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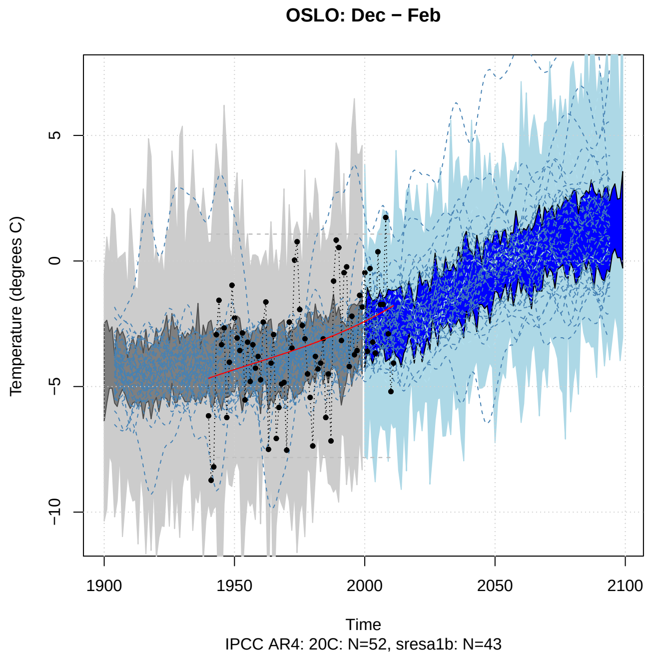
Climate

Updated temperature and precipitation scenarios for Norwegian climate regions

R.E. Benestad



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Abstract

A set of new empirical-statistical downscaling and dynamical downscaling analyses has been carried out for seasonal mean temperature and seasonal precipitation totals for a number of climate regions in Norway. The new results are based on a set-up using the most up-to-date tools and knowledge, as well as on a slightly enlarged ensemble of global climate models. The present results give a similar description as previous analysis, albeit with slightly wider confidence intervals. The analyses suggest that the warming trends will continue, and that the northernmost regions will receive more precipitation amounts in the future for all seasons. For the summer months, the results suggest the future precipitation may be similar or slightly less than at present in southern Norway. An analysis of the combination dry-autumn/cold-winter suggests decreased probabilities in the future due to the projected warming and wetter future conditions.

A crude analysis of the annual minimum of 3-day-averaged temperature over southern Fennoscandia, based on 14 different GCMs following the SRES A1b emission scenario, suggest that future cold days will unlikely be as cold as in the present day. The annual minimum 3-day mean temperature over Scandinavia correlates with observed minima in Oslo, Bergen, Trondheim and Tromsø, and estimates for these locations are made, based on a simple regression analysis. The return values for cold conditions from historical measurements are also presented.

Keywords

climate change, regional climate modelling, empirical-statistical downscaling

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Contents

1 Introduction

The results and discussion presented here is an extension of previous analysis for STATNETT published in *Benestad* (2008a), and includes new insight and new information since then.

1.1 Motivation

The motivation of this work is to provide an updated account on how a future climate change, associated with increased greenhouse gas concentrations, may affect local temperature and precipitation in Norway. This report will also discuss new and relevant studies published in the scientific literature.

Local and regional climate projections are associated with a substantial degree of uncertainty, and there have been some concerns raised about whether the climate models are capable at all of providing good information about local climate (*Oreskes* et al., 2010; *Palmer*, 2011; *Kerr*, 2011; *Pielke Sr. & Wilby*, submitted). Different models may give different accounts of future trends for regional phenomena such as the El Niño Southern Oscillation (*Solomon* et al., 2007), and all the global climate models (GCMs; here I use the abbreviation GCM also to include earth system modens, also referred to as 'ESMs') used in climate studies involve an ocean component with too coarse spatial resolution to adequately describe the ocean currents. It is also acknowledged that local land surface characteristics have an influence of the local climate. Hence, progress in the GCMs (e.g. higher resolution or better representation of processes, conditions, and model physics) will advance out capability to provide reliable climate projections, in addition to improved ways of model experiment (ensemble size and design) set up and post processing (Bayesian statistics and downscaling).

The concerns regarding the models' ability to describe local climates tend to focus entirely on the models themselves (*Oreskes* et al., 2010; *Palmer*, 2011), and do not account for the information that is embedded in empirical data. It is furthermore possible to evaluate the models in terms of their ability to predict changes in the past (*Solomon* et al., 2007; *Benestad* et al., 2007; *Benestad*, 2001). Recent analyses have also evaluated the downscaled trends against local geographical information (*Benestad*, 2011), although a good match in itself is no evidence for skillful projections for the future. The empirical information ensures realistic mean values and variance, but the future trends depend on what the GCM simulations indicate for large-scale regional conditions.

Since the analysis presented in *Benestad* (2008a), there have been further progress in this area of research. *Benestad* (2009) improved set-up of the empirical-statistical downscaling (ESD) tool, and *Hanssen-Bauer* et al. (2009) published a report with the most up-to-date description of the Norwegian climate, including a discussion about future projections. In *Hanssen-Bauer* et al. (2009), both ESD and an ensemble of regional climate model results were presented, and equal weights were attributed to both types of ensembles. Figure 2 presents a graphical reproduction of Figure 5.2.1 in *Hanssen-Bauer* et al. (2009), showing a simplified presentation of the projected change in T(2m) averaged over Norway. The spread in the estimates (different linear slopes) were based on both the ESD analysis and RCMs, and a selection of regional climate model (RCM) are shown as symbols.

Progress may also involve new types of analysis, looking at new aspects of the information provided by the GCMs. The present analysis focuses on the range of values that the different climate models provide, and include an analysis of the results from the ENSEMBLES project

Table 1: Abbreviations and glossary. The description of the emission scenarios are copied from the WMO (http://www.wmo.int/pages/themes/climate/emission_scenarios.php) and Wikipedia.

A1	Very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Convergence among regions, capacity building, and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B).
A2	A very heterogeneous world of self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing global population. Economic development is regionally oriented and per capita economic growth and technological change are more fragmented and slower than in other storylines.
B1	A convergent world with the same global population as in the A1 storyline, but with rapid changes in economic structures toward a service and information economy. Reductions in material intensity, and the introduction of clean and resource-efficient technologies. Global solutions to economic, social, and environmental sustainability, including improved equity, but without additional climate initiatives.
B2	Local solutions to economic, social, and environmental sustainability, with continuously increasing global population at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. Oriented toward environmental protection and social equity, but focuses on local and regional levels.
CMIP3	Coupled Model Intercomparison Project 3 http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php
DJF	December–February
ECMWF	European Centre for Medium Weather Forecasts www.ecmwf.int
ENSEMBLES	EU research project www.ensembles-eu.org/ & http://ensemblesrt3.dmi.dk/
ESD	empirical-statistical downscaling
ERA40	ECMWF's 40-yr reanalysis (*Simmons & Gibson,* 2000; *Hagemann* et al., 2005)
ERAINT	ECMWF's more recent interim reanalysis (*Simmons* et al., 2007)
GCM	Global climate model/General circulation model

Table 1: Table 1 continued.

IPCC	Inter-governmental Panel on Climate Change
IS92a	Emission scenario: A middle of the range scenario in which population rises to 11.3 billion by 2100, economic growth averages 2.3% year -1 between 1990 and 2100 and a mix of conventional and renewable energy sources are used. Only those emissions controls internationally agreed upon and national policies enacted into law, e.g., London Amendments to the Montreal Protocol, are included.
JJA	June-August
MAM	March–May
NAO	North-Atlantic Oscillation
NR	Precipitation ('nedbør') region.
RCM	Regional climate model
SON	September–November
SRES	IPCC special Report Emission Scenarios
	http://en.wikipedia.org/wiki/Special_Report_on_Emissions_Scenarios
TR	Temperature region
WMO	World Meteorological Organisation

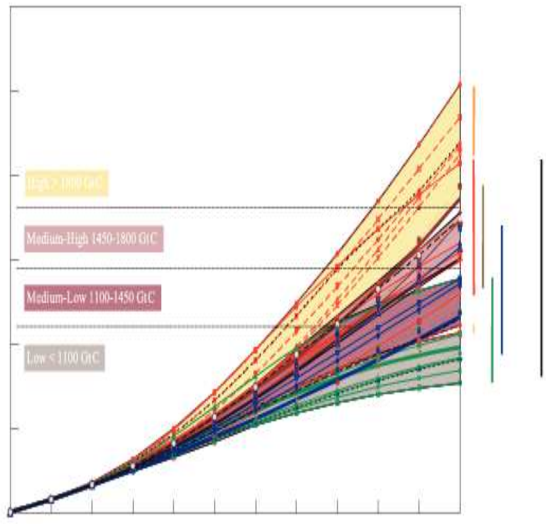

Figure 1: *Emission pathways according to the IPCC's special report on emission scenarios (http://www.ipcc.ch/pdf/special-reports/spm/sres-en.pdf).*

(*van der Linden & Mitchell*, 2009). The analysis also includes some additional GCMs, that were not available for the analysis of *Benestad* (2008a).

The outline of this report is a section describing the data and methods, followed by a discussion of the results. A table with glossary and abbreviations is also provided (Table 1).

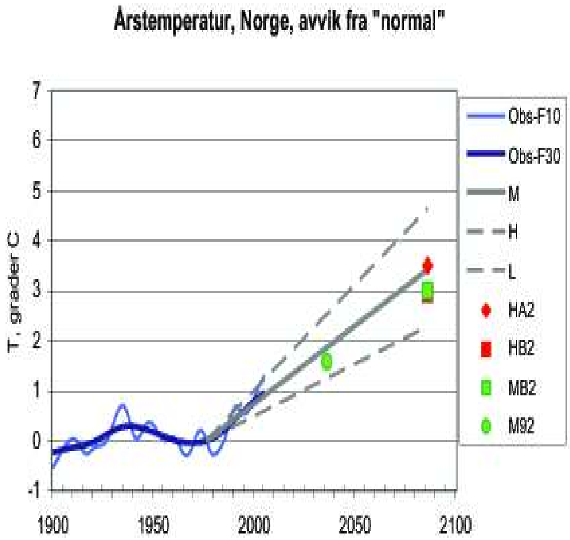

Figure 2: *Observed temperature changes in Norge throughout the 20th century, and estimated projections for the 21st century. The values are expressed as anomalies from the reference period 1961–90. The observed temperature has been smoothed and shows variability on 10-year (light blue) and 30 year (dark blue) time scales. The projections (grey lines) shows a mean trend line (solid line), as well as high and low projections which are shown as dashed lines. The points show a selection of RCM results. Figure 5.2.3 from* Hanssen-Bauer *et al. (2009).*

2 Method & Data

2.1 Method and set-up

The previous analysis (*Benestad*, 2008a) was based on an adjustment setting the mean of the 1995–2007 intervals for the projections to that of the observations, but this new analysis used a new set of base levels: Precipitation: 1970–1999; Temperature: 1961–1990. New time slices were also defined: 2011–2040 ("2025") and 2036–2065 ("2050"). The 'inflation correction' (*von Storch*, 1999; *Benestad* et al., 2008) was no longer used for precipitation in this newer analysis, as opposed to *Benestad* (2008a).

In the revised results, the precipitation predictors from ERA40 (*Simmons & Gibson*, 2000) had been replaced with a new field, as the previous version by accident had consisted of the monthly sum of only the first 6 hours of daily precipitation (these monthly 6-hour fields are correlated with the monthly 24-hr fields, but do not give quite as strong relationship to the local monthly precipitation totals). The new precipitation predictors describe the full 24 hours. Hence, the older analysis were expected to perform poorer than the new analysis, as the link between the monthly mean of 6-hour fields are less representative for the monthly mean of 24-hour accumulated precipitation than fields with full 24-hour accumulated amounts.

The analysis in *Benestad* (2008a) was based on `clim.pact` version 2.2.14, which has been subject to continuous evolution (*Benestad*, 2009). Here the 3.2-10-version was used. The version of R used in the present analysis was 2.12.1, and the R-environment has also evolved since *Benestad* (2008a). The `met.no.REB`-package was used for post-processing the ESD results, and version 1.2-11 was used for the present analysis, and represented some new solutions in terms of splicing downscaled temperatures for the past and the future (*Benestad*, 2009, 2008b,c).

In addition to the ESD, the results from a number of RCMs are discussed, taken from the ENSEMLBES (*van der Linden & Mitchell*, 2009) project. Both results from RCMs and GCMs may exhibit biases in terms of systematic differences in the mean temperature or precipitation to that is observed. There may be several reasons for these biases: different altitudes due to smoothed topography, decadal internal variability, parameterisation of soil and boundary layers, parameterisation of cloud and biases in precipitation, or biases in the driving GCMs. For this reason, both RCM and GCM results have been adjusted by subtracting the mean value for a common reference period from the entire series and then adding the corresponding mean value from the observations. RCM results were adjusted by setting their mean value for 1961–1990 equal to that of the observations.

2.2 Data

The predictands used in the ESD were the same region series as in *Benestad* (2008a), but updated to include the most recent years. Note, the region number differs from those used in *Benestad* (2008a). An overview of the temperature region (TR) and perciptation region (NR) numbers is provided in Table 2, and Figure 3 provides maps for these regions.

The winter season was defined as December–February, and the values estimated involved data from two years, the December month preceding the stated year. However the annual mean shown here is not exactly the same as the mean of the four seasons presented in the tables, as it was estimated over January–December for one given year rather than using winter values spanning two calendar years.

Table 2: List of temperature and precipitation regions (c.f. Figure 3).

TR	Temperature
1	Østlandet
2	Vestlandet
3	Trøndelag
4	Nordland+Troms
5	Finnmarksvidda
6	Varanger
NR	Precipitation
1	Østfold
2	Østlandet
3	Sørlandet
4	Sør-Vestlandet
5	Sunnhordland
6	Sogn
7	Dovre Nord+Østerdal
8	Møre+Romsdal
9	Inntrøndelag
10	Trøndelag+Helgeland
11	Halogaland
12	Finnmarksvidda
13	Varanger

Table 3 provides a list of GCMs that are included in this ESD analysis, but were not available for the analysis of *Benestad* (2008a). The RCMs from ENSEMBLES used here are listed in Table 4, but did not include all the RCMs of the ENSEMBLES project (Figure 4). The RCM results were stored in a number of different ways, all in the netCDF format. The files with data in a rotated grid were not included here, as the additional processing would be require significant amount of resources, and it was not seen as worth while the effort as most of the RCMs were driven by a small set of GCMs (HadCM3, ECHAM5, IPSL, ARPEGE, & BCCR).

For 3-day-mean T(2m), 14 GCMs from the CMIP3 (*Meehl* et al., 2007) were used rather than the ENSEMBLES data, as these represented a larger sample of GCMs. The GCMs do not provide the best information about local and regional scale climate (e.g. see Figure 5), but a small selection of RCMs based on even a smaller subset of GCMs, on the other hand, is more

Table 3: Additional GCM runs since *Benestad* (2008a)

GCM	experiment	run	additional
cccma_cgcm3_1	sresa1b	run2	t47
cccma_cgcm3_1	sresa1b	run4	t47
cccma_cgcm3_1	sresa1b	run5	t47
iap_fgoals1_0_g	20c3m	run2	
iap_fgoals1_0_g	20c3m	run3	
iap_fgoals1_0_g	20c3m	run2	
iap_fgoals1_0_g	sresa1b	run2	

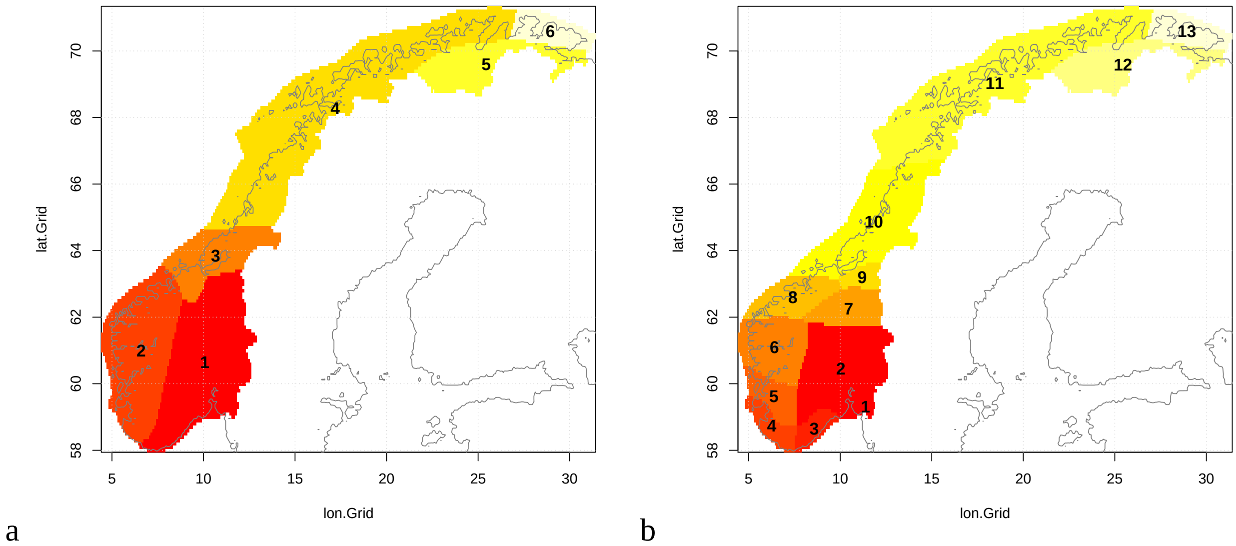

Figure 3: Maps showing (a) the six temperature regions and (b) 13 precipitation regions (see *Hanssen-Bauer* et al. (2009)).

Table 4: 16 RCMs from ENSEMBLES. The codes are as follows (h) for RCMs driven by HadCM3, (e) by ECHAM5, (i) by IPSL, (a) ARPEGE, & (b) BCCR.

C4IRCA3 (h,e)	CNRM.RM5.1 (a)	DMI.HIRHAM5 (a,e,b)	ETHZ.CLM (h)
GKSS.CLM3 (i)	KNMI.RACMO2 (e)	METNOHIRHAM (h)	METO.HC (h)
MPI.M.REMO (e)	SMHIRCA (b,e)	UCLM.PROMES (h)	VMGO.RRCM (h)

problematic in terms of providing statistics from a sample of results. Nevertheless, the RCMs should provide a description which is consistent with the large-scale picture given by the GCMs, albeit with more details. Hence, the RCMs description of cold conditions should reflect the cold conditions over similar regions in the GCM results.

