Climate change: Sources of uncertainty in precipitation and temperature projections for Denmark

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General Circulation Models (GCMs) are the main tools used to assess the impacts of climate change. Due to their coarse resolution, with cells of 100 km × 100 km, GCMs are dynamically downscaled using Regional Climate Models (RCMs) that better incorporate the local physical features and simulate the climate of a smaller region, e.g. a country. However, RCMs tend to have systematic biases when compared with local observations, such as deviations from day-to-day measurements, and from the mean and extreme events. As a result, confidence in the model projections decreases. One way to address this is to correct the RCM output using statistical methods that relate the simulations with the observations, producing bias-corrected (BC) projections.

Here, we present the first assessment of a previously published method to bias-correct 21 RCM projections of daily temperature and precipitation for Denmark. We assess the projected changes and sources of uncertainty. The study provides an initial assessment of the bias correction procedure applied to this set of model outputs to adjust projections of annual temperature, precipitation and potential evapotranspiration (PET). This method is expected to provide a foundation for further analysis of climate change impacts in Denmark.

Material and Methods

Climate models

We analysed 21 RCMs from the Euro-CORDEX initiative (Jacob *et al.* 2014) driven by GCMs from the Coupled Model Intercomparison Project phase 5 (Taylor *et al.* 2012). Of these, 16 combinations are driven by the greenhouse gas concentration scenario (Representative Concentration Pathway) RCP 8.5 and five are driven by RCP 4.5 (Table 1). RCPs are based on a review of existing scientific literature considering different descriptions of future socioeconomic conditions, technological development, the environment, climate and emission of greenhouse gases and aerosols (Moss *et al.* 2010). RCP 8.5 represents a rising radiative forcing reaching 8.5 W/m^2 by 2100 whereas RCP 4.5 represents a scenario of stabilised radiative forcing at 4.5 W/m^2, both relative to pre-industrial levels (van Vuuren *et al.* 2011). The RCM daily outputs were remapped using the Climate Data Operators – a collection of command line operators to analyse climate model data (Schulzweida 2019) – to match the grids of the observed temperature (20 km) and precipitation (10 km) obtained from the Danish Meteorological Institute (DMI). We remapped temperature using a bilinear interpolation and a conservative interpolation for precipitation.

Bias-correction

Precipitation and temperature data were bias-corrected using a distribution-based scaling method, whereby daily simulations were fitted to daily observations, as described by Seaby *et al.* (2013). We used the double gamma distribution with a cut-off threshold set to the 90th percentile to bias-correct precipitation, and a normal distribution for temperature. Bias correction has limitations. For example, the correction depends on the training period used to define the distribution parameters that will be used to bias-correct the simulated precipitation and temperature (Lafon *et al.* 2013), biases associated with the driving data (Maraun 2016) and any possible alterations in the signal of change in the projection (Maraun 2013). Bias correction also assumes stationarity in the trained parameters (Chen *et al.* 2015). These and other limitations have been discussed in detail by Maraun & Widmann (2018). In our method, we used gridded observations from 1991 to 2010 as the training dataset. The parameters obtained during this training period were used to generate BC time series from 1971 to 2100. The correction method was cross-validated using a five-fold method (Maraun *et al.* 2015), where five non-overlapping periods of equal length are defined. Four periods were used to train the parameters and then the parameters were used to bias-correct the remaining

Table 1. Projected change in the mean annual temperature (T), precipitation (P) and potential evapotranspiration (PET)

