Scenarios of extreme daily precipitation for Norway under climate change

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Abstract Based on downscaled daily precipitation values from the global climate model of the Max Planck Institute in Hamburg, time series of 20 years have been generated to describe the current climate of 1980–1999 (control data) and the future climate of 2030–2049 (scenario data) for Norway. These time series serve as training data for the Randomised Bartlett-Lewis Rectangular Pulse Model (RBLRPM), a precipitation simulation model, and time series of 1000 years length have been generated to assess possible changes in the extreme precipitation regime due to climate change. The analysis of changes in extreme value patterns for annual and seasonal values in the scenario and control data sets shows tendencies towards increased extreme values and seasonal shifts for the scenario period. A general increase in mean and standard deviation of the extreme value sample and for values of 10 and 100 years return period is found, although the regional variability is significant. For some regions the increase is in the order of 10 to 50 % for both annual and seasonal values.

Keywords Climate change; extreme precipitation; rainfall generator; synthetic time series

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Introduction

According to the Intergovernmental Panel on Climate Change (IPCC 2001), an increase in precipitation is likely to affect large continental areas in the tropics and the higher latitudes. More intense precipitation events are very likely over many areas. For Norway, Groisman *et al.* (1999) found that a 7 % increase in mean summer precipitation in western Norway might lead to an increase of 12 % in the frequency of heavy rainfalls ($>$ 25 mm/day). The effects of possible climatic change on extreme values of precipitation are of interest for several sectors of society, for natural systems, and are of particular concern for the hydro-electricity producing community, causing major impacts on the safety, operation and economy of hydraulic structures (IPCC 2002). The data from which we can assess possible changes in extreme precipitation patterns are the output from general circulation models (GCM), run with various scenarios for emission of greenhouse gases and aerosols.

The current spatial resolution of the output from GCMs is incompatible with the scales for which estimates of extreme values of precipitation are needed, such as various hydrological applications including urban drainage design and other flood-related issues, transportation, biology and agriculture. The problem of reducing the spatial scales (*i.e.* downscaling) to scales suitable for *e.g.* hydrological analysis has been a major research task in the Norwegian RegClim project (Iversen *et al.* 1997). Two methods have been investigated. In *dynamic downscaling* the results from a global climate model with spatial resolution $300 \times 300\,\mathrm{km}^2$ are used as input for a regional weather forecast model of spatial resolution $55 \times 55\,\mathrm{km}^2$ (Bjørge *et al.* 2000). In *empirical downscaling* statistical links between observed local climate elements (*e.g.* temperature and precipitation) and large-scale atmospheric fields are identified. These relationships are then used to estimate local climate from large-scale fields produced by global climate models (Hanssen-Bauer *et al.* 2001). For extreme value analysis of point precipitation, it is of crucial importance that the statistical parameters of the downscaled series (especially the variance) compare with those of the observed. Imbert (2002) compared the statistical properties of extreme observed precipitation series with the extreme precipitation values from the dynamically downscaled series of Bjørge *et al.* (2000) for the control period for Norway. The downscaled series were interpolated to points, using bilinear interpolation, so that comparisons with point observations could be made. Imbert (2002) found discrepancies in both the mean and the variance. There are some methodological problems associated with the study of Imbert (2000), in that the downscaled values are areal averages, and when areal averages are interpolated, the interpolated values continue to be areal averages with different statistical properties from true point observations. Consequently, to avoid problems associated with different spatial scales, in this study we carry out the extreme value analysis on dynamically downscaled and interpolated control and scenario series, and analyse the relative differences between the extreme values of the two series. If both data series have systematic errors, it is assumed that the relative difference between them could still give valuable information on possible changes in extreme value patterns.

The length of the available time series for modelled data of the current and future climate is in the order of a few decades, which is insufficient for estimation of extreme values of high return periods (low probability of occurrence). To obtain time series of a length suitable for extreme value analysis, we use a time series to train a stochastic rainfall generator (the Randomised Bartlett-Lewis Rectangular Pulse Model, RBLRPM; Onof and Weather 1993). Time series of 1000 years length are generated, and extreme value analysis is performed.

Data

Dynamically downscaled time series of precipitation (see Bjørge *et al.* 2000) are provided for several sites in Norway, where meteorological stations, considered to be regionally representative, are operative. The daily time series are downscaled from the ECHAM4/OPYC3 GSDIO simulation of the Max Planck Institute, Hamburg, Germany, for a "control period" (1980–1999) and a "scenario period" (2030–2049). The sites are chosen in such a way that 12 of the 13 precipitation regions, defined according to Hanssen-Bauer *et al.* (2001), are represented. Figure 1 shows the location of the meteorological stations and the precipitation regions.

Considerable uncertainty is associated with how well the downscaled and interpolated climatic output corresponds to real observations, *i.e.* does the time series of the control period for a certain station show similar statistical characteristics to that of the observations? Figure 2 shows the ratio between observations and control data of the mean and standard deviation of the precipitation extremes (annual maxima series, AMS). The record length of the observed time series is equal to, or longer than 20 years. Large discrepancies are observed, but systematic differences, like consistent higher or lower values of the statistical parameters, are not present for the different data sets. The comparison presented in Figure 2, however, points out the necessity to evaluate changes in extreme precipitation on relative differences between control and scenario data rather than scenario data compared with observations.

