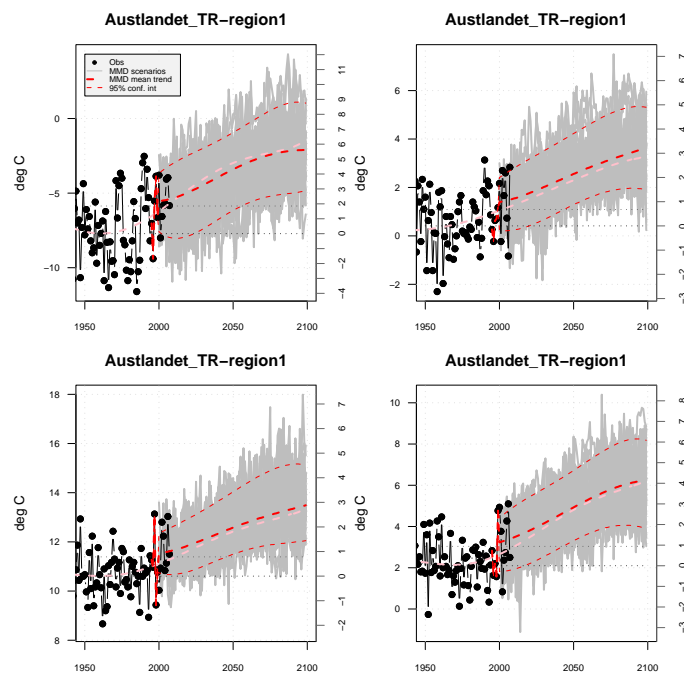# Downscaled regional Norwegian temperature and precipitation series

Analysis for Statnett and CES

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report

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Downscaled regional Norwegian temperature and precipitation series	April 22, 2008
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Abstract

Empirical-Statistical downscaling has been carried out for six different regional temperature and 13 different precipitation regions, based on the most recent global climate model simulations described in the Intergovernmental Panel on Climate Change (IPCC) fourth assessment report (AR4) from 2007. The downscaling analysis incorporated multi-model ensembles based on 37 integrations for temperature and 33 runs for precipitation.

New future normals were estimated for both temperature and precipitation, based on the 1995–2025 and 2010–2040 periods. The present climate simulations do not incorporate initial conditions that give the best description of the present state of the climate, such as the exact distribution of heat in the oceans (the Atlantic), and are designed for making scenarios for the long-term when the changes in the external forcings outweight effects from initial conditions (present). Thus, these scenarios do in principle not represent the best estimate of the next decade or so, although it is the best one can do at the present. Decadal prediction is in the pipe line, taking into account both the evolution from the present situation and the changes in the forcings.

Keywords
Empirical-Statistical downscaling, region climate series, years 1995–2025, years 2010–2040.

Disciplinary signature	Responsible signature
Inger Hanssen-Bauer	Eirik Førland

Contents

1 Introduction

The objective of this report is primarily to document a set of calculations done for Statnett and the Climate and Energy Systems (CES) project. The focus will be on the methodological details and the results. However, a short introduction to background is also provided for the readers who are new to the subject. The lay out of the report is as follows: a brief introduction, description of the data, methods, the results, discussion, conclusion and an appendix.

1.1 The problem

Since the industrial revolution, the levels of atmospheric concentrations of long-lived greenhouse gases such as CO_2 have risen (*IPCC*, 1995; *Houghton* et al., 2001; *Solomon* et al., 2007) and the most recent estimate suggests that the global mean surface temperature on Earth has increased by $0.74 \pm 0.18°C$ over the last 100 years (*Solomon* et al., 2007). It has been well-known within the scientific community for a long time that the effect of raised levels of atmospheric CO_2 will lead to a surface warming (*Weart*, 2003; *Peixoto & Oort*, 1992; *Fleagle & Businger*, 1980; *Houghton*, 1991), and that future increases in the levels of greenhouse gases will warm the surface further (*Meehls* et al., 2007; *Christensen* et al., 2007a).

1.2 Introduction to downscaling

Global Climate models (GCMs) represent the most important tool for simulating Earth's climate, but they do not give a realistic description of the local climate in general. It is therefore common to downscale the results from the GCMs either through a nested high-resolution regional climate model (RCM) (*Christensen & Christensen*, 2002; *Christensen* et al., 2001, 1998; *Haugen* et al., 2000; *Haugen & Ødegaard*, 2003) or through empirical/statistical downscaling (*von Storch* et al., 1993a; *Rummukainen*, 1997; *Easterling*, 1999; *Benestad*, 2004; *Wilby* et al., 2004; *Hanssen-Bauer* et al., 2005; *Fowler* et al., 2007; *Benestad* et al., in press 2008) (here referred to as 'empirical-statistical downscaling', or the abbreviation 'ESD'). The GCMs do not give a perfect description of the real climate system as they include 'parameterisations' that involve simple statistical models giving an approximate or ad-hoc representation of sub-grid processes.

Here we will define downscaling as *the process of making the link between the state of some variable representing a large space* (henceforth referred to as the 'large scale') *and the state of some variable representing a much smaller space* (henceforth referred to as the 'small scale'.)

Another view of ESD is that it basically is just an advanced statistical analysis of the model results (*Benestad* et al., in press 2008)[1].

The large-scale variable may for instance represent the circulation pattern over a large region whereas the small scale may be the local temperature as measured at one given point (station measurement).

It is important to keep in mind the limitations of statistical downscaling, especially when applied to model results from greenhouse gas (GHG) integrations using GCMs. The statistical models are based on historical data, and there is no guarantee that the past statistical relationships between different data fields will hold in the future.

One should also be concerned about the uncertainties associated with the GCM results as well as those of the downscaling methods themselves (*Wilby* et al., 1998). It is well known that low resolution GCMs are far from perfect, and that they have problems associated with for instance cloud representation, atmosphere-ocean coupling, and artificial climate drift (*Bengtsson*, 1996; *Anderson & Carrington*, 1994; *Treut*, 1994; *Christensen* et al., 2007b).

Part of the problems are due to incomplete understanding of the climate system. The important mechanisms causing variability such as El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) for instance are probably still not completely understood (*Sarachik* et al., 1996; *Anderson & Carrington*, 1994; *Philander*, 1989; *Christensen* et al., 2007b). Due to discretisation and gridding of data, it is unlikely that the global GCMs will simulate regional details realistically (*Crane & Hewitson*, 1998; *Zorita & von Storch*, 1997; *von Storch* et al., 1993b; *Robinson & Finkelstein*, 1991).

However, because a wide range of global GCMs predict observed regional features (e.g. the NAO, ENSO, the Hadley Cell, atmospheric jets), it is believed that the GCMs may be useful for predicting large scale features.

Global climate models tend to have a coarse spatial resolution (Figure 1), and are unable to represent aspects with spatial scales smaller than the grid box size. The global climate models are also unable to account for substantial variations in the climate statistics within a small region, such as the temperature differences within a small region.

2 Data

The multi-model ensemble of global climate model (GCM) simulations made with a range of different GCMs, used here and reported in Intergovernmental Panel on climate Change (IPCC)

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[1]Early version of the compendium also available at http://www.gvc2.gu.se/ngeo/rcg/edu/esd.pdf
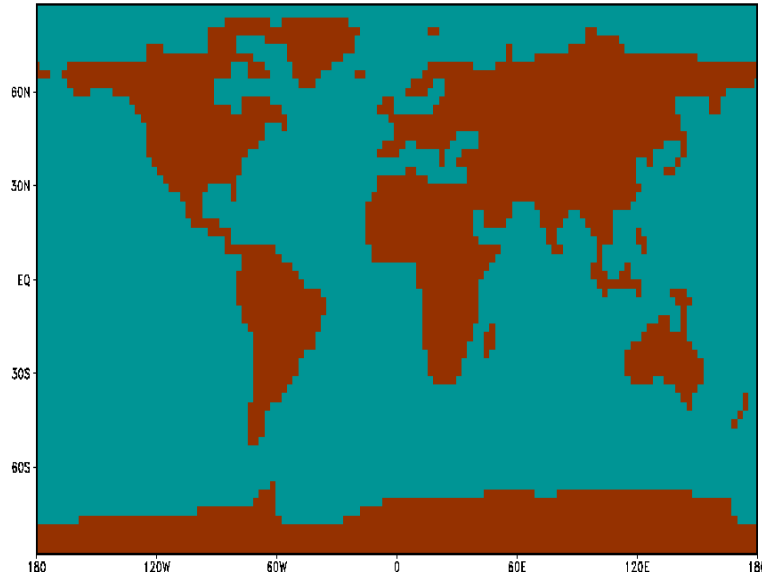
File 1 : ECHAM4 land-sea mask

Figure 1: *An example of land-sea mask of a general circulation model (GCM) with $\sim 2° \times 2°$ spatial resolution (T42). Notice that Italy and Denmark are not represented in the model.*

fourth assessment report (AR4) (*Meehl* et al., 2007), are freely available from Program for Climate Model Diagnosis and Intercomparison[2]. This model ensemble includes both simulations for the 20th century (C20) and scenario runs for the 21th century following the Special Report Emission Scenarios (SRES) A1b (SRES A1b) (*Nakicenovic* et al., 2000). Some of the GCMs have been used to make several parallel runs, differing only by using different initial conditions (starting point). Table 5 in the appendix provides a complete list of the GCMs and runs (integrations) included in this analysis. The choice of the GCMs was somewhat arbitrary, as (*i*) results from some models were not available on-line at the time of the downloads, (*ii*) there has been several rounds of fetching GCM data, (*iii*) the impact of adding further GCM results was not expected to add much new information about the inter-model spread, and (em iv) there was no attempt to have a systematic strategy for a complete set of GCMs and runs (the reason - see points *i–iii*).

Regional temperature or precipitation series (*Hanssen-Bauer & Nordli*, 1998; *Hanssen-Bauer & Førland*, 1998) were used as predictand in a Empirical-Statistical Downscaling (ESD) analysis, taking gridded European Centre for Medium-range Weather Forecasts (ECMWF) ERA40 re-analysis (*Simmons & Gibson*, 2000; *Bengtsson* et al., 2004) precipitation or temperature over a larger region as predictors.

The observations used as predictands were taken from met.no *KlimaDataVareHus* based

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[2]PCMDI; https://esg.llnl.gov:8443/index.jsp

on gridded data[3], and the regions are shown in the maps in Figure 2. Figure 2 shows the temperature and precipitation regions. The numbering of these regions, however, are different to those in the original reports *Hanssen-Bauer & Nordli* (1998) and *Hanssen-Bauer & Førland* (1998), but refer to the numbers given in the climate archive. The numbering of the regions are consistent throughout this report and with the present data archive.
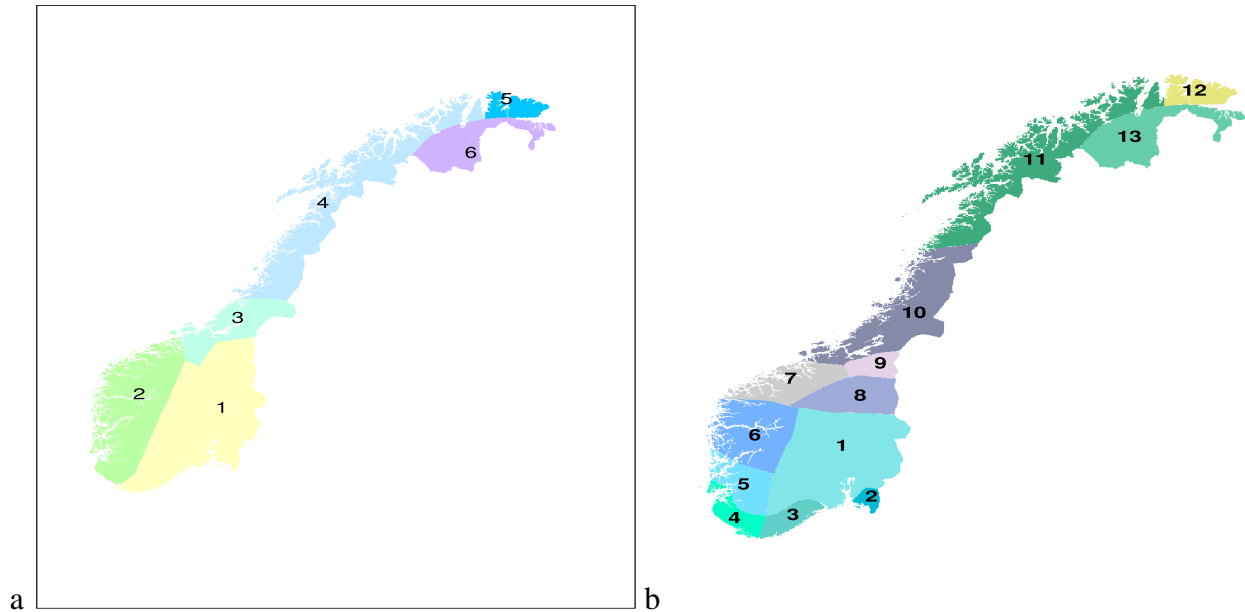

Figure 2: Maps showing (a) the six temperature regions and (b) 13 precipitation described in *Hanssen-Bauer & Nordli* (1998) and *Hanssen-Bauer & Førland* (1998). Courtesy of Inger Hanssen-Bauer. Note: these are numbered differently from those in the original (cited) reports.

3   Methods

The method on which these results are based has been used in several previous studies and is therefore well-documented. This study uses similar approach as those used in *Engen-Skaugen* et al. (2007) to downscale river run-off and similar analysis where catchment-scale temperature and precipitation were downscaled (*Engen-Skaugen* et al., 2008). The method and the implementation were similar to the work documented in *Benestad* (2005) for each GCM implemented, and performed for monthly mean values. Large-scale precipitation was used to downscale the local precipitation, as in *Benestad* et al. (2007), and large-scale temperature was used to estimate the local temperature.

The ESD was applied to the IPCC AR4 (*Meehl* et al., 2007) MMD (also referred to as

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[3]Internal web-site: http://dokit/klima/userservices/urlinterface

'CMIP3') GCM ensemble for both the 20th century and the 21st century simulations separately. The tool clim.pact (*Benestad*, 2003, 2004; *Benestad* et al., in press 2008) was used to carry out the calculations, using a common empirical orthogonal function (EOF) based framework (*Benestad*, 2001) and linear multiple regression as a basis for the empirical-statistical model.

The ESD was based on a 'finger-print' type technique whereby spatial patterns describing the large-scale anomalies correlated with the local variations were identified in the gridded observations (re-analysis) and then matched with the same spatial structures found in the model results.

A common EOF framework combined large-scale gridded temperature or precipitation anomalies estimated from the ERA40 re-analysis with corresponding anomalies from a simulation performed by a GCM (interpolated onto the same grid as the former). An ordinary EOF analysis is applied to this combined data set. The common EOF framework yields both the spatial structures (referred to as 'EOFs' or 'modes') as well as weights describing their temporal evolution/variation (referred to as 'principal components').

By combining anomalies rather than the total values, constant biases are removed, however, the constant level of the end results become more arbitrary. Thus, when analysing the final results, we choose to focus on trends and long-term transient behaviour rather than the initial level (e.g. the first 10 years) of the downscaled time series.

The principal components (PCs) describing the temporal variations of the different modes (dominant spatial temperature or precipitation pattern) represent exactly the same spatial structures for GCMs and the ERA40.

A step-wise regression analysis was employed that used the part of the PCs describing the ERA40 data together with the predictand (run-off series) to calibrate the model. This calibration returns R^2-statistics, describing how well the run-off can be reproduced with the statistical model if the ERA40 data is used as predictor.

The clim.pact tool makes predictions based on the calibration data (here ERA40) as well as the GCM (here either 20th century or the 21st century). However, the ESD-results derived from ERA40 are not independent and only serves as a visual check of the quality of the statistical downscaling model. The downscaling for the 20th century, on the other hand, provides independent data which can be used in the validation against the actual observations. This validation will test whether the ESD-model is good (here the R^2-statistic is also a measure of skill).

For the 1995–2025 period, the future climatological estimates were calculated from a combination of the mean values observed values for 1995–2007 and downscaled scenarios for the remaining period. The 2010–2040 climatology was based entirely on the downscaled scenarios, but only after these have been adjusted to start at a realistic level (matching mean value over

2000–2007).

In order to ensure representative values, the downscaled scenarios were adjusted by sub-
tracting the mean downscaled value and then adding the mean observed value for overlapping
years: the constant level of the future scenarios starting at year '2000' have been adjusted to
(*a*) either provide similar mean values for the 2000–2007 period as those in the observations or
(*b*) so that the starting point of the scenarios match the final parts of the simulations of the past.
The 'future climatologies' were derived adopting the former approach.

Then trends were estimated for the observations and scenarios respectively, taking the best-
fit to a third-order polynomial for the observed and a fifth-order polynomial for the ensemble
median (or quantile for the confidence bounds). A lower-order polynomial was used for the
former since the observed series were shorter than the scenarios. The combined trend estimate
was then derived fitting a seventh-order polynomial to the two polynomial trends combined,
thus merging the observations with ESD-results (these trends are shown in the graphics below).

The local temperature tends to exhibit a closer co-variation with the large-scale temperature
pattern than does local precipitation with large-scale precipitation. Thus, the ESD tends to
capture more of the variance in temperature than in precipitation - the latter being systematically
underestimated.

In order to compensate for the reduced variance in the downscaled precipitation, a so-called
'inflation' was applied in most of the post-process analysis for precipitation but not for tempera-
ture, although *von Storch* (1999) has argued that this technique does not have any justification in
general. Here, an underestimate of the variance may lead to an underestimate of the uncertainty
limits, and the technique was introduced merely as a means to provide a more appropriate un-
certainty bound. The 'inflation' involved scaling the downscaled results by a factor of s_o/s_d (the
ratio of standard deviations of the observations to those of the downscaled scenarios), where s_o
was based on the entire observed data series while s_d was estimated from the first 30 years. The
s_o/s_d-ratio was sensitive to reference period, as trials with using the short overlapping years
resulted in near-zero values for s_d for some of the ensemble members - the period must be
sufficiently must be long avoid large biases from decadal variations.

The complete listing of the R-script used to make the computations presented here is given
in the Appendix.

4 Results

The following figures are shown to provide a quick idea of the main features present in the downscaled results. These should be considered as part of the documentation of these results together with the tables. The results in the figures speak for them selves: there is a general tendency towards warmer climate in the future and there is a considerable spread in the values derived from the different GCM.

Two types of results will be shown here: (*a*) ESD-derived scenarios for the future (SRES A1b) which have been adjusted to match the past observations for a common overlap interval (2000-2007) and (*b*) ESD-derived scenarios for the future (SRES A1b) for which the entire ensemble has been adjusted to match the ensemble of C20 simulations so that the ensemble-time median of the 5 first years of the future scenarios (blue) equales the ensemble-time median of the 5 last years in C20. For precipitation, the former (approach *a*) results have been subject to 'inflation' while the later (approach *b*) has not. The latter results correspond to results presented in *Benestad* (2005), *Benestad* et al. (2007), and *Engen-Skaugen* et al. (2007), whereas the former approach was an attempt to provide a better description of the near-future climatologies. The estimation of the near-future climatologies is problematic in this case as the GCMs are not initialised with the present oceanic and atmospheric state, but rather from a model spin-up. In other words, the upper results have been fitted the observations whereas the lower results have not (since C20 are GCM simulations by their own right).

Here 'winter' is taken as December–February, 'spring' is March–May, 'summer' June–August, and 'autumn' is September–November.

4.1 Temperature

The scenarios for the 6 different temperature regions are presented in the 6 figures below. The upper part of the figures shows the observations and ESD results adjusted in such a fashion that they have the same mean value for the overlapping time interval 2000–2007. A polynomial trend fit has been fitted to the combined series of observations and downscaled results. Here the ensemble median is chosen to represent the most likely trend (thick line).

The lower part shows the same data in a more 'standard' format where the A1b scenarios are adjusted so that the SRES A1b ensemble median for 2000-2005 equals the C20 ensemble median for 1994–1999 (this is done automatically in the R-package called 'met.no' through the function 'ESD.results with the default the argument setting 'adjust=TRUE').

The light shaded regions in the lower part show the ESD ensemble range (minimum–

maximum) whereas the darker regions mark the ensemble IQR (25%–75%) (*Wilks*, 1995). The thin dashed lines show the polynomial best-fit to the 5% and 95% quantiles of the ensemble members, and thus provide a description of a smoothly varying trend in the 90% confidence interval.