Included in the uncertainty analysis								Projected change by 2071–2100 compared to 1981–2010					
								Raw			BC		
GCM	RCM	RCP	NV	GCM	RCM	Ensemble	RCP	T (°C)	P (mm)	PET (mm)	T (°C)	P (mm)	PET (mm)
x				CanESM2	REMO2015	r1i1p1	8.5	3.5	265	115	5.1	310	173
			x	EC-EARTH	RACMO 2.2	r1i1p1	8.5	3.0	51	97	3.4	126	112
				EC-EARTH	HIRHAM5	r3i1p1	8.5	3.1	71	100	3.9	113	135
			x	EC-EARTH	RACMO 2.2	r12i1p1	8.5	3.2	92	100	3.7	144	124
x		x		IPSL-CM5A-MR	RCA4	r1i1p1	8.5	3.2	215	98	3.6	241	120
x				MIROC5	REMO2015	r1i1p1	8.5	4.1	156	134	4.9	156	167
		x	x	MPI-ESM-LR	REMO2009	r1i1p1	8.5	2.5	108	70	3.3	133	104
x				MPI-ESM-LR	RCA4	r1i1p1	8.5	2.6	150	78	3.0	173	112
			x	MPI-ESM-LR	REMO2009	r12i1p1	8.5	2.4	120	73	3.3	154	107
				NorESM1-M	HIRHAM5	r1i1p1	8.5	2.8	162	95	3.5	158	129
	x			HadGEM2-ES	CCLM 4.8.17	r1i1p1	8.5	4.3	73	140	4.6	75	150
	x			HadGEM2-ES	HIRHAM5	r1i1p1	8.5	3.8	176	121	4.7	200	159
x	x			HadGEM2-ES	REMO2015	r1i1p1	8.5	4.1	88	130	5.6	110	186
	x	x		HadGEM2-ES	RACMO 2.2	r1i1p1	8.5	4.1	133	131	4.6	181	149
x	x			HadGEM2-ES	RCA4	r1i1p1	8.5	3.9	165	120	4.4	219	143
				EC-EARTH	HIRHAM5	r3i1p1	4.5	1.6	50	55	2.1	70	75
		x		IPSL-CM5A-MR	RCA4	r1i1p1	4.5	2.0	86	39	2.3	106	79
		x		MPI-ESM-LR	REMO2009	r1i1p1	4.5	1.2	–25	38	1.7	–10	58
				MPI-ESM-LR	REMO2009	r12i1p1	4.5	1.2	43	38	1.7	58	57
		x		HadGEM2-ES	RACMO 2.2	r1i1p1	4.5	2.5	112	77	2.8	147	91
				Ensemble mean change			8.5	3.3	133	105	4	165	135
							4.5	1.7	53	50	2.1	74	72
				Ensemble standard deviation			8.5	0.6	56.8	22.4	0.8	56.9	27.4
							4.5	0.5	51.9	16.9	0.5	58.5	14.7

Changes are for 2071–2100, relative to the 1981–2010 reference period for the uncorrected (raw) and bias-corrected (BC) simulations. GCM: General Circulation Model. RCM: Regional Climate Model. RCP: Representative Concentration Pathway. NV: natural variability.

period. Following this approach, cross-validated time series were developed for the entire period.

Potential evapotranspiration (PET)

PET was estimated using the Oudin formula (Oudin *et al.* 2005), which uses temperature as the only climate input. The formula accurately reproduces the annual accumulated PET over Denmark when compared to observations, but they are offset from the observed monthly distributions, and a correction parameter needs to be applied. Here, we estimated daily PET using the climate model temperature (uncorrected and BC) as the input and applied the correction parameter.

Results and discussion

We validated the bias correction method by comparing how well the uncorrected and BC models simulate the observed mean annual temperature and precipitation. Then, we assessed the projected changes in temperature, precipitation, and PET by the end of this century for the whole ensemble and for each individual combination of GCM and RCM. We then assessed the contribution of individual sources of uncertainty in the projections. Finally, we assessed the spatial distribution of the projected change for mean annual precipitation under RCP 8.5 by the end of the century along with a measure of its uncertainty. Here, we assess the change in precipitation only, as its variation throughout the country is larger than that of temperature and PET.

