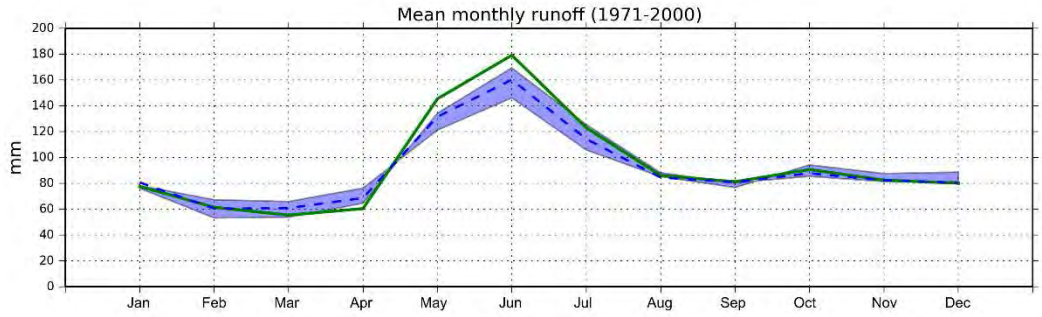

Figure 14. Mean monthly runoff averaged over the whole country for the period 1971-2000. Runoff was simulated by the HBV model. The green line refers to runoff simulations using observed (seNorge) inputs. The blue dashed line represents the median runoff projection using the corrected RCM inputs. Shaded areas surrounding the median runoff curve indicate the spread of the runoff simulation results based on corrected RCM inputs (10th and 90th percentiles).

4.1.2 Snow water equivalent

The combined effect of increased precipitation and temperature on snow water equivalent is shown in Figure 15. For most of the country, there is a reduction in the maximum amount of snow by the end of this century. However, it is worth noting that in some high-lying areas, an increase is expected in the far future.

Figure 16 shows changes in the expected number of days with a snow cover under a future climate. The snow season can be 1- 5 months shorter and 1- 7 months shorter for RCP4.5 and RCP8.5, respectively. At low altitudes where the winter temperature today is only slightly below zero, the snow will be negligible in most years towards the end of the century under the high emission scenario.

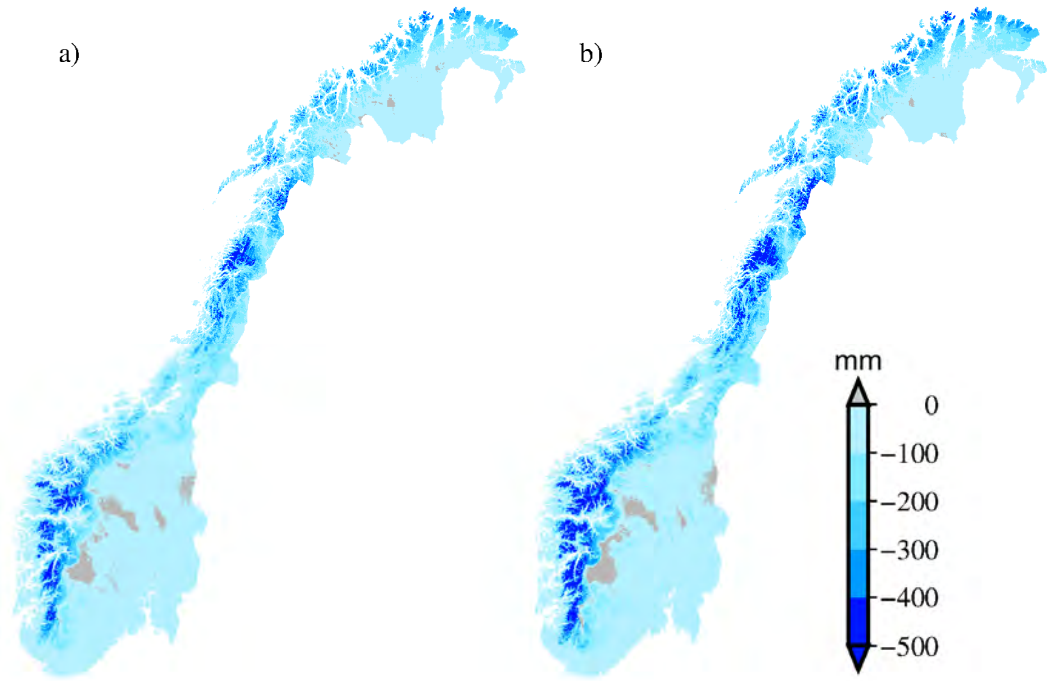

Figure 15. Changes in maximum annual snow water equivalent (SWE) in mm from 1971-2000 to 2071-2100 for a) RCP4.5 and b) RCP8.5, both median projections.