The ESD results point to a general warming in all the temperature regions and for all seasons (Figures 3–8).
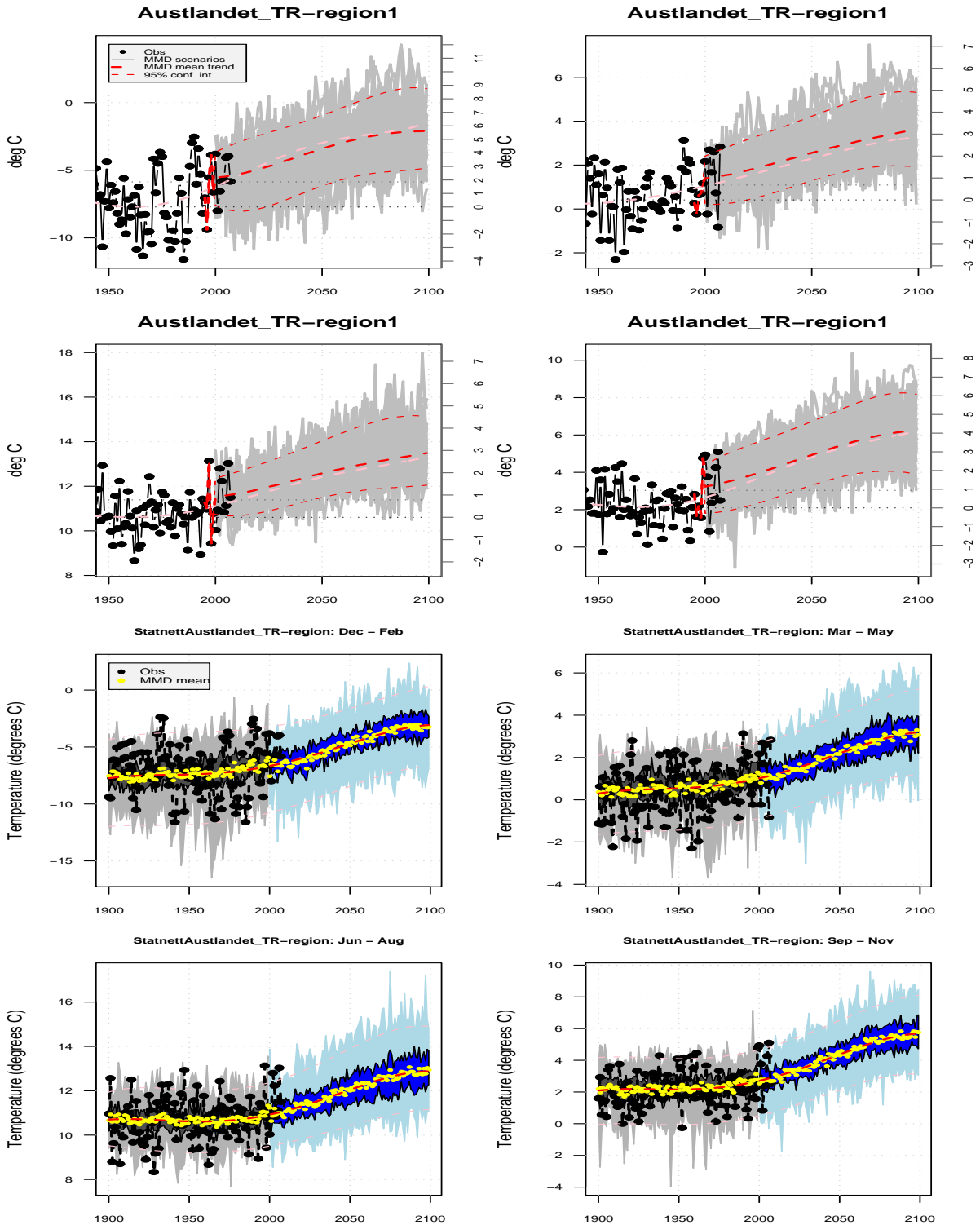
Figure 3: Region 1 ('Østlandet'), showing from upper left to right, lower left to right: Winter (December–February), Spring (March-May), Summer (June–August), and Autumn (September–November). Upper: The pink curve marks the combined observation-scenario trend while the red lines show the median of the results since 1995 (thick) and the 90% confidence region (thin). The grey lines show each of the ensemble members (downscaled scenarios), and black shows the observations. Lower: ESD-results adjusted to C20; Yellow symbols mark the ensemble mean values.
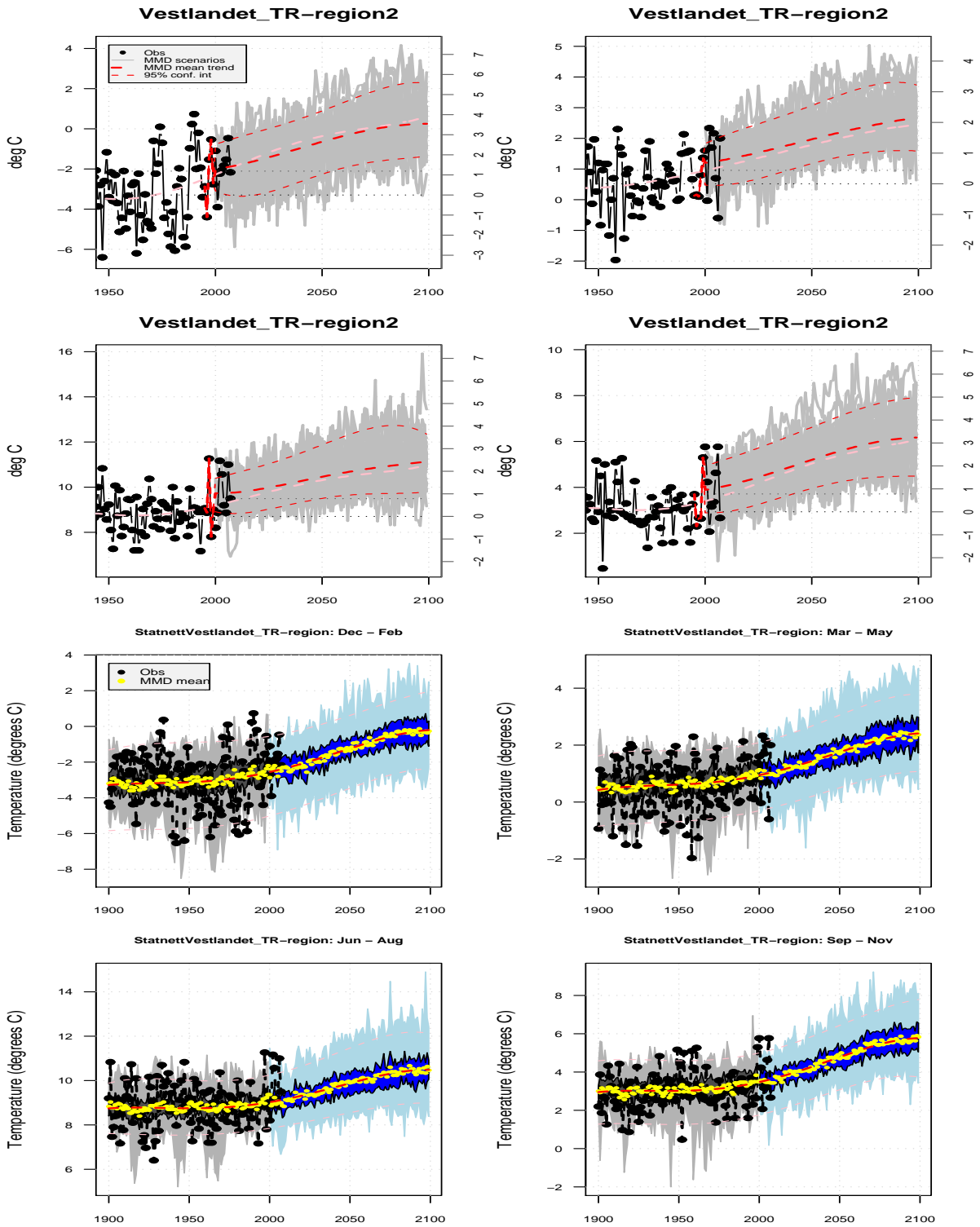
12

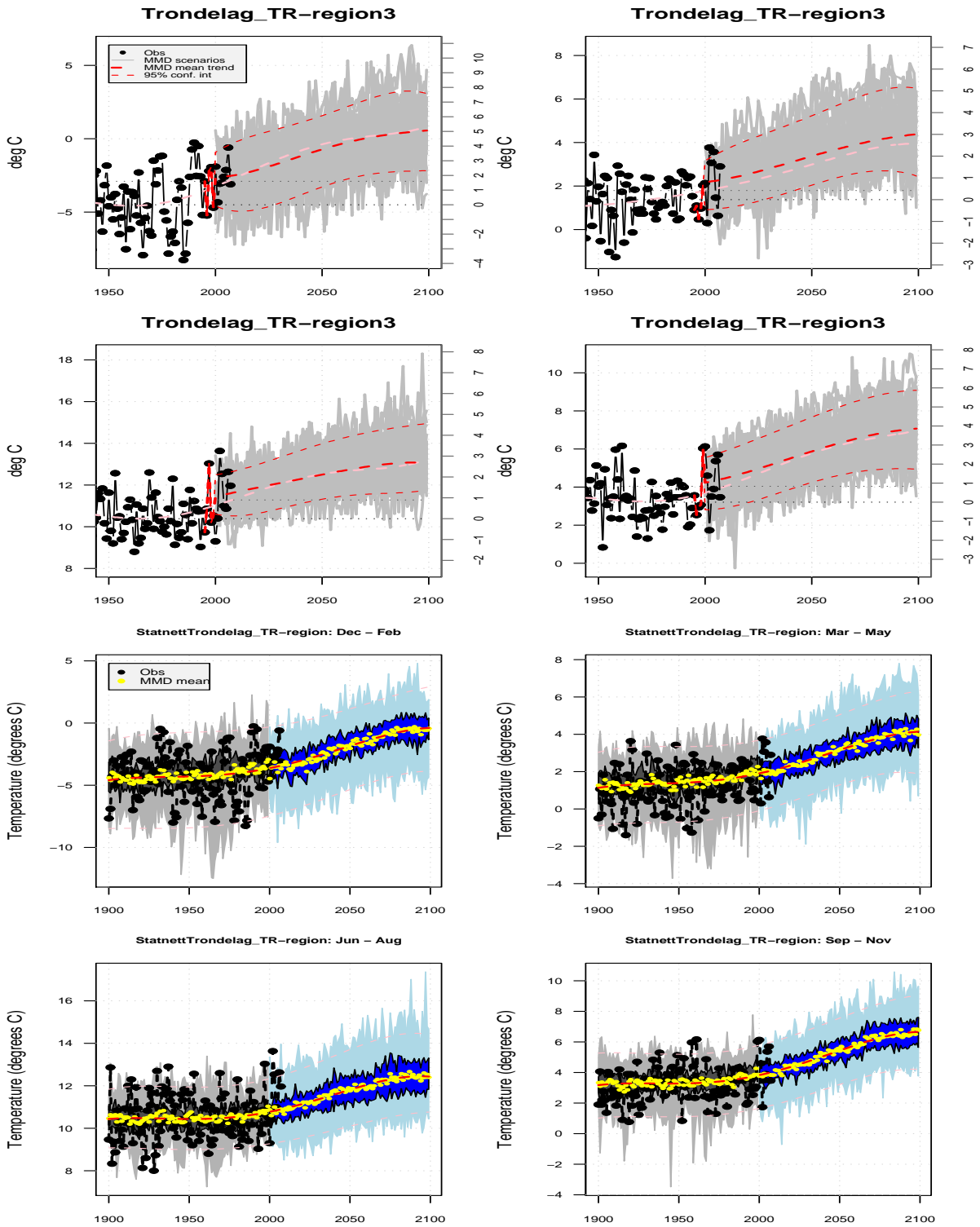Figure 4: As in Figure 3, but for temperature region 2 ('Vestlandet').

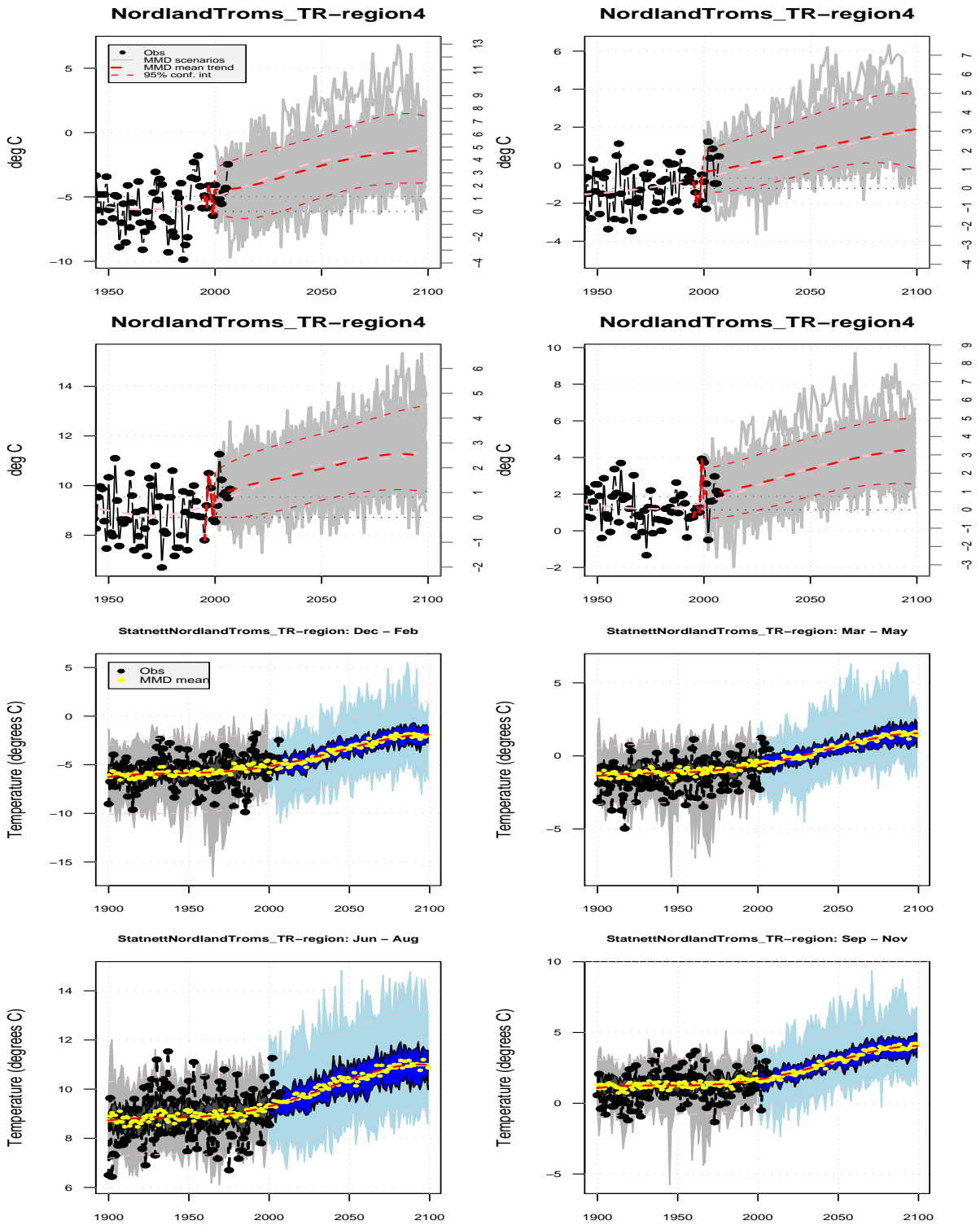Figure 5: As in Figure 3, but for temperature region 3 ('Trøndelag').

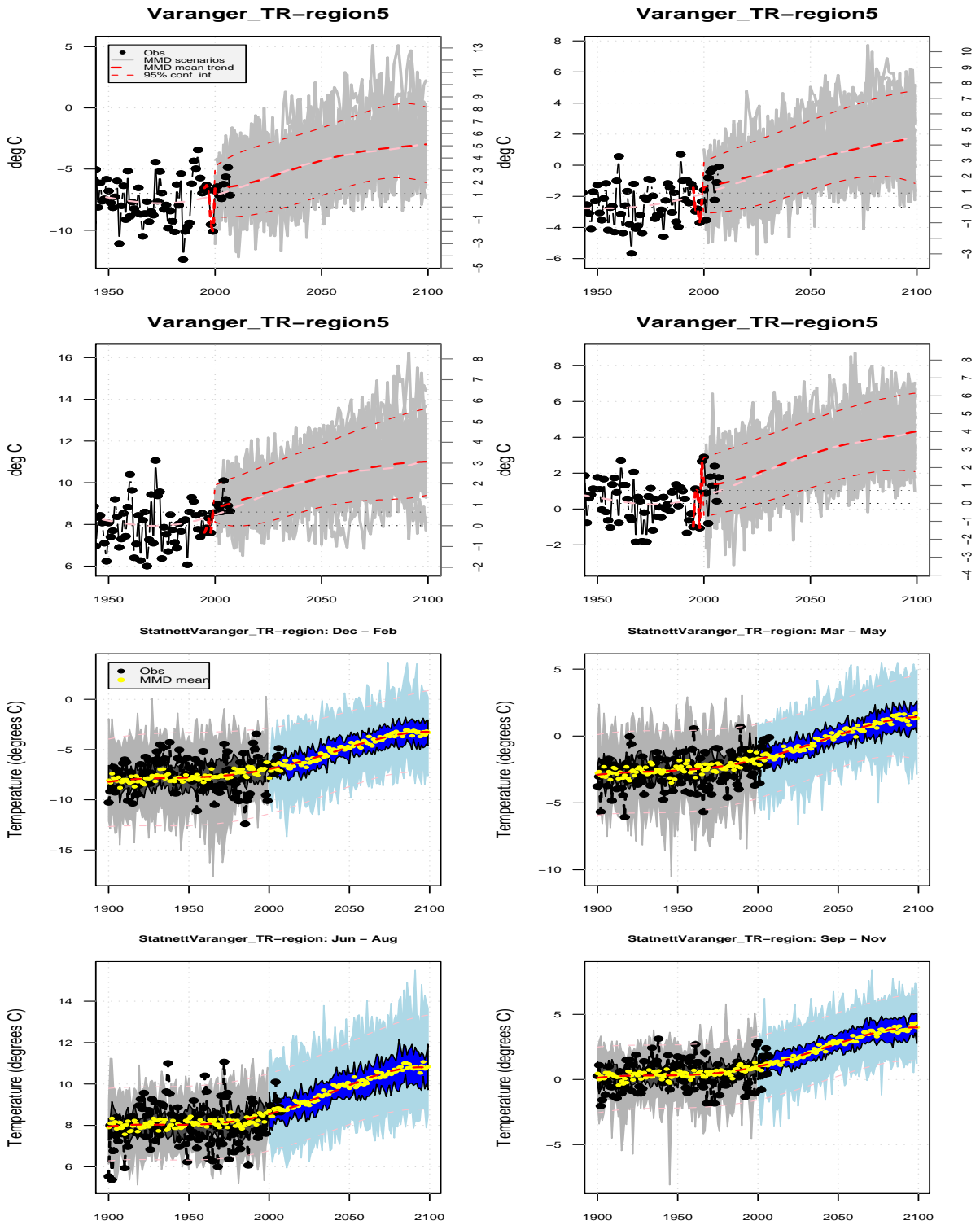Figure 6: As in Figure 3, but for temperature region 4 ('Nordland & Troms').

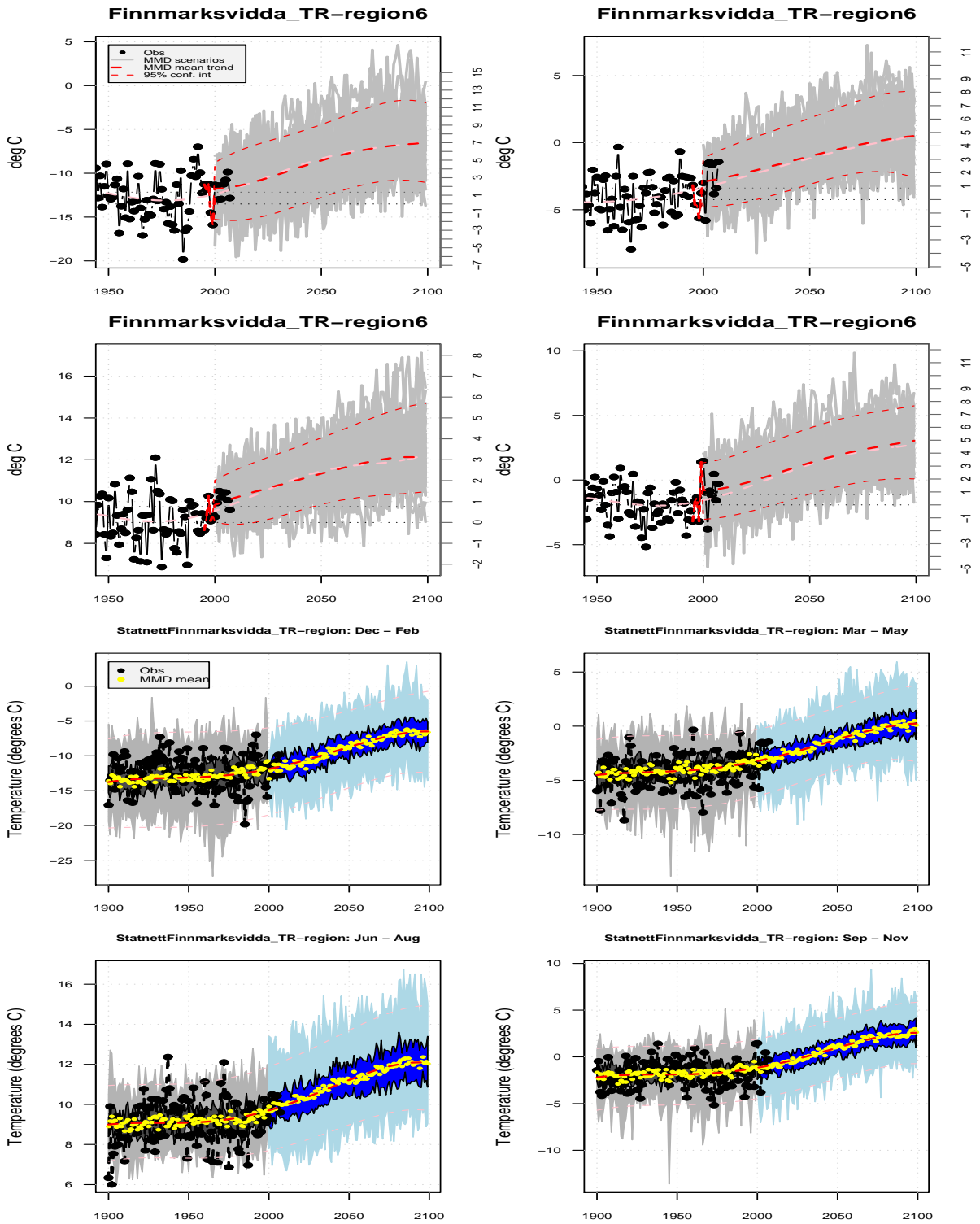Figure 7: As in Figure 3, but for temperature region 5 ('Varanger').

Figure 8: As in Figure 3, but for temperature region 6 ('Finnmarksvidda').

Table 1:

Temperature (unit: °C): *climatology for estimated from the combined observed-MMD median for 1995–2025; 90-percent confidence interval given as [q05% – q95%]. (Note, these values are* not *anomalies)*

	Winter	Spring	Summer	Autumn
Austlandet TR-1	-5.4 [-7.7– -3.5]	1.4 [0.3– 2.5]	11.6 [10.8– 12.5]	3.4 [2.1– 4.7]
Vestlandet TR-2	-1.9 [-3.1– -0.7]	1.2 [0.5– 1.9]	9.7 [8.9– 10.5]	4.0 [3.1– 5]
Trøndelag TR-3	-2.5 [-4.6– -0.6]	2.2 [1.1– 3.3]	11.6 [10.6– 12.5]	4.4 [3.1– 5.6]
Nordland+Troms TR-4	-4.4 [-6.4– -2.6]	-0.3 [-1.3– 0.8]	9.8 [8.8– 10.8]	2.1 [1.0– 3.4]
Varanger TR-5	-6.5 [-8.6– -4.3]	-1.3 [-2.9– 0.4]	9.0 [8.0– 10]	1.4 [0.0– 2.9]
Finnmarksvidda TR-6	-11.5 [-14.9– -8.3]	-2.8 [-4.6– -1.0]	10.1 [9.0– 11.2]	-0.7 [-2.6– 1.3]

MMD median over 2010–2040; 90-percent confidence interval [q05% – q95%]

	Winter	Spring	Summer	Autumn
Austlandet TR-1	-4.7 [-7.6– -2.2]	1.9 [0.6– 3.3]	12.0 [10.9– 13.1]	4.0 [2.4– 5.6]
Vestlandet TR-2	-1.4 [-3.1– 0]	1.5 [0.7– 2.5]	10.0 [9.0– 11.1]	4.5 [3.3– 5.7]
Trøndelag TR-3	-1.9 [-4.5– 0.5]	2.7 [1.3– 4.3]	12.0 [10.8– 13.2]	5.0 [3.4– 6.6]
Nordland+Troms TR-4	-3.8 [-6.4– -1.5]	0.2 [-1.1– 1.7]	10.2 [8.9– 11.5]	2.6 [1.1– 4.1]
Varanger TR-5	-5.7 [-8.4– -2.9]	-0.6 [-2.6– 1.6]	9.5 [8.2– 10.9]	2.0 [0.3– 3.9]
Finnmarksvidda TR-6	-10.5 [-14.7– -6.3]	-2.0 [-4.2– 0.4]	10.6 [9.2– 12.1]	0.0 [-2.3– 2.5]

Table 1 lists the estimated future climatologies (the values are the actual temperatures - *not* anomalies) for the 6 temperature regions in Norway. These climatologies correspond to the upper panels shown in Figures 3–8, where the SRES A1b scenarios have been adjusted to provide a best match with the 2000-2007 observations rather than the C20 simulations (which is the case for the lower panels).