Methodology

The model used to generate precipitation time series is a randomized version of the Poisson process based (independent and exponentially distributed inter-arrival times) Bartlett-Lewis Rectangular Pulse Model (BLRPM), the Randomised BLRPM (RBLRPM) (Onof and Weather 1993; Onof 2000). This model is chosen because the Bartlett-Lewis approach to the

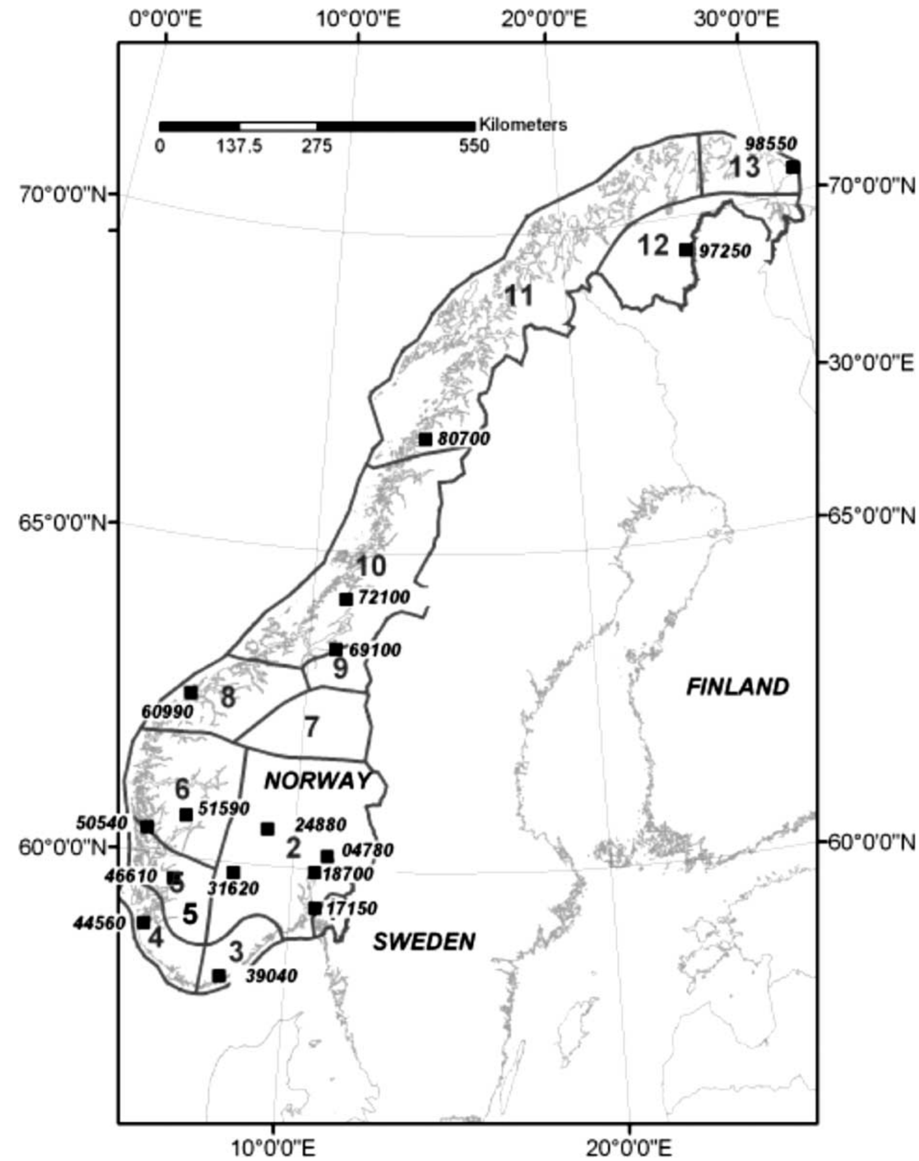

Figure 1 Location of meteorological stations and precipitation regions

clustering of cells within larger storms is used in the current developments in spatio-temporal rainfall modelling (Onof 2000). In BLRPM, storms arrive according to a Poisson process with parameter λ. Each storm is followed by a Poisson process of cell arrivals with rate β which have a finite duration V. V is chosen as an exponentially distributed random variable with parameter γ. The precipitation is then added to this wet/dry picture in the form of precipitation pulses of exponentially distributed intensity (parameter $1/\mu_x$) and independently exponentially distributed duration with parameter η. In order to improve the reproduction of dry periods, the parameters η, β and γ are considered to be random variables, thus the *Randomised* BLRPM. The total number of parameters in RBLRPM is thus 6. The model assumes stationary precipitation data, so to take the variability across the year into account, each month is parameterised separately. Inter-annual variability was not considered for the modelling of precipitation. Analytical relations between monthly rainfall

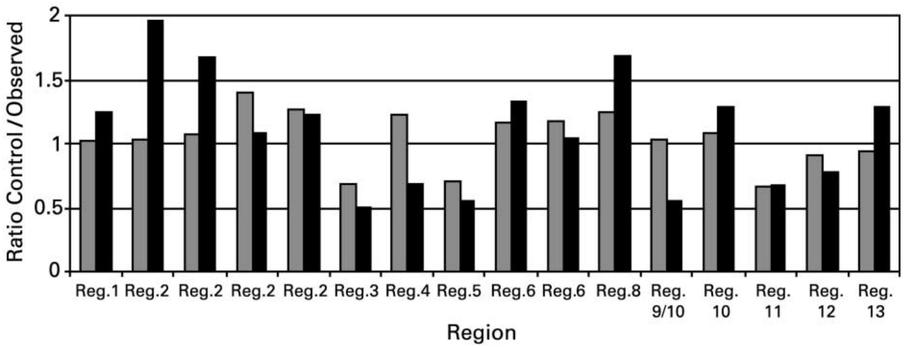

Figure 2 Ratios between the means (grey bar) and the standard deviations (black bar) of the extreme values of control data and observations. Every pair of bars represents a precipitation station

statistics such as the probability of a dry day, mean duration of a dry period, mean, variance, and autocovariance, and monthly values of the above parameters are presented by Onof and Weather (1993) and Onof *et al.* (1994).