Another justification for using the GCM results directly for this is that it is cold conditions over extensive areas that matter for energy consumption, rather than isolated cold spots in some valleys. The GCMs can provide useful information for a region with greater spatial extent than their skillful scale of ∼8 grid boxes (*von Storch* et al., 1993; *Zorita & von Storch*, 1997; *Benestad* et al., 2008), which here was taken to be 0°W–30°E/55–70°N (Figure 5).

The GCMs nevertheless have biases, and it is important to relate simulations for the future to the simulations for the present conditions. This bias was removed by setting the 1958–2002 average of the area-mean annual minimum temperature equal to corresponing average from the ERA40 re-analysis. A regression analysis was used to relate the annual 3-day minimum of the temperature averaged over 0°W–30°E/55–70°N to actual observations made in Oslo, Bergen, Trondheim, and Tromsø. In order to maximise the length of the time series, the ERA40 reanalysis was spliced with ERAINT (*Simmons* et al., 2007), taking ERAINT when EAR40 and ERAINT overlap, as ERAINT succeeds ERA40 and is regarded to be superior to ERA40.

The daily GCM fields for T(2m) also involve much greater data volumes than the monthly, and CMIP3 archive did not contain daily values for as many GCM runs as for monthly results. The daily GCM data was in general available in a limited set of time slices. Furthermore, the

Table 5: GCMs used for analysis of 3-daily means. For all the GCMs time slices were extracted for the present climate ('20C3M') and the SRES A1b scenario.

BCCR BCM2	CCCMA CGCM 3.1	CNRM CM3	CSIRO MK3.0
GFDL CM2.0	GISS AOM	GISS MODEL ER	FGOALS 1.0 G
ECHAM4	ECHAM5	IPSL CM4	ECHO 3.0
NCAR CCSM3.0	MRI CGCM2.3.2a		

large data volume was also more time consuming in terms of downloading, processing, and analysis. Hence, due to practical limitations concerning large data files, the analysis of the 3-daily means only involved short time slices, and the set of GCMs was therefore more limited (14 GCMs; see Table 5) than for the ESD results based on monthly GCM results. The analysis tool `Ferret` (*Hankin* et al., 1992) was used to extract the relevant data from the large volume.

A return-level analysis was carried out, based on general extreme value (GEV) theory, fitting the extreme value distribution to the annual minimum 3-day values. The GEV was implemented through the `R`-package `evd`.

Daily fields of T(2m) were extracted for this region from the re-analyses and the GCMs respectively, the area mean was estimated, and a 3-day moving average was computed. The lowest value of the 3-day average was extracted for each year and plotted in the figure. In order to estimate the 5–95 percentile bounds, presented as linear dashed lines, the data was divided into sequential 10-year batches. For each of these (140 data points), the 5- and 95- percentiles were estimated, and a linear regression was carried out with respect to these values and time (center year of each decade).

ENSEMBLES GCM-RCM Matrix 8/6/2010

Global model Regional inst.	METO-HC Standard	METO-HC Low sens.	METO-HC HI sens.	MPIMET Standard	MPIMET Ens.m. 1	MPIMET Ens.m. 2	IPSL	CNRM	NERSC	MIROC	CGCM3	Total number
METO-HC	2100	2100*	2100*	2100 (late 2010)								4
MPIMET				2100			2050*					2
CNRM								2100				1
DMI				2100*				2100	2100*			3
ETH	2100											1
KNMI				2100* 2100	2100*	2100*				2100*		1+4
ICTP				2100								1
SMHI		2100*		2100* 2100*					2100			3+1
UCLM	2050											1
C4I			2100*		2050 (A2)*							2
GKSS							2050*					1
METNO	2050*								2050*			1
CHMI								2050* (12/2009)				1
OURANOS**											2050*	1
VMGO**	2050*											1
Total (1951-2050)	5	2	2	7+2	0+1	0+1	2	3	3	0+1	1	25+5

Red: Online now; *: non-contractual runs; **:affiliated partners without obligations; underscore: 50km resolution; (in parantheses): Expected date. For partner acronym explanations, see the participant list. **NOTE** that all partners also did an ERA-40 driven analysis 1951(1961)-2000

Figure 4: *Overview of the complete ENSEMBLES RCM/GCM matrix (source: http://ensemblesrt3.dmi.dk/100608_TheMatrix.pdf)*

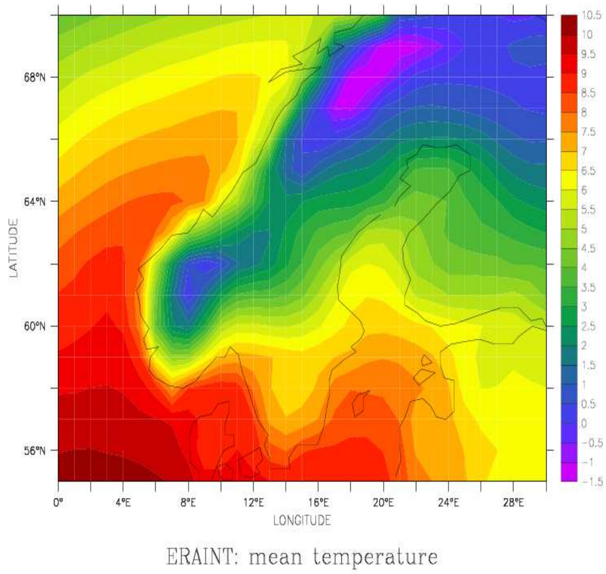

Figure 5: *An overview of the region extracted for the GCMs and used in the study of 3-day cold events. The figure shows the 1989–2009 annual mean temperature from ERAINT (in degrees C).*

3 Results

3.1 Monthly values

3.1.1 ESD results

The values for the quantiles for ESD-results in Tables 6 & 7 were estimated from the fitted polynomials, shown as the dashed red lines in Figures 6 & 7. For the ENSEMBLES results, on the other hand, the corresponding quantiles were derived from the interval mean of the year-to-year values of the quantiles for the RCM ensemble (Table 4). The domain of some of the RCM models did not include the northernmost parts of Norway, as seen in Figure 8.

Table 6 presents the results for the ESD analysis, presenting the 5–95 percentiles for the three time intervals 1961–1990, 2011–2040, and 2036–2065. The corresponding analysis is also presented graphically in Figure 6 and figures in the appendix. The 5–95 percentiles in this analysis represent internal (natural) variability (on inter-annual to decadal time scales) as well as the differences between the GCMs.

A corresponding analysis for the ESD analysis for precipitation is presented in Table 7 and in Figure 7 (and in the appendix). The reference period for the precipitation was taken to be 1970–1999 rather than 1961–1990, to follow the norms more commonly used in hydrology. Tables 8 and 9 correspond to Tables 6 and 7, but show 5–95 percentiles derived from 16 RCMs from the ENSEMBLE project, rather than $\sim$50 GCMs downscaled through ESD. Not all RCMs had results for the period 2050–2100, and for the ENSEMBLES results the ranges for the 2036–2065 period involved a smaller sample than 2011–2040. The RCM results are also shown as blue symbols superimposed on top of the grey curves marking the ESD results in Figures 6 & 7.

Some of the domains used in the ENSEMBLES do not extend all the way to the northernmost part of mainland Norway, (and hence make the 5–95 percentile range more uncertain when some of the results were excluded from the analysis), as seen in Figure 8.

Table 6: Seasonal and annual temperature: 5–95 percentiles for periods based on the ESD results

Region	winter	Spring	Summer	Autumn	annual
1961–1990					
Region 1	-11.3 – -3.3	-1.2 – 3.1	9.7 – 12.3	0.0 – 4.0	0.3 – 3.4
Region 2	-6.5 – -0.5	-1.1 – 2.5	7.8 – 10.5	1.0 – 4.6	1.2 – 3.8
Region 3	-7.6 – -0.8	-0.6 – 3.7	9.9 – 12.6	0.9 – 5.3	1.7 – 4.6
Region 4	-8.9 – -3.0	-3.6 – 1.1	7.9 – 10.6	-1.1 – 3.1	-0.5 – 2.3
Region 5	-18.7 – -8.6	-7.6 – -0.8	7.3 – 10.6	-5.3 – 0.9	-4.8 – -0.5
Region 6	-10.5 – -4.5	-5.0 – 0.2	6.5 – 9.3	-1.7 – 2.8	-1.7 – 1.2
2011–2040					
Region 1	-8.8 – -1.6	0.2 – 4.3	10.7 – 13.3	1.8 – 5.3	1.9 – 4.8
Region 2	-4.3 – 1.1	0.4 – 3.8	8.9 – 11.5	2.7 – 5.7	2.7 – 5.1
Region 3	-5.5 – 0.7	1.1 – 5.2	10.7 – 13.3	2.9 – 6.5	3.3 – 6
Region 4	-6.6 – -1.3	-1.7 – 2.6	8.7 – 11.4	0.8 – 4.2	1.1 – 3.7
Region 5	-14.8 – -5.8	-4.8 – 1.5	8.9 – 12.2	-2.4 – 2.7	-2.1 – 1.8
Region 6	-8.5 – -3.0	-2.9 – 1.8	8.0 – 10.6	0.1 – 3.8	0.0 – 2.7
2036–2065					
Region 1	-7.1 – 0.3	1.1 – 5.3	11.3 – 14.3	3.0 – 6.7	2.9 – 6.2
Region 2	-3.0 – 3.0	1.2 – 4.9	9.5 – 12.5	3.6 – 7.0	3.6 – 6.5
Region 3	-4.1 – 2.3	2.1 – 6.5	11.0 – 14.0	4 – 7.8	4.1 – 7.2
Region 4	-5.3 – 0.2	-0.5 – 4.0	9.2 – 12.1	1.9 – 5.4	2.1 – 4.9
Region 5	-12.4 – -3.4	-3.1 – 3.4	9.8 – 13.5	-0.6 – 4.6	-0.5 – 3.7
Region 6	-7.2 – -1.6	-1.5 – 3.2	8.9 – 11.9	1.2 – 4.8	1.1 – 4.0

Table 7: Seasonal and annual precipitation: 5–95 percentiles for periods based on the ESD results (accumulated amount in mm)

Region	winter	Spring	Summer	Autumn	annual
1970–1999					
Region 1	135 – 292	101 – 208	186 – 325	186 – 367	729 – 1030
Region 2	105 – 219	110 – 204	228 – 362	164 – 325	709 – 967
Region 3	219 – 448	148 – 331	244 – 446	283 – 580	1110 – 1573
Region 4	370 – 793	200 – 470	285 – 510	441 – 839	1570 – 2290
Region 5	319 – 873	219 – 503	279 – 489	391 – 839	1518 – 2336
Region 6	334 – 817	229 – 494	285 – 463	356 – 764	1456 – 2201
Region 7	103 – 175	87 – 134	194 – 282	127 – 214	568 – 717
Region 8	349 – 636	189 – 384	272 – 395	323 – 625	1322 – 1803
Region 9	191 – 338	135 – 232	215 – 353	175 – 359	835 – 1131
Region 10	324 – 572	226 – 395	198 – 371	282 – 553	1220 – 1663
Region 11	261 – 418	181 – 297	161 – 270	257 – 445	989 – 1298
Region 12	87 – 128	72 – 108	150 – 216	84 – 140	443 – 546
Region 13	130 – 191	112 – 160	147 – 225	154 – 210	586 – 713
2011–2040					
Region 1	145 – 310	104 – 217	176 – 323	197 – 386	758 – 1074
Region 2	113 – 232	111 – 210	218 – 358	171 – 337	725 – 994
Region 3	238 – 476	151 – 343	228 – 437	296 – 601	1143 – 1621
Region 4	385 – 828	205 – 486	284 – 521	476 – 898	1660 – 2379
Region 5	344 – 913	220 – 520	288 – 512	440 – 910	1636 – 2461
Region 6	362 – 855	230 – 509	292 – 482	399 – 827	1568 – 2309
Region 7	109 – 181	88 – 137	194 – 289	138 – 224	588 – 740
Region 8	366 – 663	191 – 404	283 – 414	357 – 664	1397 – 1897
Region 9	193 – 341	134 – 240	231 – 372	193 – 377	874 – 1174
Region 10	324 – 585	227 – 407	216 – 395	305 – 589	1262 – 1734
Region 11	256 – 424	184 – 308	167 – 283	256 – 455	1000 – 1327
Region 12	90 – 132	75 – 112	153 – 223	89 – 150	456 – 566
Region 13	130 – 193	115 – 164	148 – 230	156 – 217	596 – 732
2036–2065					
Region 1	151 – 328	104 – 226	168 – 326	203 – 400	776 – 1112
Region 2	119 – 246	111 – 217	210 – 359	173 – 345	735 – 1019
Region 3	248 – 500	153 – 356	216 – 435	298 – 620	1159 – 1660
Region 4	398 – 863	211 – 504	279 – 536	494 – 942	1722 – 2474
Region 5	361 – 954	224 – 538	291 – 531	468 – 969	1713 – 2585
Region 6	381 – 893	232 – 524	295 – 500	423 – 879	1641 – 2422
Region 7	112 – 188	90 – 141	194 – 296	142 – 232	600 – 763
Region 8	379 – 690	194 – 422	290 – 431	369 – 700	1443 – 1988
Region 9	191 – 347	135 – 248	241 – 388	197 – 395	893 – 1218
Region 10	323 – 601	227 – 417	228 – 416	318 – 623	1293 – 1804
Region 11	252 – 434	184 – 316	171 – 294	256 – 471	1009 – 1358
Region 12	90 – 136	77 – 116	155 – 229	93 – 159	466 – 585
Region 13	129 – 197	116 – 169	149 – 235	158 – 224	604 – 749

Table 8: Seasonal and annual temperature: 5–95 percentiles from ENSEMBLES

Region	winter	Spring	Summer	Autumn	annual
1961–1990					
Region 1	-9.7 – -5.8	-1.4 – 2.1	9.5 – 11.8	0.9 – 3.2	0.4 – 2.3
Region 2	-5.1 – -1.6	-1.0 – 2.0	7.7 – 9.8	1.8 – 4.0	1.4 – 3.0
Region 3	-6.4 – -2.6	-0.3 – 3.0	9.3 – 11.7	2.1 – 4.3	1.8 – 3.5
Region 4	-8.1 – -4.1	-3.1 – 0.6	7.7 – 9.9	-0.1 – 2.3	-0.4 – 1.6
Region 5	-16.2 – -10.9	-6.8 – -1.8	7.7 – 10.4	-3.5 – -0.4	-4.1 – -1.4
Region 6	-10.9 – -5.6	-5.8 – 0.0	6.6 – 9.4	-1.4 – 1.9	-2.5 – 1.0
2011–2040					
Region 1	-8.5 – -4.3	-0.4 – 3.5	10.2 – 12.8	1.8 – 4.6	1.4 – 3.6
Region 2	-4.0 – -0.2	-0.1 – 3.2	8.3 – 10.8	2.7 – 5.4	2.2 – 4.3
Region 3	-5.2 – -1.4	0.6 – 4.2	9.9 – 12.5	2.9 – 5.7	2.6 – 4.7
Region 4	-6.6 – -2.7	-1.7 – 1.8	8.7 – 11.0	1.1 – 3.9	0.9 – 3.0
Region 5	-13.9 – -8.7	-4.8 – 0.0	8.9 – 11.6	-2.1 – 1.5	-2.2 – 0.5
Region 6	-8.3 – -2.0	-3.2 – 2.7	8.0 – 10.9	0.4 – 4.4	-0.2 – 3.7
2036–2065					
Region 1	-7.4 – -3.2	1.1 – 4.5	11.1 – 13.6	2.8 – 5.3	2.4 – 4.6
Region 2	-3.1 – 0.8	1.2 – 4.2	9.1 – 11.5	3.6 – 6.0	3.2 – 5.2
Region 3	-4.1 – -0.3	1.9 – 5.2	10.6 – 13.2	3.8 – 6.3	3.6 – 5.7
Region 4	-4.9 – -1.4	-0.2 – 3.1	9.5 – 11.6	2.3 – 4.7	2.2 – 4.1
Region 5	-11.4 – -6.0	-2.8 – 2.1	9.8 – 12.5	-0.5 – 2.7	-0.7 – 2.1
Region 6	-6.1 – 2.7	-1.0 – 5.9	9.1 – 12.0	2.0 – 6.2	1.3 – 6.4

Table 9: Seasonal and annual precipitation: 5–95 percentiles from ENSEMBLES

Region	winter	Spring	Summer	Autumn	annual
1970–1999					
Region 1	91 – 254	84 – 222	159 – 316	205 – 379	681 – 1007
Region 2	77 – 229	70 – 218	162 – 335	174 – 355	638 – 971
Region 3	171 – 415	112 – 337	186 – 390	324 – 582	1017 – 1474
Region 4	259 – 702	158 – 473	271 – 472	504 – 833	1460 – 2173
Region 5	284 – 808	142 – 526	269 – 492	514 – 880	1510 – 2341
Region 6	305 – 764	131 – 495	254 – 468	500 – 833	1475 – 2219
Region 7	73 – 171	58 – 146	149 – 280	117 – 239	504 – 729
Region 8	268 – 628	120 – 429	212 – 392	372 – 683	1221 – 1829
Region 9	108 – 359	79 – 284	177 – 357	176 – 414	729 – 1192
Region 10	270 – 533	142 – 369	209 – 367	353 – 588	1168 – 1623
Region 11	217 – 404	113 – 273	142 – 291	275 – 463	897 – 1251
Region 12	48 – 135	24 – 114	82 – 251	54 – 206	313 – 588
Region 13	107 – 222	43 – 165	63 – 269	94 – 287	433 – 781
2011–2040					
Region 1	103 – 268	84 – 241	164 – 340	209 – 400	714 – 1071
Region 2	83 – 251	69 – 236	163 – 352	171 – 369	661 – 1031
Region 3	167 – 435	104 – 346	190 – 404	326 – 599	1024 – 1531
Region 4	303 – 735	163 – 515	272 – 492	499 – 865	1540 – 2258
Region 5	328 – 859	150 – 579	271 – 531	504 – 919	1605 – 2481
Region 6	324 – 799	143 – 551	264 – 516	492 – 900	1556 – 2373
Region 7	83 – 180	62 – 162	152 – 302	125 – 258	536 – 787
Region 8	274 – 639	136 – 442	233 – 416	377 – 712	1278 – 1898
Region 9	115 – 366	83 – 309	201 – 382	178 – 423	762 – 1257
Region 10	283 – 576	154 – 404	231 – 391	369 – 628	1246 – 1764
Region 11	232 – 440	120 – 300	168 – 325	300 – 501	977 – 1365
Region 12	53 – 146	23 – 118	103 – 278	74 – 228	371 – 641
Region 13	123 – 253	46 – 179	84 – 329	110 – 329	503 – 900
2036–2065					
Region 1	94 – 289	100 – 253	161 – 328	212 – 393	712 – 1094
Region 2	82 – 273	91 – 264	166 – 346	184 – 380	682 – 1083
Region 3	171 – 457	133 – 386	186 – 385	332 – 590	1047 – 1589
Region 4	308 – 806	197 – 552	258 – 482	526 – 875	1596 – 2381
Region 5	327 – 934	190 – 632	261 – 517	538 – 940	1685 – 2621
Region 6	338 – 870	182 – 588	255 – 510	543 – 899	1671 – 2478
Region 7	89 – 195	76 – 181	168 – 320	138 – 274	584 – 842
Region 8	299 – 678	163 – 462	237 – 432	412 – 705	1363 – 1951
Region 9	121 – 396	104 – 315	212 – 397	196 – 440	830 – 1297
Region 10	290 – 605	176 – 403	234 – 404	385 – 618	1298 – 1812
Region 11	242 – 455	135 – 298	168 – 328	305 – 493	1020 – 1390
Region 12	60 – 163	41 – 138	94 – 282	83 – 270	406 – 702
Region 13	135 – 292	62 – 201	73 – 339	135 – 381	576 – 998

Table 10: Seasonal and annual temperature: medians from ESD. The standard deviation of the ensemble is given in parentheses.