By comparing the number of times (counts) when the observed temperature has exceeded the $q_{0.95}$ or been below $q_{0.05}$ (derived from the multi-model ensemble C20 simulations) in the past and assuming that the corresponding quantiles for the future (SRES A1b) are equally representative, one can assess whether the ESD results provide a reasonable description of the temperature variability. The expected number of events outside these thresholds can be estimated from a simple binomial distribution. This is a discrete distribution $Pr(X = x) = \frac{n!}{x!(n-x)!}p^x(1-p)^{n-x}$ for which n is the sample size and p (=0.05) is the probability of one event taking place and Pr is the probability of x events being realised. The confidence interval can be estimated from the cumulative probability function derived from Pr, suggesting a 90% confidence interval of 1–8 for the sample size n=108.

In the case of many parallel statistical tests as presented in Table 2, one will expect to see a number of cases for which the results happen to be outside the 90% confidence interval from

Table 2: *Counts of times when observed temperatures exceed the polynomial fit to $q_{0.95}$ for the past or drop below $q_{0.05}$. The 90% confidence intterval was estimated using a binomial distribution of the same sample size as the observations, $p = 0.05$ is 1–8 (Sample size=108). The cases where the count is outside the 90% confidence intterval are shown in* **bold font**.

		Winter	Spring	Summer	Autumn
Region 1	over $q_{0.95}$	4	2	**10**	7
	under $q_{0.05}$	1	8	**10**	2
Region 2	over $q_{0.95}$	**0**	1	3	1
	under $q_{0.05}$	1	3	**9**	1
Region 3	over $q_{0.95}$	1	2	5	5
	under $q_{0.05}$	1	6	8	5
Region 4	over $q_{0.95}$	3	3	**12**	5
	under $q_{0.05}$	1	6	8	3
Region 5	over $q_{0.95}$	**0**	2	3	1
	under $q_{0.05}$	1	2	8	**0**
Region 6	over $q_{0.95}$	**9**	**9**	**15**	**8**
	under $q_{0.05}$	**9**	**13**	**12**	6

pure chance (about one in ten in this case). This behaviour is often referred to as 'problem of multiplicity' or 'field significance' (*Wilks*, 1995). Here, however, we see that temperature region 6 ('Finnmarksvidda') has a high number of events outside range, suggesting that the derived confidence interval for this region is too narrow. For the other regions, however, there appears to be a reasonable agreement between the confidence thresholds and the empirical data.

4.2   Precipitation

The scenarios for the 13 different temperature regions are presented in the 13 figures below. As for temperature, the results are shown with two different strategies for adjustment: the upper panels show ESD (SRES A1b) with their mean level shifted so that they have the same mean value over the 2000–2007 period as the actual observations. To re-capitulate: the lower part shows corresponding results, but now adjusted so that the ensemble-time median of the 5 first years of the future scenarios (blue) equals the ensemble-time median of the 5 last years in C20. Thus, the upper results have been fitted the observations whereas the lower results have not (since C20 are GCM simulations by their own right). Note: the results presented in the lower part have not been subject to 'inflation', which was merely introduced to give a more realistic confidence intervals for the near-future climatologies shown in the upper part.

The ESD results suggest a general trend of increased future precipitation in winter, spring, and autumn. In the southern regions (precipitation regions 1–4; Figures 9–12), the summer-time rainfall is projected to decrease, while on the west coast and to the north (regions 5–13; Figures 13–21) the outlook for future summers also is increasingly wet.

Projected climatologies for 1995–2025 and 2010–2040 ('inflated') precipitation are given in Table 3.
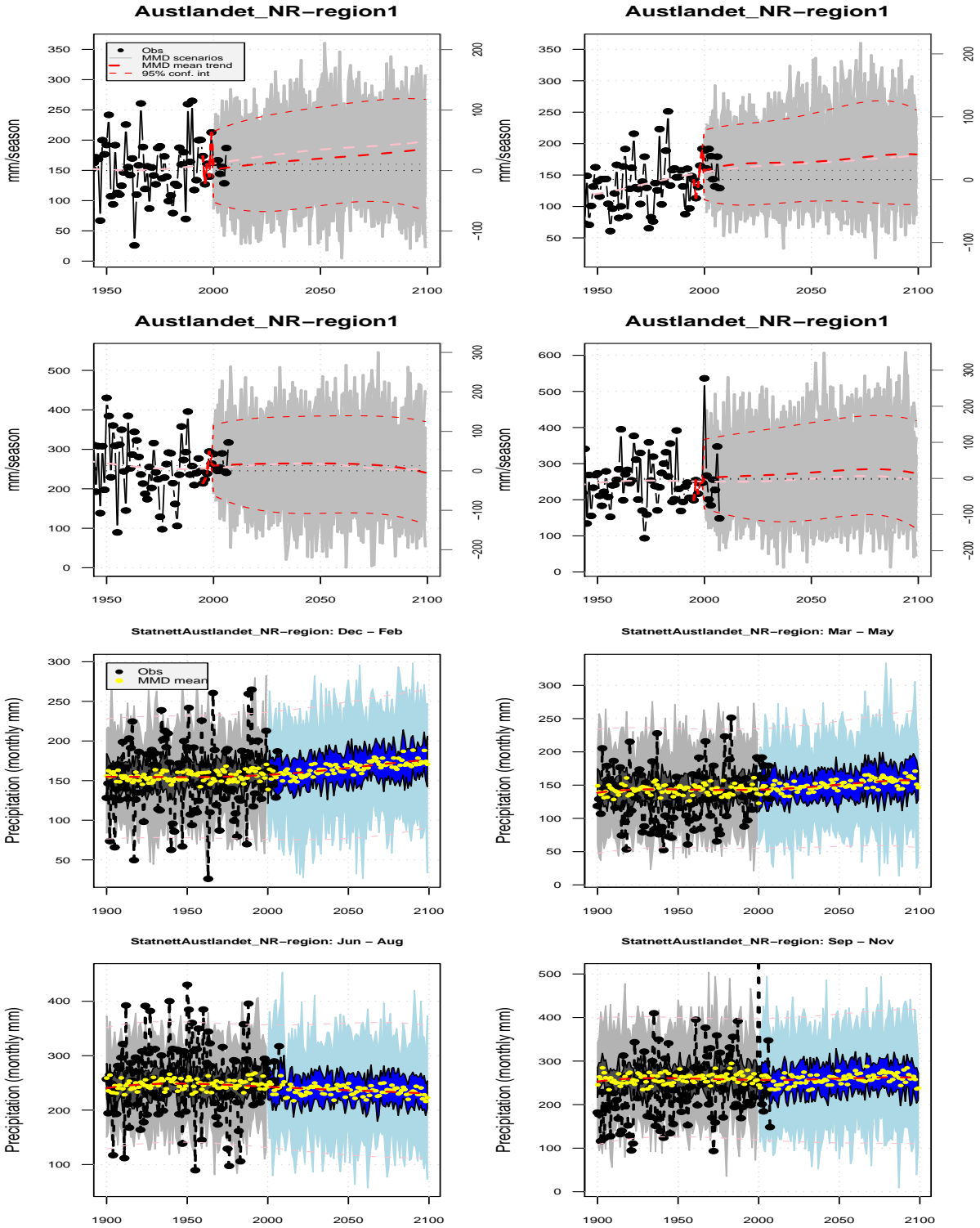
Figure 9: Region 1 ('Østlandet'), showing from upper left to right, lower left to right: Winter (December–February), Spring (March-May), Summer (June–August), and Autumn (September–November). Upper: The pink curve marks the combined observation-scenario trend while the red lines show the median (thick) and the 90% confidence region (thin). The grey lines show each of the ensemble members (downscaled scenarios), and black shows the observations. Lower: Lower: ESd-results adjusted to C20; Yellow symbols mark the ensemble mean values.

Figure 10: As in Figure 9, but for precipitation region 2 ('Østfold').

Figure 11: As in Figure 9, but for precipitation region 3 ('Sørlandet')

Figure 12: As in Figure 9, but for precipitation region 4 ('Sør-Vestlandet')

Figure 13: As in Figure 9, but for precipitation region 5 ('Sunnhordland')

Figure 14: As in Figure 9, but for precipitation region 6 ('Sogn')

Figure 15: As in Figure 9, but for precipitation region 7 ('Møre+Romsdal')

Figure 16: As in Figure 9, but for precipitation region 8 ('Dovre Nord+Østerdal')
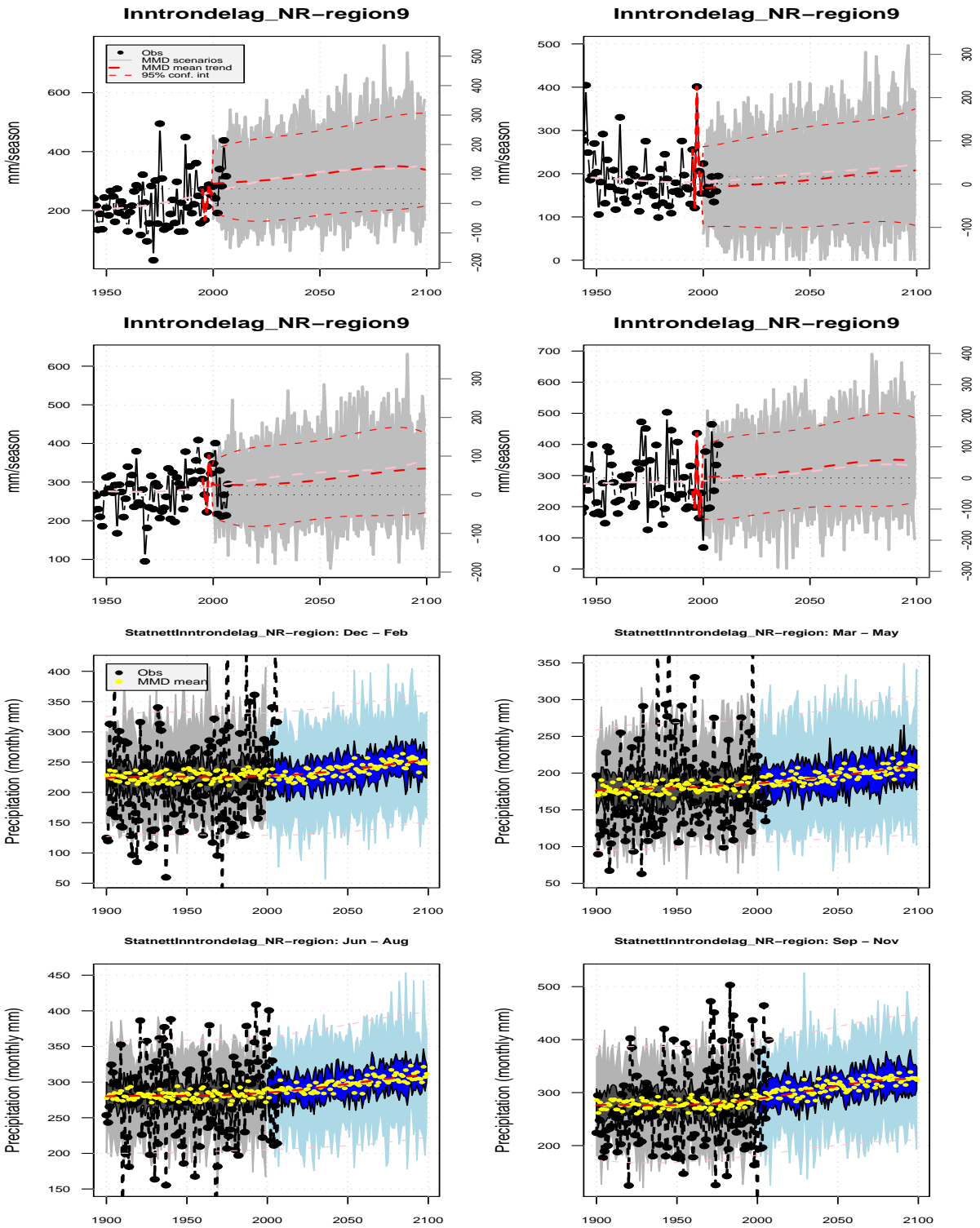
Figure 17: As in Figure 9, but for precipitation region 9 ('Inntrøndelag')
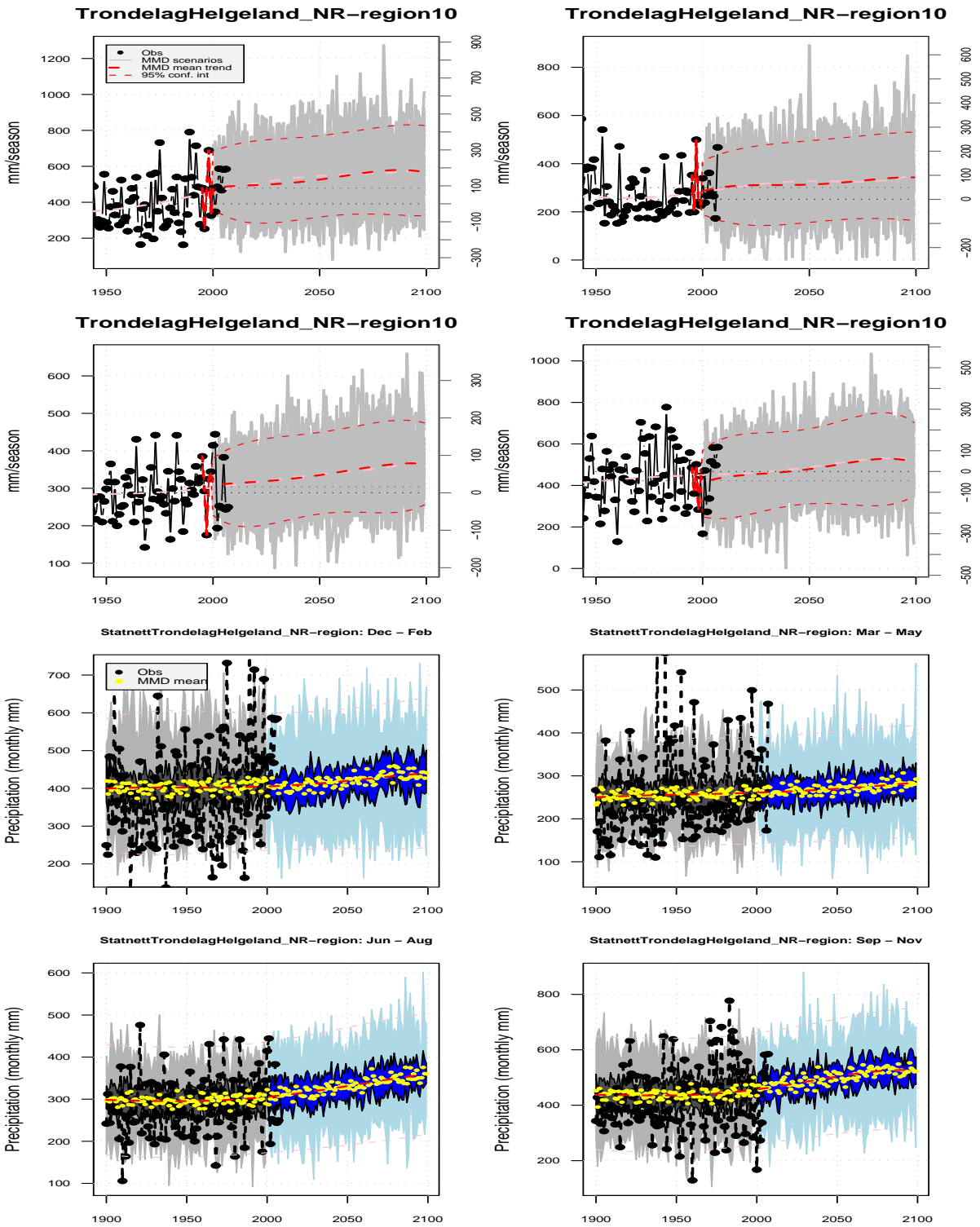
Figure 18: As in Figure 9, but for precipitation region 10 ('Trøndelag+Helgeland')