It can be argued that no new statistical information is provided beyond that of the calibration data. However, information is added in that the simulation model extrapolates, from a limited amount of data, a certain physical structure of temporal rainfall. A way of justifying the appropriateness of the temporal structure is the fact that the simulation model reproduces properties of the observations over a range of temporal scales. The simulation model has been used to estimate design rainfall for durations ranging from one hour to one day (Smithers *et al.* 2002). Also, the RBLRPM was used at the Norwegian Water Resources and Energy Directorate (NVE) in a study to simulate spring flood scenarios using simulated precipitation and temperature series together with a rainfall-runoff model (Skaugen *et al.* 2002).

The RBLRPM was calibrated from the 20 years of data for both the control and scenario period and 20 years were simulated and validated against the calibration data. The validation consisted of a visual comparison between values of the original and the simulated data of monthly values of mean, variance, autocovariance, probability of a dry day and duration of dry periods (see Figure 3). In Figure 3, the monthly median and the 25 % and 75 % quartiles (dashed lines) of different statistical parameters, based on ten series of 20 years, are shown together with the monthly mean values for the control period (solid line) for the station 18700 in region 2. It can be observed that the mean of the control period series corresponds rather well with the median for the simulated series, with an exception for the probability of a dry day, which, in general, was poorly estimated.

With the RBLRPM, time series of 1000 years were simulated for the control period and for the scenario period. Standard frequency analysis was performed on the AMS derived from the simulated 1000-year series.

Results

The chosen extreme value distribution used for estimating the 10 and 100-year return periods is either the general extreme value distribution, or the three parameter log normal distribution according to best fit from visual inspection of the frequency plots. The parameters of the distributions were estimated by probability weighted moments (or *L*-moments) and maximum likelihood respectively (Hosking and Wallis 1997). Durations of 1 day and 5 days are analysed in order to investigate changes in extreme precipitation pattern for different temporal scales.