Region	winter	Spring	Summer	Autumn	annual
1961–1990					
Region 1	-6.9 (2.6)	1.0 (1.4)	11.0 (0.9)	2.2 (1.3)	2.0 (1.0)
Region 2	-3.2 (1.9)	0.7 (1.2)	9.2 (0.9)	3.0 (1.2)	2.6 (0.9)
Region 3	-4.1 (2.2)	1.6 (1.4)	11.3 (0.9)	3.4 (1.4)	3.2 (1.0)
Region 4	-5.9 (2.0)	-1.1 (1.5)	9.2 (0.9)	1.3 (1.4)	1.0 (0.9)
Region 5	-13.5 (3.3)	-4.0 (2.2)	9.0 (1.1)	-2.1 (2.0)	-2.5 (1.4)
Region 6	-7.3 (1.9)	-2.3 (1.7)	7.8 (0.9)	0.7 (1.4)	-0.2 (1.0)
2011–2040					
Region 1	-4.9 (2.4)	2.3 (1.3)	12.0 (0.8)	3.7 (1.2)	3.4 (1.0)
Region 2	-1.4 (1.8)	2.0 (1.2)	10.1 (0.8)	4.3 (1.1)	3.9 (0.8)
Region 3	-2.1 (2.0)	3.1 (1.4)	12.0 (0.9)	4.8 (1.3)	4.6 (0.9)
Region 4	-3.9 (1.8)	0.5 (1.4)	10.0 (0.9)	2.5 (1.2)	2.4 (0.8)
Region 5	-10.2 (3.0)	-1.6 (2.1)	10.4 (1.1)	0.2 (1.7)	-0.1 (1.3)
Region 6	-5.7 (1.8)	-0.5 (1.5)	9.3 (0.9)	2.0 (1.2)	1.3 (0.9)
2036–2065					
Region 1	-3.3 (2.5)	3.2 (1.4)	12.7 (1.0)	4.7 (1.3)	4.5 (1.1)
Region 2	-0.1 (2.1)	3.0 (1.2)	10.9 (1.0)	5.2 (1.2)	4.9 (1.0)
Region 3	-0.7 (2.1)	4.1 (1.5)	12.5 (1.0)	5.9 (1.4)	5.7 (1.0)
Region 4	-2.5 (1.8)	1.6 (1.5)	10.5 (0.9)	3.5 (1.2)	3.4 (0.9)
Region 5	-7.6 (3.0)	0.0 (2.1)	11.5 (1.2)	1.9 (1.8)	1.6 (1.4)
Region 6	-4.4 (1.8)	0.8 (1.5)	10.3 (1.0)	2.9 (1.2)	2.5 (0.9)

Table 11: Seasonal and annual precipitation: medians from ESD. The standard deviation of the ensemble is given in parentheses.

Region	winter	Spring	Summer	Autumn	annual
1970–1999					
Region 1	210 (51)	155 (35)	254 (46)	277 (58)	888 (100)
Region 2	163 (37)	157 (31)	296 (44)	243 (52)	848 (85)
Region 3	336 (75)	238 (60)	347 (67)	432 (96)	1343 (152)
Region 4	573 (137)	324 (89)	401 (74)	647 (131)	1925 (237)
Region 5	589 (179)	344 (93)	388 (68)	617 (147)	1916 (269)
Region 6	572 (155)	347 (87)	375 (58)	557 (134)	1819 (241)
Region 7	138 (23)	110 (15)	240 (29)	171 (28)	642 (49)
Region 8	490 (93)	280 (64)	335 (41)	466 (98)	1551 (159)
Region 9	260 (49)	182 (33)	287 (46)	267 (59)	982 (96)
Region 10	438 (80)	305 (56)	285 (57)	419 (88)	1436 (146)
Region 11	337 (52)	237 (38)	213 (36)	347 (62)	1138 (101)
Region 12	107 (13)	89 (12)	183 (22)	113 (18)	492 (34)
Region 13	160 (20)	135 (16)	184 (26)	181 (19)	649 (42)
2011–2040					
Region 1	226 (53)	161 (37)	252 (48)	294 (61)	921 (103)
Region 2	174 (39)	161 (32)	291 (46)	255 (55)	866 (88)
Region 3	360 (79)	246 (62)	338 (68)	449 (100)	1380 (157)
Region 4	603 (141)	340 (91)	407 (77)	696 (138)	2018 (235)
Region 5	616 (183)	359 (98)	400 (72)	676 (153)	2031 (270)
Region 6	598 (159)	357 (92)	385 (62)	608 (139)	1915 (241)
Region 7	145 (24)	113 (16)	243 (31)	182 (28)	665 (50)
Region 8	507 (97)	289 (69)	347 (45)	500 (102)	1630 (164)
Region 9	264 (50)	186 (35)	303 (47)	283 (60)	1022 (98)
Region 10	443 (85)	309 (59)	303 (59)	444 (93)	1489 (153)
Region 11	333 (56)	240 (40)	221 (38)	356 (66)	1156 (106)
Region 12	110 (14)	92 (12)	187 (23)	120 (20)	511 (36)
Region 13	162 (21)	138 (16)	188 (27)	187 (20)	663 (44)
2036–2065					
Region 1	239 (57)	165 (40)	251 (52)	306 (64)	945 (109)
Region 2	182 (41)	164 (34)	289 (49)	263 (57)	880 (93)
Region 3	377 (83)	252 (66)	332 (71)	460 (106)	1408 (166)
Region 4	629 (149)	354 (94)	413 (81)	729 (146)	2094 (245)
Region 5	643 (193)	374 (102)	411 (77)	718 (163)	2129 (286)
Region 6	624 (168)	367 (96)	395 (67)	645 (148)	2001 (254)
Region 7	152 (25)	115 (17)	247 (33)	189 (29)	685 (53)
Region 8	526 (103)	298 (74)	357 (49)	528 (110)	1697 (177)
Region 9	267 (52)	189 (37)	315 (49)	297 (65)	1056 (106)
Region 10	452 (92)	314 (63)	317 (61)	463 (100)	1536 (166)
Region 11	333 (60)	244 (43)	229 (40)	363 (71)	1177 (113)
Region 12	112 (15)	95 (13)	191 (23)	126 (22)	527 (39)
Region 13	164 (23)	142 (17)	191 (28)	191 (22)	675 (47)

Table 12: Seasonal and annual temperature: medians from ENSEMBLES. The standard deviation of the ensemble is given in parentheses.

Region	winter	Spring	Summer	Autumn	annual
1961–1990					
Region 1	-7.8 (1.4)	0.4 (1.2)	10.5 (0.8)	2.2 (0.8)	1.3 (0.7)
Region 2	-3.4 (1.3)	0.5 (1.1)	8.6 (0.8)	3.0 (0.8)	2.2 (0.6)
Region 3	-4.6 (1.4)	1.4 (1.2)	10.3 (0.8)	3.2 (0.8)	2.6 (0.6)
Region 4	-6.3 (1.5)	-1.2 (1.3)	8.6 (0.8)	1.2 (0.9)	0.6 (0.7)
Region 5	-13.6 (2.0)	-4.2 (1.8)	8.9 (1.0)	-1.9 (1.2)	-2.6 (1.0)
Region 6	-8.2 (2.0)	-2.6 (2.0)	7.9 (1.0)	0.3 (1.2)	-0.6 (1.2)
2011–2040					
Region 1	-6.4 (1.5)	1.6 (1.4)	11.4 (0.9)	3.1 (1.0)	2.5 (0.8)
Region 2	-2.1 (1.4)	1.6 (1.2)	9.5 (0.9)	3.9 (1.0)	3.2 (0.7)
Region 3	-3.2 (1.4)	2.5 (1.3)	11.2 (0.9)	4.1 (1.0)	3.7 (0.8)
Region 4	-4.8 (1.4)	0.1 (1.3)	9.7 (0.9)	2.3 (1.1)	1.9 (0.8)
Region 5	-11.8 (1.9)	-2.5 (1.8)	10.2 (1.0)	-0.6 (1.3)	-1.1 (1.0)
Region 6	-6.5 (2.4)	-0.8 (2.1)	9.2 (1.0)	1.8 (1.5)	1.0 (1.5)
2036–2065					
Region 1	-5.4 (1.6)	2.7 (1.3)	12.1 (0.9)	4.0 (1.0)	3.3 (0.8)
Region 2	-1.2 (1.5)	2.6 (1.1)	10.2 (0.9)	4.8 (0.9)	4.1 (0.7)
Region 3	-2.4 (1.4)	3.6 (1.2)	11.7 (0.9)	5.0 (0.9)	4.5 (0.8)
Region 4	-3.5 (1.3)	1.3 (1.2)	10.5 (0.8)	3.3 (0.9)	2.9 (0.7)
Region 5	-9.8 (2.1)	-1.0 (1.9)	11.0 (1.0)	0.6 (1.2)	0.3 (1.1)
Region 6	-4.9 (3.6)	0.8 (2.7)	10.4 (1.1)	3.2 (1.6)	2.5 (2.0)

Table 13: Seasonal and annual precipitation: medians from ENSEMBLES. The standard deviation of the ensemble is given in parentheses.

Region	winter	Spring	Summer	Autumn	annual
1970–1999					
Region 1	169 (58)	150 (49)	226 (55)	286 (61)	836 (116)
Region 2	148 (54)	141 (52)	245 (62)	254 (64)	788 (119)
Region 3	284 (86)	222 (79)	285 (73)	434 (91)	1233 (163)
Region 4	469 (158)	298 (113)	362 (72)	656 (119)	1802 (256)
Region 5	527 (188)	312 (137)	375 (79)	689 (131)	1926 (295)
Region 6	510 (166)	301 (128)	359 (75)	659 (120)	1838 (260)
Region 7	119 (35)	99 (31)	213 (46)	179 (42)	609 (79)
Region 8	423 (134)	257 (106)	297 (63)	522 (108)	1522 (215)
Region 9	216 (92)	167 (73)	265 (63)	291 (83)	957 (165)
Region 10	386 (95)	249 (81)	292 (57)	464 (83)	1397 (161)
Region 11	298 (67)	184 (58)	220 (53)	361 (68)	1073 (129)
Region 12	85 (32)	64 (33)	159 (60)	122 (57)	439 (97)
Region 13	158 (42)	98 (43)	151 (74)	188 (71)	598 (126)
2011–2040					
Region 1	177 (60)	160 (57)	237 (64)	299 (69)	881 (126)
Region 2	162 (60)	153 (60)	246 (66)	271 (71)	830 (132)
Region 3	301 (95)	231 (85)	281 (75)	453 (98)	1270 (180)
Region 4	494 (154)	327 (128)	383 (78)	677 (132)	1881 (260)
Region 5	553 (192)	343 (156)	399 (94)	700 (149)	2016 (317)
Region 6	526 (174)	329 (148)	386 (91)	677 (145)	1952 (296)
Region 7	125 (35)	111 (36)	224 (52)	187 (48)	650 (89)
Region 8	442 (129)	280 (110)	316 (65)	525 (119)	1584 (221)
Region 9	222 (90)	186 (82)	285 (65)	291 (87)	1008 (174)
Region 10	403 (104)	266 (91)	302 (58)	471 (94)	1473 (188)
Region 11	313 (75)	198 (66)	237 (56)	382 (72)	1158 (141)
Region 12	94 (34)	71 (35)	174 (64)	142 (56)	486 (98)
Region 13	178 (47)	109 (48)	170 (91)	209 (80)	693 (145)
2036–2065					
Region 1	185 (73)	173 (55)	239 (61)	299 (67)	915 (139)
Region 2	173 (70)	175 (62)	254 (66)	265 (73)	876 (148)
Region 3	315 (105)	256 (90)	286 (73)	439 (97)	1301 (196)
Region 4	529 (185)	358 (132)	366 (81)	689 (127)	1949 (293)
Region 5	604 (228)	381 (166)	384 (94)	721 (147)	2102 (344)
Region 6	570 (199)	360 (150)	380 (94)	712 (132)	2042 (293)
Region 7	139 (39)	122 (39)	233 (55)	199 (50)	700 (95)
Region 8	461 (139)	288 (108)	328 (72)	545 (107)	1657 (215)
Region 9	242 (101)	194 (77)	295 (69)	312 (90)	1068 (172)
Region 10	427 (117)	275 (85)	316 (62)	493 (87)	1512 (188)
Region 11	331 (79)	210 (61)	242 (60)	392 (70)	1182 (139)
Region 12	101 (39)	85 (36)	177 (68)	146 (71)	522 (113)
Region 13	206 (57)	120 (52)	168 (100)	216 (96)	732 (159)

Tables 14–17 present changes in the median values shown in Tables 10–13. These changes can be compared with the results in *Hanssen-Bauer* et al. (2009) (Table 5.2.2), although the choices of intervals differ. Here the ESD-results give changes in the annual mean temperature in the range 1.3–2.4°C between 1961–1990 and 2011–2040 (Table 14), whereas the *Hanssen-Bauer* et al. (2009) suggest 1.7–2.3°C (the 'M' scenario) between 1961–1990 and 2021–2050. In particular, the ESD results in Table 14 suggests that the annual mean warming in Finnmark (region 5) between 1961–1990 and 2011–2040 was 2.4°C and 4.1°C by 2036–2065, and hence more substantial than suggested in *Hanssen-Bauer* et al. (2009) (2.3°C by 2021–2050 and 4.1 by 2071–2100).

The ENSEMBLES results, on the other hand, prescribe temperature changes in the range 1.0–1.6°C for the same interval as the ESD-results (2011–2040). The difference between the tables in *Hanssen-Bauer* et al. (2009) and here is due to the weighting of the ESD- and RCM-results. For TR6 *Hanssen-Bauer* et al. (2009) suggests a 2.3°C warming by 2021–2050 (compared to 1961–1990) while the ESD results in Table 16 gives 1.6°C for 2011–2040 and 3.1°C for 2036–2065. A simple linear interpolation between the two periods (1.5° difference over 25 years) can be used to scale the ESD results to the 2021–2050 interval, giving a 2.2°C warming which is approximately in line with *Hanssen-Bauer* et al. (2009).

For precipitation, *Hanssen-Bauer* et al. (2009) only cites the RCM-results in Table 5.2.4, and for the period 2021–2050, the annual precipitation amount (compared to 1961–1990) was estimated to be 105–113%. The present ESD-results, however, suggest 102–106% of the 1970–1999 values for the period 2011–2040 (Table 15), and the RCMs from the ENSEMBLES project give 103–116% (Table 17).

The ESD-results suggest a continued increase in the annual precipitation for 2036–2065, ranging between 103–111%, while the ENSEMBLES RCMs project 106–122%. The *Hanssen-Bauer* et al. (2009) projections for 2071–2100 is in the range 109–123%.

For the annual values, the ESD-results suggest slightly stronger warming than the RCM results, but also weaker precipitation trends. On a seasonal scale, the ESD results indicate an increase in the rainfall amount for all seasons apart from the summers in southern Norway (NR 1–3) and winter in NR 11 (Table 15). The ENSEMBLES RCMs, on the other hand, only hints to a slight decrease in summer precipitation in NR 3 by 2011–2040, and no change by 2036–2065. The 'M' scenario in (*Hanssen-Bauer* et al., 2009, Table 5.2.4) projects 95–98% for the summer precipitation in NR 1–3 by 2021–2050 and 91–96% by 2021–2050.

Table 14: Changes in median seasonal and annual T(2m): ESD-results.

Region	winter	Spring	Summer	Autumn	annual
2011–2040 - 1961–1990					
Region 1	2.0	1.3	1.0	1.5	1.4
Region 2	1.8	1.3	0.9	1.3	1.3
Region 3	2.0	1.5	0.7	1.4	1.4
Region 4	2.0	1.6	0.8	1.2	1.4
Region 5	3.3	2.4	1.4	2.3	2.4
Region 6	1.6	1.8	1.5	1.3	1.5
2036–2065 - 1961–1990					
Region 1	3.6	2.2	1.7	2.5	2.5
Region 2	3.1	2.3	1.7	2.2	2.3
Region 3	3.4	2.5	1.2	2.5	2.5
Region 4	3.4	2.7	1.3	2.2	2.4
Region 5	5.9	4.0	2.5	4.0	4.1
Region 6	2.9	3.1	2.5	2.2	2.7

Table 15: Changes in median seasonal and annual precipitation (%): ESD-results.

Region	winter	Spring	Summer	Autumn	annual
2011–2040/1970–1999					
Region 1	108	104	99	106	104
Region 2	107	103	98	105	102
Region 3	107	103	97	104	103
Region 4	105	105	101	108	105
Region 5	105	104	103	110	106
Region 6	105	103	103	109	105
Region 7	105	103	101	106	104
Region 8	103	103	104	107	105
Region 9	102	102	106	106	104
Region 10	101	101	106	106	104
Region 11	99	101	104	103	102
Region 12	103	103	102	106	104
Region 13	101	102	102	103	102
2036–2065/1970–1999					
Region 1	114	106	99	110	106
Region 2	112	104	98	108	104
Region 3	112	106	96	106	105
Region 4	110	109	103	113	109
Region 5	109	109	106	116	111
Region 6	109	106	105	116	110
Region 7	110	105	103	111	107
Region 8	107	106	107	113	109
Region 9	103	104	110	111	108
Region 10	103	103	111	111	107
Region 11	99	103	108	105	103
Region 12	105	107	104	112	107
Region 13	102	105	104	106	104

Table 16: Changes in median seasonal and annual T(2m): ENSEMBLES-results.