Halogaland_NR-region11

Obs
MMD scenarios
MMD mean trend
95% conf. int

Halogaland_NR-region11

Halogaland_NR-region11

Halogaland_NR-region11

StatnettHalogaland_NR-region: Dec – Feb

Obs
MMD mean

StatnettHalogaland_NR-region: Mar – May

StatnettHalogaland_NR-region: Jun – Aug

StatnettHalogaland_NR-region: Sep – Nov
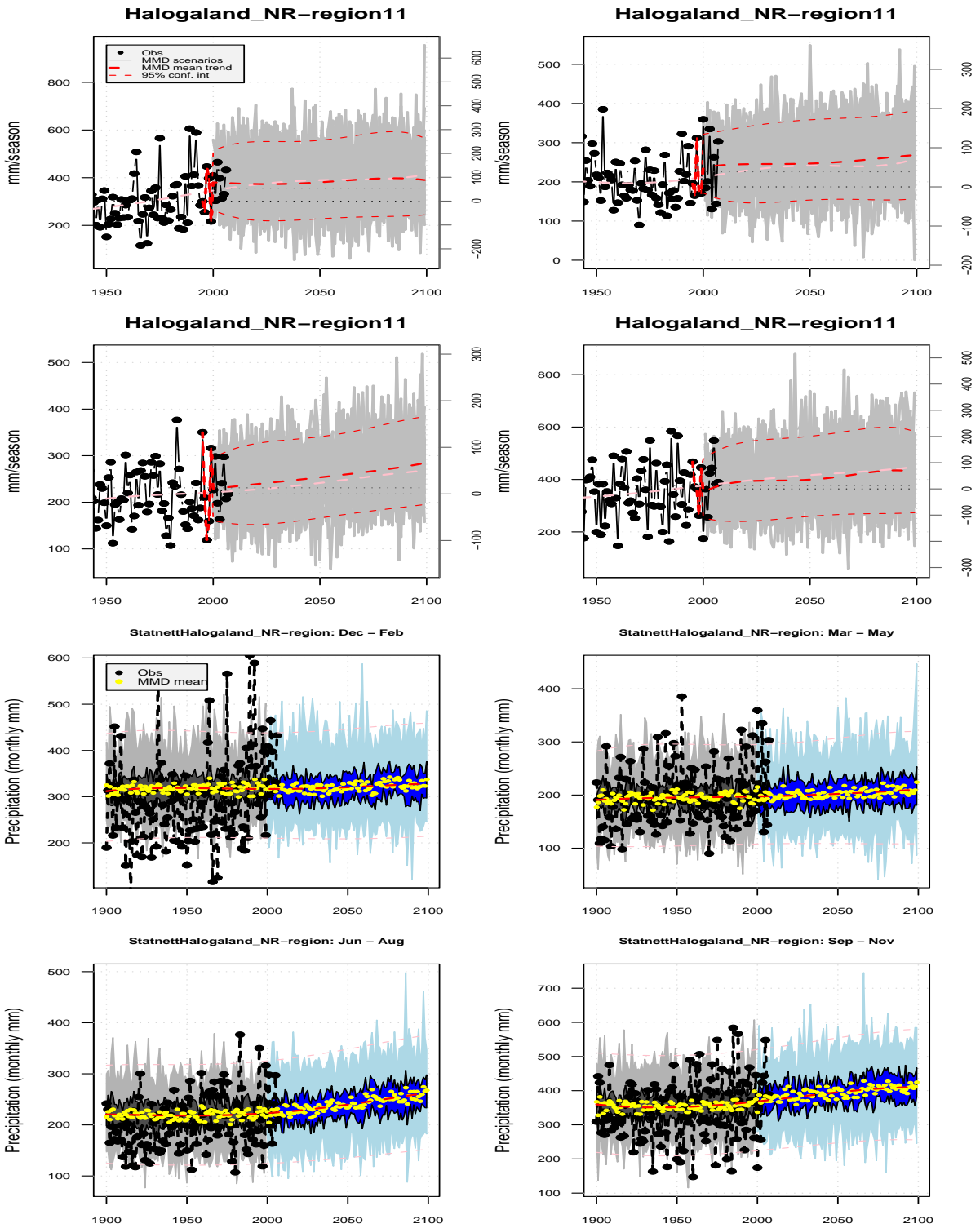
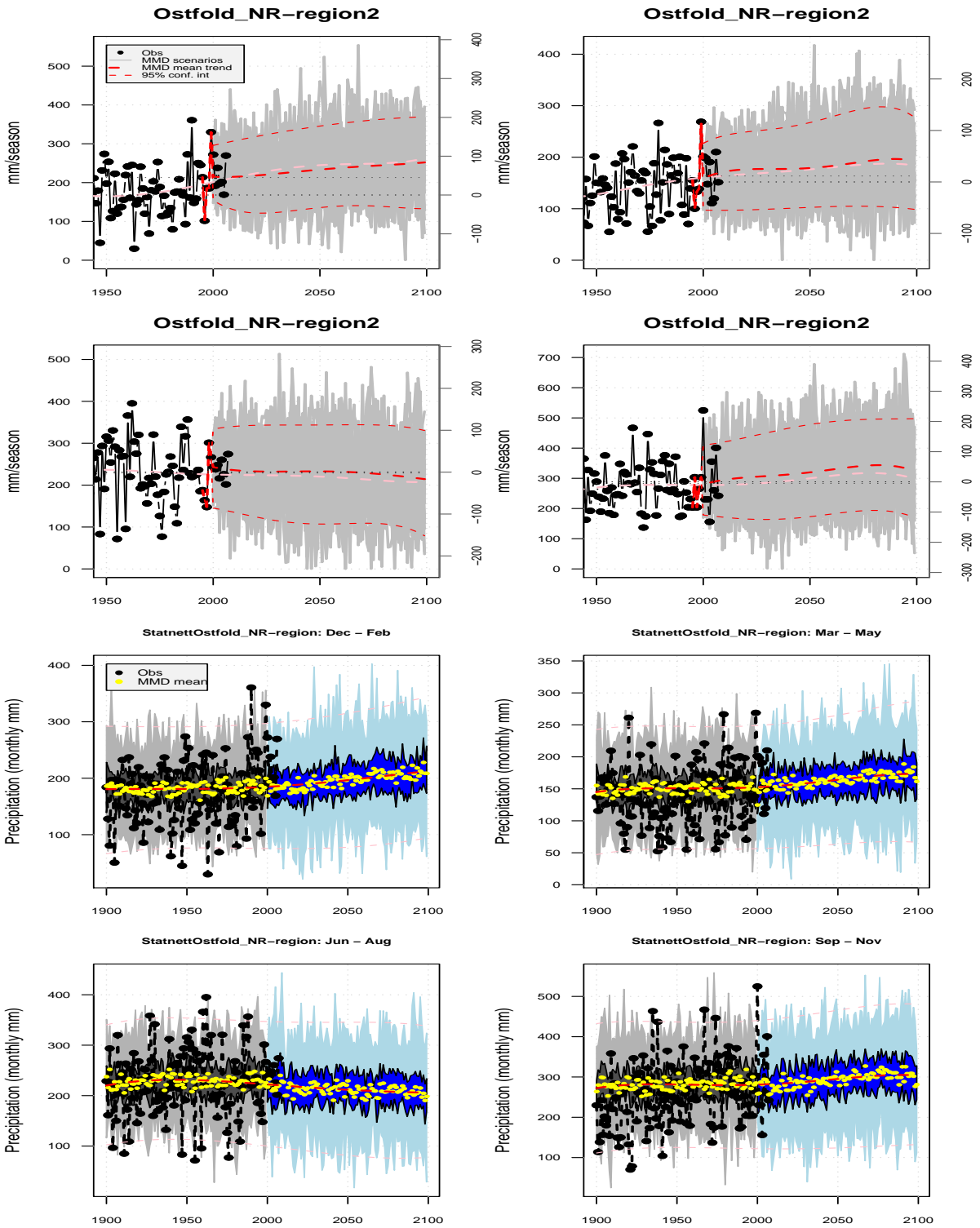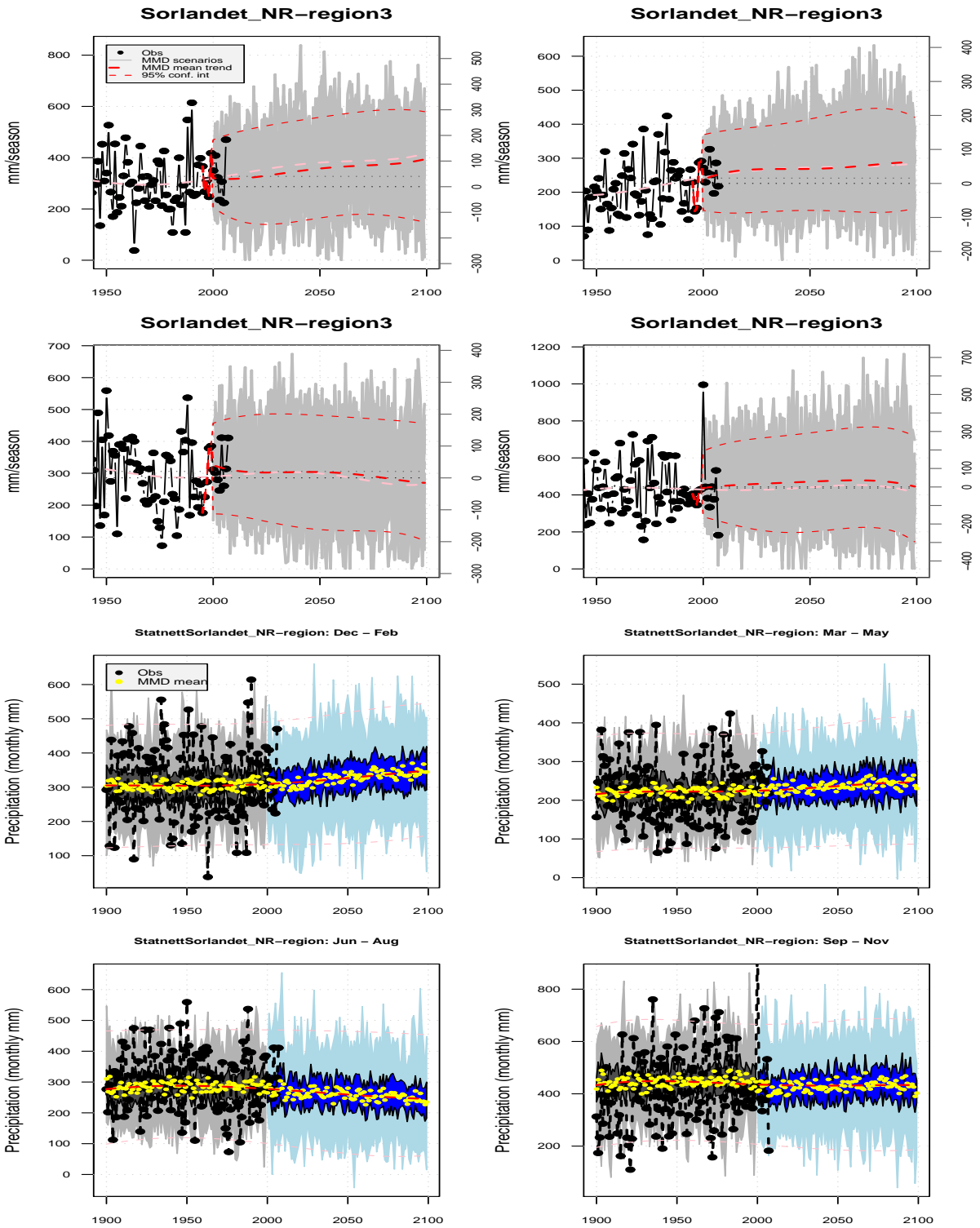Figure 19: As in Figure 9, but for precipitation region 11 ('Halogaland')

31
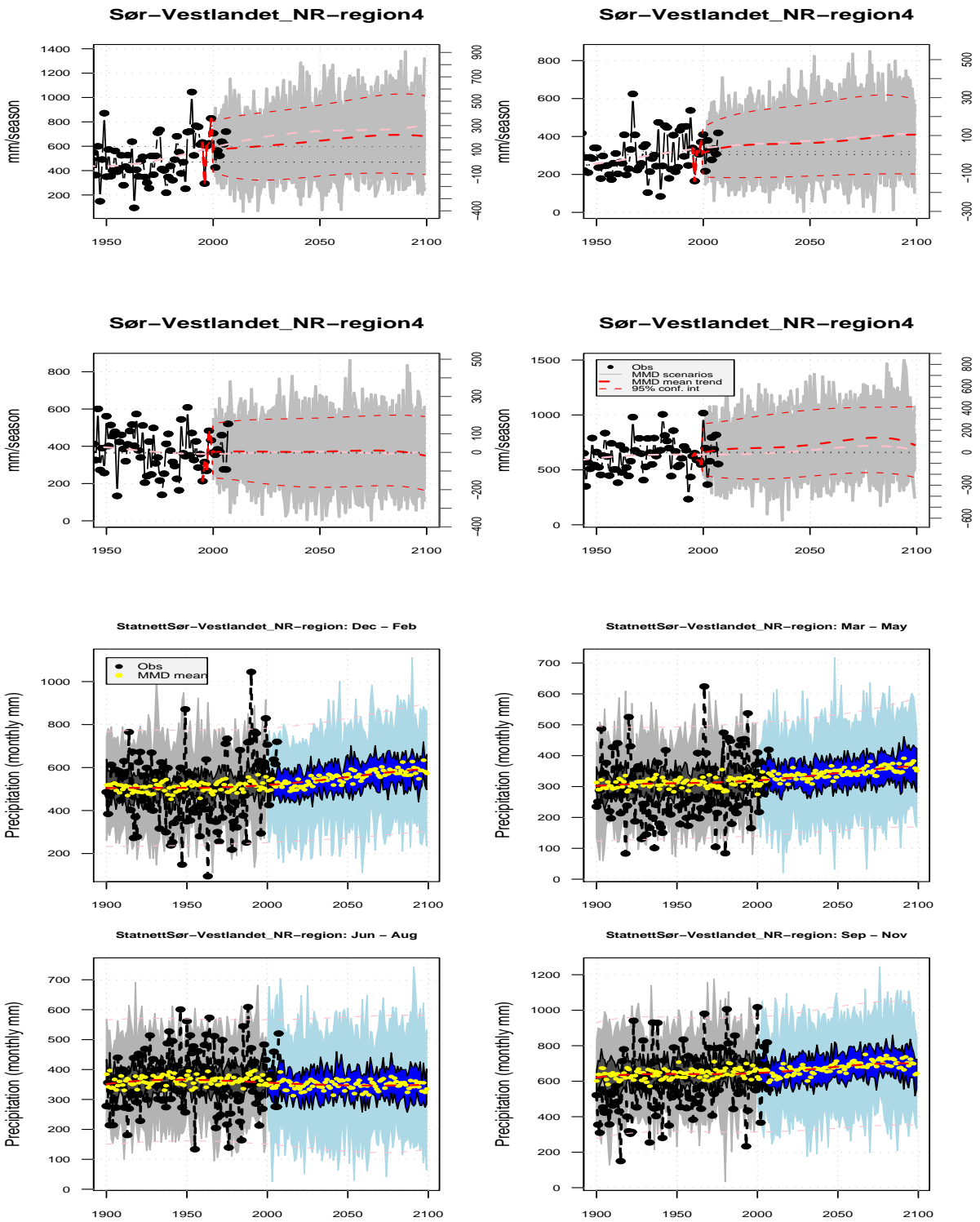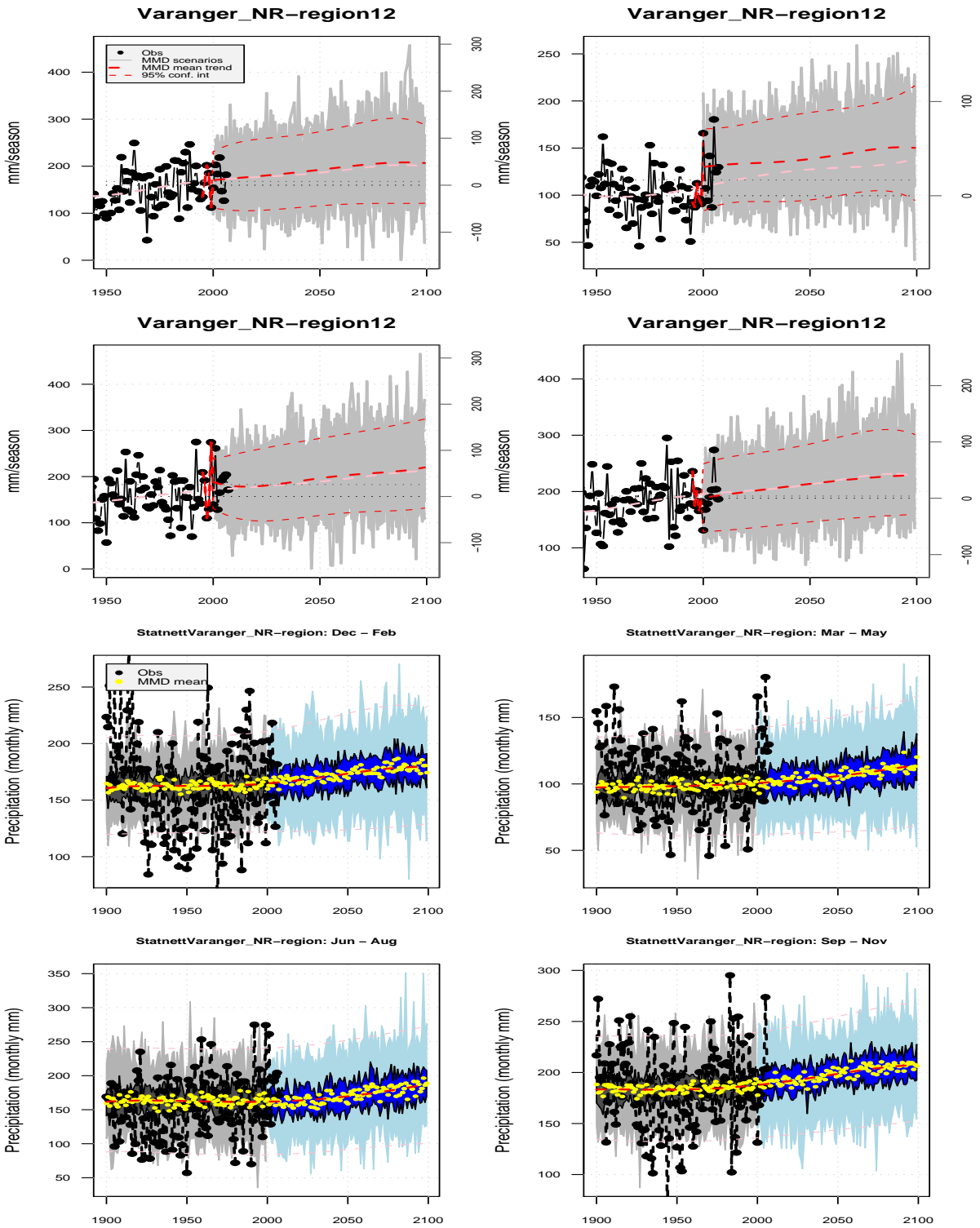
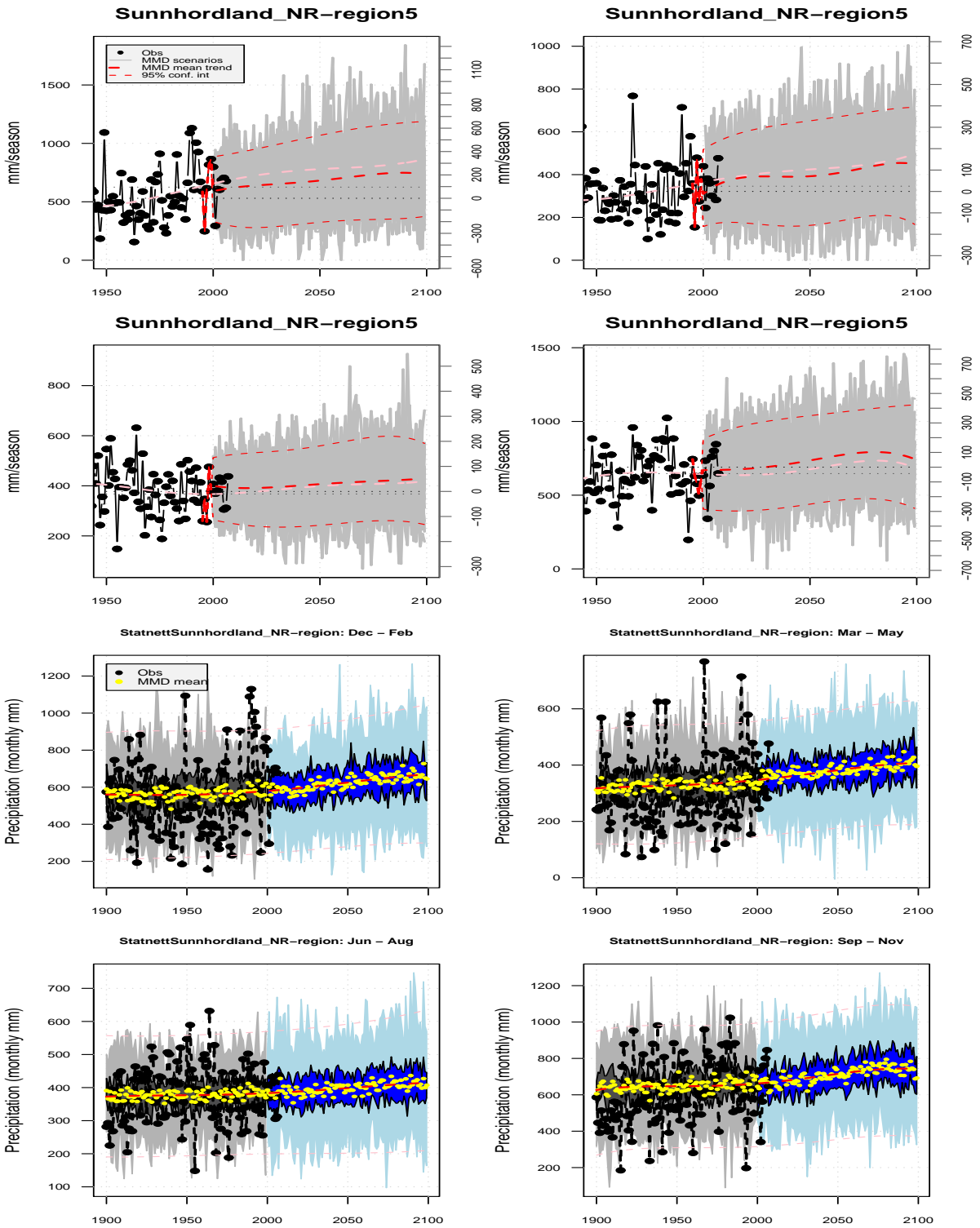Figure 20: As in Figure 9, but for precipitation region 12 ('Varanger')