Bias-corrected results

Mean annual temperature biases range from –1.2°C to +1.0°C in the uncorrected models and –0.1°C to +0.3°C in the BC models (data not shown). The mean annual precipitation (857 mm) biases range from –26% to +39% for the uncorrected models and between –3% and +5% for the BC simulations. Even though PET is not a direct output of the climate models, we assessed the biases associated with it using uncorrected and BC temperature data as the input to the Oudin formula. The biases associated with mean annual

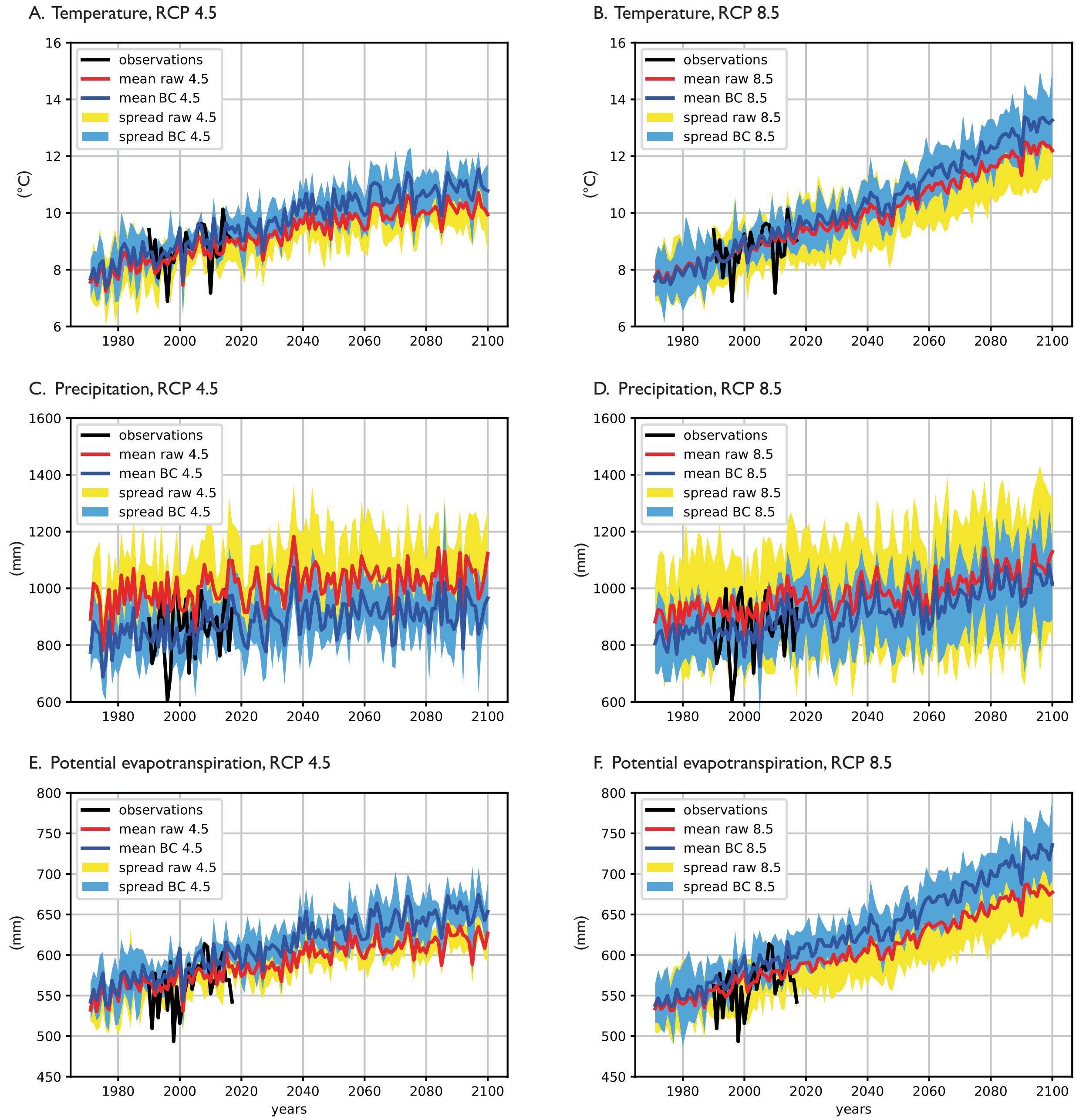

Fig 1. Observations and uncorrected (raw) and bias-corrected (BC) projections under two RCP scenarios. Mean annual temperature under **A**: RCP 4.5 and **B**: RCP 8.5. Mean annual precipitation under **C**: RCP 4.5 and **D**: RCP 8.5. Mean annual potential evapotranspiration under **E**: RCP 4.5 and **F**: RCP 8.5.

PET (564 mm) range from −6% to +8% in the uncorrected models and +2% to +5% in the BC models.

Projected changes

The BC simulations project higher temperatures and PET compared to the uncorrected simulations (Fig. 1). In contrast, the uncorrected models project higher precipitation than the BC models. The change in temperature and PET by the end of the century is larger when driven by RCP 8.5 compared to RCP 4.5. The same is true for precipitation, but the difference between the two RCPs is small.

When driven by RCP 4.5, the mean of the uncorrected models projects an increase in temperature of 1.7°C by the end of the century, while the BC simulations project an increase of 2.1°C. Under RCP 8.5, the uncorrected ensemble mean projects an increase of 3.3°C and the BC models project an increase of 4°C (Table 1).

Table 2. Signal to noise ratio for temperature (T) and precipitation (P)

	Raw				BC			
	T (°C)		P (mm)		T (°C)		P (mm)	
Uncertainty source	2041–2070	2071–2100	2041–2070	2071–2100	2041–2070	2071–2100	2041–2070	2071–2100