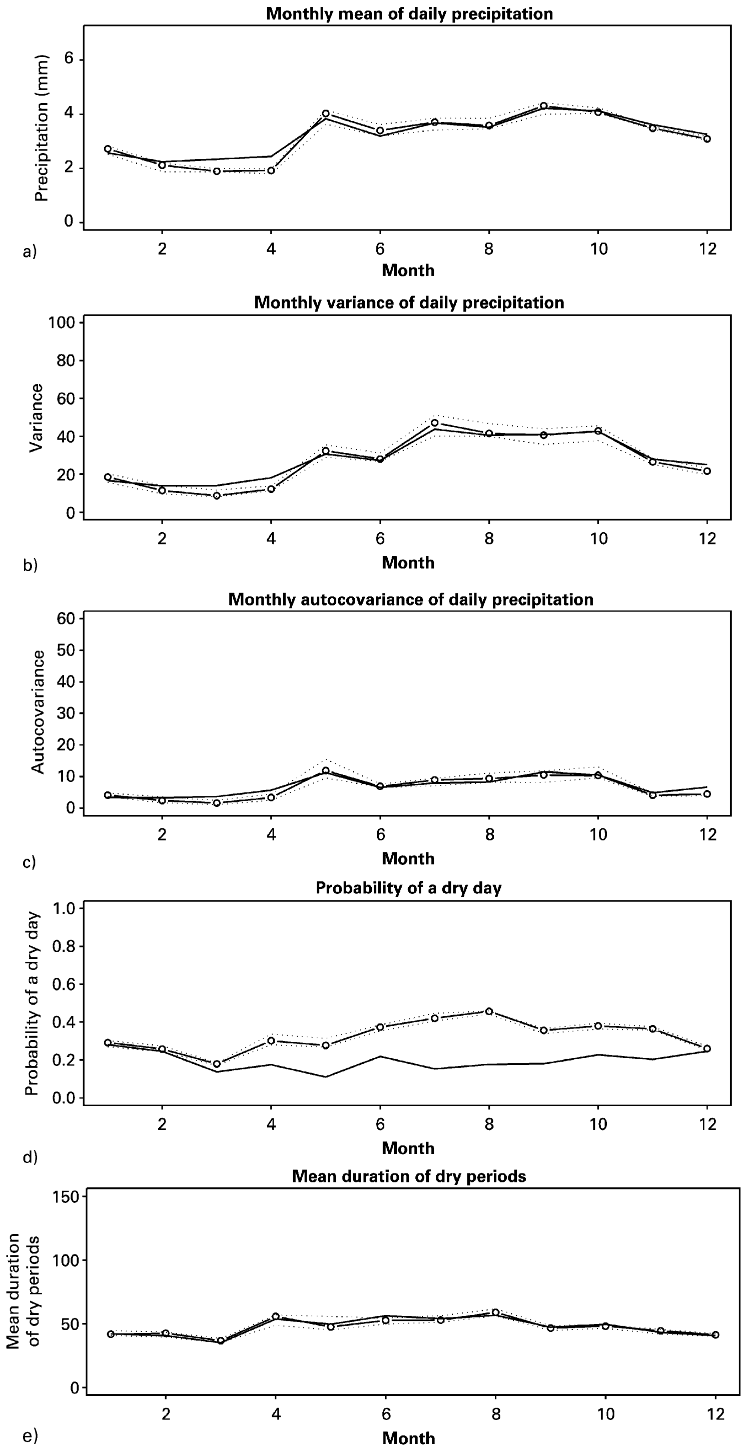

Figure 3 Comparison between control data (solid line) and the median, the 25 % and the 75 % quartiles based on ten simulation runs of simulated control series (dashed lines) for the station 18700 in region 2; a) monthly mean of daily precipitation, b) monthly mean variance of daily precipitation, c) monthly mean autocovariance of daily precipitation, d) monthly mean probability of a dry day and e) monthly mean duration of dry periods (hours)

Annual extremes

Figure 4 shows the ratio between scenario and control series for the mean (a) and the standard deviation (b) of the extreme value sample and for the 10 (c) and 100 (d) year return periods. The general tendency is that annual precipitation extreme values tend to increase and the variability of the extreme value sample increases more than the mean. The values of 1-day duration appear to increase more than for 5 days. The increase is in the order of 10 to 50 % for the 1-day duration for the regions 2–5, 8–9/10 and 13, and slightly less for the 5-day duration. The easternmost regions 1 and 12 show little change whereas the variability in the extreme values sample for region 10 is reduced, thus giving lower values for the 10 and 100 years return periods.

Seasonal values

Figure 5 shows the relative changes due to climate change in the mean of the extreme value samples for the different seasons, winter (a), spring (b), summer (c) and autumn (d). The changes are similar for 1-day and 5-day durations and no clear regional pattern appears. The spring ratios are unchanged or slightly decreased (regions 6–12), whereas the winter and autumn ratios are equal or higher. The summer season shows a variable pattern with

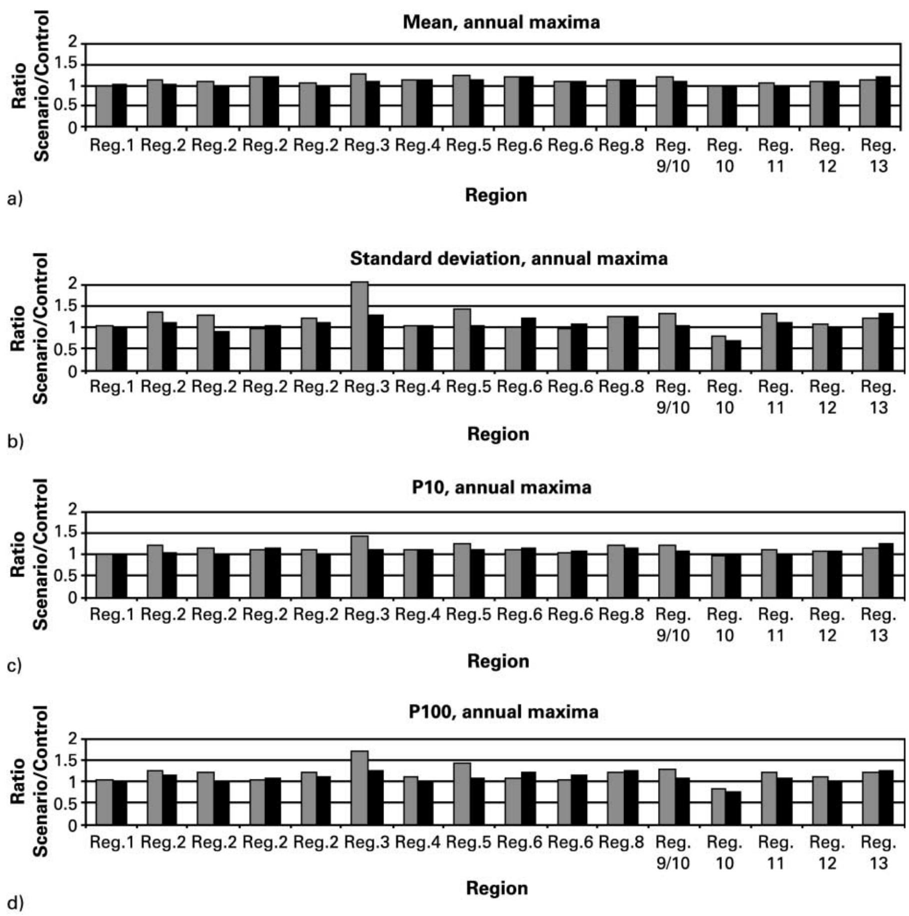

Figure 4 Ratio between scenario and control data of a) mean and b) standard deviation of extreme precipitation and for the c) 10-year and d) 100-year return values. Duration 1 day (grey bar) and 5 days (black bar). Every pair of bars represents a precipitation station