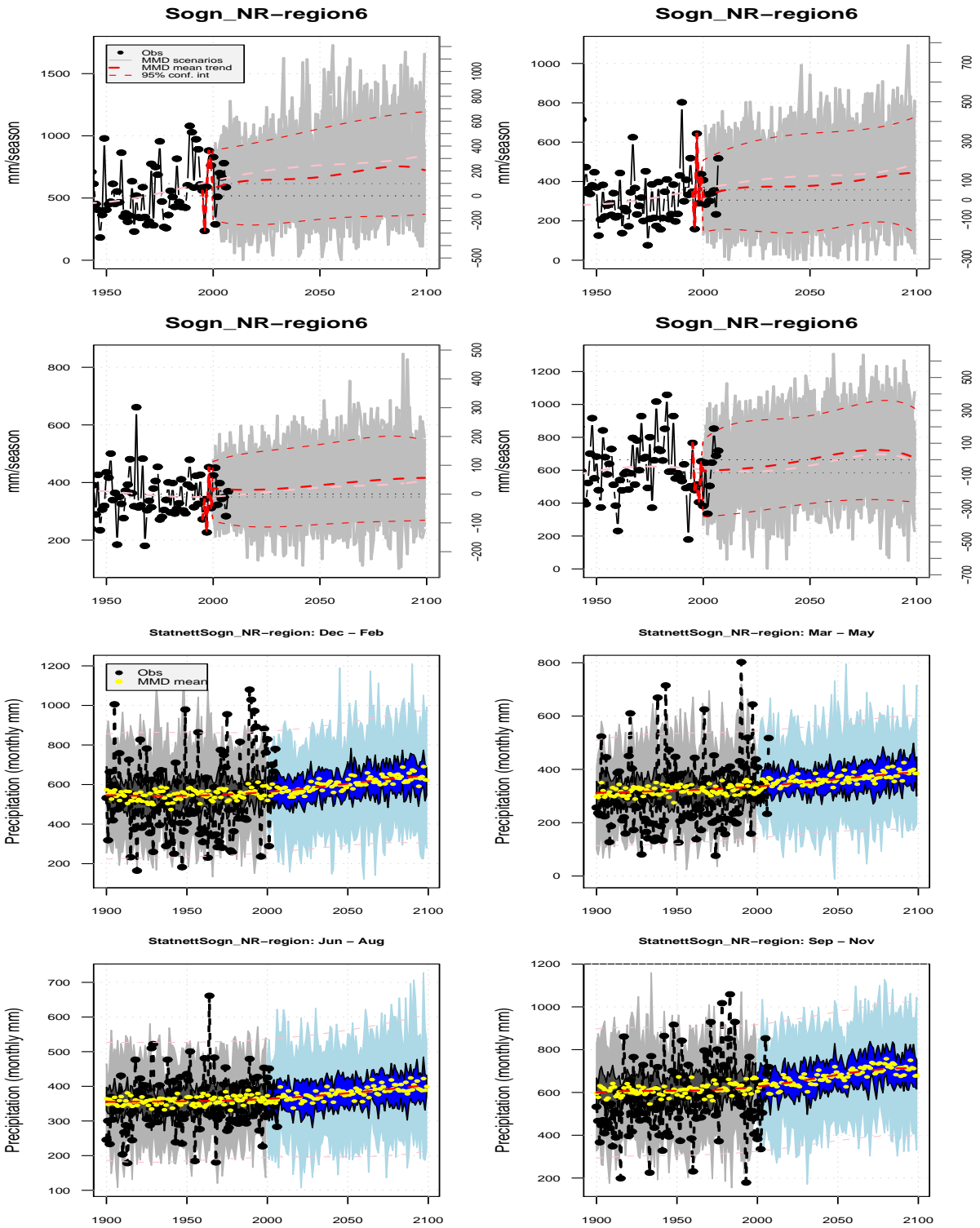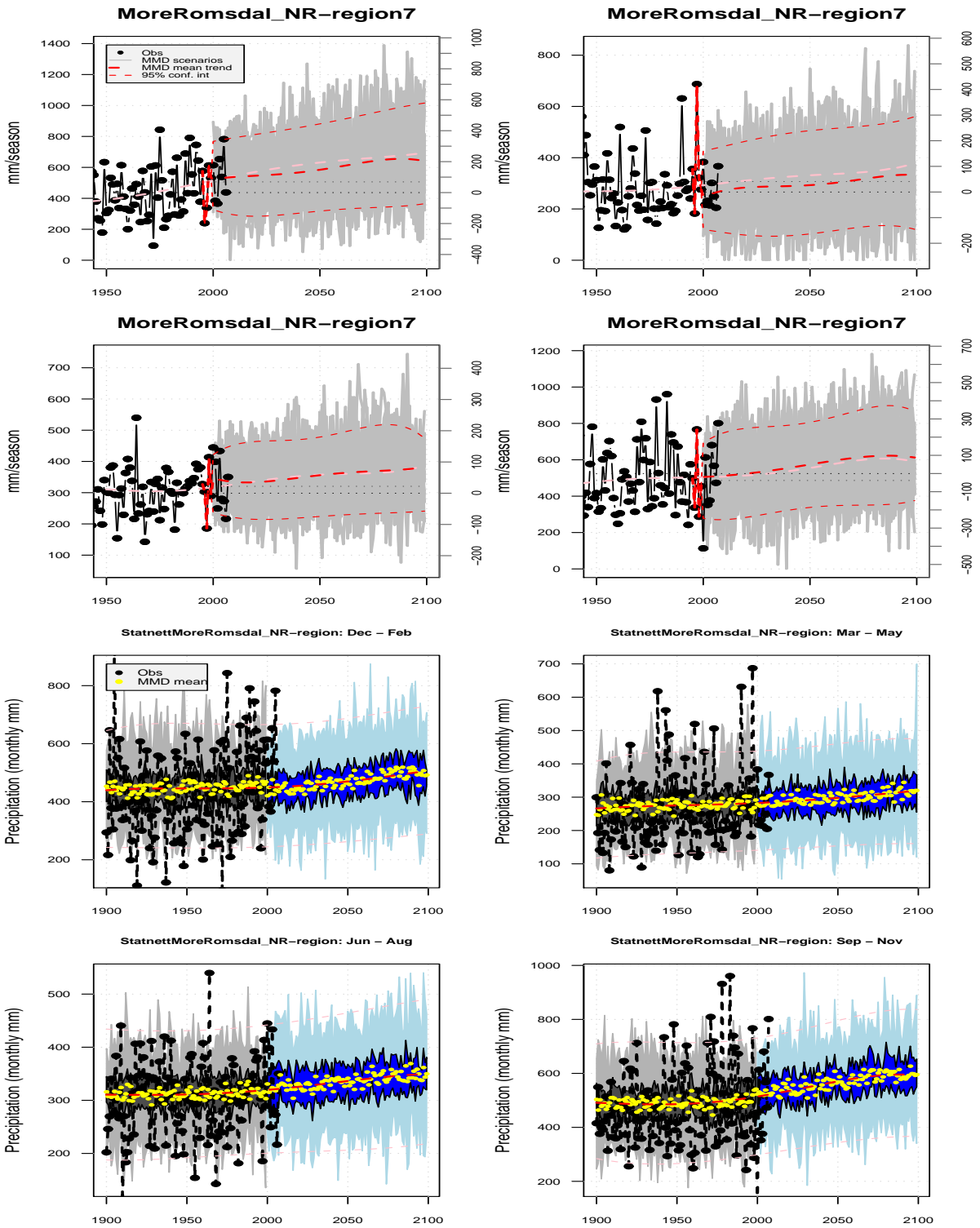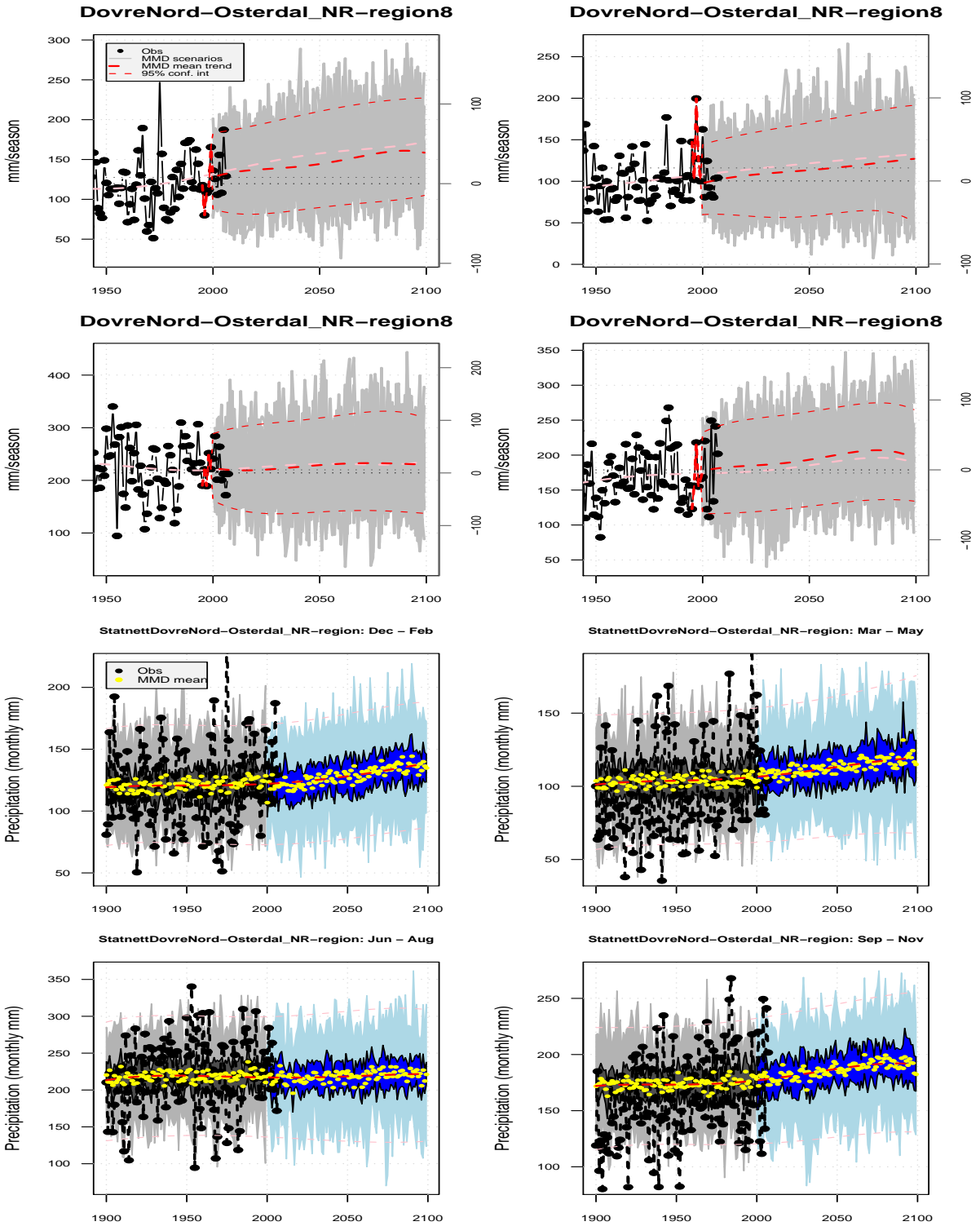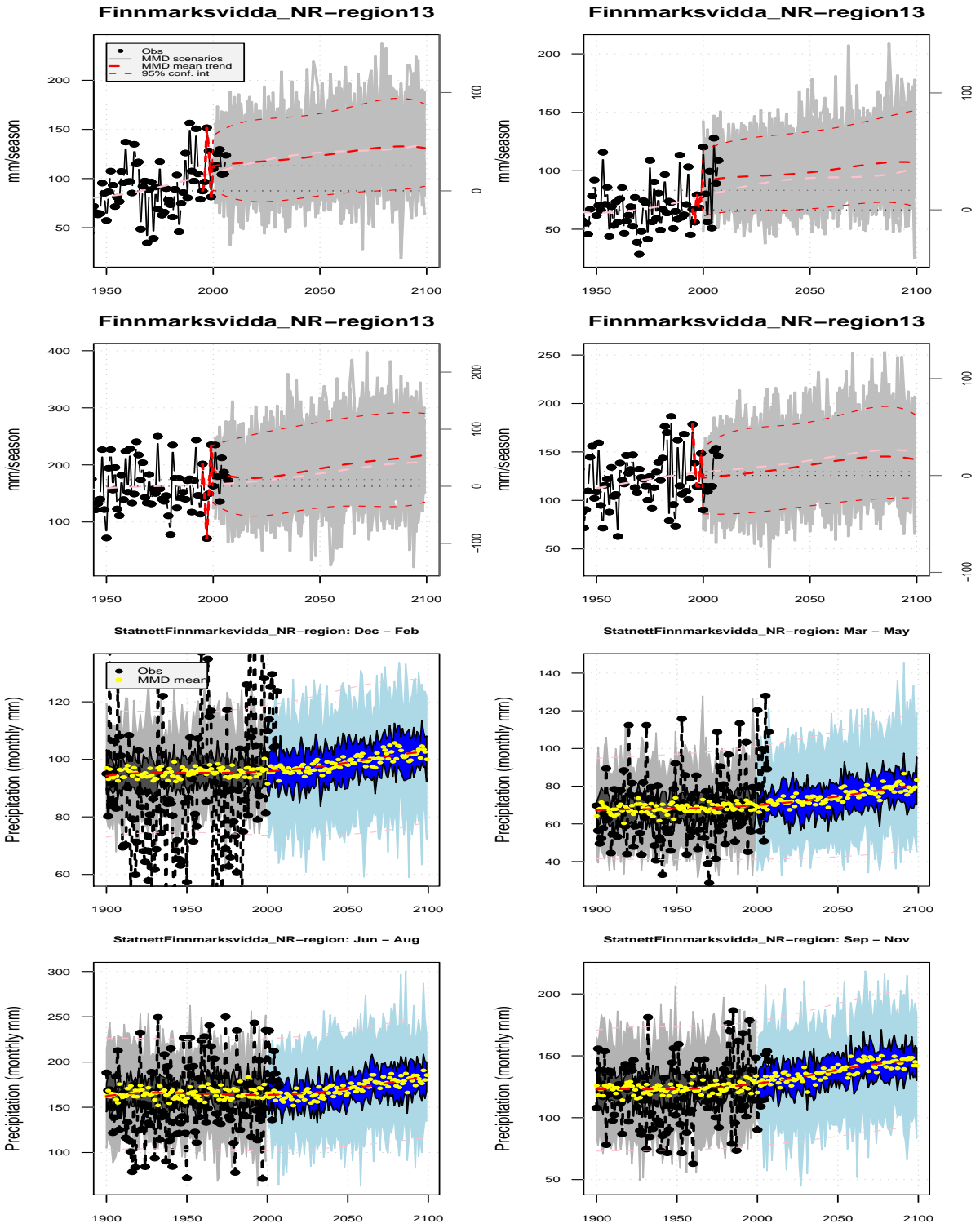Figure 21: As in Figure 9, but for precipitation region 13 ('Finnmarksvidda')

Table 3 shows the estimated climatology for precipitation (the actual accumulated precipitation - *not* anomalies) and for the ESD results (SRES A1b) adjusted to the 2000-2007 observations. This table corresponds to Table 1 for temperatures, and the data shown have been subject to 'inflation' (the table represents the results shown in the upper parts of Figures 9–21).

Table 4 shows analysis for precipitation corresponding to Table 2, and again the 'problem of multiplicity'/'field significance' (*Wilks*, 1995) should be kept in mind when considering these results. There are some regions with over-weight of anomalous counts, such as precipitation regions 3–6 and 13 ('Sørlandet', 'Sør-Vestlandet', 'Sunnhordland', 'Sogn' and 'Finnmarksvidda'). The results in Table 4 represents ESD results that have *not* been 'inflated', however, and thus provide one justification for the application of the re-scaling for the purpose of providing more realistic confidence intervals.

Table 3:

Precipitation (mm/season): *climatology estimated from the combined observation-MMD median for the period 1995–2025; 90-percent confidence interval [q05% – q95%] (Note: these values are* not *anomalies, and the table presents ESD results that have been subject to 'inflation')*

	Winter	Spring	Summer	Autumn
Austlandet NR-1	158 [99–218]	162 [111–216]	259 [173–353]	259 [169–356]
Østfold NR-2	214 [142–293]	170 [107–229]	232 [145–320]	289 [184–398]
Sørlandet NR-3	321 [186–472]	251 [154–356]	306 [183–445]	441 [269–633]
Sør-Vestlandet NR-4	589 [382–807]	336 [203–470]	367 [236–505]	672 [454–895]
Sunnhordland NR-5	625 [347–878]	360 [197–534]	385 [263–497]	665 [431–890]
Sogn NR-6	621 [343–870]	359 [189–534]	367 [263–467]	598 [370–816]
Møre+Romsdal NR-7	526 [322–742]	288 [148–436]	331 [234–428]	509 [308–704]
Dovre Nord+Østerdal NR-8	131 [88–177]	109 [72–150]	219 [157–286]	179 [125–232]
Inntrøndelag NR-9	288 [183–400]	180 [102–266]	294 [208–366]	292 [179–394]
Trøndelag+Helgeland NR-10	483 [328–678]	303 [182–424]	313 [221–395]	436 [275–592]
Halogaland NR-11	367 [248–506]	236 [162–312]	234 [167–302]	381 [265–501]
Varanger NR-12	173 [115–235]	127 [91–161]	181 [123–239]	195 [142–249]
Finnmarksvidda NR-13	115 [84–148]	90 [65–116]	177 [123–233]	128 [95–163]

MMD median 2010–2040; 90-percent confidence interval [q05% – q95%]

	Winter	Spring	Summer	Autumn
Austlandet NR-1	162 [84–240]	169 [104–234]	263 [145–380]	267 [145–391]
Østfold NR-2	221 [124–323]	176 [99–251]	233 [120–343]	305 [166–443]
Sørlandet NR-3	331 [145–523]	266 [141–392]	304 [149–484]	459 [216–703]
Sør-Vestlandet NR-4	605 [328–879]	356 [184–534]	371 [199–544]	699 [420–986]
Sunnhordland NR-5	646 [288–972]	387 [169–610]	394 [238–536]	687 [400–986]
Sogn NR-6	644 [292–964]	370 [148–604]	377 [247–509]	619 [353–899]
Møre+Romsdal NR-7	551 [290–824]	284 [97–472]	338 [216–464]	532 [294–775]
Dovre Nord+Østerdal NR-8	138 [83–196]	108 [58–159]	221 [139–307]	186 [119–252]
Inntrøndelag NR-9	304 [167–446]	175 [76–286]	295 [189–392]	304 [175–433]
Trøndelag+Helgeland NR-10	499 [290–745]	310 [147–470]	320 [206–431]	454 [268–649]
Halogaland NR-11	374 [222–550]	245 [148–344]	241 [154–328]	393 [244–546]
Varanger NR-12	181 [108–259]	134 [93–178]	182 [106–262]	202 [136–268]
Finnmarksvidda NR-13	118 [78–160]	96 [66–128]	180 [113–258]	129 [88–174]

Table 4: *Counts of times when observed temperatures exceed the polynomial fit to $q_{0.95}$ for the past or drop below $q_{0.05}$. The 90% confidence intterval was estimated using a binomial distribution of the same sample size as the observations, $p = 0.05$ is 1–8 (Sample size=108). The cases where the count is outside the 90% confidence intterval are shown in* bold font. *Note: these results have not been subject to inflation.*

		Winter	spring	Summer	Autumn
Region 1	over $q_{0.95}$	5	1	**9**	2
	under $q_{0.05}$	7	2	7	4
Region 2	over $q_{0.95}$	8	5	6	6
	under $q_{0.05}$	7	**9**	7	**16**
Region 3	over $q_{0.95}$	**16**	9	**11**	4
	under $q_{0.05}$	**31**	4	**10**	5
Region 4	over $q_{0.95}$	8	**10**	2	5
	under $q_{0.05}$	**20**	2	6	9
Region 5	over $q_{0.95}$	8	**11**	**10**	**12**
	under $q_{0.05}$	**13**	5	**11**	6
Region 6	over $q_{0.95}$	6	9	3	9
	under $q_{0.05}$	**11**	6	6	5
Region 7	over $q_{0.95}$	2	3	4	4
	under $q_{0.05}$	5	3	6	3
Region 8	over $q_{0.95}$	**9**	7	1	5
	under $q_{0.05}$	4	2	3	4
Region 9	over $q_{0.95}$	4	6	7	6
	under $q_{0.05}$	5	3	3	7
Region 10	over $q_{0.95}$	6	8	2	2
	under $q_{0.05}$	5	5	2	5
Region 11	over $q_{0.95}$	3	3	3	3
	under $q_{0.05}$	3	4	2	5
Region 12	over $q_{0.95}$	6	**11**	5	5
	under $q_{0.05}$	7	4	4	5
Region 13	over $q_{0.95}$	**17**	**11**	5	**11**
	under $q_{0.05}$	**24**	4	8	**14**

5   Discussion & Conclusions

The analysis indicated a warming for all the regions downscaled. The results for the temperature were associated with high R^2-scores and thus of high quality. For precipitation, however, the connection between large-scale and local variability was weaker, thus yielding lower R^2-scores and explained variance. The general picture, after an inflation adjustment, was a general increase in winter, spring and autumn, but weaker summer trends in some regions and even a negative trend for regions 1–3 (southern Norway). For region 11 (Halogaland), the winter trend was less pronounced than the summer trend. The ESD results have been adjusted to provide a realistic description of the initial part of the series, as the ESD-procedure has focused on large-scale anomalies rather than the full values. The advantage of analysing anomalies is that constant model biases (systematic errors) can be circumvented, but is also means that the constant level of the end results may need to be adjusted to match the real world. Therefore, it is more sensible to focus on the long-term changes - trends - in the ESD-results. Alternatively, box-plots such as those in Figures 22–23 in the appendix, may be used to show the difference between two periods. In this case, the two periods are taken from the C20 and SRES A1b respectively after the latter has been adjusted as shown in the lower parts of Figures 3–21.

Climatic normals were estimated for the periods 1995–2025 and 2010–2040, however, these are associated with an important caveat: The initial conditions used in the GCM simulations do not reflect the current state of the climate. Estimates for the 1995–2025 and 2010–2040 periods involve predictability of the first (from given initial conditions) and second (from given boundary conditions) kinds (*Palmer*, 1996), but the GCMs employed here only involved the latter. The GCMs have been initialised from a spun-up model state rather than taking observations as a starting point (which would involve model assimilation). The climate signal (trends) forced by boundary conditions is weak compared to the natural decadal variations which in these model results are not predicted. New model simulations for decadal prediction are emerging.

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Acknowledgement

Appendix

Box-plots for temperature

The box-plot diagrams shown here correspond to the lower panels in Figures 3–8.

a   2070–2099 scenario w.r.t. 1961–1990N sce=37 N 20c=29

b   2070–2099 scenario w.r.t. 1961–1990N sce=37 N 20c=27

c   2070–2099 scenario w.r.t. 1961–1990N sce=37 N 20c=29

d   2070–2099 scenario w.r.t. 1961–1990N sce=37 N 20c=29

Figure 22: Box-plots showing spread of 20c ESD results (light) and A1b (dark) showing 4 seasons (grey) and the annual mean (blue). Temperature regions 1–4

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StatnettVaranger_TR−region

Temperature change (degrees C)

winter.ctl spring.ctl summer.ctl autumn.ctl annual.ctl

e 2070−−2099 scenario w.r.t. 1961−−1990N sce=37 N 20c=27

StatnettFinnmarksvidda_TR−region

Temperature change (degrees C)

winter.ctl spring.ctl summer.ctl autumn.ctl annual.ctl
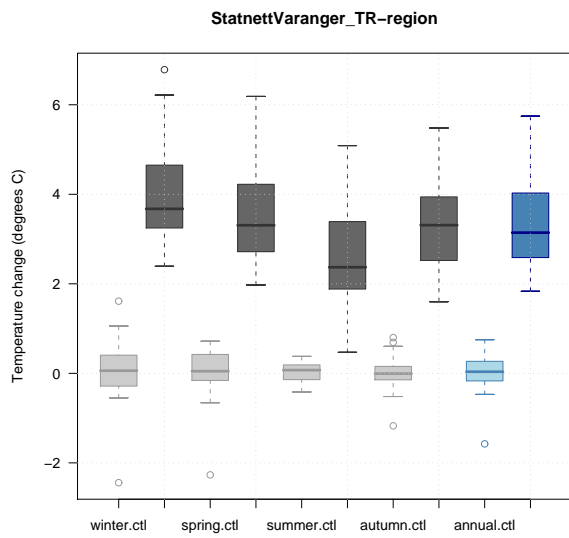
f 2070−−2099 scenario w.r.t. 1961−−1990N sce=37 N 20c=27

Figure 22 continued. Temperature regions 5–6

Box-plots for precipitation

The box-plot diagrams shown here correspond to the lower panels in Figures 9–21.