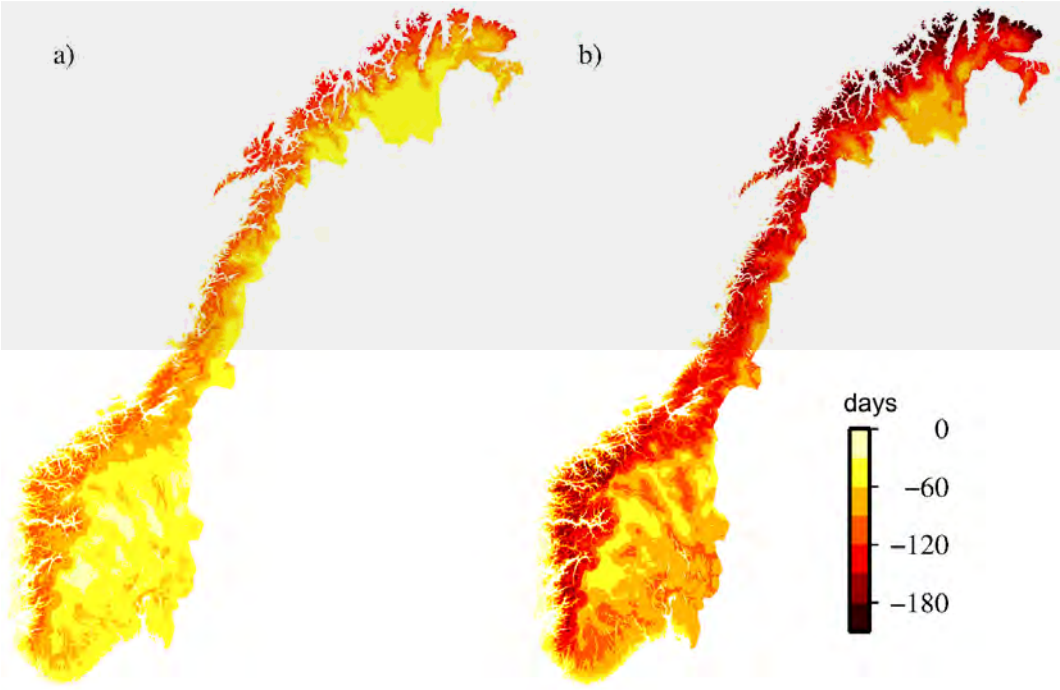

Figure 16. Changes in the annual number of days with snow cover from 1971-2000 to 2071-2100 for a) RCP4.5 and b) RCP8.5, both median projections.

5 Discussion

Since the bias-correction method corrects only one variable at a time, it can lead to a loss of physical consistency between the variables in the corrected datasets. Although applying bias-correction to precipitation conditioned on the bias-corrected temperature data can improve the precipitation-temperature dependency (e.g. Piani and Haerter, 2012), the substantially increased computational time may render this method infeasible for high-resolution datasets containing long time series.

The EQM method employed in this study gives a significant improvement in the simulated mean monthly temperature and accumulated precipitation. However, applying calendar-month-specific transfer function can result in discontinuities in the data at the start of each month, though the use of 3-month moving windows to derive monthly transfer function can partly compensate for this issue. Moreover, the EQM method did not change the temporal order of the original climate model data and hence it was not able to correct any temporal biases that might exist in the climate model outputs, such as the length of dry and wet spells. Similar concern can be raised about the spatial structure because the EQM method was applied to each grid cell individually and basically reproduced the spatial structure of the climate model.

The transfer functions derived from the control period were also used in the projection period for bias-adjustment. However, the underlying assumption that the relationship between model and observations remains unchanged between the control and the projection periods may not hold in a changing climate. It is also questionable whether or not the

stationarity assumption of the hydrological model parameters is fulfilled. A hydrological model is normally calibrated for a specific period. However, temporal variations in climate or human induced land-use changes such as deforestation, changes in vegetation type and urbanisation can have significant impacts on a hydrological system. Although it is possible to adjust the model parameters explicitly to account for changing catchment characteristics, this approach requires *a priori* knowledge of such changes, which makes it poorly suited for use with future projections.

The temperature index method used in the hydrological model to estimate potential evapotranspiration probably overestimates evapotranspiration, and hence underestimates runoff because the future conditions are warmer than what the model has been calibrated for. An alternative method, which also takes into account factors that may influence the feedback between the land surface and the atmosphere such as wind, humidity and radiation, has recently been implemented in the hydrological model used here. Input data requirements have, however, so far limited the test of the new method and its use in our hydrological simulations.

The results presented in this study assume that the areas covered by glacier are constant over the whole projection period. However, the projected temperature increase in the future can lead to a change in glacier mass balance and areal coverage, which will result in altered runoff patterns in catchments with significant contributions from glaciers. The effect of rising temperatures and its impact on glaciers and runoff is an ongoing research topic at NVE, and a new approach to simulate glacier dynamics may be included in future hydrological simulations.

Generally, the uncertainty of the climate and hydrological projections increases with decreasing grid size. In particular, use of only a single grid cell value to represent a site of interest is not recommended. The eight surrounding neighbour cells should also be considered and an average value derived from these nine grid cells is a better representation of a 'point value'. For assessing runoff or discharge from a catchment, grid cells covering the entire catchment area rather than the grid cell where the outlet of the catchment is located should be selected.