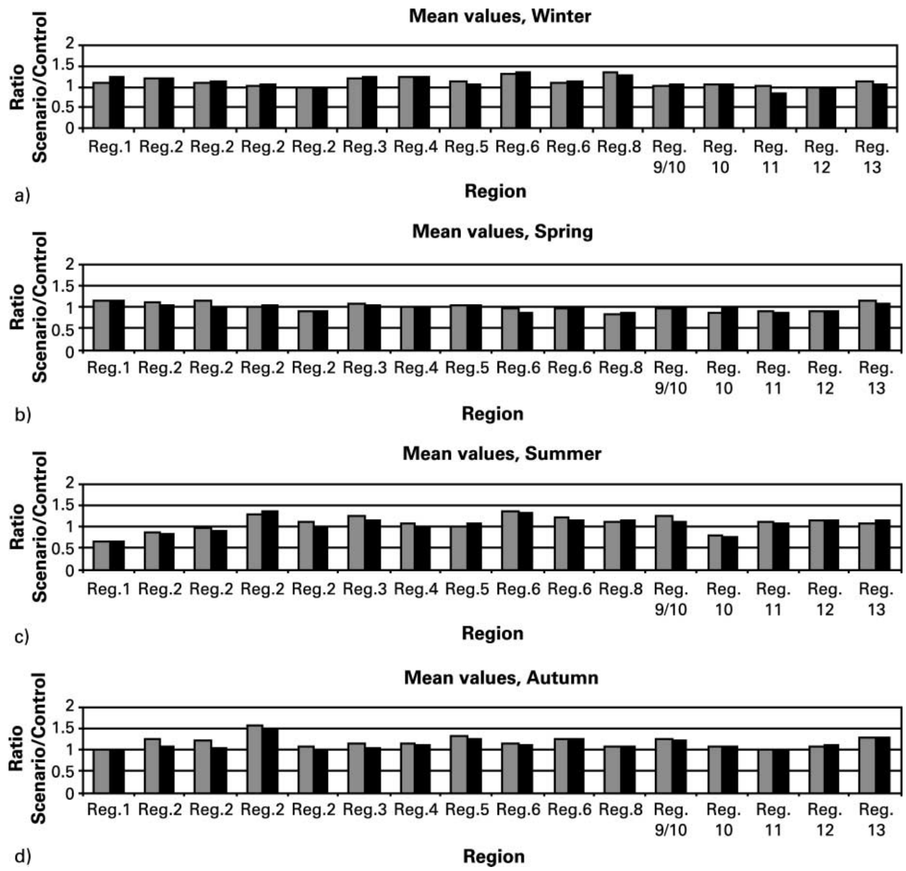

Figure 5 Ratio of the mean of extreme value samples between scenario and control data of a) winter, b) spring, c) summer and d) autumn. Duration 1 day (grey bar) and 5 days (black bar). Every pair of bars represents a precipitation station

decreased ratios for regions 1 and 10 and unchanged or increased ratios for the other regions. It is noticed that the ratio for one of the stations in region 2 (24880, see Figure 1) has an increase around 50 % for the summer and autumn seasons.

Figure 6 shows the relative changes in the standard deviation of the extreme value samples for the different seasons, winter (a), spring (b), summer (c) and autumn (d). There is a clear pattern that the ratios are consistently higher for 1-day duration than for 5-day duration for summer and autumn, suggesting an increased showery nature of precipitation. For most of the regions, the spring ratios are decreased (continuous area consisting of regions 6–10), whereas for the other seasons, there is a tendency to increased ratios. Regions 2 (stations 4870 and 18700, see Figure 1), 3, 5 and 13 have consistent increases for all seasons.

Figure 7 shows the relative changes for the 10-year return period for the different seasons, winter (a), spring (b), summer (c) and autumn (d). Here also, there is a clear pattern that the ratios are consistently higher for 1-day duration than for 5-day duration for summer and autumn, suggesting an increased showery nature of precipitation. Winter and autumn also appear to have consistently higher ratios (10–40 % increase) for all regions, whereas the spring has unchanged or lower ratios (regions 6–10), and the summer has a variable pattern.

Figure 8 shows the relative changes for the 100-year return period for the different seasons, winter (a), spring (b), summer (c) and autumn (d). Again, there is a clear pattern that