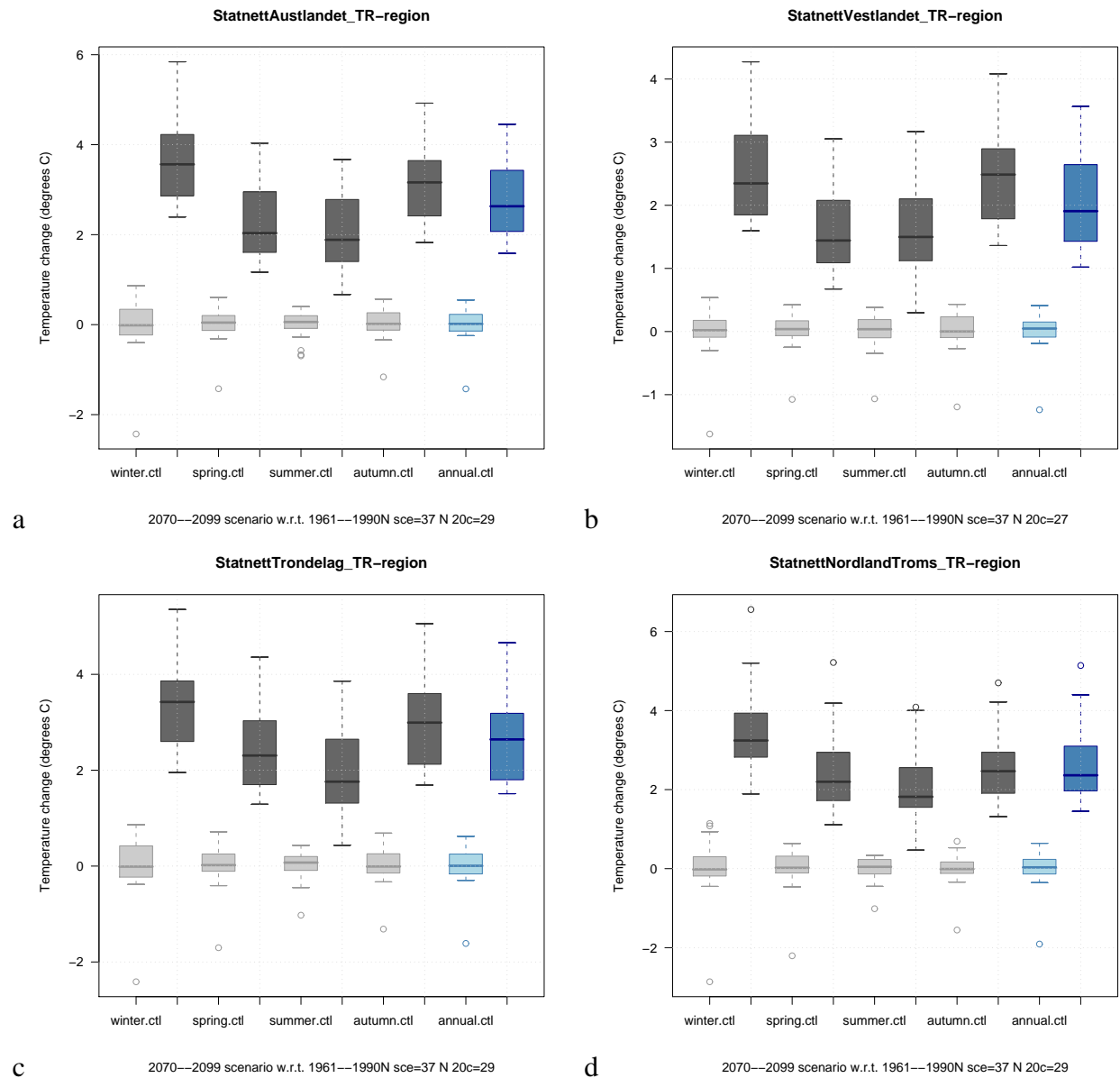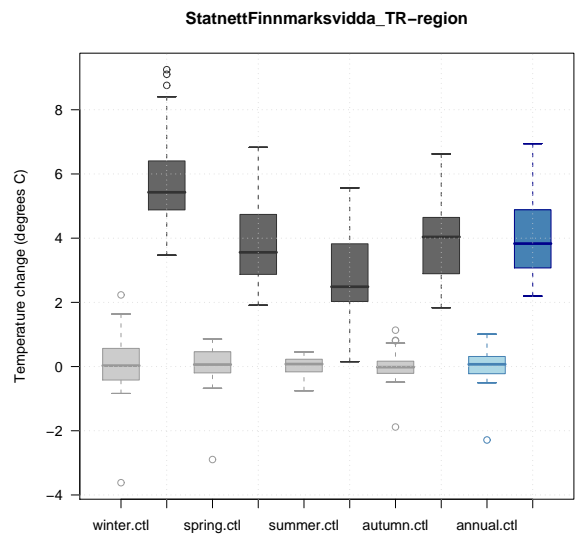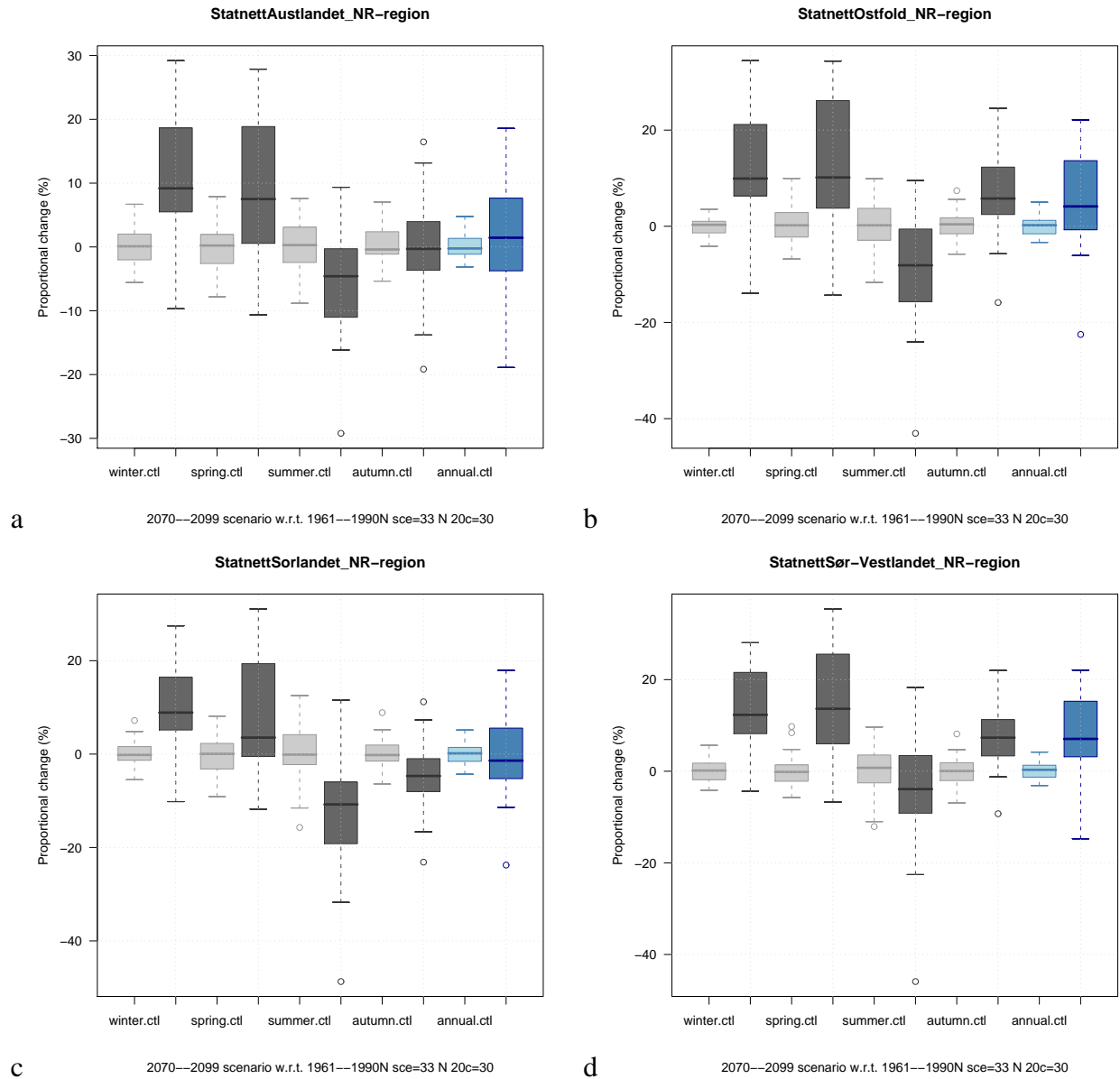
Figure 23: Box-plots showing spread of 20c ESD results (light) and A1b (dark) showing 4 seasons (grey) and the annual mean (blue). Precipitation regions 1–4
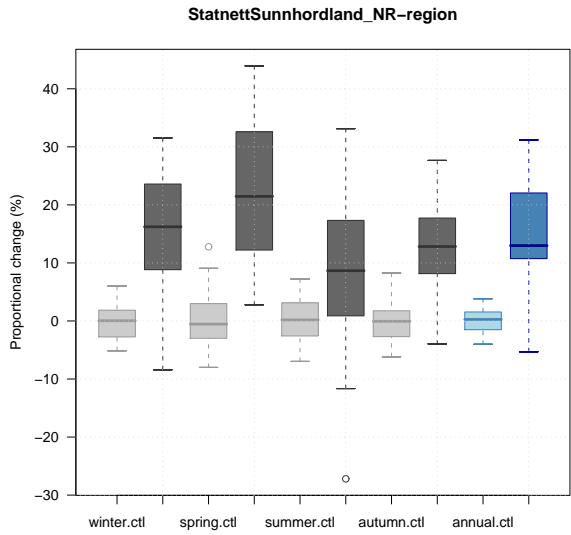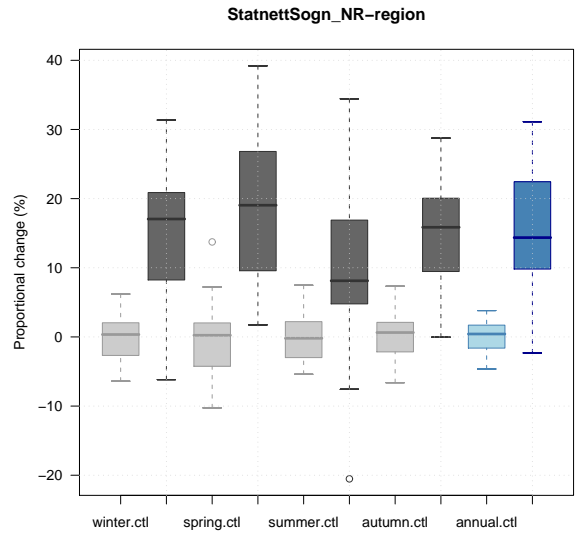
StatnettSunnhordland_NR−region

a   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

StatnettSogn_NR−region

b   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

StatnettMoreRomsdal_NR−region

c   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

StatnettDovreNord−Osterdal_NR−region

d   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

Figure 23 continued. Precipitation regions 5–8

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StatnettInntrondelag_NR–region

a   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

StatnettTrondelagHelgeland_NR–region

b   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

StatnettHalogaland_NR–region

c   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

StatnettVaranger_NR–region

d   2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

Figure 23 continued. Precipitation regions 9–12

48

StatnettFinnmarksvidda_NR−region

2070−−2099 scenario w.r.t. 1961−−1990N sce=33 N 20c=30

a
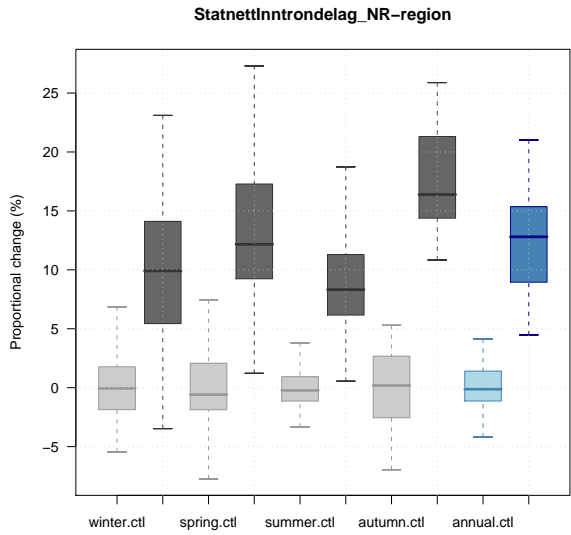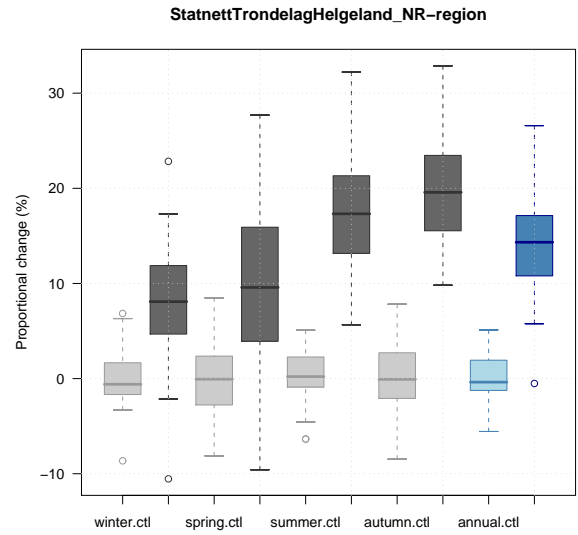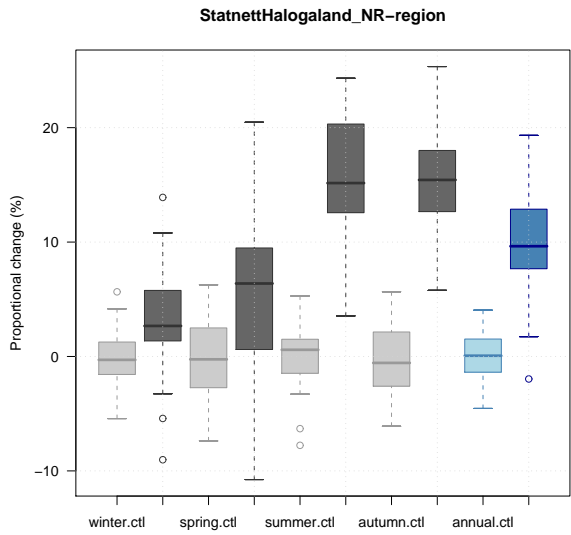
Figure 23 continued. Precipitation region 13

Quality evaluation of downscaling of temperature

In order to get a feeling for uncertainties involved in the ESD, the R^2-statstics from the regression analysis was checked for two arbitrary selected regions. Figure 24 show how the R^2-statstics varies between GCMs (left) and the calendar month (right) for temperature regions 1 and 2. These results veryfy the impression from Figures 3–8 which show corresponding variance in the observations and the downscaled results (indicative of a high R^2-score).

Because the various GCMs may differ in their ability to provide an exact representation of the spatio-temporal structure of the temperature or precipitation modes, the common EOFs may differ somewhat from GCM to GCM. Thus the R^2-statistics may vary with the GCM, although the variation in the R^2-statistics should be small for realistic GCMs (large deviations in the R^2-statistics may be an indicator of model problems).

Figure 25–26 provide additional probe-checks for region 1. To do a systematic diagnosis of all the regions and all the statistics would be over-exhausting. Figure 24 shows the R^2-statistics for all the models and the calendar months, suggesting that these are insensitive to the choice of GCM (left panels) and that the variation with calendar month is modest (right panels). Thus, these results suggest that the outcome is as expected.

The ESD fit (grey) in Figure 25 closely reproduces the observations (dark blue; left), and the scenario (red) indicate similar variance. The regression weights shown in the maps on the left indicate that the local temperature is also most strongly connected with a large-scale patterns centred on the location of the given region, as expected.

An initial set of computations was performed (not shown) where the temperature region 2 contained an error which was identified to be due to incorrect longitude provided to the clim.pact functions. This lead to a poor selection of the predictor domain that did not span the predictand location. The error spotted by Inger Hanssen-Bauer also suggests that the tool works as expected - if the choice of predictor domain is taken from a remote location with weak or no statistical association with the given site, then the analysis should yield unexpected results. The bug was corrected and the analysis was repeated, and the results presented here have passed the human (subjective) quality control.

Additional quality control ensuring smooth variation in the trend estimates throughout the year was not used here (*Benestad*, 2004), but the change in the trend characteristics through the year can then be used to assess the quality of the results. The upper right panel in Figure 26 does indeed show some abrupt variations in the trend estimates around September. December and January trends are also weaker than those of November and February, however, some of these variations are likely due to random statistical fluctuations (note, the statistical fluctuation

from calendar month to calendar month is distinct to the uncertainty associated with the trend estimate marked by the 90% confidence interval in Figure 26) are distinct - both in principle and in practise - to month-to-month statistical fluctuations. The general structure indicates stronger warming in winter and weaker in summer.

The residuals do not reveal any clear trend structures (c) and their distribution is centered around zero and do not deviate too strongly from a Gaussian shape; they are not asymmetric (d). Thus, the quality of the ESD results appear to be of reasonably good quality and hence reliable, given that the GCMs provide a good description of the future evolution.

In summary, the diagnostics from the ESD look re-assuring.
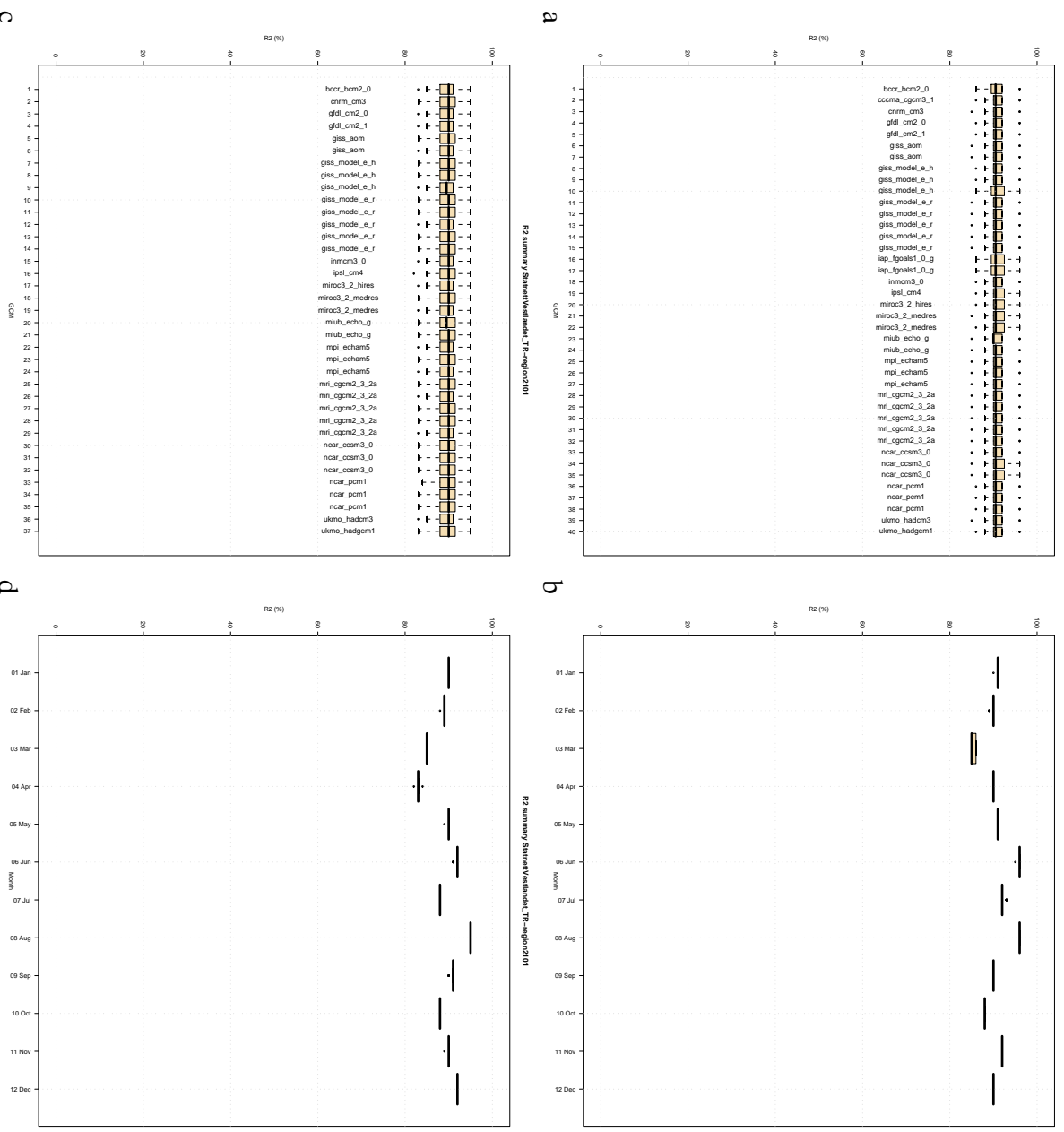
Figure 24: R^2-statistics as a function of GCM (left) and Calendar month (right).

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Empirical Downscaling (era40_t2m [18W50E−40N75N] −> Regional temperature anomaly)

Jan: Trend fit: P−value=0%; Projected trend= 0.34+−0.09 deg C/decade

a   Calibration: Jan Regional temperature anomaly at Austlandet_TR−region1 using era40_t2m: R2=91%, p−value=

Empirical Downscaling (era40_t2m [18W50E−40N75N] −> Regional temperature anomaly)

b   Calibration: Jan Regional temperature anomaly at Austlandet_TR−region1 using era40_t2m: R2=91%, p−value=

Empirical Downscaling (era40_t2m [25W38E−50N75N] −> Regional temperature anomaly)

Jun: Trend fit: P−value=0%; Projected trend= 0.26+−0.04 deg C/decade

c   Calibration: Jun Regional temperature anomaly at Austlandet_TR−region1 using era40_t2m: R2=96%, p−value=

Empirical Downscaling (era40_t2m [25W38E−50N75N] −> Regional temperature anomaly)

d   Calibration: Jun Regional temperature anomaly at Austlandet_TR−region1 using era40_t2m: R2=96%, p−value=

Figure 25: Examples of ESD diagnostics for arbitrary selected GCM, region and two calendar months: January (upper) and June (lower).

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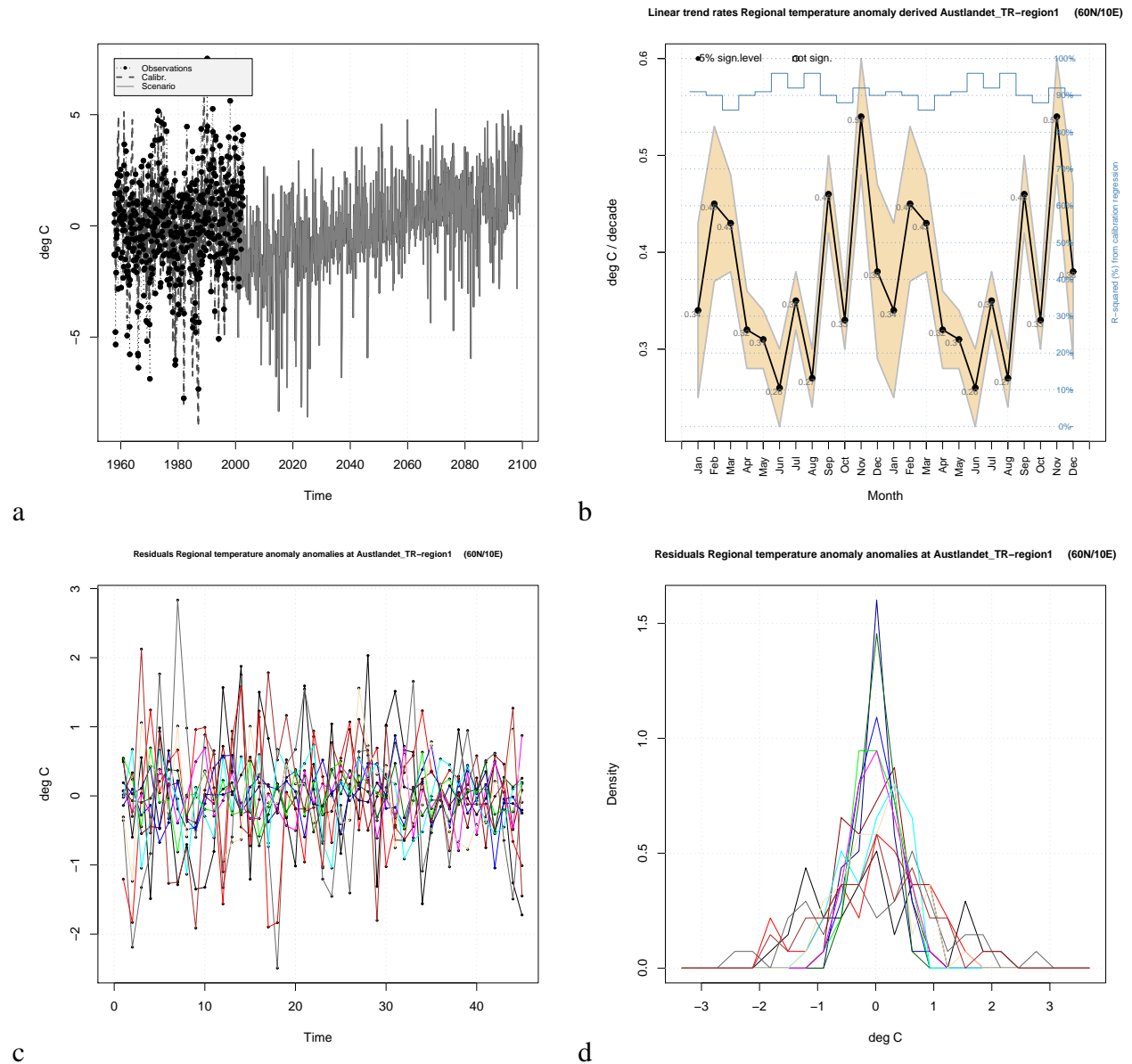
Figure 26: Examples of ESD diagnostics for arbitrary selected GCM, and region: all-year time series (upper left), the variation of trend estimates with the calendar year (upper right; note the year is repeated twice to properly show the December–January transitions), time structure in each of the residuals for each calendar month (lower left), and the distribution of the 12 residuals (lower left). The blue line in the upper left panel marks the R^2 scores for each month, and the yellow-hatched region indicates the 90% confidence interval for the trend estimates.