GCM	5.7	5.7	1.2	2.0	6.3	6.3	2.0	2.7
RCM	15.3	19.9	2.4	2.8	9.9	10.1	1.8	2.5
RCP	2.6	2.6	1.7	1.4	3.2	3.0	2.1	1.6
NV	5.0	42.0	12.9	4.5	6.3	16.1	3.7	11.4

GCM: General Circulation Model. RCM: Regional Climate Model. RCP: Representative Concentration Pathway. NV: natural variability.

Under RCP 4.5, uncorrected models project an increase in inland precipitation of 53 mm/yr by the end of the century, in contrast to the 76 mm/yr projected by the BC models. Under RCP 8.5, the uncorrected ensemble projects an increase of 133 mm/yr by the end of the century whilst the BC ensemble projects an increase of 165 mm/yr. The bias-correction method applied here, clearly changes the climate signal from the combined GCM-RCM. This contrasts with other bias-correction methods, such as the delta change bias-correction, which has no such effect.

PET projections follow a similar pattern as temperature, with larger increases projected by the BC models compared to the uncorrected projections, and with the largest increase by the end of the century. Notably, the ensemble change for PET is always lower than the change projected for precipitation.
Table 1 shows the projected changes in mean annual temperature, PET and precipitation for individual models by the end of the century. Clusters are observed, such as models that project a warmer (e.g. CanESM2-REMO2015 and all RCMs driven by HadGEM2-ES under RCP 8.5) or a wetter climate (CanESM2-REMO2015, IPSL-CM5A-MR-RCA4, HadGEM2-ES-HIRHAM5 under RCP 8.5) compared to the ensemble mean. Further clusters emerge among models that project an increase in water stress (where the increase in PET is larger than the increase in precipitation), such as HadGEM2-ES-CCLM and HadGEM2-ES-REMO2015 when driven by RCP 8.5. These clusters can provide insights into the impacts of climate change on Danish water resources.