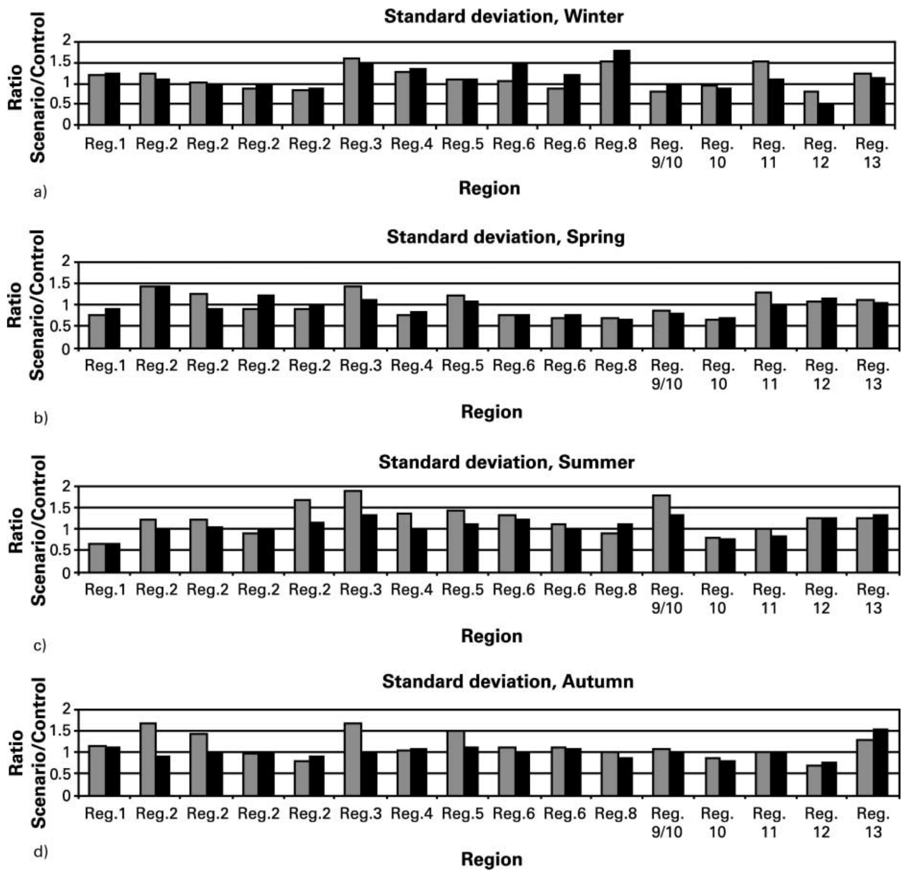

Figure 6 Ratio of the standard deviation of extreme value samples between scenario and control data of a) winter, b) spring, c) summer and d) autumn. Duration 1 day (grey bar) and 5 days (black bar). Every pair of bars represents a precipitation station

the ratios are consistently higher for 1-day duration than for 5-day duration for summer and autumn, suggesting an increased showery nature of precipitation. The spring ratios display a variable pattern, with regions 6–10 showing low ratios and the others close to one or higher. For the other seasons, we find that the ratios indicate a general increase in the order of 10 up to 60 % with no clear regional pattern except for region 3 which has a consistently high increase for all seasons.

Discussion and conclusions

The lack of clear regional patterns might be due to the very limited number of meteorological stations we use to represent the different regions. Also for regions with more than one station, the different stations do not behave in a consistent manner. Førland *et al.* (1998) found that trends in extreme rainfall at individual stations could differ substantially, even for neighbouring stations belonging to the same climatic region. As a result of the large local gradients, Heino *et al.* (1999) concluded that series from a single station are not an ideal indicator for trend analysis in extreme rainfall, and that conclusions concerning regional trends of maximum daily precipitation preferably should be based on a dense network of stations.

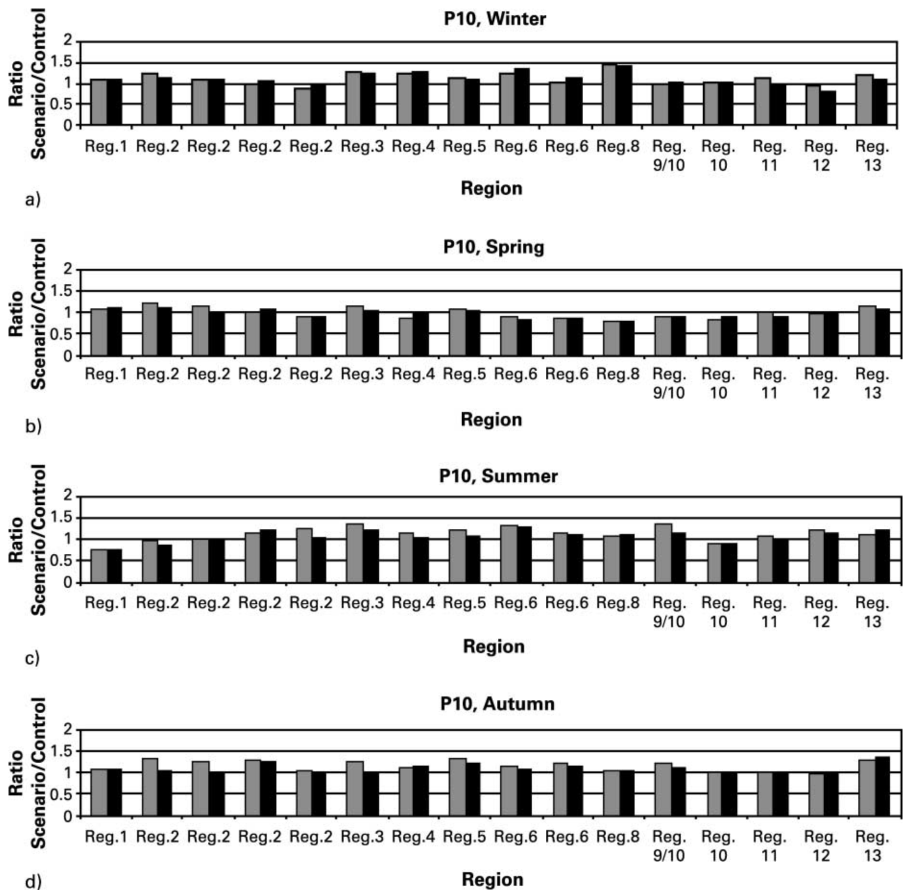

Figure 7 Ratio of the 10-year return period between scenario and control data of a) winter, b) spring, c) summer and d) autumn. Duration 1 day (grey bar) and 5 days (black bar). Every pair of bars represents a precipitation station

The choice of extreme value distribution is, for each of the simulated series, based on best fit according to visual assessment of frequency plots. Figures 9 and 10 show examples of such frequency plots, and we can observe that the choice of extreme value distributions is of little interest for return periods lower than $T = 200$ years. The general extreme value distribution (GEV) and three-parameter log normal distribution (LN3) give very similar results for all return periods for nearly all stations.