Figure 27: Region 1:

Quality evaluation of downscaling of precipitation
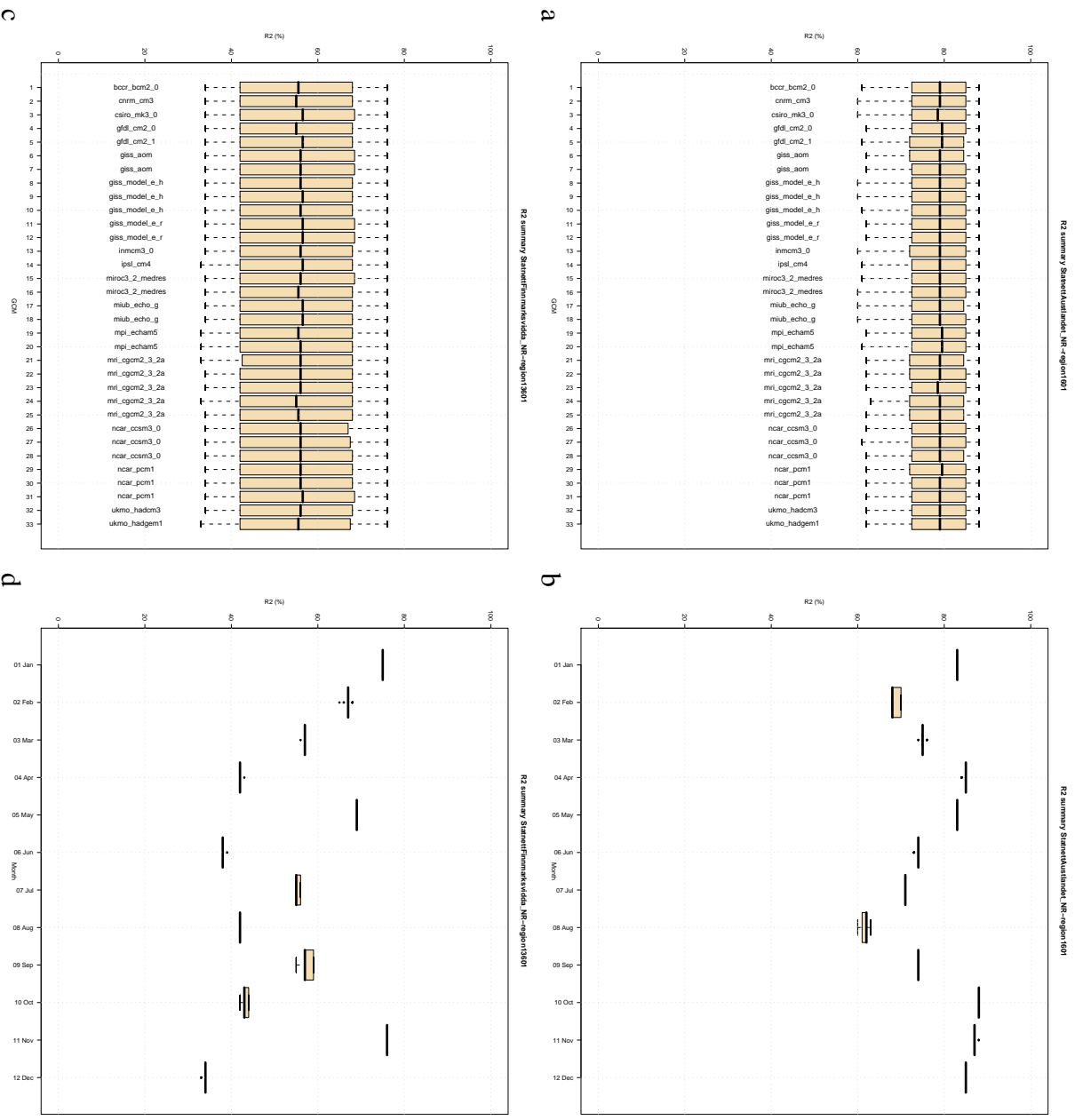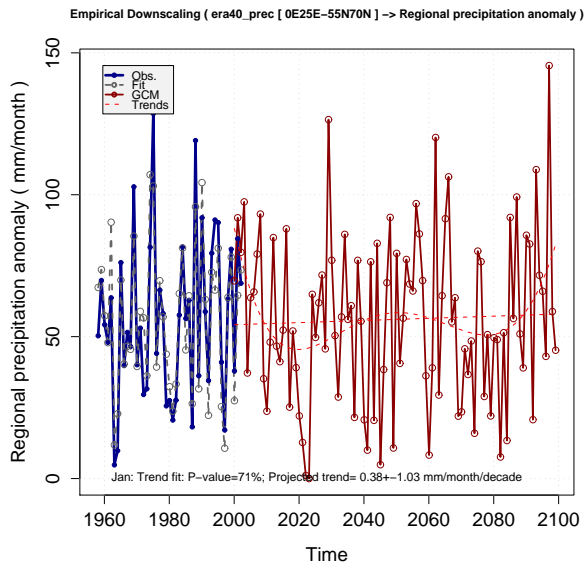
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Empirical Downscaling (era40_prec [0E25E−55N70N] −> Regional precipitation anomaly)

a Calibration: Jan Regional precipitation anomaly at Austlandet_NR−region1 using era40_prec: R2=83%, p−value
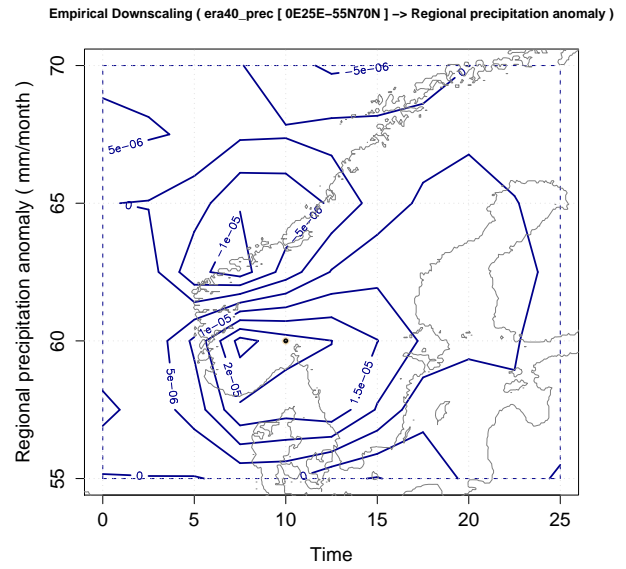
b Calibration: Jan Regional precipitation anomaly at Austlandet_NR−region1 using era40_prec: R2=83%, p−value
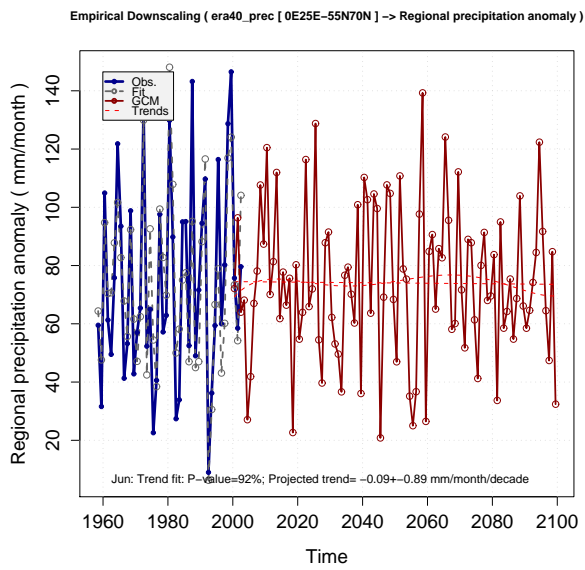
c Calibration: Jun Regional precipitation anomaly at Austlandet_NR−region1 using era40_prec: R2=74%, p−value
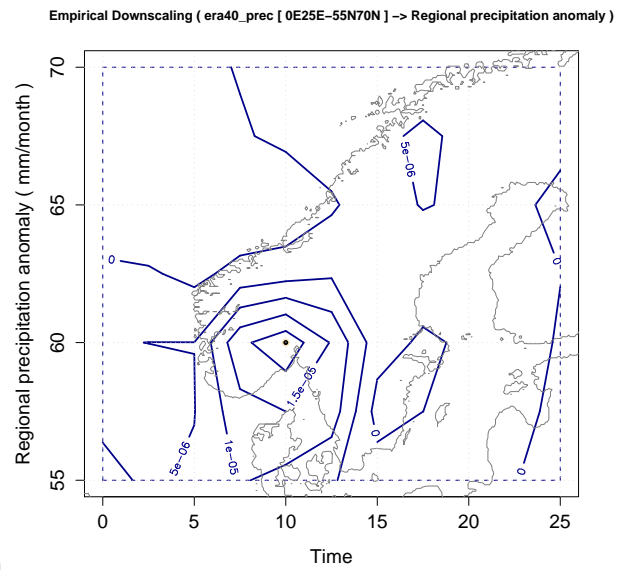
d Calibration: Jun Regional precipitation anomaly at Austlandet_NR−region1 using era40_prec: R2=74%, p−value

Figure 28: Region 1:
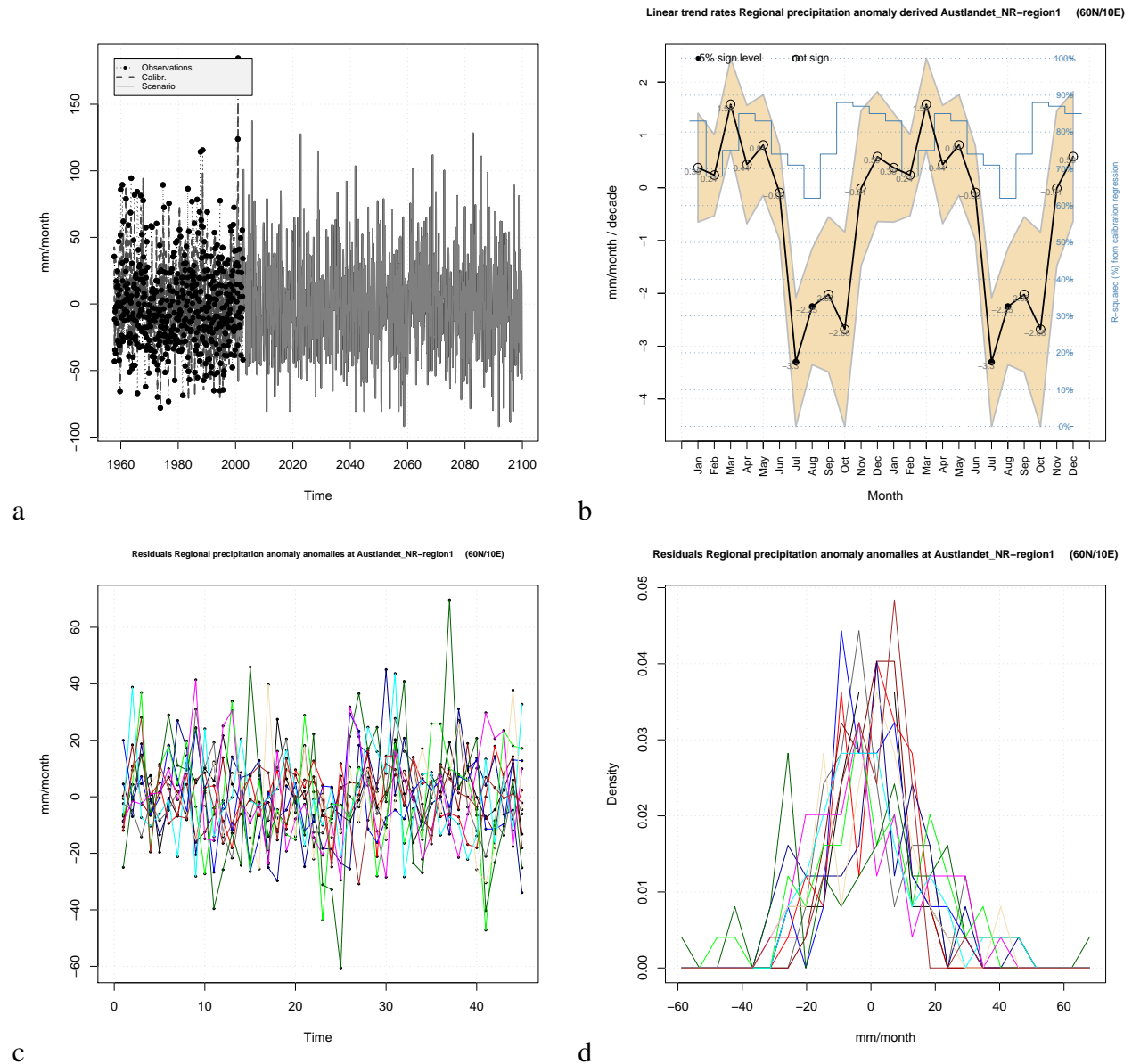
Figure 29: Examples of ESD diagnostics for arbitrary selected GCM, and region: all-year 'un-inflated' time series (upper left), the variation of trend estimates with the calendar year (upper right; note the year is repeated twice to properly show the December–January transitions), time structure in each of the residuals for each calendar month (lower left), and the distribution of the 12 residuals (lower left). The blue line in the upper left panel marks the R^2 scores for each month, and the yellow-hatched region indicates the 90% confidence interval for the trend estimates.

List of GCMs

Table 5: List of the GCMs and the scenario simulations used as input for the ESD-based scenario production. The choice of runs was arbitrary in the sense that only those results that were available at the time of the downloading were selected. The GCMs iap_fgoals1_0_g and cccma_cgcm3_1 were excluded from the present analysis, due to questionable results.

Temperature:

GCM	SRES A1b	c20
bcc_cm1		run 1–2
bccr_bcm2_0	run 1	run 1
cnrm_cm3	run 1	run 1
csiro_mk3_0		run 1
gfdl_cm2_0	run 1	run 1
gfdl_cm2_1	run 1	run 1–3
giss_aom	run 1–2	run 2
giss_model_e_h	run 1–3	run 1–5
giss_model_e_r	run 1–5	
inmcm3_0	run 1	run 1
ipsl_cm4	run 1	run 1
miroc3_2_hires	run 1	
miroc3_2_medres	run 2,3	
miub_echo_g	run 1,3	
mpi_echam5	run 1–3	run 1–3
mri_cgcm2_3_2a	run 1–5	
ncar_ccsm3_0	run 1,2,3	run 1,3,6,9
ncar_pcm1	run 1–3	run 2,3,4
ukmo_hadcm3	run1	run 1,2
ukmo_hadgem1	run1	

Precipitation:

GCM	SRES A1b	c20
bccr_bcm2_0	run 1	run 1
cnrm_cm3	run 1	run 1
csiro_mk3_0	run 1	run 1
gfdl_cm2_0	run 1	run 1
gfdl_cm2_1	run 1	run 1–3
giss_aom	run 1–2	
giss_model_e_h	run 1–3	run 1,3–5
giss_model_e_r	run 2,4	
inmcm3_0	run 1	run 1
ipsl_cm4	run 1	run 1
miroc3_2_medres	run 2,3	
miroc3_2_hires		run1
miub_echo_g	run 1,3	
mpi_echam5	run 1,3	run 1–3
mri_cgcm2_3_2a	run 1–5	
ncar_ccsm3_0	run 1–3	run 1,3,5–7,9
ncar_pcm1	run 1–3	run 2–4
ukmo_hadcm3	run 1	
ukmo_hadgem1	run 1	run 1–2

R-script

Listing of the R-script used to derive these results (file name is `dsStatnett.R`):

```
library(clim.pact)
source("ds_one.R")
#source("met.no/R/ESD.results.R")

chk.R2 <- function(path,scenario="sresa1b") {
  print("Check R2.")

  cmon<-c("01 Jan","02 Feb","03 Mar","04 Apr","05 May","06 Jun",
          "07 Jul","08 Aug","09 Sep","10 Oct","11 Nov","12 Dec")
  precip.list <- list.files(path=path,pattern="Statnett",full.name=TRUE)
  precip.list <- precip.list[grep(".Rdata",precip.list)]
  precip.list <- precip.list[grep(scenario,precip.list)]
  nf <- length(precip.list)
  if (nf > 0) {
    r2 <- rep(NA,nf*12); dim (r2) <- c(nf,12)
    gcms <- rep("NA",nf)
    for (ii in 1:nf) {
      dot <- instring(".",precip.list[ii])
      gcms[ii] <- substr(precip.list[ii],dot[2]+1,dot[3]-nchar(scenario)-1)
    }
    colnames(r2) <- cmon
    rownames(r2) <- gcms
    GCMs <- 1:nf
    print(gcms)
    site <- rep(NA,nf); gcm <- site; run <- site

    for (i in 1:nf) {
      #print(precip.list[i])
      load(precip.list[i])
      #print(ls())
      r2[i,1] <- ds.station$Jan$fit.r2
      r2[i,2] <- ds.station$Feb$fit.r2
      r2[i,3] <- ds.station$Mar$fit.r2
      r2[i,4] <- ds.station$Apr$fit.r2
      r2[i,5] <- ds.station$May$fit.r2
      r2[i,6] <- ds.station$Jun$fit.r2
      r2[i,7] <- ds.station$Jul$fit.r2
      r2[i,8] <- ds.station$Aug$fit.r2
      r2[i,9] <- ds.station$Sep$fit.r2
      r2[i,10] <- ds.station$Oct$fit.r2
      r2[i,11] <- ds.station$Nov$fit.r2
      r2[i,12] <- ds.station$Dec$fit.r2
      print(paste(precip.list[i],i,nf,min(r2[i,]),max(r2[i,])))
    }
    save(file=paste(path,"/chkQ-pr.rdata",sep=""),r2)

    slsh <- instring("/",path)
    path <- substr(path,slsh[length(slsh)]+1,nchar(path))
    par(las=2,cex=0.5)
    boxplot(r2 ~ GCMs,col="wheat",ylim=c(0,100),
            main=paste("R2 summary",path),xlab="GCM",ylab="R2 (%)")
    text(1:nf,min(r2)-15,gcms,srt=90,cex=1.1)
    grid()
    print(paste("Fig-",path,"_chk-r2-gcm.eps",sep=""))
    dev.copy2eps(file=paste("Fig-",path,"_chk-r2-gcm.eps",sep=""))

    boxplot(t(r2) ~ cmon,col="wheat",ylim=c(0,100),
            main=paste("R2 summary",path),xlab="Month",ylab="R2 (%)")
    grid()
    print(paste("Fig-",path,"_chk-r2-cmon.eps",sep=""))
    dev.copy2eps(file=paste("Fig-",path,"_chk-r2-cmon.eps",sep=""))
  } else print("No rdata files")
  invisible(r2)
}

eval.GCMs <- function(path="STATNETT/",ele="101",mon=1:12) {
```

```
    par(cex.axis=1,las=1,mfrow=c(1,1))
    element <- switch(ele,"101"="Temperature","601"="Precipitation")
    subdir.list <- list.files(path=path,pattern=ele,full.name=TRUE)
    print(subdir.list)
    N <- length(subdir.list)
    gcms <- rownames(chk.R2(subdir.list[1]))
    M <- length(gcms)
    Y <- rep(NA,N*12*M); dim(Y) <- c(M,12,N)
    R2 <- list(gcm=gcms,Y=Y)
    for (i in 1:N) {
      y <- chk.R2(subdir.list[i])
      #print("HERE")
      #print(c(dim(R2$Y[i,,]),NA,dim(y)))
      d <- dim(y)
      R2$Y[1:d[1],,i] <- t(y)
    }
    print(summary(R2))


    boxplot(Y[,,mon] ~ gcm,data=R2,col="wheat",ylim=c(0,100),
            main=paste("R2 summary:",element),xlab="",ylab="R2 (%)",sub="")
    text(1:length(R2$gcm),rep(40,length(R2$gcm)),R2$gcm)
    grid()
    dev.copy2eps(file=paste("Fig-GCMs_chk-",ele,"-R2.eps",sep=""))
    invisible(R2)
}

showStatnett <- function(location="unspecified",ele=101,method="rowSums") {
    print(paste("showStatnett: location=",location))
    snett <- ESD.results(station=location,ele=ele,predictand="Statnett",
                         directory="STATNETT/",case.sens=TRUE)

    plotESD.box(snett)
    plotESD.plume(snett,method=method)
    loc <- substr(location,1,nchar(location))
    print(paste("Look up: STATNETT/",loc,".Rdata",sep=""))
    if (file.exists(paste("STATNETT/",loc,".Rdata",sep=""))) {
      load(paste("STATNETT/",loc,".Rdata",sep=""))
      obs.hdd <- eval(parse(text=paste(method,"(obs$val)",sep="")))
      points(obs$yy,obs.hdd,pch=19)
      lines(obs$yy,obs.hdd,lwd=2,lty=2)
    }
    invisible(snett)
}


computeStatnett <- function(ds=TRUE,param="TAM",rt="TR",exclude=c("iap_fgoals","cccma_cgcm3_1","bcc_cm1")) {

  ele <- switch(param,"TAM"=101,"RR"=601)
  unit <- switch(param,"TAM"="deg C","RR"="mm/month")
  obs.name <- switch(param,"TAM"="Regional temperature","RR"="Regional precipitation")

  url <- paste("http://klapp.oslo.dnmi.no/metnopub/production/metno?re=20&ct=text/plain&p=",
                    param,"&fy=1900&r_type=",rt,sep="")
  print(url)
  region.curve <- read.table(url,header=TRUE)
  regions <- as.numeric(rownames(table(region.curve$region_no)))
  for (i in regions) {
    if (rt=="GR") location <- switch(as.character(i),
                                     "0"="Heile_landet","1"="Austlandet","2"="Agder",
                                     "3"="Vestlandet","4"="Trondelag","5"="Nord-Noreg") else
    if (rt=="TR") location <- switch(as.character(i),
                                     "0"="Heile_landet","1"="Austlandet","2"="Vestlandet",
                                     "3"="Trondelag","4"="Nordland+Troms","5"="Varanger",
                                     "6"="Finnmarksvidda") else

    if (rt=="NR") location <- switch(as.character(i),
                                     "0"="Heile_landet","1"="Austlandet","2"="Ostfold",
                                     "3"="Sorlandet","4"="Sør-Vestlandet","5"="Sunnhordland",
                                     "6"="Sogn","7"="More+Romsdal","8"="Dovre+Nord-Osterdal",
```