Region	winter	Spring	Summer	Autumn	annual
2011–2040 - 1961–1990					
Region 1	1.4	1.2	0.9	0.9	1.2
Region 2	1.3	1.1	0.9	0.9	1.0
Region 3	1.4	1.1	0.9	0.9	1.1
Region 4	1.5	1.3	1.1	1.1	1.3
Region 5	1.8	1.7	1.3	1.3	1.5
Region 6	1.7	1.8	1.3	1.5	1.6
2036–2065 - 1961–1990					
Region 1	2.4	2.3	1.6	1.8	2.0
Region 2	2.2	2.1	1.6	1.8	1.9
Region 3	2.2	2.2	1.4	1.8	1.9
Region 4	2.8	2.5	1.9	2.1	2.3
Region 5	3.8	3.2	2.1	2.5	2.9
Region 6	3.3	3.4	2.5	2.9	3.1

Table 17: Changes in median seasonal and annual precipitation (%): ENSEMBLES-results.

Region	winter	Spring	Summer	Autumn	annual
2011–2040/1970–1999					
Region 1	105	107	105	105	105
Region 2	109	109	100	107	105
Region 3	106	104	99	104	103
Region 4	105	110	106	103	104
Region 5	105	110	106	102	105
Region 6	103	109	108	103	106
Region 7	105	112	105	104	107
Region 8	104	109	106	101	104
Region 9	103	111	108	100	105
Region 10	104	107	103	102	105
Region 11	105	108	108	106	108
Region 12	111	111	109	116	111
Region 13	113	111	113	111	116
2036–2065/1970–1999					
Region 1	109	115	106	105	109
Region 2	117	124	104	104	111
Region 3	111	115	100	101	106
Region 4	113	120	101	105	108
Region 5	115	122	102	105	109
Region 6	112	120	106	108	111
Region 7	117	123	109	111	115
Region 8	109	112	110	104	109
Region 9	112	116	111	107	112
Region 10	111	110	108	106	108
Region 11	111	114	110	109	110
Region 12	119	133	111	120	119
Region 13	130	122	111	115	122

A comparison between Tables 6 and 8 reveals a smaller range between 5–95 percentiles in the RCMs from ENSEMBLES compared with the ESD results. This impression is confirmed through a visual inspection of Figure 6 (The other figures are given in the appendix), except for temperature region 6, where two RCMs (CNRM.RM5.1 & DMI.HIRHAM5; Figure 8) describe significantly higher winter temperatures than the rest. For precipitation, the RCMs from the ENSEMBLES project appears to provide a similar range of values as the ESD results.

The median values for the scenarios are presented in Tables 10–13 toghether with the standard deviation (in parentheses). The median for the annual mean is estimated from the downscaled results independently to those of the seasons, but should roughly agree but may not be exactly the same (e.g. due to different adjustments for the different seasons and the annual mean). The standard deviation describes the spread of the ensemble members.

In order to assess the likelihood of the occurrence of extreme years in terms of precipitation, two thresholds levels were set to 60% and 150% of mean 1970–1999 values. Then a Gaussian distribution function was fitted to the results (seasonal or annual) for the intervals 2011–2040 and 2036–2065 respectively. The fraction of the lower tail of the fitted distribution below 60% was taken to describe the likelihood of extremely dry seasons/years and the fraction above 150% as extremely wet seasons/years. The results from this exercise are shown in Tables 18–25 in the appendix.

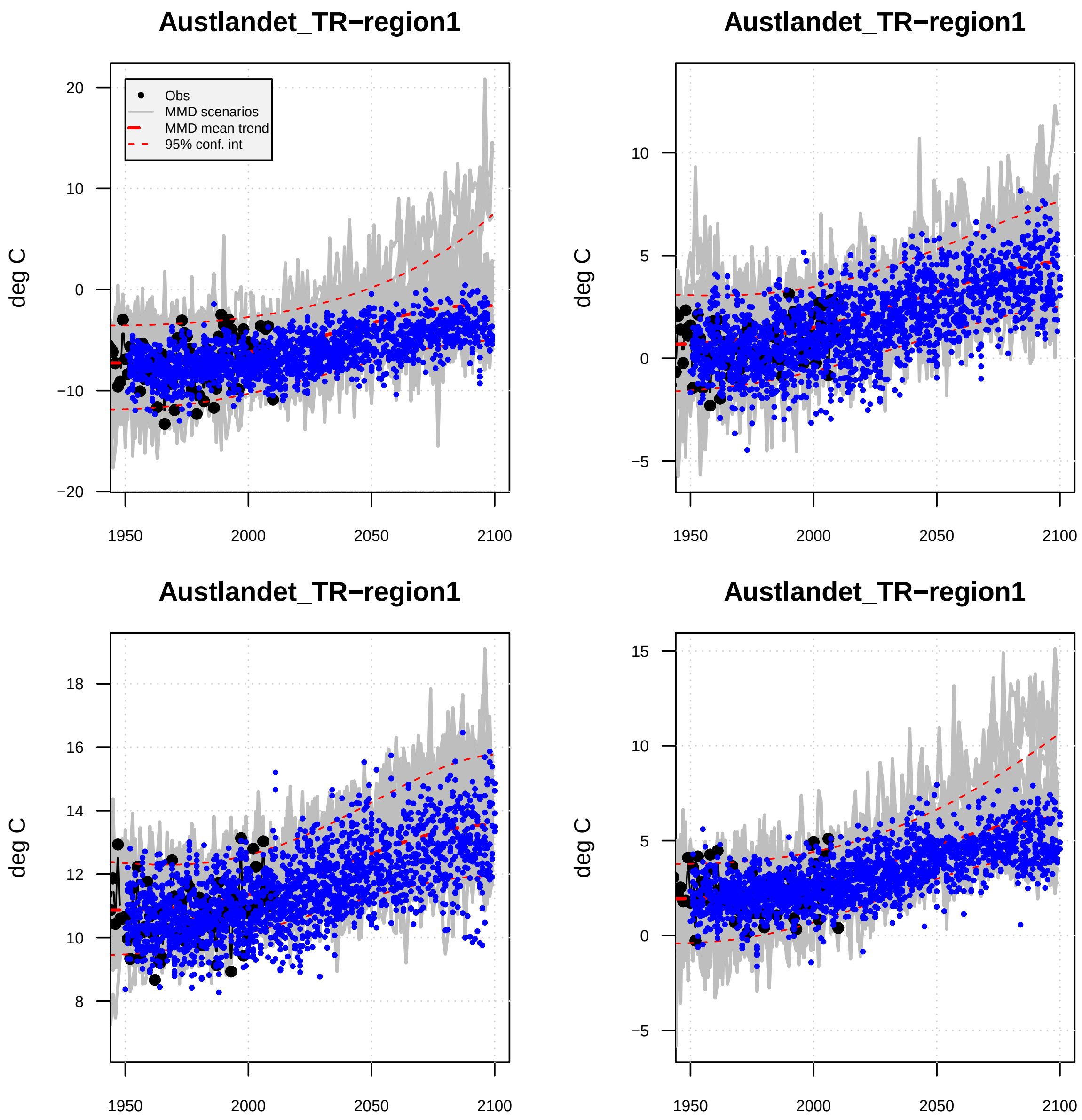

Figure 6: *Plume plots showing the seasonal mean temperature in temperature region 1 based on observations (black), ESD results (grey shading), and RCM results (blue symbols) for the four seasons (top left to bottom right DJF, MAM, JJA, and SON). The RCM results have been adjusted to have the same mean for the interval overlapping with the observations, applying the adjustment separately for each calendar month.*

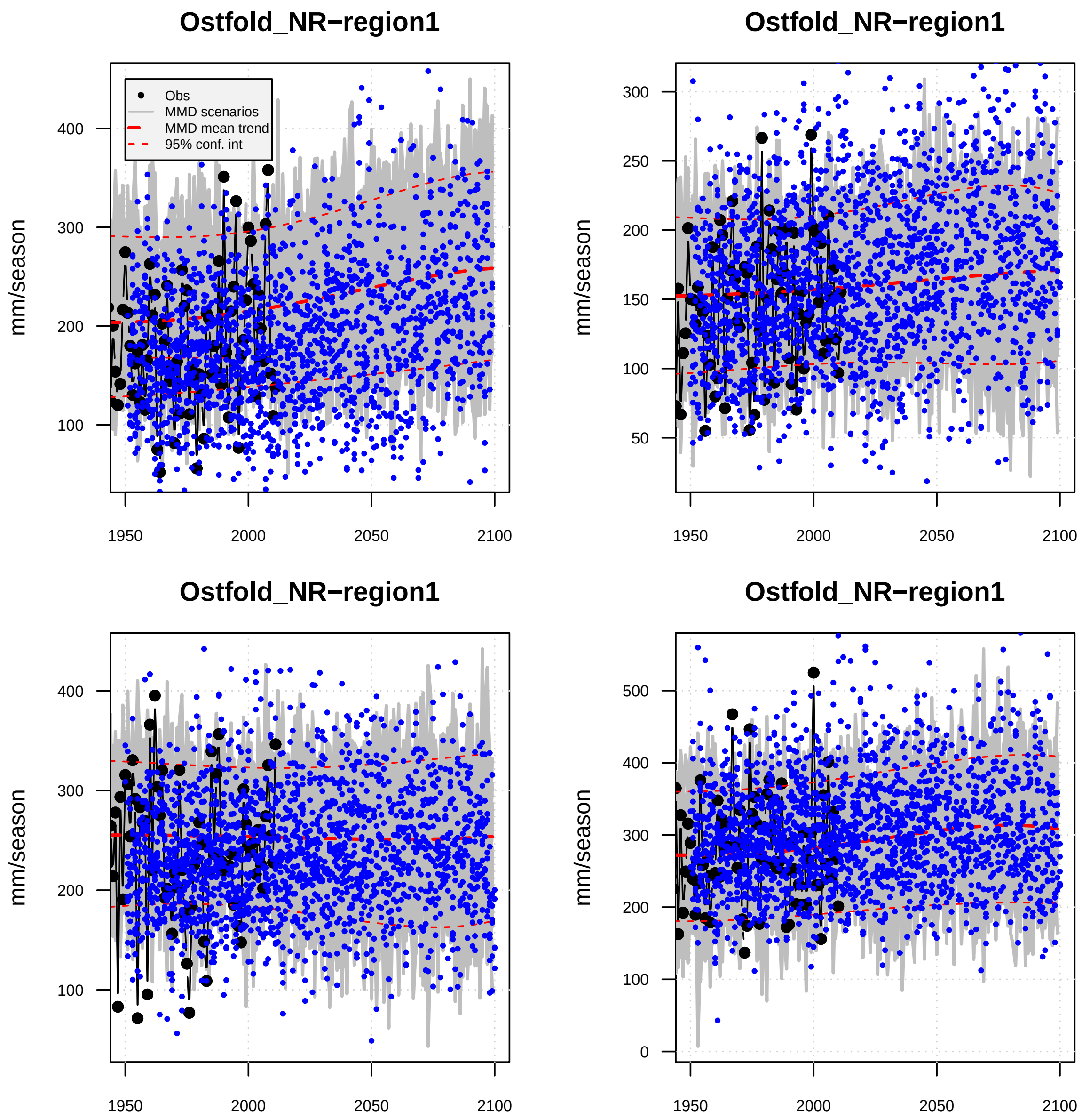

Figure 7: *Plume plots showing the seasonal mean precipitation in precipitation region 1 based on observations (black), ESD results (grey shading), and RCM results (blue symbols) for the four seasons (top left to bottom right DJF, MAM, JJA, and SON). The RCM results have been adjusted to have the same mean for the interval overlapping with the observations, applying the adjustment separately for each calendar month.*

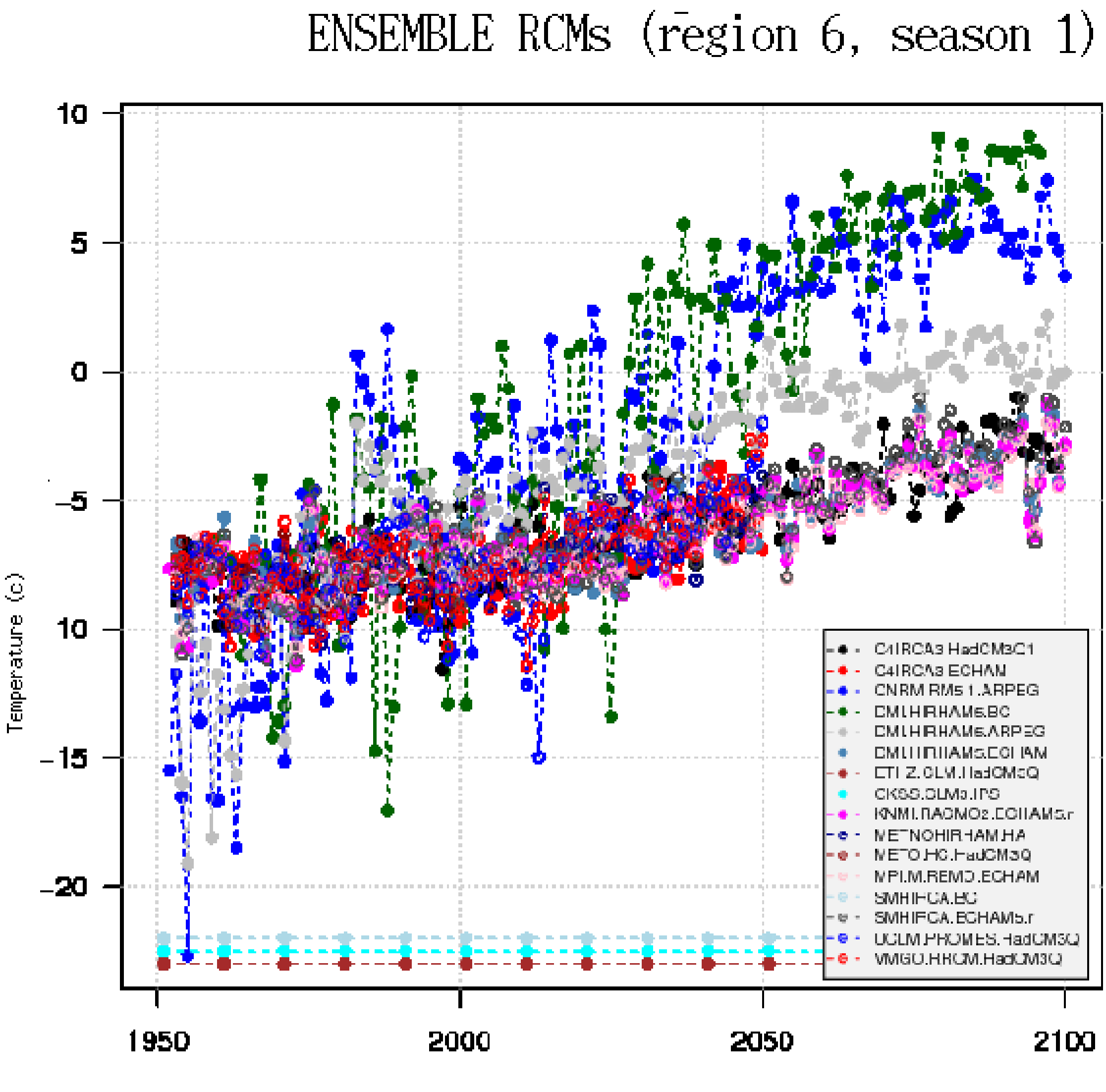

Figure 8: *Detailed comparison between ENSEMBLE RCMs for temperature in Vardø. Note: the horizontal curves towards the bottom of the figure mark those RCMs which did not have valid data for this region.*

3.2 Combination of cold winter following a dry autumn

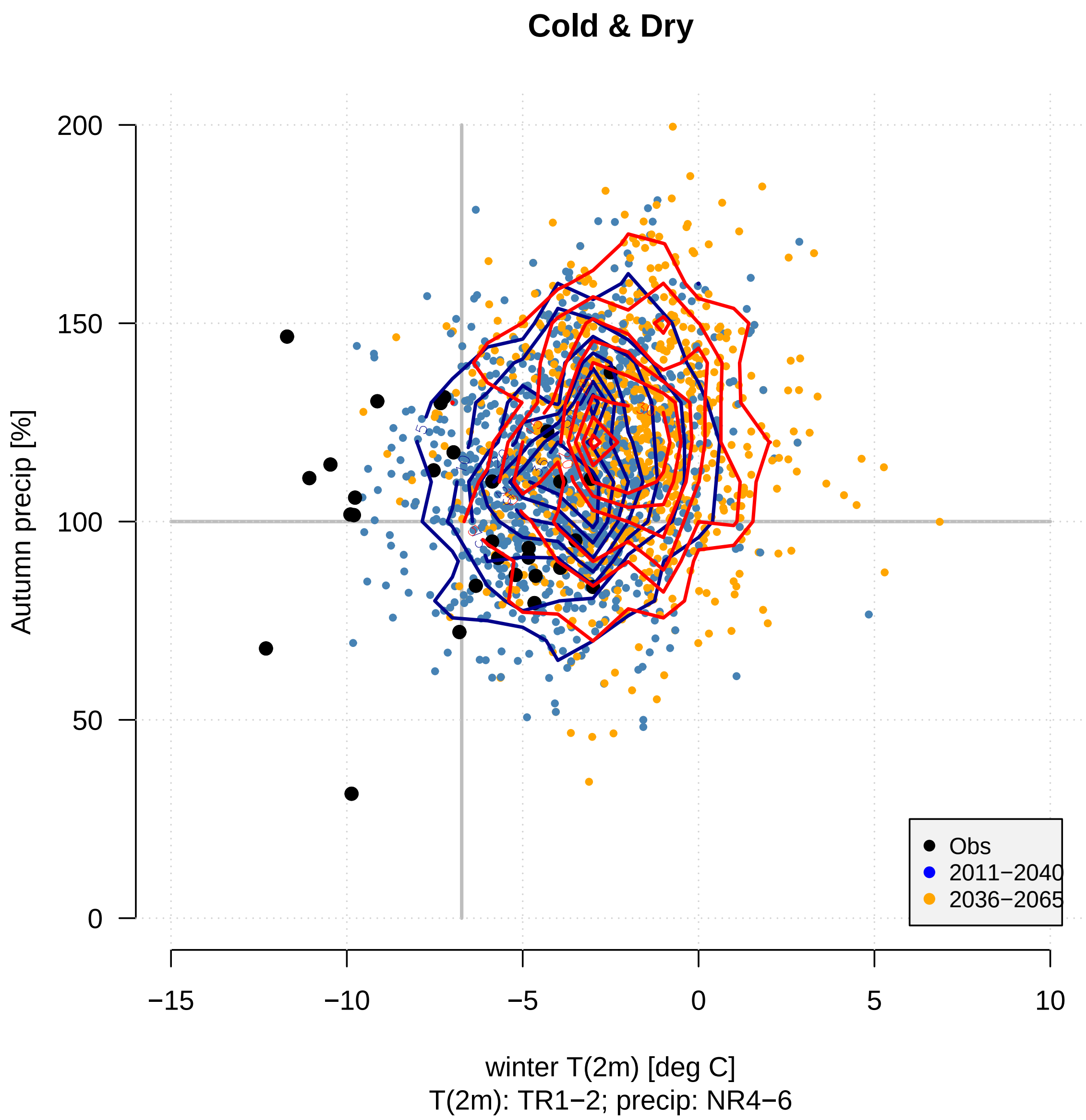

Figure 9: *Scatter-plot of winter temperature in TR1–2 against preceding autumn precipitation in NR 4–6. The contours mark the density of points for the ESD results: 2011–2040 (dark blue) and 2036–2065 (light blue). The grey axes mark the observed mean values.*

The question whether the probability of the combination a dry autumn (with less supply of water to hydroelectric reservoirs) followed by a cold winter (with high demand for hydroelectric power) will change can tentatively be addressed with large ensembles of climate model scenarios. Figures 9 and 10 show scatter plots, with temperature against precipitation for the southern and middle part of Norway respectively. The dry-autumn/cold-winter events are represented with points in the lower left corner, and black symbols mark the observations for 1961–1990/1970–1999 (temperature/precipitation). The points with darker blue shading represent the 2011–2040 interval, while the lighter blue shading marks the 2036–2065 period. Each point represents one year and one downscaled GCM. Hence 50 ESD-results times 30 years gives 150 data points for each interval.