A source of uncertainty that has to be taken into account is the simulation model, RBLRPM itself. Although the simulated series have been validated on monthly mean values for different statistics, a much more demanding test is the comparison of the extreme values. Table 1 shows the mean and standard deviation of the extreme value series of the original control data (20 years) and the simulated control series (1000 years). As Table 1 shows, no systematic deviations between the original control data (20 years) and the simulated control series (1000 years) can be observed. The mean is increased for 8 stations out of 16 for the 1000 years series and the standard deviation is increased for 9 stations out of 16. This suggests that RBLRPM is neutral in that it does not change the statistical parameters of the original extreme value distribution in a systematic way.

It must be stressed that the increase in extreme precipitation for some regions in the order of 10–50 % is dramatic. An illustration of the effects is that an increase of 50 % in the value

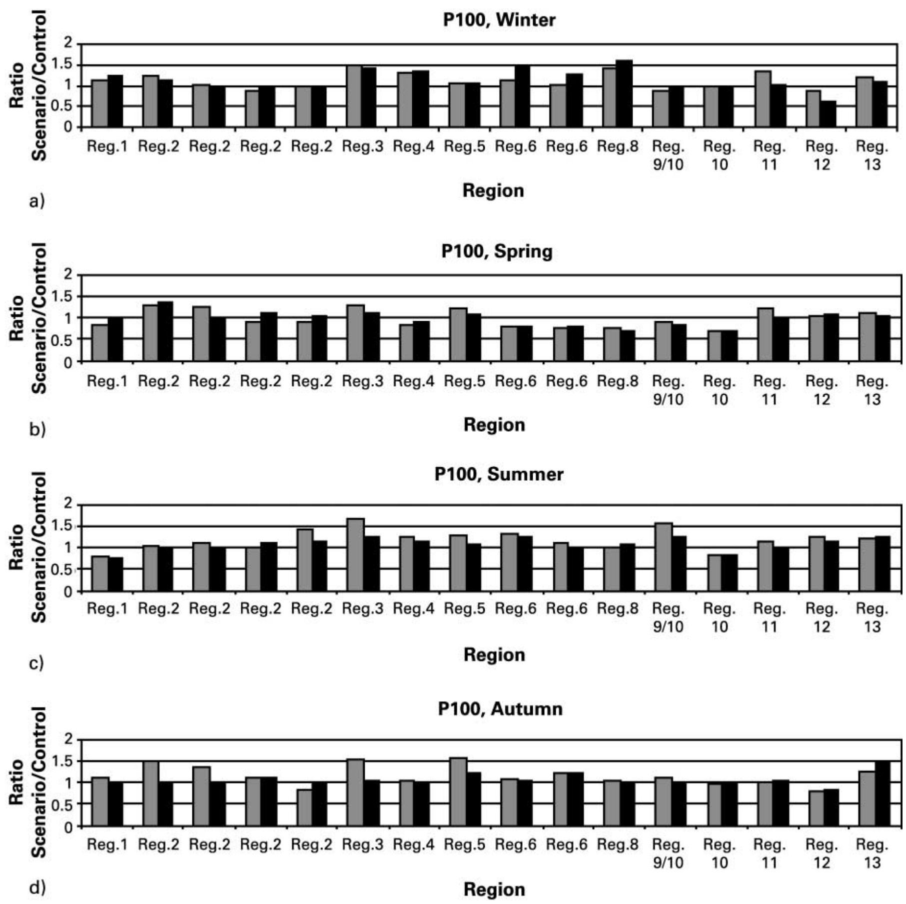

Figure 8 Ratio of the 100-year return period between scenario and control data of a) winter, b) spring, c) summer and d) autumn. Duration 1 day (grey bar) and 5 days (black bar). Every pair of bars represents a precipitation station

of the 100 years return period implies a value close to the 1000 years return period value. The value associated with the 1000 years return period of the current climate can be expected to appear 10 times as frequently for the climate scenario for 2030–2049. Although there are uncertainties associated with several of the methodological aspects of this study, the assessments carried out here imply serious economical and societal impacts. The implications are redesign of dams, other hydraulic structures and urban drainage networks, and an increase in flood-related damages.

The scoping paper of the IPCC workshop on *Changes in Extreme Weather and Climate Events* (IPCC 2002) stresses the impacts of changes in severe weather on society and the natural environment and this study illustrates the possible dramatic impacts of changed extreme precipitation regimes for Norway. More research on the topic of changes in extreme value patterns is obviously needed in order to reduce the uncertainties. A particular topic for further research is to improve the downscaling methods. Under the assumption that atmospheric models are able to reproduce the current climate for the large scale, we need theoretical tools for describing the transformation of the statistical parameters going from one scale to another.