Despite their limitations, these high-resolution datasets represent a valuable data source for different types of impact studies at a national and local scale. However, it is of uttermost importance to be aware of these limitations and their implications for climate change impact studies. Further research is recommended to develop further methods for providing climate projections which preserve climate signals at the finer spatial resolutions required for climate impact studies.

Acknowledgements

We acknowledge the World Climate Research Programme's Working Group on Regional Climate, and the Working Group on Coupled Modelling, former coordinating body of CORDEX and responsible panel for CMIP5. We also thank the climate modelling groups (listed in Table 1 of this report) for producing and making available their model output. We also acknowledge the Earth System Grid Federation infrastructure an international effort led by the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison, the European Network for Earth System Modelling and other partners in the Global Organisation for Earth System Science Portals (GO-ESSP).

References

Beldring, S. (2008) Distributed element water balance model system. Norwegian Water Resources and Energy Directorate, Report no. 4/2008, 40 pp.

Beldring, S., Engeland, K., Roald, L.A., Sælthun, N.R. and Voksø, A. (2003) Estimation of parameters in a distributed precipitation-runoff model for Norway. *Hydrol. Earth Syst. Sci*., 7, 304-316, doi:10.5194/hess-7-304-2003

Bergström, S. (1995): The HBV model. Computer Models of Watershed Hydrology, V.P. Singh, Ed., Water Resources Publications, Highlands Ranch, 443-476.

Frei, C., Christensen, J.H., Déqué, M., Jacob, D., Jones, R.G., and Vidale, P.L. (2003): Daily Precipitation Statistics in Regional Climate Models: Evaluation and Intercomparison for the European Alps. *J. Geophys. Res.*, 108(D3), 4124. doi:10.1029/2002JD002287.

Gottschalk, L., Beldring, S., Engeland, K., Tallaksen, L., Sælthun, N.R., Kolberg, S. and Motovilov, Y. (2001) Regional/macroscale hydrological modelling: a Scandinavian experience. *Hydrological Sciences Journal*, 46, 963-982.

Gudmundsson, L. (2014) qmap: Statistical transformations for post-processing climate model output. R package version 1.0-2.

Gudmundsson, L., Bremnes, J. B., Haugen, J. E. and Engen-Skaugen, T. (2012) Technical Note: Downscaling RCM precipitation to the station scale using statistical transformations - a comparison of methods. *Hydrology and Earth System Sciences*, 16, 3383-3390, doi:10.5194/hess-16-3383-2012.

Hanssen-Bauer,I., Førland, E.J., Haddeland, I., Hisdal, H., Mayer, S., Nesje, A., Nilsen, J.E.Ø., Sandven, S., Sandø, A.B., Sorteberg, A. and Ådlandsvik, A. (2015) Klima i Norge 2100 – Kunnskapsgrunnlag for Klimatilpasning, oppdatert i 2015. (In English: Climate in Norway 2100 – Knowledge base for climate adaptation, updated in 2015). Norwegian Centre for Climate Services, Report 2/2015 203pp. (https://klimaservicesenter.files.wordpress.com/2015/02/klimainorge2100_hoyoppl.pdf)

Hempel, S., Frieler, K., Warszawski, L., Schewe, J. and Piontek, F. (2013) A trend-preserving bias-correction – the ISI-MPI approach. *Earth System Dynamics*, 4, 219-236, doi:10.5194/esd-4-219-2013.

Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O., Bouwer, L., Braun, A., Colette, A., Déqué, M., Georgievski, G., Georgopoulou, E., Gobiet, A., Menut, A., Nikulin, G., Haensler, A., Hempelmann, N., Jones, C., Keuler, K., Kovats, S., Kröner, N., Kotlarski, S., Kriegsmann, A., Martin, E., van Meijgaard, E., Moseley, C., Pfeifer, S., Preuschmann, S., Radermacher, C., Radtke, K., Rechid, D., Rounsevell, M., Samuelsson, P., Somot, S., Soussana, J.-F., Teichmann, C.,

Valentini, R., Vautard, R., Weber B. and Yiou P. (2014) EURO-CORDEX: new high-resolution climate change projections for European impact research. *Reg. Environ. Change*, 14, 563-578, doi:10.1007/s10113-013-0499-2

Mohr, M. (2008) New Routines for Gridding of Temperature and Precipitation Observations for "seNorge.no". Norwegian Meteorological Institute. Report no. 8/2008, 40 pp.

Piani, C. and Haerter, J.O. (2012) Two dimensional bias correction of temperature and precipitation copulas in climate models. *Geophys. Res. Lett*., doi:10.1029/2012GL053839.

Sorteberg A., Haddeland, I., Haugen, J., Sobolowski, S. and Wong, W.K. (2014) Evaluation of distribution mapping based bias correction methods. Norwegian Centre for Climate Services. Report 1/2014. ISSN 2387-3027, Oslo, Norway

Tveito, O.E., Bjørdal, I., Skjelvåg, A.O. and Aune, B. (2005) A GIS-based agro-ecological decision system based on gridded climatology. *Meteorological Applications*, 12, 57-68.

van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J. and Steven, K. R. (2011) The representative concentration pathways: an overview, *Climatic Change*, 109, 5-31, doi: 10.1007/s10584-011-0148-z

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