The light blue points for 2036–2065 representing southern Norway are displaced towards the upper right corner compared to the observations and 2011–2040 (Figure 9), although cold winters will also occur in the future, albeit at a lower frequency. Dry autumns will also take place in the future according to these scenarios, but less points in the lower left corner translates to lower probabilities of the combination of the two: a dry autumn followed by a cold winter in the future. These results are in qualitative agreement with the a similar analysis carried out by *Engen-Skaugen & Førland* (2007).

For mid-Norway, the points representing 2036–2065 are displaced more along the temperature axis than the precipitation axis, suggesting that the warming trend dominates over the precipitation trends (Figure 10).

It is important to keep in mind the uncertainties associated with the models - we do not know if they account for all processes that may play a role. Furthermore, an ensemble of $\sim$150 data points is also small for estimating changes in extremes (adding the RCM results will not improve these, as they are not independent, but driven by a subset of GCMs used in the ESD-analysis). It is therefore important to assess whether the downscaled ensemble can reproduce the statistics of extremes of the past.

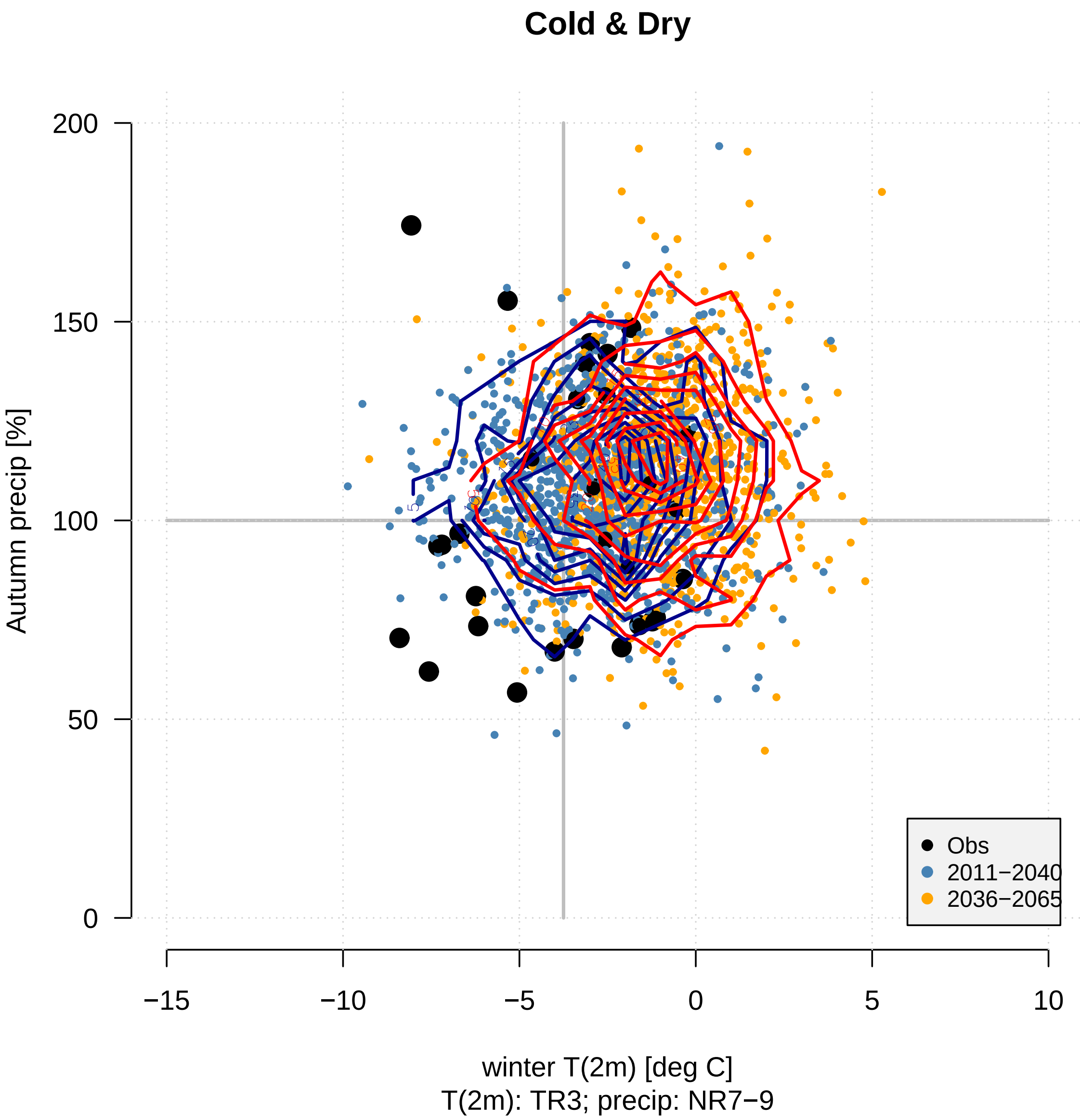

Figure 10: *Scatter-plot of winter temperature in TR3 against preceding autumn precipitation in NR 7–9. The contours mark the density of points for the ESD results: 2011–2040 (dark blue) and 2036–2065 (light blue).*

3.3 Evaluation

3.3.1 The ability of ESD and CMIP3 to describe high-pressure regions

Persistent cold winter conditions in Scandinavia tend to be associated with lasting blocking high-pressure systems, and it is therefore of great interest to evaluate the models' ability to describe the statistics of these high-pressure regions. The location of high- and low-pressure systems over Europe can be described by a single number: the NAO index (Figures 11). A low NAO-index is usually associated with high-pressure over Scandinavia, whereas a high NAO-index often mark more low pressure systems coming in over Norway and milder winters (Figure 12). The winter 2009-2010 was cold in southern Norway, and the NAO-index reached the second lowest value since 1950.

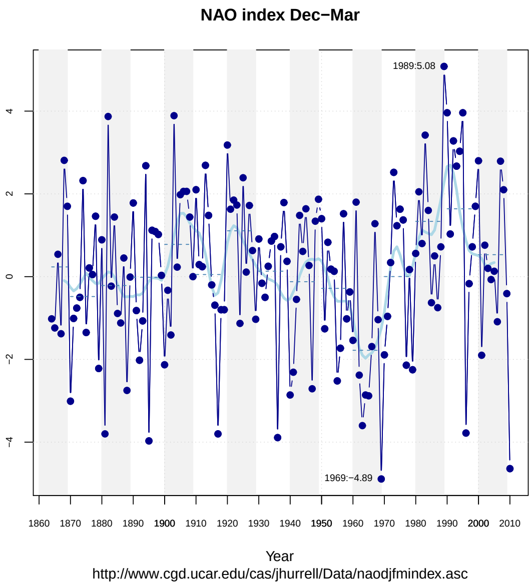

Figure 11: *December–March NAO-index (*Hurrell, *1995).*

Figure 13 compares the ESD results for Oslo-Blindern with the actual observations. Winter 2009-2010 were seen as relatively cold, but was not extreme in terms of the historical record. The ESD results envelopes both the cold winter of 2009-2010 as well as even colder winters in the earlier part of the record. When contrasting these with the extreme NAO-index value of 2009-2010, it appears that an underlying trend may explain why 2009-2010 still was warmer than the winters of the 1960s–1970s. It is likely that the NAO-index will continue to vary between high and low values in the future, explaining the low temperatures in Figures 9–10.

High-pressure systems also affect the summer weather statistics, but as opposed to favouring colder conditions in winter, a high pressure system tends to be associated with anomalous warm summer temperatures. Hence, an evaluation of heat waves is of interest because these are associated with lingering high-pressure regions during summer. One could examine the models' reproduction of the sea-level pressure systems, but since we are interested in the effect of these systems on the temperature, it is more instructive to assess the extreme temperature ranges derived through downscaling.

Figure 14 presents ESD results for Langres, France, and the extreme heat wave of the summer 2003 is visible in the observations (black symbols). Since the ESD results are derived from

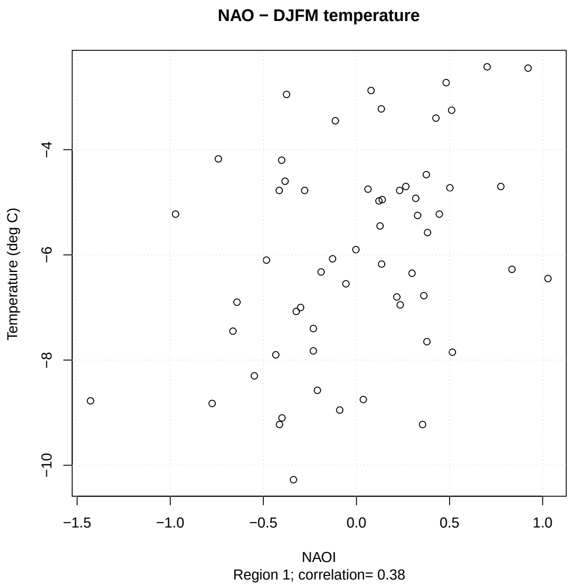

Figure 12: *Scatter-plot between the December–March NAO-index and temperature for TR1.*

coupled ocean-atmosphere models, the timing of individual events will not correspond to the observed ones, but nevertheless, their statistics (magnitude, frequency) should be reproduced. Trends for extremes and rare events with irregular recurrences are in general difficult to specify, and good analysis requires a large volume of data. In some cases, it is possible to analyse the recurrence of record-breaking events in long and parallel series (*Benestad*, 2008d). Here the evaluation is based on a much simpler approach. The analysis suggests that there are peaks in the ESD results both before and after model time stamp "2003" with roughly similar magnitude as the *real* 2003 event (upper bound of the shaded region). Figure 14 also shows that at the end of the century, summer temperatures like that seen in 2003 in Europe will be well within the 10–90% interval.

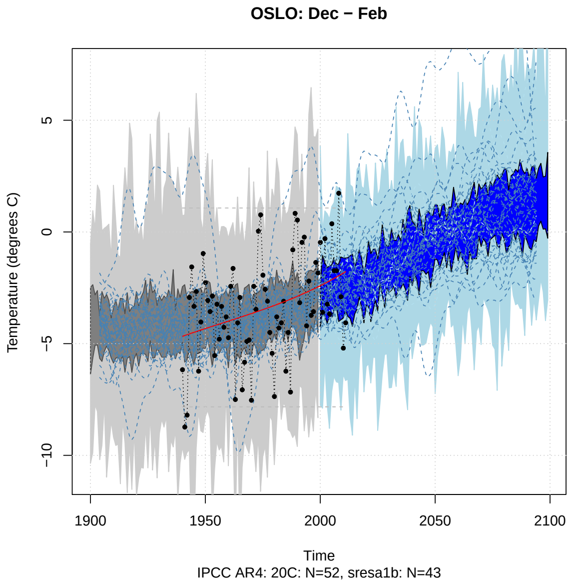

Figure 13: *The winter temperature in Oslo (Blindern). The relatively low 2009–2010 winter temperature is spanned by the ESD results. The light shading shows the envelope of the ESD ensemble, whereas the dark shading mark the inter-quartile range (25–75% interval). The black symbols show the observations, and the blue dashed lines show 10-year low-pass filtered individual runs (Gaussian filter).*

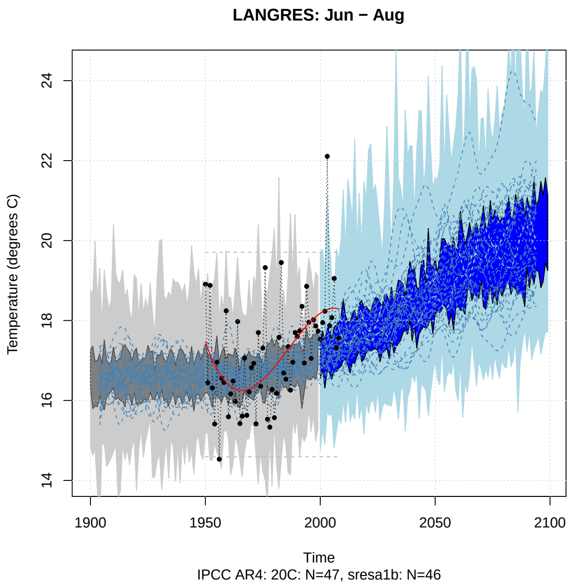

Figure 14: *The summer temperature in Langres, France, which was affected by the 2003 summer heat wave. The light shading shows the envelope of the ESD ensemble, whereas the dark shading mark the inter-quartile range (25–75% interval). The black symbols show the observations, and the blue dashed lines show 10-year low-pass filtered individual runs (Gaussian filter).*

3.3.2 Comparison with previous results

The present ESD-analysis and the RCMs from the ENSEMBLES provide information about regional climates in Norway correspond to the projections in *Hanssen-Bauer* et al. (2009). It is also important to place these projections in the context of the recent assessment report from the Intergovernmental Panel on Climate Change (IPCC) (*Christensen* et al., 2007). According to *Knutti* et al. (2010), recommendations for regional assessments should include four considerations: historical change, process change (e.g. changes in the driving circulation), global climate change projected by GCMs, and downscaled projected change. In addition, scenarios based on ensembles should follow the *Knutti* et al. (2010) recommendations for reproducibility, model selection, averaging/weighting, model evaluation, performance metrics, and general recommendations for ensembles.

The projections in *Hanssen-Bauer* et al. (2009) can be contrasted with the large-scale picture from a range of GCMs from *Christensen* et al. (2007), reproduced in Figure 15. The mean change based on the CMIP3 (*Meehl* et al., 2007) suggests an annual mean temperature increase of the order 4.5–6°C in the vicinity of Norway and for the period 2080–2099 ("2090") for the SRES A1b scenario, and even higher for the SRES A2 scenario. Since this represents the ensemble mean, there are GCMs with even higher values. This estimate is substantially higher than the RCMs presented in *Hanssen-Bauer* et al. (2009) although their time slices should represent a slightly different time period: 2070–2100 (all show $\Delta T < 4.2$°C, Figure 2 and (*Hanssen-Bauer* et al., 2009, Table 5.2.2)). The high-end scenario in (*Hanssen-Bauer* et al., 2009, Table 5.2.2), which accounts for the faster warming projected through ESD gives $\Delta T < 5.4$°C which is closer to the IPCC SRES A1b range of 4.5–6°C. In a similar vein as in *Hanssen-Bauer* et al. (2009), the RCMs presented here suggest a more modest warming than the ESD and Figure 15. A more detailed comparison between the RCMs and ESD is presented in Figure 16, suggesting that ESD produces much more pronounced warming for the winter season.

Hence the results in *Hanssen-Bauer* et al. (2009) seem to confirm the finding here, where the 5-95 percentile range is smaller in the RCMs than for the ESD results, albeit based on a smaller number GCMs for the RCMs. However, the RCMs in *Hanssen-Bauer* et al. (2009) represented a smaller ensemble than ENSEMBLES used here.