Uncertainty of the projections

The ensemble spread from the BC simulations is smaller than the spread of the uncorrected models for temperature and PET when driven by RCP 8.5. For precipitation, the ensemble spread decreases for both RCPs. The standard deviation of the mean annual precipitation from 2071 to 2100 is reduced by bias-correction from 166 mm to 122 mm for RCP 4.5 and from 211 mm to 139 mm for RCP 8.5.

The spread or 'uncertainty' in projections comes from the choice of GCM, RCM or RCP and the natural variability expressed in the models. To assess the contribution of each source of uncertainty to the overall spread of projections, we analysed the signal-to-noise ratio (SNR) of the precipitation and temperature projections driven by RCP 8.5 for the middle and end of the century (Table 2). The SNR of an ensemble is defined as the projected mean divided by the standard deviation of the ensemble. Thus, a low SNR implies that the uncertainty of the projection is high.

Our analysis has some limitations, which we acknowledge here. First, the full range of all possible combinations of GCMs and RCMs were not available for the uncertainty analysis. Second, some of the available GCM-RCM combinations were run with different initial conditions and third, not all RCMs are driven by the same GCMs. Considering these limitations, we used the GCM-RCM combinations driven by HadGEM2-ES to assess RCM uncertainty. GCM uncertainty was estimated by averaging the output of the REMO2015 and RCA4 RCMs (each one driven by three different GCMs). RCP uncertainty was evaluated using the GCM-RCM combinations available for both scenarios. Uncertainty associated with natural variability was assessed using simulations with two different initial conditions (Table 1).

For temperature, the largest source of uncertainty in the uncorrected models is the choice of RCP scenario used. The uncertainty associated with natural variability is largest by the middle of the century and then reduces. Finally, the uncertainty associated with the GCM is larger than that of the RCM, which represents the smallest source of uncertainty, overall. These results are similar to the findings of Hawkins & Sutton (2011) for projections of global mean temperature.

For precipitation, the choice of GCM and RCP provides the largest sources of uncertainty by the middle of the century and the end of the century, respectively. The next largest source of uncertainty is the RCM followed by natural variability. Hawkins & Sutton (2011) estimated that the model uncertainty is larger than the uncertainty associated with