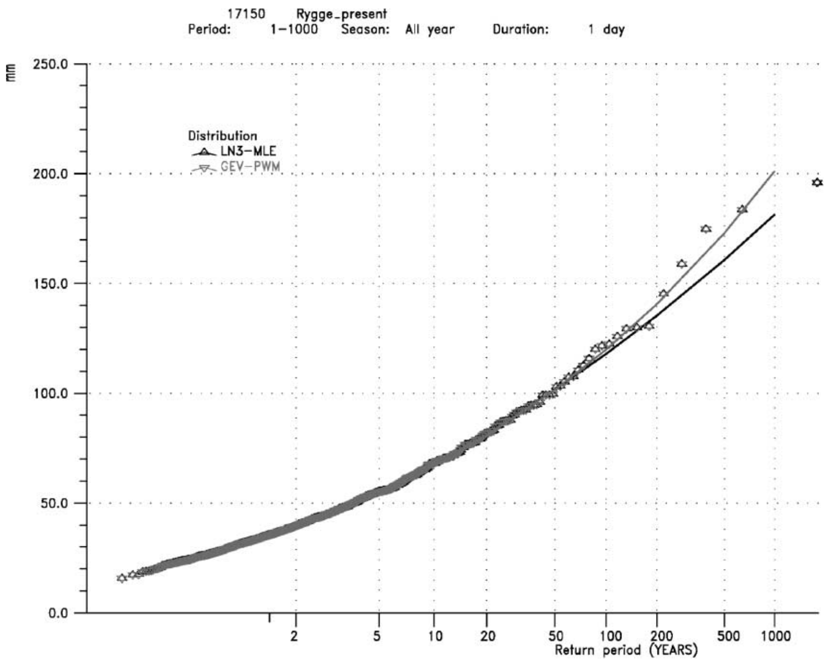

Figure 9 Fit of extreme value distribution functions for station 17150, simulated control series. Duration 1 day. The Log Normal 3-parameter distribution (black line) and the General Extreme Value distribution (grey line) are fitted to the simulated extreme values

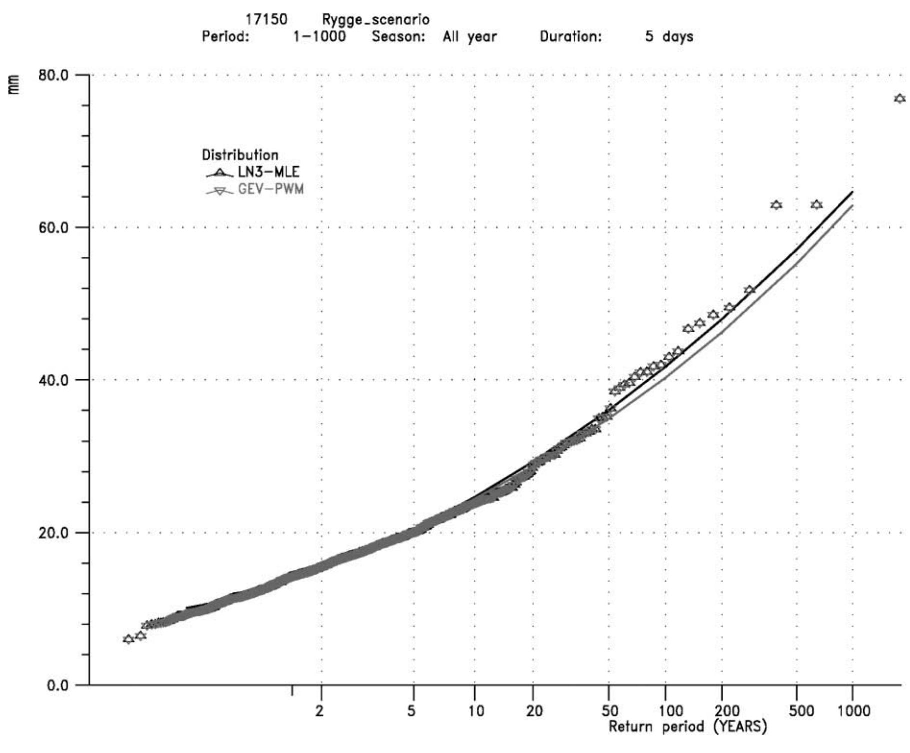

Figure 10 Fit of extreme value distribution functions for station 17150, simulated scenario series. Duration 5 days. The Log Normal 3-parameter distribution (black line) and the General Extreme Value distribution (grey line) are fitted to the simulated extreme values

Table 1 Comparison of mean and standard deviation of extreme value series from original control data (20 years) and simulated control series (1000 years). (+) and (−) indicate higher and lower parameter values of the simulated control series.

Station	Control data – original (20 years)		Control data – simulated (1000 years)	
	mean	std. dev.	mean	std. dev.
17150, region 1	38.4	12.5	44.7 (+)	19.9 (+)
4780, region 2	37.2	16.1	35.3 (−)	9.4 (−)
18700, region 2	38.3	14.6	37.8 (−)	9.8 (−)
24880, region 2	41.2	11.1	35.5 (−)	13.9 (+)
31620, region 2	35.2	8.8	36.7 (+)	10.5 (+)
39040, region 3	41.6	7.8	41.8 (+)	9.1 (+)
44560, region 4	53.8	9.8	55.3 (+)	18.6 (+)
46610, region 5	50.9	8.6	58.7 (+)	15.4 (+)
50540, region 6	79.8	22.3	76.5 (−)	23.1 (+)
51590, region 6	53.2	10.0	57.2 (+)	17.2 (+)
60990, region 8	56.3	18.9	49.2 (−)	12.9 (−)
69100, region 9/10	34.6	5.6	35.4 (+)	8.6 (+)
72100, region 10	43.3	14.7	41.0 (−)	11.4 (−)
80700, region 11	55.5	19.3	46.5 (−)	11.5 (−)
97250, region 12	23.1	6.2	20.9 (−)	5.6 (−)
98550, region 13	22.5	10.2	22.7 (+)	8.4 (−)

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