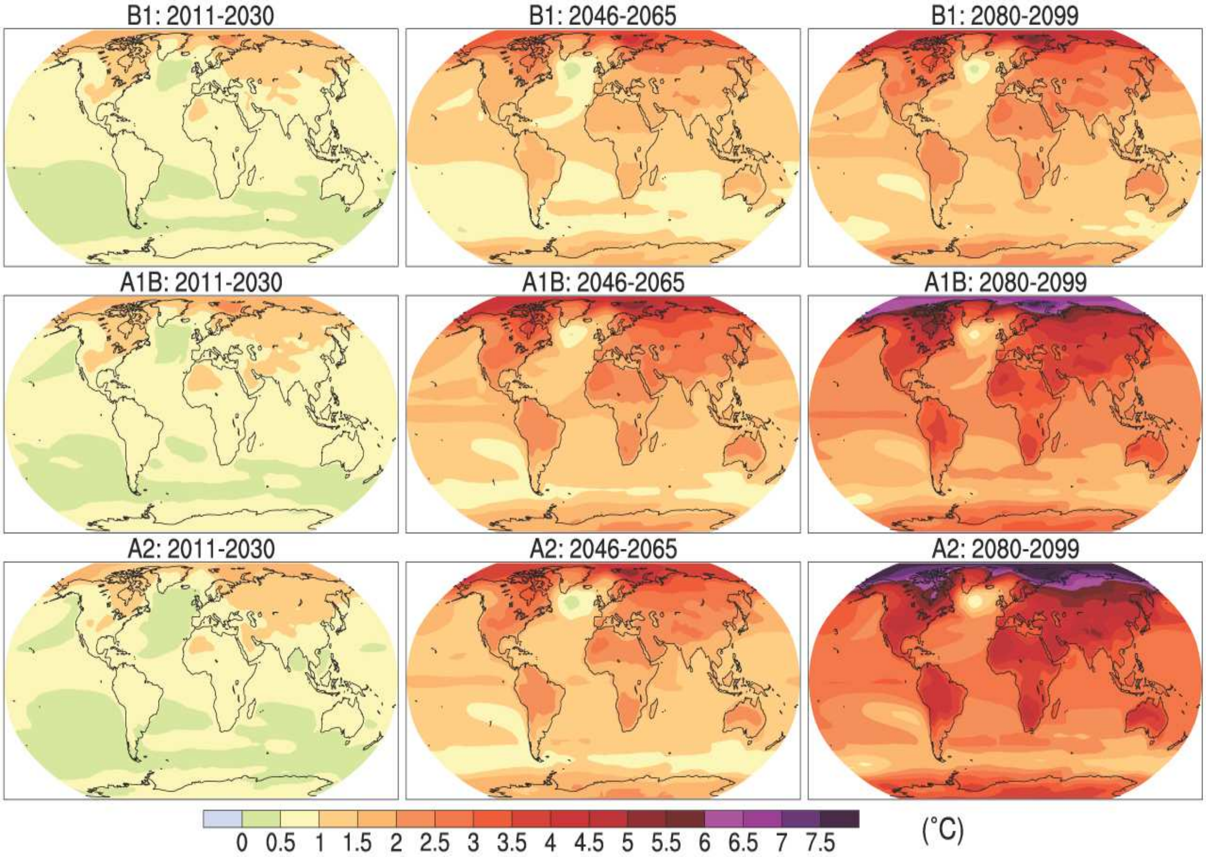

Figure 15: *A reproduction of Figure 10.8 from AR4.*

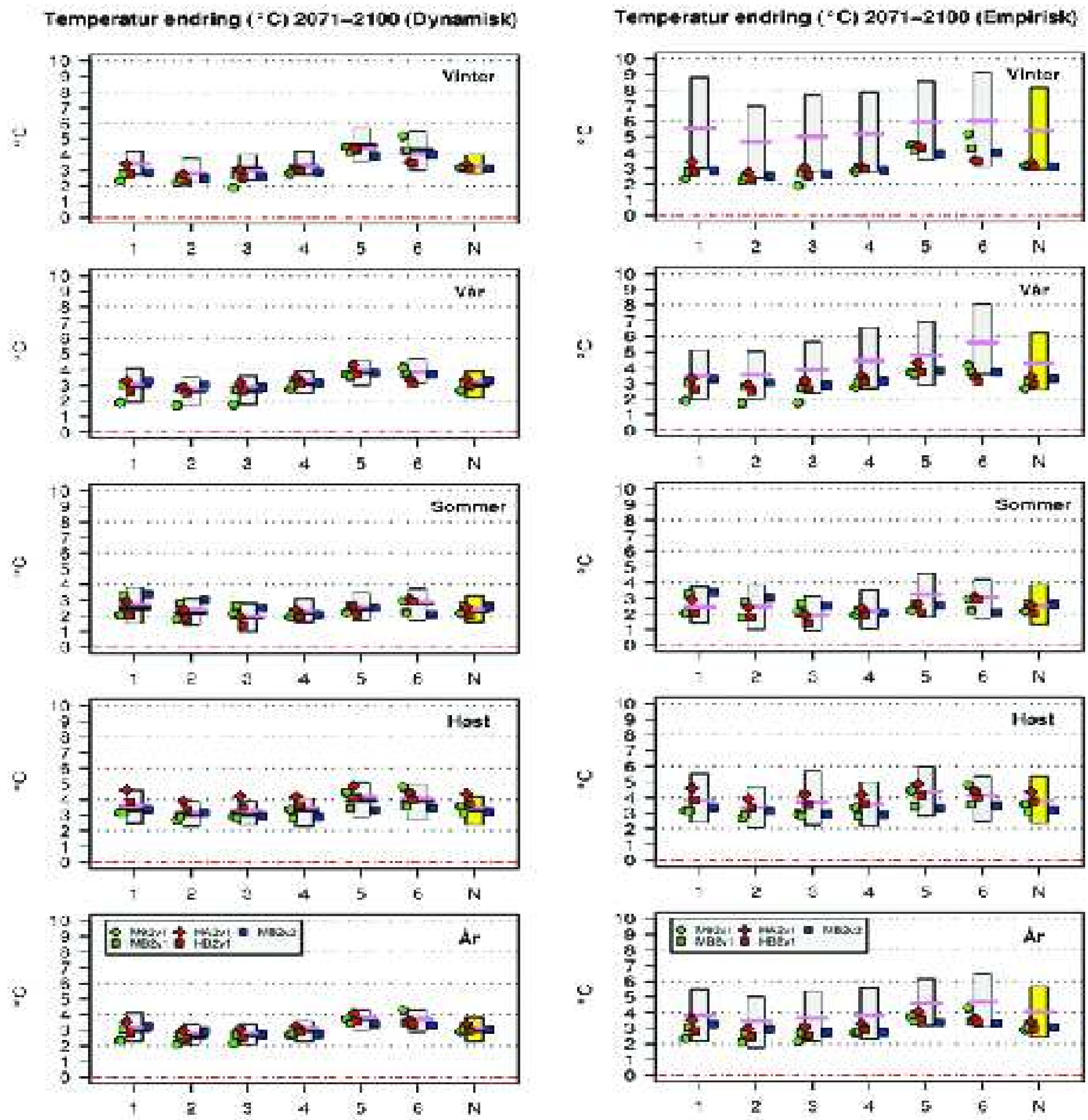

Figure 16: *Estimated seasonal and annual temperature change derived from RCMs (left) and ESD (right) at different regions. The numbers 1–6 on the x-axis refers to temperature region, and the label 'N' denotes the average values for all of Norway. The changes are estimated over the periods 1961–90 to 2071–2100. Black (left panels) and pink lines mark the ensemble mean (left: 22 RCM simulations some of which are driven with the same GCM, different spatial resolution, or following different emission scenarios; right: ≈ 50 members from the CMIP3 ensemble all following the SRES A1b). The black lines show weighted mean whereas pink lines show unweighted results. The boxes mark the 10–90% quantiles, and the symbols represent a selection of the RCMs. Reference: Figure 5.2.1–5.2.2 from* Hanssen-Bauer *et al. (2009).*

3.4 Running 3-day-mean analysis

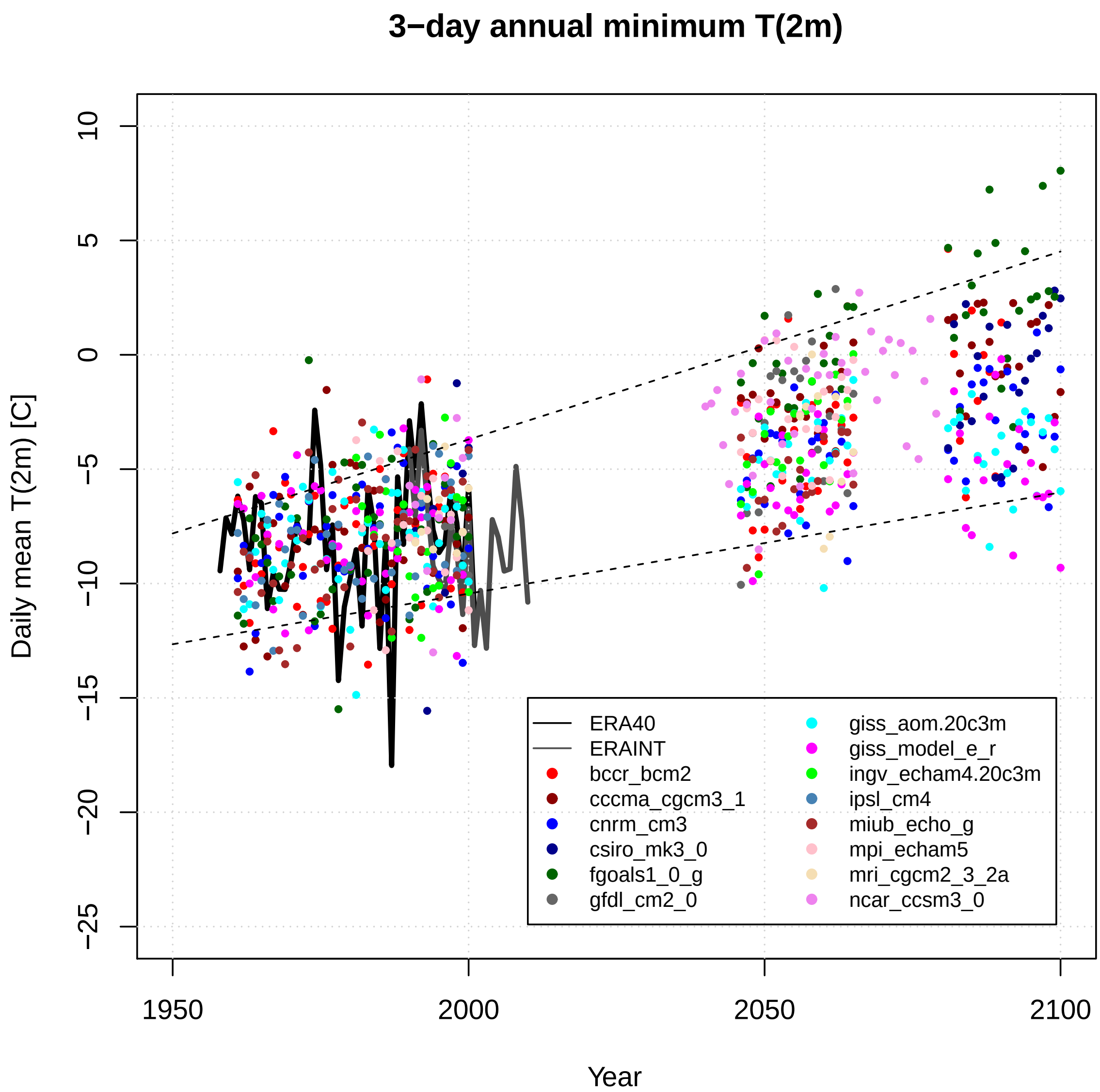

Figure 17: *Annual minimum of 3-daily mean temperatures T_{3DM} over the region 0°W–30°E/55–70°N estimated from ERA40, ERAINT, and GCMs. The dashed lines mark the 5 and 95 percentiles of the scatter for successive 10-year intervals.*

Figure 17 shows the annual minimum of 3-daily mean temperatures T_{3DM} over the region 0°W–30°E/55–70°N (Figure 5). The GCM results suggest a general warming trend in the coldest 3-day averages for the future. The re-analyses suggest large year-to-year differences that several times extend beyond the central 90% of the range between the dashed lines that are based on the RCMs. There is a number of RCM points that lie outside this region too, and from the expectation that 90% lie within this region, we expect to see ∼14 RCM points outside these lines for each decade. The combined time span of ERA40 and ERAINT is ∼50 years, and we should expect about 5 events to fall outside the central 90% range. Figure 17 suggests that 10 of the points from the re-analysis are outside the range, and hence that the RCMs may underestimate the magnitude of the year-to-year variation in T_{3DM}.

A comparison between the annual 3-day minimum temperatures from ERA40 averaged over 0°W–30°E/55–70°N and corresponding values estimated from actual measurements made in Oslo, Bergen, Trondheim, and Tromsø is presented as scatter plots in Figure 18. These scatter plots show that the large-scale situation to some degree reflects the local conditions, and the non-zero correlation suggests that the information about the large-scale average over 0°W–30°E/55–70°N can be utilised for inferring local changes.

A regression based on a combination of ERA40/ERAINT (1958–2010) against the station data from Oslo, Bergen, Trondheim, and Tromsø was used to translate the confidence interval for the 0°W–30°E/55–70°N region, estimated from GCM results in Figure 17, to local conditions. These are shown as gray hatching in Figure 19, together with the observations (symbols), the regression fit (lines), and the transfer equation. It is important to bear in mind that predictions from regression analyses account for less variance than the original series. Hence, the area of the grey-shaded regions in Figure 19 may be under-estimated.

The 1958–2010 annual minimum 3-day mean temperature was also used to estimate the 2-, 10-, and 50-year return levels. Since these already were block maxima (the values were inverted by multiplying with -1), a GEV (*Coles*, 2001) was used for this purpose. The return-level analysis is shown in Figure 20, and the return levels are provided as text in the different panels.

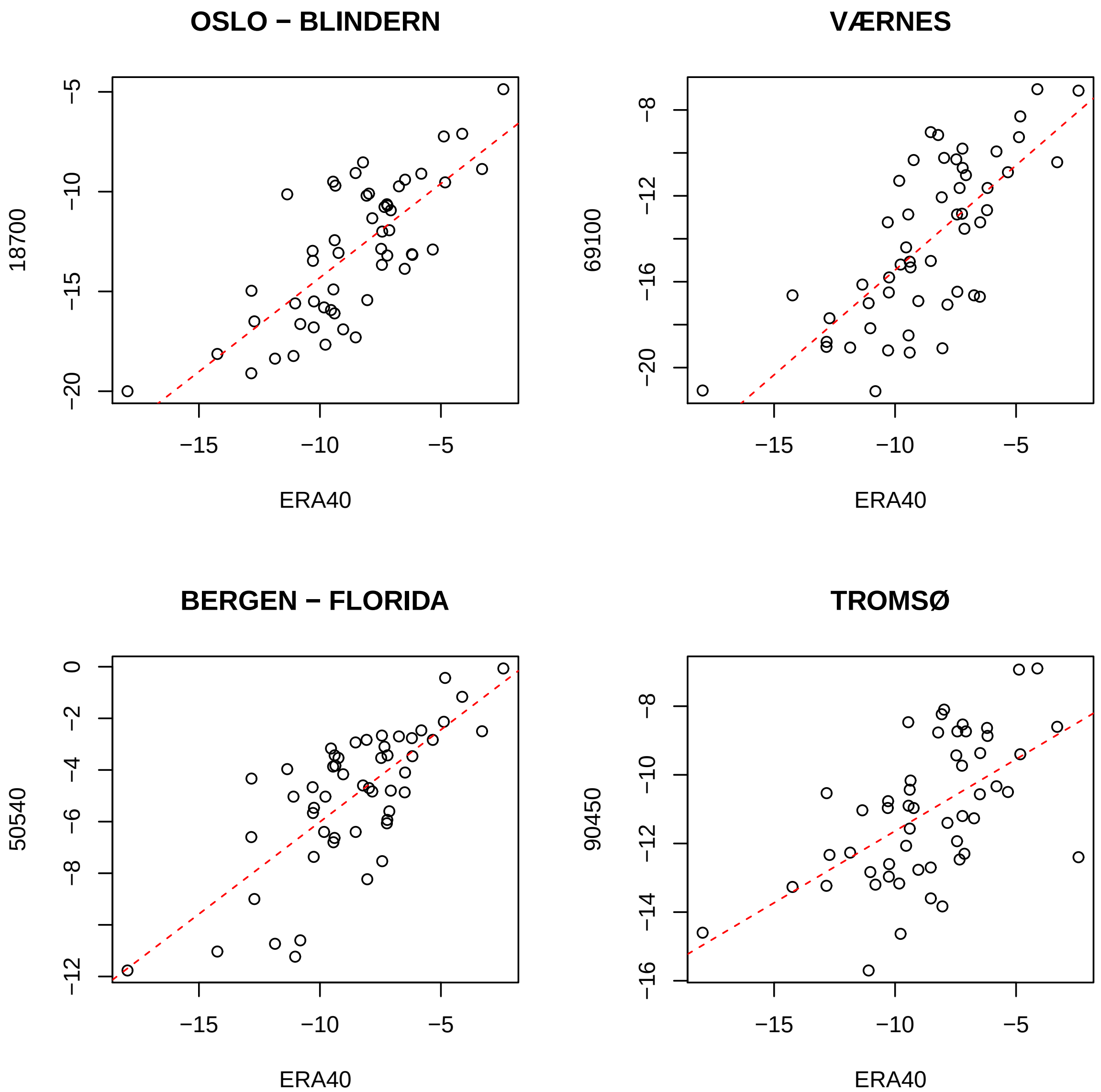

Figure 18: *Scatter plots showing the correlation between 3-day minimum temperatures from ERA40/ERAINT averaged over 0°W–30°E/55–70°N and corresponding values estimated from actual measurements for the interval 1958–2010. The red lines show linear regression fits.*

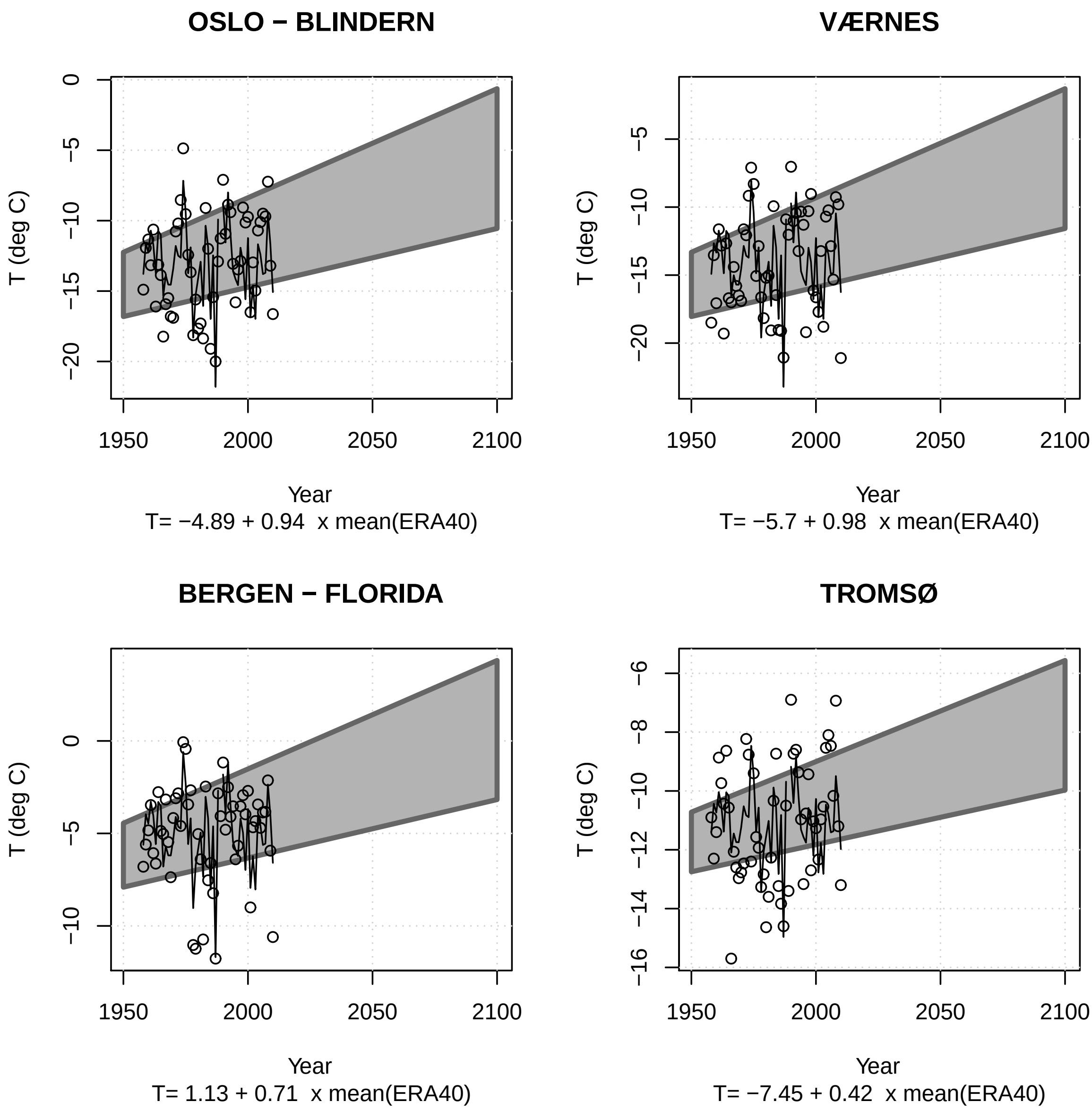

Figure 19: *Plots of local 3-day minimum temperatures estimated from station measurements and predicted from ERA40/ERAINT (dashed lines). The grey shaded regions show the 5 and 95 percentiles of the scatter for successive 10-year intervals from Figure 17 adjusted to the local conditions based on the regression analysis against ERA40/ERAINT. The coeffiecients from the regression analysis is provided at the bottom.*