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```
                          "9"="Inntrondelag","10"="Trondelag+Helgeland","11"="Halogaland",
                          "12"="Varanger","13"="Finnmarksvidda")
    location <- paste(location,"_",rt,"-region",i,sep="")

    if (rt=="GR") lon <- switch(as.character(i),"0"=20,"1"=10,"2"=8,"3"=6,"4"=11,"5"=15) else
    if (rt=="TR") lon <- switch(as.character(i),"0"=20,"1"=10,"2"=6,"3"=11,"4"=13,"5"=25,"6"=20) else
    if (rt=="NR") lon <- switch(as.character(i),"0"=20,"1"=10,"2"=12,"3"=8,"4"=7,"5"=6,
                                "6"=6,"7"=7,"8"=10,"9"=12,"10"=11,"11"=12,"12"=25,"13"=20)
    if (rt=="GR") lat <- switch(as.character(i),"0"=65,"1"=60,"2"=58,"3"=61,"4"=63,"5"=67) else
    if (rt=="TR") lat <- switch(as.character(i),"0"=65,"1"=60,"2"=62,"3"=63,"4"=66,"5"=70,"6"=68) else
    if (rt=="NR") lat <- switch(as.character(i),"0"=65,"1"=60,"2"=59,"3"=58,"4"=58,"5"=61,
                                "6"=62,"7"=63,"8"=62,"9"=63,"10"=64,"11"=65,"12"=70,"13"=68)

    iextract <- is.element(region.curve$region_no,i) & is.element(region.curve$month,1:12)

    x <- region.curve$region_value[iextract]
    year <- region.curve$year[iextract]
    month <- region.curve$month[iextract]
    obs <- station.obj(x=x,yy=year,mm=month,ele=ele,unit=unit,
                       location=location,obs.name=obs.name,
                       lon=lon,lat=lat)

    plotStation(obs,what="t",l.anom=FALSE,type="b",lty=1,pch=19)

    if (ele==101) {
      lon=c(-90,50); lat=c(40,75)
    } else {
      lon=c(0,40); lat=c(55,73)}

    if (ds) ds.one(ele=ele,cmons=1:12,silent=FALSE,
            do.a1b=TRUE,do.rcm=0,qc=FALSE,station=obs,predictand = "Statnett",
            dir="/home/rasmusb/data/ipcc_FoAR/GCMs/",op.path="STATNETT",exclude=exclude,
            lon=lon,lat=lat)

    save(obs,file=paste("STATNETT/",obs$location,".Rdata",sep=""))
    while (dev.cur() > 1) dev.off()
  }
}


finalStatnett <- function(ele=101,inflation=FALSE,period=1995:2025) {
  seasons <- matrix(c(12,1,2,3:5,6:8,9:11),3,4)
  cols <- c("blue","green","darkgreen","red")
  locations <- list.files(path="STATNETT",pattern=".Rdata")
  print(locations)
  regtype <- switch(as.character(ele),"101"="TR","601"="NR")
  dig     <- switch(as.character(ele),"101"=1,"601"=0)
  locations <- locations[grep(regtype,locations)]
  M <- rep(NA,101*4); dim(M) <- c(101,4); Q1 <- M; Q2 <- M; M.0 <-  M
  m <- rep(NA,106*4); dim(m) <- c(106,4); q1 <- m; q2 <- m; m.0 <- m
  trend <- rep(NA,201*4); dim(trend) <- c(201,4)
  print(locations)
  n <- length(locations)
  sce.2000.2040 <- rep("NA",n*4); dim(sce.2000.2040) <- c(n,4); sce.0.2000.2040 <- sce.2000.2040
  clim <- rep(NA,4*n); dim(clim) <- c(n,4)

  colnames(sce.2000.2040) <- c("Winter","Spring","Summer","Autumn")
  colnames(clim) <- c("Winter","Spring","Summer","Autumn")
  Clim <- clim

  locs <- rep("?",n)
  for (i in 1:n) {
    t <- 2000:2100
#print(paste("HERE1",locs[i]))
    load(paste("STATNETT/",locations[i],sep=""))
    locs[i] <- substr(locations[i],1,nchar(locations[i])-6)
    print(paste("locs[i]=",locs[i]))
    statnett <- showStatnett(locs[i],ele=ele)
    par(cex.axis=1,las=1,mfrow=c(1,1))
    plot(c(1900,2100),range(statnett$sce,na.rm=TRUE),type="n",main=locs[i])
```

```
    grid()
    N <- length(statnett$scen.files.a1b)
    Z <- rep(NA,101*4); dim(Z) <- c(101,4)
    z <- rep(NA,101*N*4); dim(z) <- c(101,N,4); z.0 <- z
    X <- obs$yy
    XX <- rep(NA,101)
    #print(summary(obs))
    for (igcm in 1:N) {
#print(paste("HERE2",igcm,statnett$scen.files.a1b))
      for (is in 1:4) {
        if (ele==101) Y <- rowMeans(obs$val[,seasons[,is]]) else
        if (ele==601) Y <- rowSums(obs$val[,seasons[,is]])
        iii1 <- is.element(1910:2010,X)
        iii2 <- is.element(X,1910:2010)
        #print(Y); print(dim(Z)); print(length(iii1))
        Z[iii1,is]<- Y[iii2]; XX[iii1] <- X[iii2]
        if (ele==101) {
          y <- colMeans(statnett$sce[igcm,seasons[,is],])
          clim[i,is] <- mean(obs$val[is.element(obs$yy,1961:1990),seasons[,is]],na.rm=TRUE)
          Clim[i,is] <- mean(obs$val[is.element(obs$yy,1995:2007),seasons[,is]],na.rm=TRUE)
        } else if (ele==601) {
          y <- colSums(statnett$sce[igcm,seasons[,is],])
          clim[i,is] <- mean(rowSums(obs$val[is.element(obs$yy,1961:1990),seasons[,is]]),na.rm=TRUE)
          Clim[i,is] <- mean(rowSums(obs$val[is.element(obs$yy,1995:2007),seasons[,is]]),na.rm=TRUE)
          obs$unit <- "mm/season"
        }
        x <- statnett$yy.21c
        match1 <- is.element(x,X)
        match2 <- is.element(X,x)
        if (inflation) scal <- sd(Y,na.rm=TRUE)/sd(y[1:30],na.rm=TRUE) else
                       scal <- 1
        y.0 <- (y - min(y,na.rm=TRUE))*scal + clim[i,is]
        y   <- (y - mean(y[match1],na.rm=TRUE))*scal +  mean(Y[match2],na.rm=TRUE)
        if (ele==601) { y[y < 0] <- 0;  y.0[y.0 < 0] <- 0}
        #y[y > 1000] <- NA;  y.0[y.0 > 1000] <- NA
        iii1 <- is.element(2000:2100,x)
        iii2 <- is.element(x,2000:2100)
        #print(dim(z)); print(length(iii1));print(length(iii2)); print(length(y)); print(x)
        z.0[iii1,igcm,is] <- y.0[iii2]
        z[iii1,igcm,is] <- y[iii2]
        lines(x,y - mean(y,na.rm=TRUE),col=cols[is],lwd=2)
#print(paste("HERE3",is))
      }
    }


#print("HERE4")
    for (is in 1:4) {
    for (it in 1:101) {
      M.0[it,is] <-  median(z.0[it,,is],na.rm=TRUE)
      M[it,is] <-  median(z[it,,is],na.rm=TRUE)
      Q1[it,is] <- quantile(z[it,,is],0.05,na.rm=TRUE)
      Q2[it,is] <- quantile(z[it,,is],0.95,na.rm=TRUE)
    }
    # print(length(Z[,is])); print(length(XX))

    # Match and combine observed and predicted trends.
    ok <- is.finite(Z[,is]) & is.finite(XX)
    trend.obs <- lm(Z[ok,is]   ~ XX[ok] + I(XX[ok]^2) + I(XX[ok]^3))
    trendM.0  <- lm(M.0[,is]   ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5))
    jj1 <- is.element(XX[ok],t)
    jj2 <- is.element(t,XX[ok])
    predict.obs <- predict(trend.obs)
    predict.0 <- predict(trendM.0)
    predict.0 <- predict.0 - mean(predict.0[jj2],na.rm=TRUE) + mean(predict.obs[jj1],na.rm=TRUE)
    tt <- c(XX[ok],t[!jj2])
    m.0 <- c(predict.obs,predict.0[!jj2])
    jj3 <- is.element(1900:2100,c(XX[ok],t[!jj2])) & is.finite(m.0)
    trend[jj3,is]  <- round(predict(lm(m.0  ~ tt + I(tt^2) + I(tt^3) + I(tt^4) + I(tt^5) + I(tt^6) + I(tt^7))),2)


    trendM  <- lm(M[,is]   ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5))
```

```
    trendQ1 <- lm(Q1[,is] ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5))
    trendQ2 <- lm(Q2[,is] ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5))
    good <- c(rep(TRUE,5),is.finite(M[,is]))
    m[good,is]  <- round(c(Z[is.element(1910:2010,1995:1999),is],predict(trendM)),2)
    q1[good,is] <- round(c(Z[is.element(1910:2010,1995:1999),is],predict(trendQ1)),2)
    q2[good,is] <- round(c(Z[is.element(1910:2010,1995:1999),is],predict(trendQ2)),2)
  }
  t <- 1995:2100
  #print(c(length(t),NA,dim(m),NA,length(Z[is.element(1910:2010,1995:1999),is]),NA,sum(good)))

  intv.0 <- is.element(1900:2100,period)
  intv <- is.element(t,period)
  par(cex.axis=1,las=1,mfrow=c(2,2),cex.axis=0.7)

  for (is in 1:4) {
    plot(c(1950,2100),range(c(z[,,is],Z[,is]),na.rm=TRUE),type="n",main=locs[i],
         ylab=obs$unit,xlab="")
    grid()
    for (igcm in 1:N) lines(2000:2100,z[,igcm,is],lwd=2,col="grey")
    lines(1910:2010, Z[,is],type="b")
    points(1910:2010, Z[,is], pch=19)
    lines(1900:2100,trend[,is],col="pink",lty=2,lwd=2)

    print(c(length(t),NA,dim(m)))
    lines(t,m[,is],lty=2,lwd=2,col="red")
    lines(t,q1[,is],lty=2,lwd=1,col="red")
    lines(t,q2[,is],lty=2,lwd=1,col="red")

    lines(c(1950,2100),rep(clim[i,is],2),lty=3,lwd=1,col="black")
    lines(c(1950,2100),rep(Clim[i,is],2),lty=3,lwd=1,col="grey30")

    jj4 <- is.element(1900:2100,t)                               # REB: 06/02/2008
    Qq1 <- q1 - m + trend[jj4,]; Qq2 <- q2 - m + trend[jj4,]     # REB: 06/02/2008

    sce.0.2000.2040[i,is] <- paste(round(mean(trend[intv.0,is]),dig)," [",             # REB: 06/02/2008
        round(mean(Qq1[intv,is]),dig)," - ",round(mean(Qq2[intv,is]),dig),"]",sep="")  # REB: 06/02/2008
    sce.2000.2040[i,is] <- paste(round(mean(m[intv,is]),dig)," [",
        round(mean(q1[intv,is]),dig)," - ",round(mean(q2[intv,is]),dig),"]",sep="")

    if (ele==101) axis(side=4,at=seq(-15,15,by=1)+clim[i,is],labels=seq(-15,15,by=1),las=0,col="grey30") else
    axis(side=4,at=seq(-1500,1500,by=100)+clim[i,is],labels=seq(-1500,1500,by=100),las=0,col="grey30")
  }
  legend(1950,max(c(z[,,is],Z[,is]),na.rm=TRUE),
         c("Obs","MMD scenarios","MMD mean trend","95% conf. int"),
         col=c("black","grey","red","red"),bg="grey95",
         cex=0.6,lty=c(0,1,2,2),lwd=c(0,1,2,1),pch=c(19,26,26,26),)
  dev2bitmap(file=paste("Fig_",locs[i],".jpg",sep=""),type="jpeg",res=200)

  dev.copy2eps(file=paste("Fig_",locs[i],".eps",sep=""))

# qQ <- q                                                          # REB: 06/02/2008
# for (iii in 1:4) {                                               # REB: 06/02/2008
#   qQ[,i] <- qQ[,i] - m[,i] + trend[[jj4,i]                       # REB: 06/02/2008
# }                                                                # REB: 06/02/2008

  scen.0 <- data.frame(Year=1900:2100,
                       DJF.ave=trend[,1],
                       MAM.ave=trend[,2],
                       JJA.ave=trend[,3],
                       SON.ave=trend[,4])

  write.table(scen.0,file=paste("Res_",locs[i],"_",ele,".0.txt",sep=""),quote=FALSE,sep="\t")

  scen <- data.frame(Year=t,
                     DJF.q05=q1[,1],DJF.ave=m[,1],DJF.q95=q2[,1],
                     MAM.q05=q1[,2],MAM.ave=m[,2],MAM.q95=q2[,2],
                     JJA.q05=q1[,3],JJA.ave=m[,3],JJA.q95=q2[,3],
                     SON.q05=q1[,4],SON.ave=m[,4],SON.q95=q2[,4])

  write.table(scen,file=paste("Res_",locs[i],"_",ele,".txt",sep=""),quote=FALSE,sep="\t")
```

```
    }

    rownames(sce.2000.2040) <- locs
    rownames(clim) <- locs
    write.table(sce.2000.2040,file=paste("Statnett_",ele,"_",min(period),"-",max(period),
                          ".txt",sep=""),quote=FALSE,sep="\t")
    write.table(sce.0.2000.2040,file=paste("Statnett_",ele,"_",min(period),"-",max(period),
                          ".0.txt",sep=""),quote=FALSE,sep="\t")
    write.table(round(clim,dig),file=paste("Clim_",ele,"_1961-1990.txt",sep=""),quote=FALSE,sep="\t")
    write.table(round(Clim,dig),file=paste("Clim_",ele,"_1995-2007.txt",sep=""),quote=FALSE,sep="\t")
    invisible(sce.2000.2040)
}

#remove.Rdata.files(path="STATNETT")


showall <- function(location="unspecified",predictand="Statnett",ele=101,months=1:12) {
    # print(location)
    method <- switch(as.character(ele),"101"="rowMeans","601"="rowSums")
    esd <- ESD.results(station=location,ele=ele,predictand=predictand,
                       directory="STATNETT/",case.sens=TRUE,verbose=FALSE)
    pref= switch(as.character(ele),"101"="t2m-","601"="rr-")
    N <- length(esd$scen.files.a1b)

    plume <- plotESD.plume(esd,method=method,month=months)
    print(paste("Look up: STATNETT/",substr(location,1,nchar(location)-3),".Rdata",sep=""))
    obs.name <- paste("STATNETT/",substr(location,1,nchar(location)-3),".Rdata",sep="")
    if (file.exists(obs.name)) {
      load(obs.name)
      cline <- paste(method,"(obs$val[,c(",months[1],",",months[2],",",months[3],")])",sep="")
      # print(cline); print(dim(obs))
      obs.hdd <- eval(parse(text=cline))
      points(obs$yy,obs.hdd,pch=19,cex=1.0)
      lines(obs$yy,obs.hdd,lwd=2,lty=2)
    } else print(paste(" --- xxx --- Could not find",obs.name))
    esd$plume <- plume
    esd$obs <- obs.hdd; esd$yy.obs <- obs$yy
    invisible(esd)
}


finalPlot <- function(path="STATNETT",pattern="Statnett",ele=101) {
  seasons <- cbind(c(12,1,2),3:5,6:8,9:11)
  nm <- 3
  locations <- list.files(path=path,pattern=pattern)
  regtype <- switch(as.character(ele),"101"="TR","601"="NR")
  locations <- locations[grep(regtype,locations)]
  if (ele==101) locations <- locations[-grep("+",locations,fixed=TRUE)]

  print(locations)
  locs <- locations
  n <- length(locations)
  hdd1 <- rep(NA,nm*100*n); dim(hdd1) <- c(nm*100,n); ci1.1 <- hdd1; ci1.2 <- hdd1
  hdd2 <- rep(NA,nm*100*n); dim(hdd2) <- c(nm*100,n); ci2.1 <- hdd1; ci2.2 <- hdd1
  Y <- rep(NA,200); X <- Y; CI1 <- Y; CI2 <-  Y
  date1 <- rep(NA,nm*100); date2 <- rep(NA,nm*100)
  count.under <- rep(0,4); count.over <- rep(0,4)
  for (ireg in 1:n) {
    par(cex.axis=1,las=1,mfrow=c(2,2),cex.axis=0.7,mar=c(2, 4, 3, 2) + 0.1,cex.main=0.7)
    count.under[] <- 0; count.over[] <- 0
    for (is in 1:4) {
      iii <- 1
      locs[ireg] <- substr(locations[ireg],9,nchar(locations[ireg]))
      esd <- showall(locs[ireg],predictand=pattern,ele=ele,months=seasons[,is])
      for (ii in 1:100) {
        for (im in seasons[,is]) {
          hdd1[iii,ireg] <- round(mean(esd$ctl[,im,ii],na.rm=TRUE),1)
          ci1.1[iii,ireg] <- round(quantile(esd$ctl[,im,ii],0.05,na.rm=TRUE),1)
```

```
            ci1.2[iii,ireg] <- round(quantile(esd$ctl[,im,ii],0.95,na.rm=TRUE),1)
            hdd2[iii,ireg] <- round(mean(esd$sce[,im,ii],na.rm=TRUE),1)
            ci2.1[iii,ireg] <- round(quantile(esd$sce[,im,ii],0.05,na.rm=TRUE),1)
            ci2.2[iii,ireg] <- round(quantile(esd$sce[,im,ii],0.95,na.rm=TRUE),1)
            date1[iii] <- esd$yy.20c[ii]*100+im
            date2[iii] <- esd$yy.21c[ii]*100+im
            iii <- iii+1
        }
        if (ele==101) {
            points(date1[iii-nm]/100,mean(hdd1[(iii-nm):(iii-1),ireg],na.rm=TRUE),col="yellow",pch=19,cex=0.5)
            points(date2[iii-nm]/100,mean(hdd2[(iii-nm):(iii-1),ireg],na.rm=TRUE),col="yellow",pch=19,cex=0.5)
            Y[ii] <- mean(hdd1[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            Y[ii+100] <- mean(hdd2[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI1[ii] <- mean(ci1.1[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI1[ii+100] <- mean(ci2.1[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI2[ii] <- mean(ci1.2[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI2[ii+100] <- mean(ci2.2[(iii-nm):(iii-1),ireg],na.rm=TRUE)
        } else {
            points(date1[iii-nm]/100,sum(hdd1[(iii-nm):(iii-1),ireg],na.rm=TRUE),col="yellow",pch=19,cex=0.5)
            points(date2[iii-nm]/100,sum(hdd2[(iii-nm):(iii-1),ireg],na.rm=TRUE),col="yellow",pch=19,cex=0.5)
            Y[ii] <- sum(hdd1[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            Y[ii+100] <- sum(hdd2[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI1[ii] <- sum(ci1.1[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI1[ii+100] <- sum(ci2.1[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI2[ii] <- sum(ci1.2[(iii-nm):(iii-1),ireg],na.rm=TRUE)
            CI2[ii+100] <- sum(ci2.2[(iii-nm):(iii-1),ireg],na.rm=TRUE)
        }
        X[ii] <- date1[iii-nm]/100; X[ii+100] <- date2[iii-nm]/100
    }
    trend <- lm(Y ~ X + I(X^2) + I(X^3)+ I(X^4) + I(X^5))
    trendQ1 <- lm(CI1 ~ X + I(X^2) + I(X^3)+ I(X^4) + I(X^5))
    trendQ2 <- lm(CI2 ~ X + I(X^2) + I(X^3)+ I(X^4) + I(X^5))
    lines(X,predict(trend),lty=2,lwd=2,col="red")
    lines(X,predict(trendQ1),lty=2,lwd=1,col="pink")
    lines(X,predict(trendQ2),lty=2,lwd=1,col="pink")

    iii1 <- is.element(round(X),esd$yy.obs)
    iii2 <- is.element(esd$yy.obs,round(X))

    # print(sum(iii1)); print(summary(esd$obs[iii2])); print(summary(predict(trendQ1)[iii1]))
    count.under[is] <- sum(esd$obs[iii2] - predict(trendQ1)[iii1] < 0,na.rm=TRUE)
    count.over[is] <-sum(esd$obs[iii2] - predict(trendQ2)[iii1] > 0,na.rm=TRUE)

    if (is==1) legend(1900,esd$plume$ylim[2],
                      c("Obs","MMD mean"),col=c("black","yellow"),bg="grey95",cex=0.7,pch=19)

    if (is==1) results <- data.frame(Year=X,winter.mean=round(predict(trend),2),
        winter.CI1=round(predict(trendQ1),2),winter.CI2=round(predict(trendQ2),2)) else
    if (is==2) {
      results$spring.mean <- round(predict(trend),2)
      results$spring.CI1 <- round(predict(trendQ1),2)
      results$spring.CI2 <- round(predict(trendQ2),2)
    } else if (is==3) {
      results$summer.mean <- round(predict(trend),2)
      results$summer.CI1 <- round(predict(trendQ1),2)
      results$summer.CI2 <- round(predict(trendQ2),2)
    } else if (is==4) {
      results$autumn.mean <- round(predict(trend),2)
      results$autumn.CI1 <- round(predict(trendQ1),2)
      results$autumn.CI2 <- round(predict(trendQ2),2)
    }
}
dev2bitmap(file=paste("Fig","_",locs[ireg],"_",pattern,"-2.jpg",sep=""),type="jpeg",res=200)
dev.copy2eps(file=paste("Fig","_",locs[ireg],"_",pattern,"-2.eps",sep=""))
filename <- paste("ds_",locs[ireg],"_",pattern,"-2.txt",sep="")
write.table(results,file=filename, quote = FALSE)
print(paste("          -------> ireg=",ireg," region=",locations[ireg],"=",locs[ireg]))
print("----------------Counts over and under:----------------")
print(count.over)
print(count.under)
```

```
    Npast <- sum(iii1)
    print(paste("90% conf. int: ",sum(pbinom(1:Npast,Npast,0.05) < 0.05),sum(pbinom(1:Npast,Npast,0.05) < 0.95),
                " N=",Npast))
    print("-------------------------------------------------------")
  }


  hdd <- rbind(hdd1,hdd2)
  print(dim(hdd)); print(length(locs))
  colnames(hdd) <- locs
  rownames(hdd) <- c(date1,date2)
  invisible(hdd)
}
```