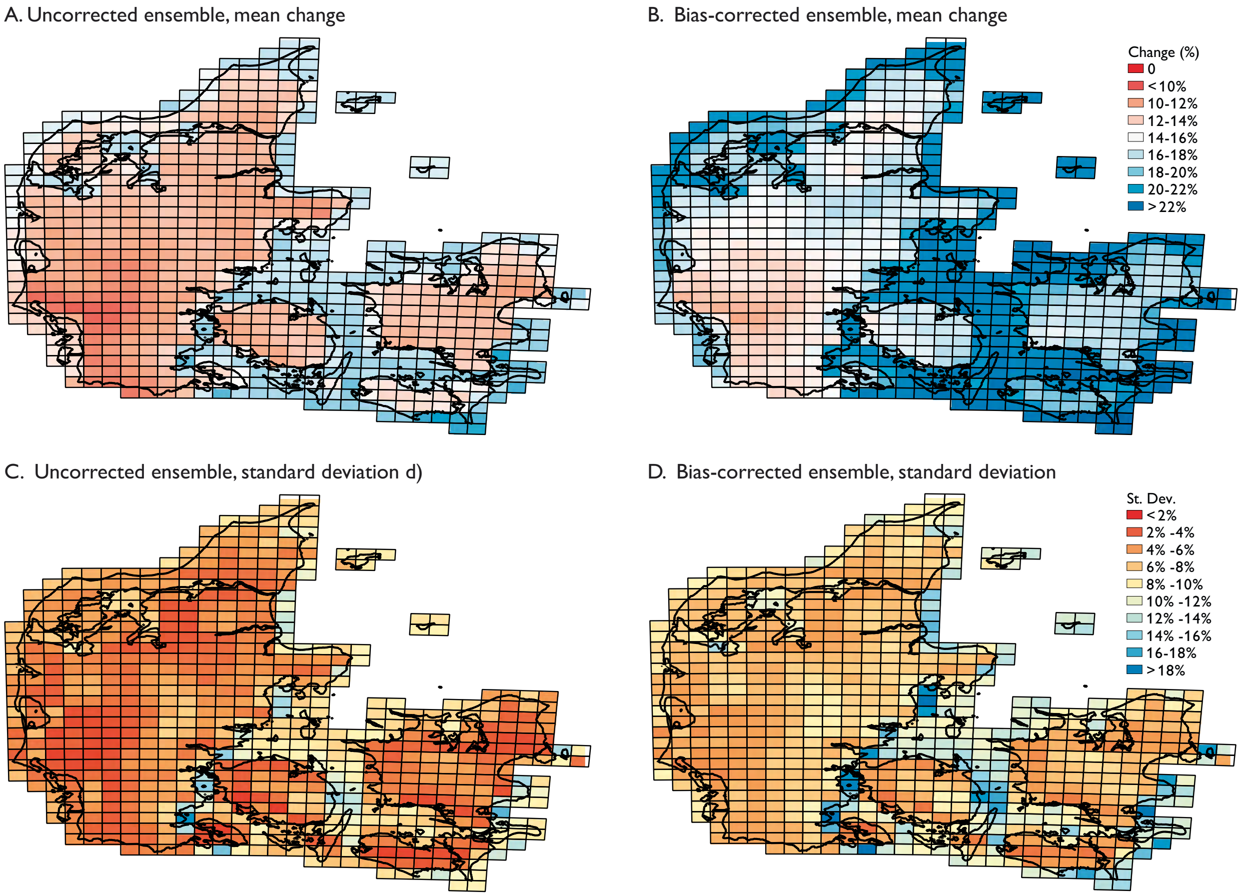

Fig. 2. RCP 8.5 annual precipitation change (%) by the end of the century (2071–2100) relative to the 1981–2010 reference period for the **A**: uncorrected and **B**: bias-corrected ensemble. Standard deviation for the **C**: uncorrected and **D**: bias-corrected ensemble.

the emission scenario, with little influence from natural variability. This agrees with our results, but in Denmark, RCP becomes the largest source of uncertainty by the end of the century.

Bias-correction does not alter the uncertainty associated with the temperature projections. However, bias correction of the precipitation data causes the choice of RCM to become the largest source of uncertainty by the middle of the century, and the second largest source of uncertainty by 2100.

Spatial distribution of the projections

Precipitation is projected to increase throughout Denmark, but the relative magnitude of this change varies according to location. The projected change in the uncorrected models ranges from +10% to +22% by the end of the century, compared to the 1981–2010 reference period (Fig. 2A), whereas the BC projections range from +12% to +31% (Fig. 2B). Similarly, the standard deviation of the uncorrected projections varies between +3% and +19% and between +4% and +21% for the BC models. Bias correction generally leads to even higher projections of precipitation by the end of the century. The standard deviation is less effected.

The spatial distribution of change is relatively homogeneous over inland Denmark. Variations in the projections are mostly observed on the coast cells in both the uncorrected and BC models. However, after bias-correction this variation along the coast increases as indicated by the large standard deviation. This could be due to the interpolation method in the observation dataset, which lacks point data in the coast cells.

Outlook

This study provides an overview of the bias-corrected projections from current state-of-the-art climate models, which were not previously available for Denmark. By identifying the contribution of each uncertainty source and providing the projected change from the ensemble and from each individual model, we provide a basis upon which to plan future assessments of the impacts of climate change on Danish water resources. The data represent a useful input to the Danish National Water Resources Model (DK-Model) for the analysis of climate change impacts. However, this initial analysis is aggregated for the whole of Denmark and projections vary across the country. Further research will focus on assessing monthly and seasonal changes in the projections as well as using these post-processed models to evaluate the projected impacts on Danish hydrology.

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