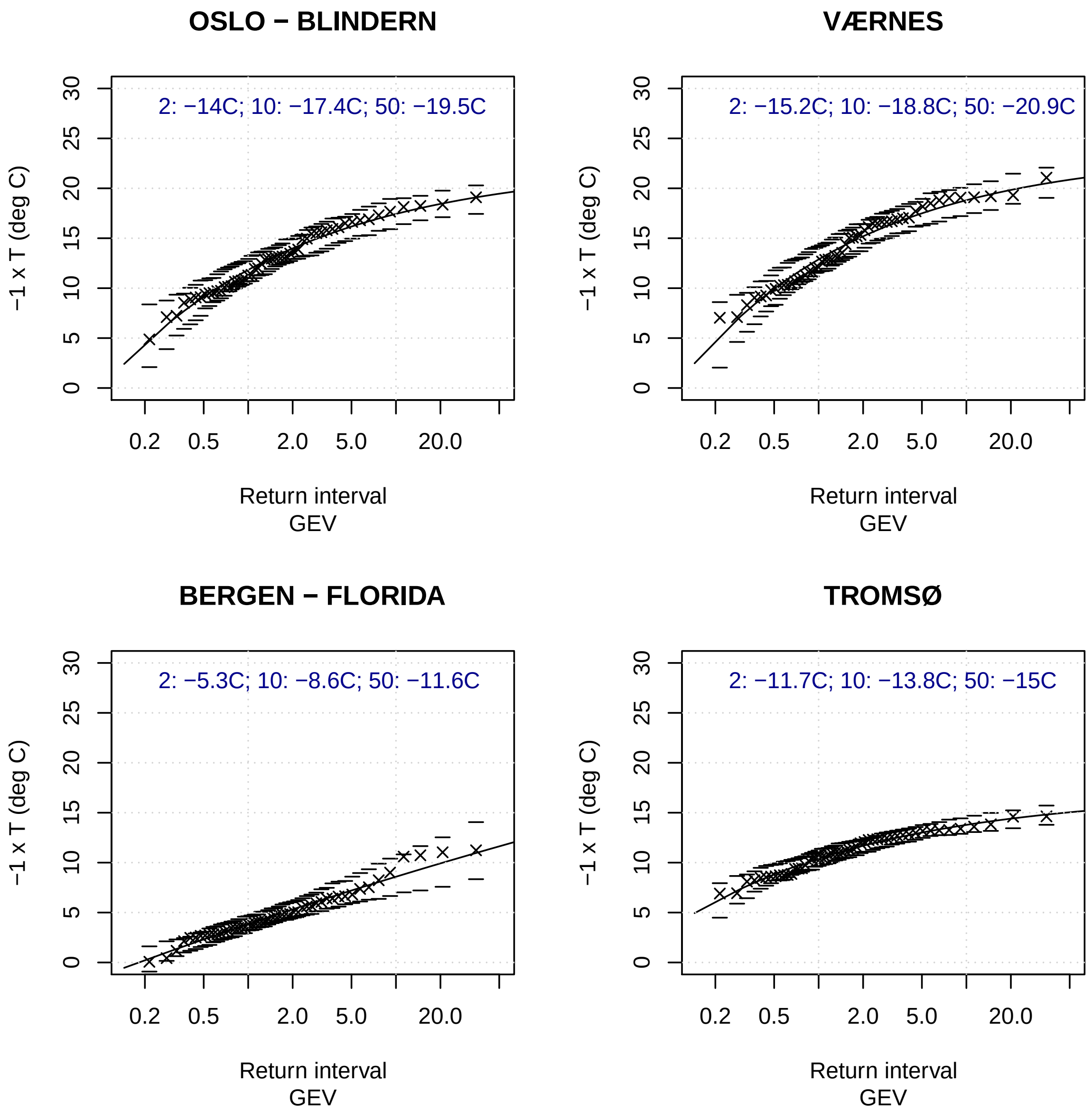

Figure 20: *Return-value analysis applied to the observed 3-day minimum temperature over the interval 1958–2010. The 2-, 10-, and 50-yr return levels are given as text in the figures. Note, the y-axis is* $-1\times$ *the temperature.*

4 Discussion

The present analysis confirms the picture given by earlier analysis, albeit with a modification in the detailed descriptions. The temperature scenarios point to a future warming, and the precipitation projections suggest slightly wetter conditions in the future for most locations except the southern part of Norway. The results hint to slightly drier summer climates in the southern part.

The ESD-results give a wider range of possible outcomes as opposed to the RCMs. It has been shown that the envelope of the ESD-results fits some of the past observations in terms of extreme heat waves and cold spells. Hence, the estimates appear to be realistic. The fact that the RCMs more or less agree with the ESD-results gives us confidence in the downscaling of the GCMs, as these two approaches are based on very different philosophies with different strengths and weaknesses (*Benestad*, 2011). But there is a concern about the quality of RCM results for locations near the lateral boundary. Some of the RCMs in the ENSEMBLES project do not extend up to northern Norway, and parts of Scandinavia are near the boundary where the RCMs do not provide free solutions.

The RCMs do suggest a weaker warming than the ESD and the GCMs, and one explanation may be that these are driven with a smaller number of more moderate GCMs. Another explanation may be that the RCMs do not provide a good description of inversion conditions (*Hanssen-Bauer* et al., 2005). On the other hand, the GCMs are not expected to describe inversions well either, and some consistency is expected between the larger spatial scales from RCMs and GCMs.

In addition to persistent high-pressure systems and their association with cold winter conditions, low-pressure systems also represent an important factor, being connected with excessive precipitation. Storms following a steady storm track will give rise to a lingering low-pressure, when averaged, and a train of low-pressure systems will bring in moist air from maritime regions.

5 Conclusion

New downscaling analysis of global climate models indicate a consistent picture of future warming, with ESD-results suggesting stronger warming than RCM results. One explanation for the higher ESD estimates is that they involve a substantially larger set of independent global climate model simulations. The new results are nevertheless roughly in line with previous results presented in *Hanssen-Bauer* et al. (2009). It is also shown that the ensemble of ESD results can reproduce similar extreme seasonal temperatures as seen in the past.

The ESD and RCMs from the ENSEMBLES project both indicate a wetter future, although the RCMs suggest a more pronounced increase in the precipitation. Again, the results are in qualitative agreement with the scenarios in *Hanssen-Bauer* et al. (2009).

An analysis of the combination dry-autumn/cold-subsequent-winter was carried out, suggesting that the probability of occurrence is likely to diminish with a global warming, due to trends towards warmer and wetter conditions in general. Caution must be used when using these results, however, as global climate models, on which they are based, are known to suffer from a range of uncertainties - especially on local and regional scales.

An analysis of mean 3-day annual minimum from a set of global climate models exhibits warming trends for Scandinavia. This can be interpreted as reduced probability of cold spells in the future. Again caution must be used when using these results, as there is no guarantee that models capture all relevant aspects in the real world, particularly when it comes to extreme events.

6 Acknowledgements

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Table 18: Fraction of cases where preciption $<$ 60% of the 1970–1999 mean value based on observations.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.16	0.12	0.10	0.06	0.00
region 2	0.10	0.08	0.09	0.06	0.00
region 3	0.16	0.15	0.20	0.10	0.01
region 4	0.14	0.12	0.13	0.03	0.00
region 5	0.16	0.16	0.05	0.04	0.01
region 6	0.16	0.18	0.02	0.06	0.01
region 7	0.16	0.08	0.03	0.03	0.00
region 8	0.15	0.17	0.02	0.11	0.01
region 9	0.17	0.12	0.01	0.11	0.01
region 10	0.13	0.11	0.03	0.09	0.01
region 11	0.09	0.10	0.08	0.08	0.01
region 12	0.07	0.08	0.08	0.03	0.00
region 13	0.04	0.09	0.09	0.02	0.00

7 Appendix

7.1 Additional tables: precipitation

In order to estimate the fraction of cases below or exceeding a set of given threshold values, data from a s specified interval (e.g. 1970–1999) were used to fit a Gaussian distribution (using moments estimators: the mean and standard deviation). The fraction was then estimated as the area under the fitted Gaussian probability distribution function satisfying the criterion: $p = Pr(X < x)$ for values below and $p = 1 - Pr(X < x)$ for values exceeding the threshold. We let $Pr = \int_{\infty}^{\infty} f(x)dx$ where $f(x) = \frac{1}{\sqrt{2\pi}} e^{(x-\mu)^2 \sigma^2}$, μ is the mean value, and σ the standard deviation.

Tables 18 and 22 provide the rates for the observed precipitation being below the lower threshold of 60% of the mean value or exceeding 150% of the mean value. These should be comparable to the corresponding tables 19 and 23, computed for the downscaled results of the historical runs and for the same time interval (1970–1999). The historical runs involve a larger sample as they are derived from an ensemble of GCM runs rather than one realisation (observations). Any discrepancy between these tables can be explained in terms of predicted variance σ^2 (the mean value μ is prescribed from the observations).

In general, the fraction outside the two thresholds derived from the downscaling was lower than suggested by the observations, indicating suppressed variance. The exception is region 8, where nearly all the results indicated too low variability.

Table 19: Fraction of cases where preciption $<$ 60% of the 1970–1999 mean value based on downscaled simulations with historic emissions.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.07	0.02	0.00	0.00	0
region 2	0.02	0.02	0.00	0.00	0
region 3	0.04	0.06	0.03	0.01	0
region 4	0.07	0.06	0.01	0.00	0
region 5	0.11	0.04	0.01	0.00	0
region 6	0.07	0.03	0.00	0.00	0
region 7	0.02	0.00	0.00	0.00	0
region 8	0.01	0.01	0.00	0.00	0
region 9	0.01	0.01	0.00	0.00	0
region 10	0.01	0.01	0.01	0.00	0
region 11	0.00	0.01	0.00	0.00	0
region 12	0.00	0.00	0.00	0.00	0
region 13	0.00	0.01	0.00	0.00	0

Table 20: Fraction of cases where preciption $<$ 60% of the 2011–2040 mean value based on downscaled simulations with SRES A1b emissions.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.08	0.02	0.06	0.00	0
region 2	0.03	0.02	0.07	0.01	0
region 3	0.06	0.05	0.14	0.03	0
region 4	0.08	0.03	0.01	0.00	0
region 5	0.10	0.03	0.00	0.00	0
region 6	0.08	0.05	0.00	0.00	0
region 7	0.00	0.00	0.00	0.00	0
region 8	0.01	0.04	0.00	0.00	0
region 9	0.03	0.03	0.00	0.01	0
region 10	0.06	0.06	0.00	0.01	0
region 11	0.04	0.04	0.00	0.02	0
region 12	0.00	0.01	0.00	0.00	0
region 13	0.00	0.01	0.01	0.00	0

Table 21: Fraction of cases where preciption $<$ 60% of the 2036–2065 mean value based on downscaled simulations with SRES A1b emissions.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.08	0.02	0.06	0.00	0
region 2	0.03	0.02	0.07	0.01	0
region 3	0.06	0.05	0.14	0.03	0
region 4	0.08	0.03	0.01	0.00	0
region 5	0.10	0.03	0.00	0.00	0
region 6	0.08	0.05	0.00	0.00	0
region 7	0.00	0.00	0.00	0.00	0
region 8	0.01	0.04	0.00	0.00	0
region 9	0.03	0.03	0.00	0.01	0
region 10	0.06	0.06	0.00	0.01	0
region 11	0.04	0.04	0.00	0.02	0
region 12	0.00	0.01	0.00	0.00	0
region 13	0.00	0.01	0.01	0.00	0

Table 22: Fraction of cases where preciption $>$ 150% of the 1970–1999 mean value based on observations.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.10	0.13	0.03	0.06	0.00
region 2	0.04	0.07	0.01	0.05	0.00
region 3	0.06	0.11	0.05	0.08	0.00
region 4	0.14	0.12	0.03	0.05	0.00
region 5	0.22	0.15	0.01	0.08	0.01
region 6	0.23	0.19	0.00	0.13	0.02
region 7	0.10	0.10	0.01	0.04	0.00
region 8	0.18	0.17	0.00	0.16	0.02
region 9	0.16	0.08	0.01	0.14	0.01
region 10	0.18	0.06	0.03	0.13	0.02
region 11	0.14	0.03	0.09	0.09	0.01
region 12	0.05	0.04	0.03	0.04	0.00
region 13	0.01	0.00	0.07	0.03	0.00

Table 23: Fraction of cases where preciption > 150% of the 1970–1999 mean value based on downscaled simulations with historic emissions.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.01	0.04	0.00	0.03	0
region 2	0.00	0.02	0.00	0.02	0
region 3	0.00	0.05	0.00	0.02	0
region 4	0.01	0.05	0.00	0.04	0
region 5	0.03	0.03	0.00	0.06	0
region 6	0.02	0.01	0.00	0.05	0
region 7	0.00	0.00	0.00	0.00	0
region 8	0.01	0.00	0.00	0.01	0
region 9	0.01	0.00	0.00	0.01	0
region 10	0.00	0.00	0.00	0.01	0
region 11	0.00	0.00	0.01	0.00	0
region 12	0.00	0.00	0.00	0.00	0
region 13	0.00	0.00	0.00	0.00	0

Table 24: Fraction of cases where preciption > 150% of the 2011–2040 mean value based on downscaled simulations with SRES A1b emissions.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.22	0.13	0.03	0.17	0.01
region 2	0.14	0.08	0.00	0.12	0.00
region 3	0.12	0.13	0.01	0.10	0.00
region 4	0.14	0.15	0.01	0.22	0.02
region 5	0.21	0.13	0.02	0.36	0.05
region 6	0.18	0.10	0.02	0.37	0.04
region 7	0.04	0.01	0.00	0.12	0.00
region 8	0.11	0.09	0.00	0.24	0.01
region 9	0.04	0.04	0.01	0.19	0.00
region 10	0.08	0.05	0.10	0.21	0.00
region 11	0.03	0.02	0.06	0.10	0.00
region 12	0.00	0.02	0.00	0.09	0.00
region 13	0.00	0.00	0.01	0.00	0.00

Table 25: Fraction of cases where preciption $>$ 150% of the 2036–2065 mean value based on downscaled simulations with SRES A1b emissions.

Region	winter	Spring	Summer	Autumn	annual
region 1	0.22	0.13	0.03	0.17	0.01
region 2	0.14	0.08	0.00	0.12	0.00
region 3	0.12	0.13	0.01	0.10	0.00
region 4	0.14	0.15	0.01	0.22	0.02
region 5	0.21	0.13	0.02	0.36	0.05
region 6	0.18	0.10	0.02	0.37	0.04
region 7	0.04	0.01	0.00	0.12	0.00
region 8	0.11	0.09	0.00	0.24	0.01
region 9	0.04	0.04	0.01	0.19	0.00
region 10	0.08	0.05	0.10	0.21	0.00
region 11	0.03	0.02	0.06	0.10	0.00
region 12	0.00	0.02	0.00	0.09	0.00
region 13	0.00	0.00	0.01	0.00	0.00

Table 26: Correlation matrix for NR 1–12 based on historical data from met.no.

1.00	0.99	0.98	0.97	0.95	0.93	0.96	0.91	0.92	0.91	0.91	0.94
0.99	1.00	0.98	0.96	0.94	0.92	0.97	0.91	0.92	0.91	0.91	0.94
0.98	0.98	1.00	0.97	0.94	0.92	0.94	0.89	0.90	0.90	0.90	0.92
0.97	0.96	0.97	1.00	0.99	0.98	0.95	0.95	0.94	0.95	0.94	0.93
0.95	0.94	0.94	0.99	1.00	0.99	0.95	0.97	0.95	0.96	0.95	0.93
0.93	0.92	0.92	0.98	0.99	1.00	0.94	0.98	0.96	0.98	0.96	0.93
0.96	0.97	0.94	0.95	0.95	0.94	1.00	0.95	0.97	0.95	0.93	0.96
0.91	0.91	0.89	0.95	0.97	0.98	0.95	1.00	0.98	0.99	0.97	0.94
0.92	0.92	0.90	0.94	0.95	0.96	0.97	0.98	1.00	0.98	0.96	0.95
0.91	0.91	0.90	0.95	0.96	0.98	0.95	0.99	0.98	1.00	0.99	0.95
0.91	0.91	0.90	0.94	0.95	0.96	0.93	0.97	0.96	0.99	1.00	0.96
0.94	0.94	0.92	0.93	0.93	0.93	0.96	0.94	0.95	0.95	0.96	1.00

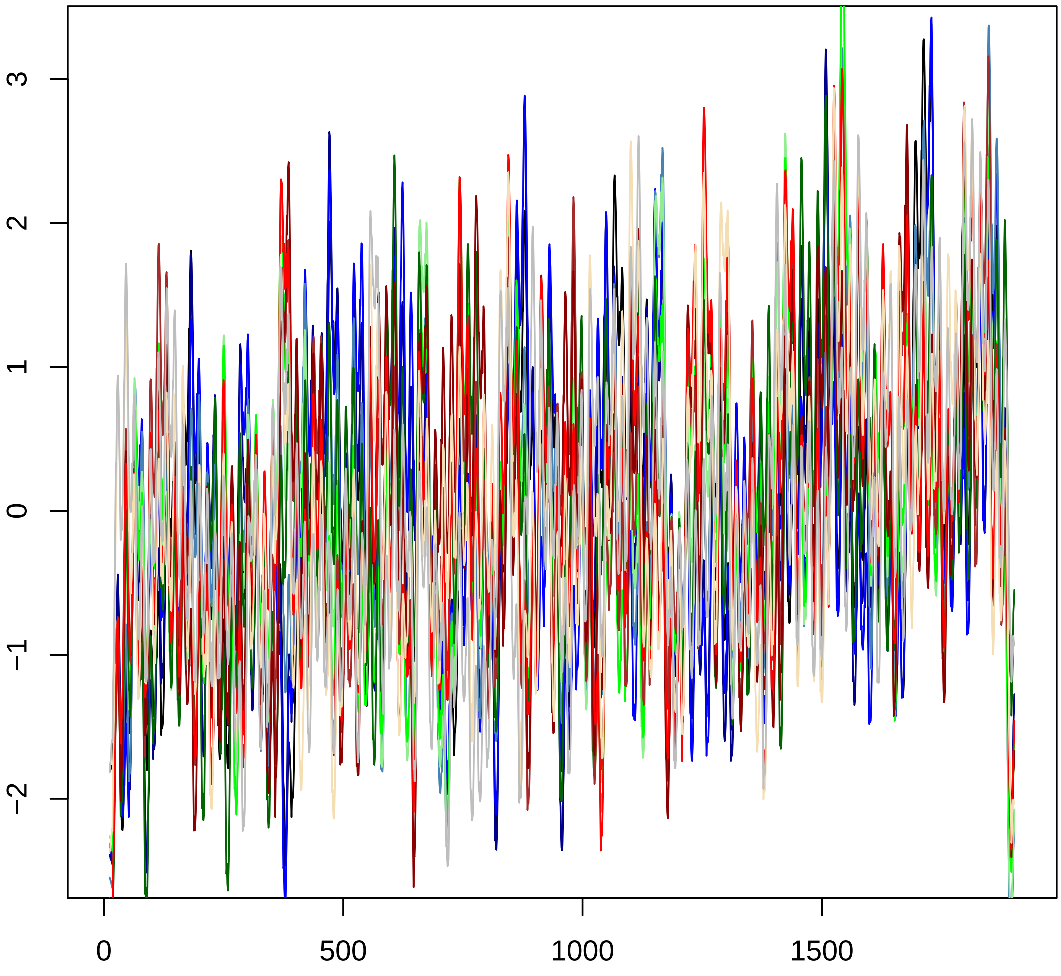

Figure 21: *Time evolution of standardised precipitation in NR1–12 after smoothing with a 24-month Gaussian filter. These curves provide the basis for the correlation matrix in Table 26.*

7.2 Additional figures: T(2m)

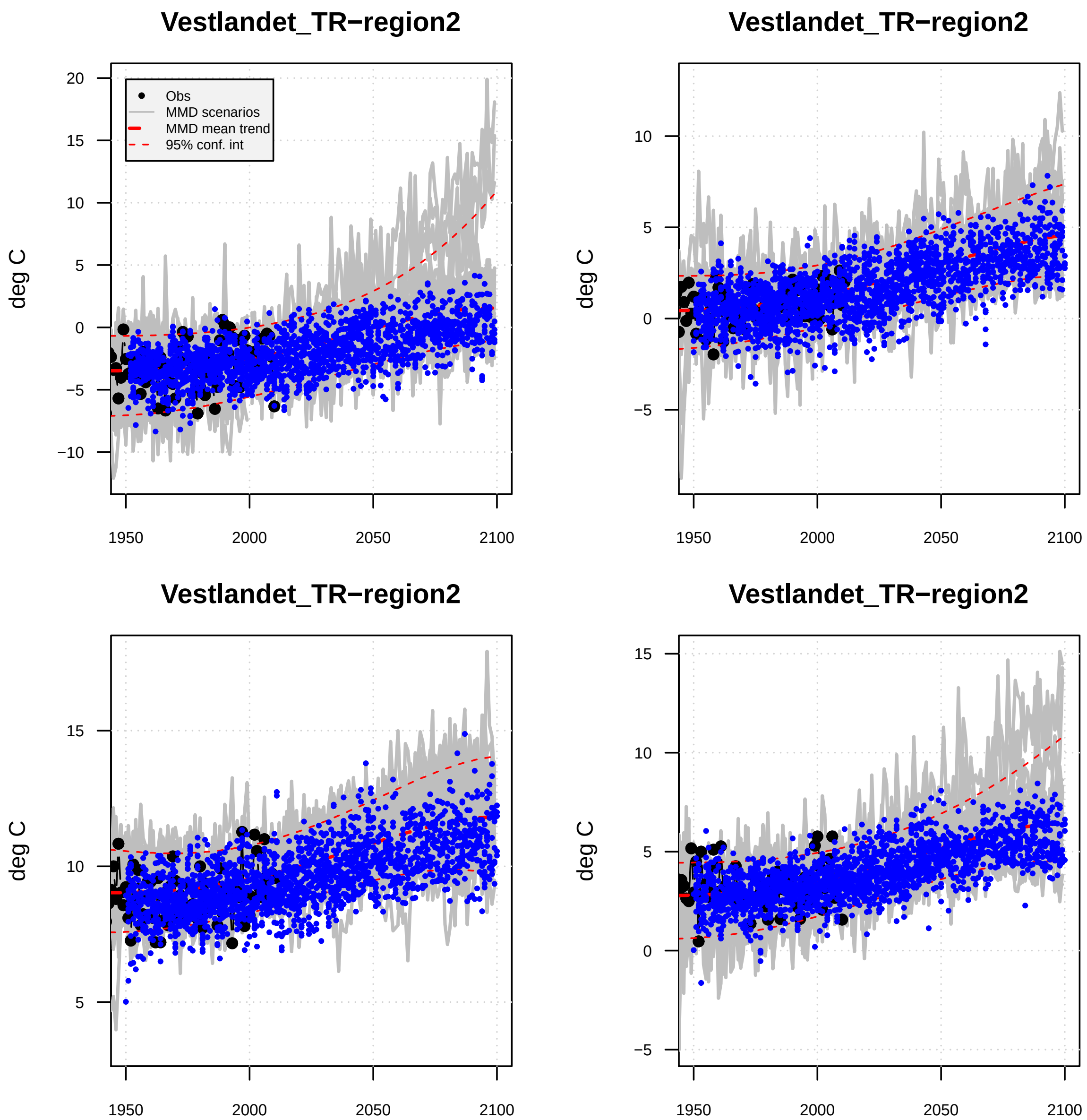

Figure 22: *Plume plots showing the the mean temperature in temperature region 2 based on observations (black), ESD results (grey shading), and RCM results (blue symbols) for the four seasons (top left to bottom right DJF, MAM, JJA, and SON). The RCM results have been adjusted to have the same mean for the interval overlapping with the observations, applying the adjustment separately for each calendar month.*

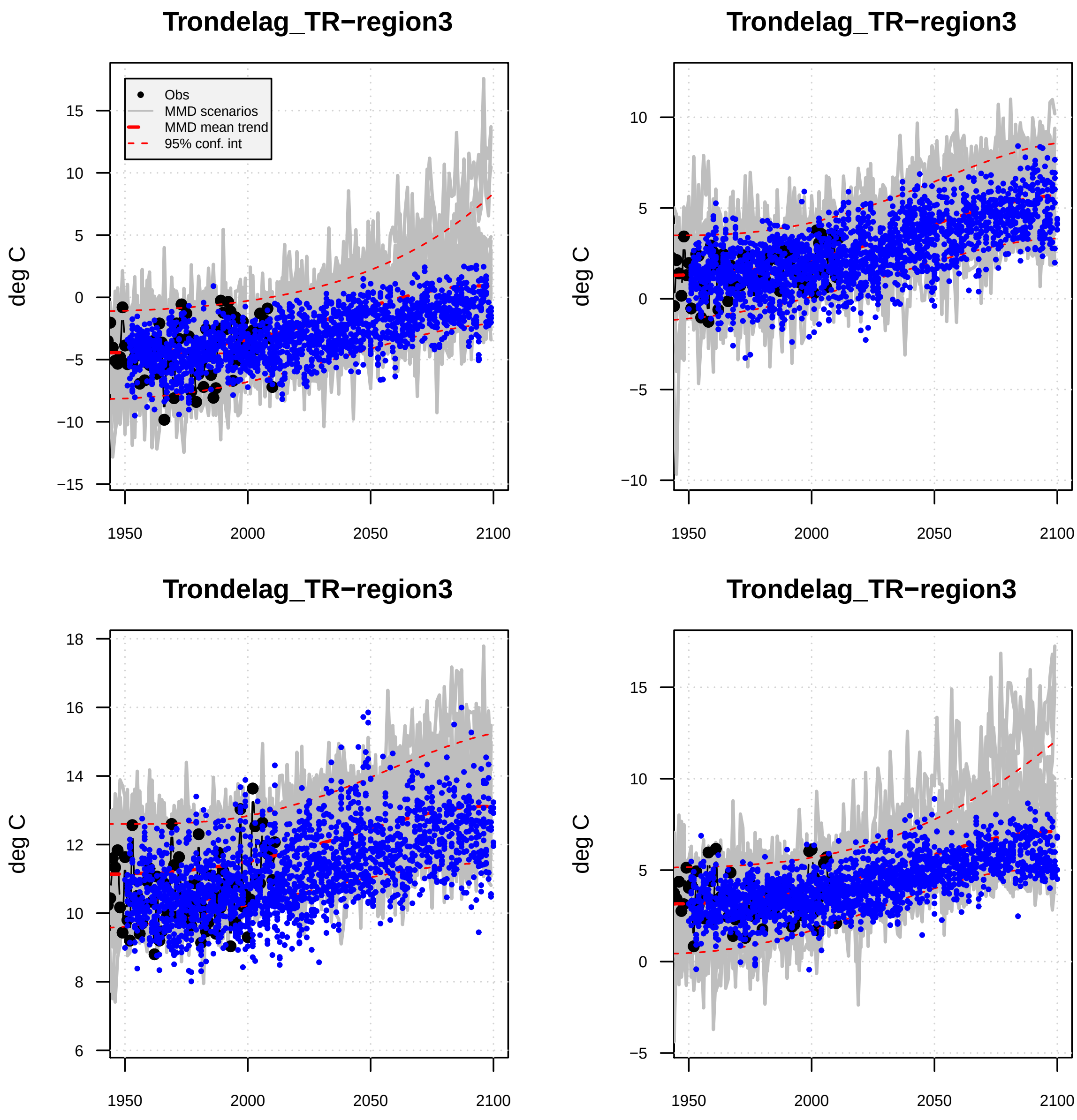

Figure 23: *Same as Figure 22, but for temperature region 3.*

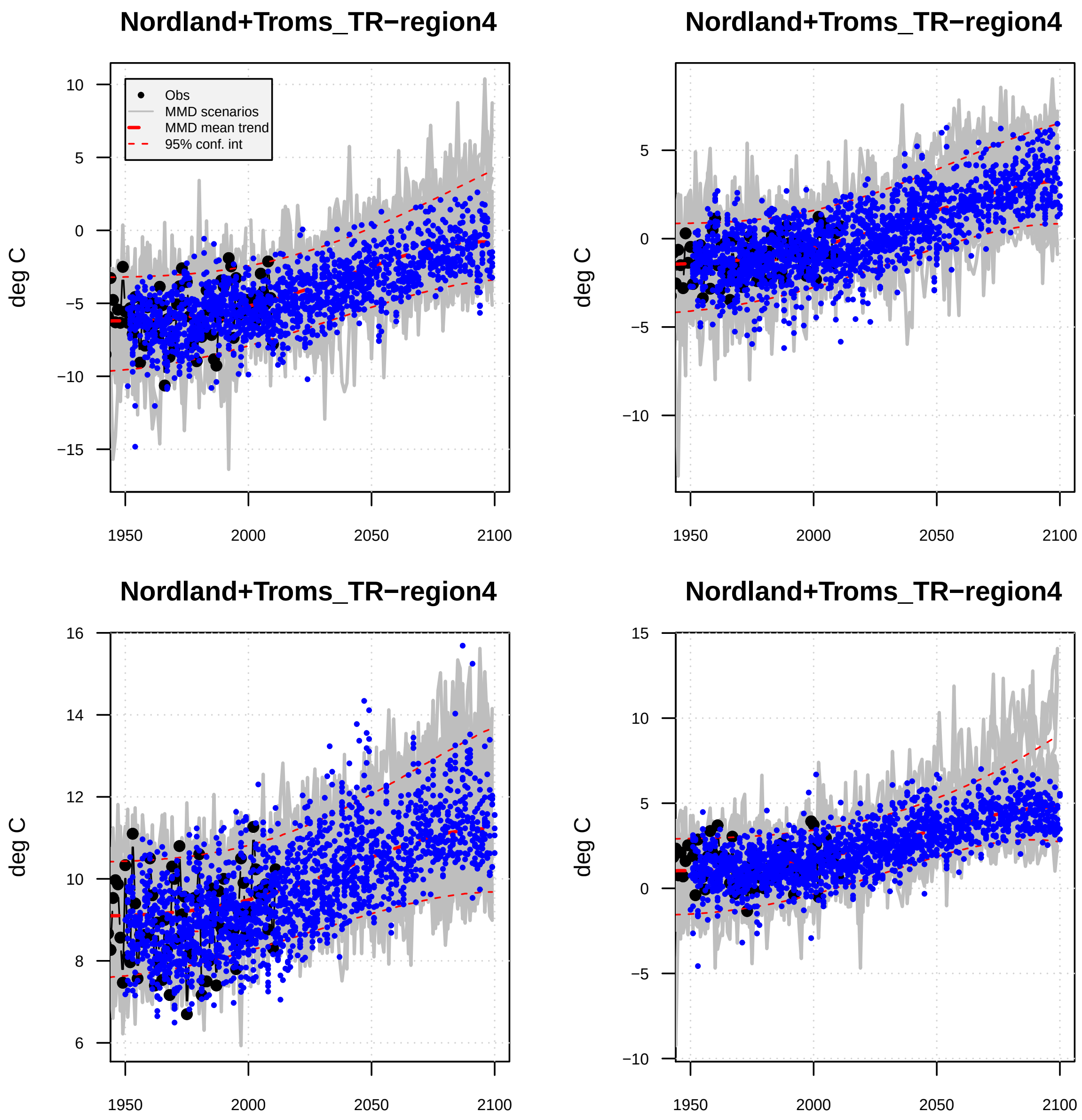

Figure 24: *Same as Figure 22, but for temperature region 4.*

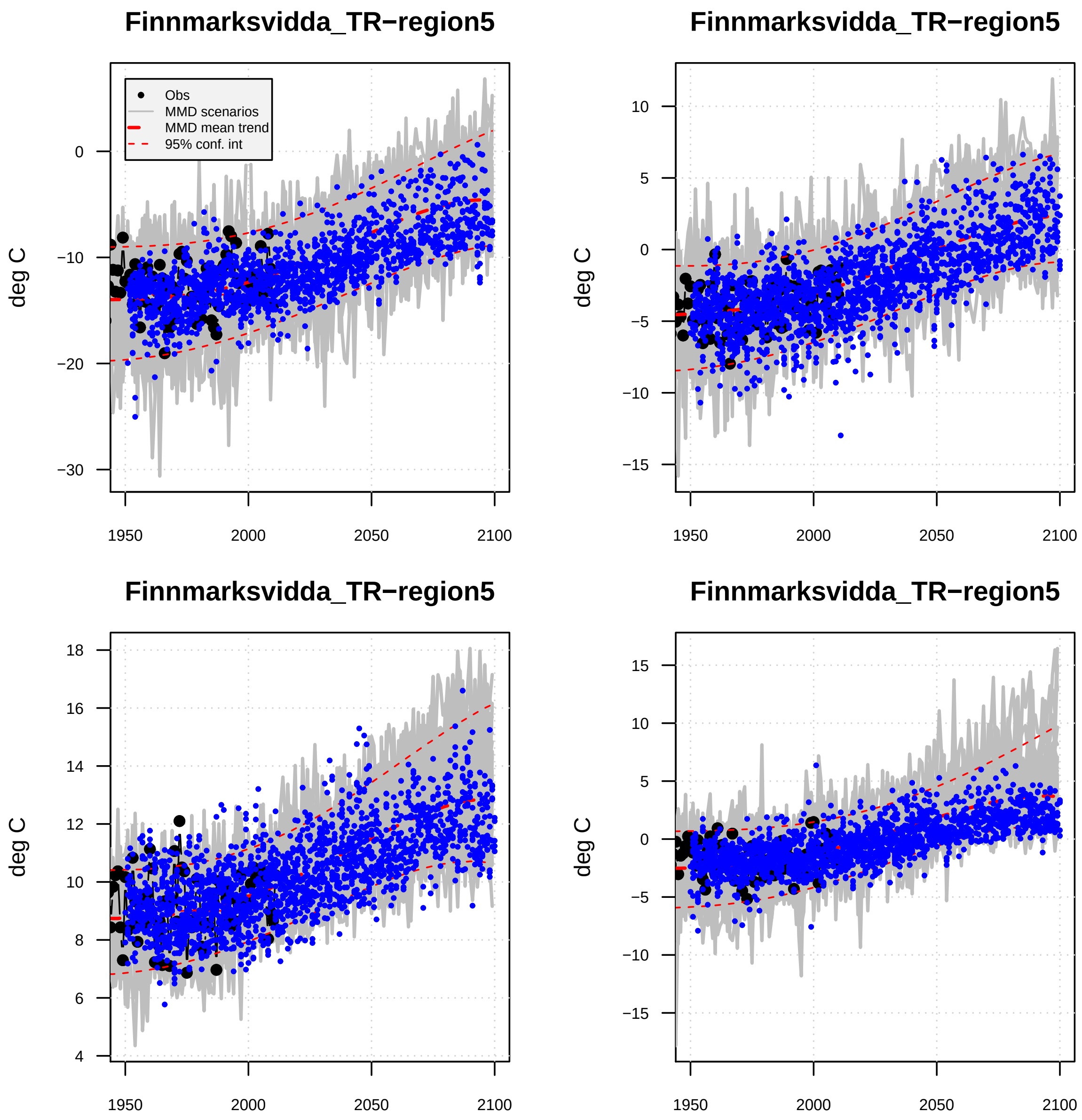

Figure 25: *Same as Figure 22, but for temperature region 5.*

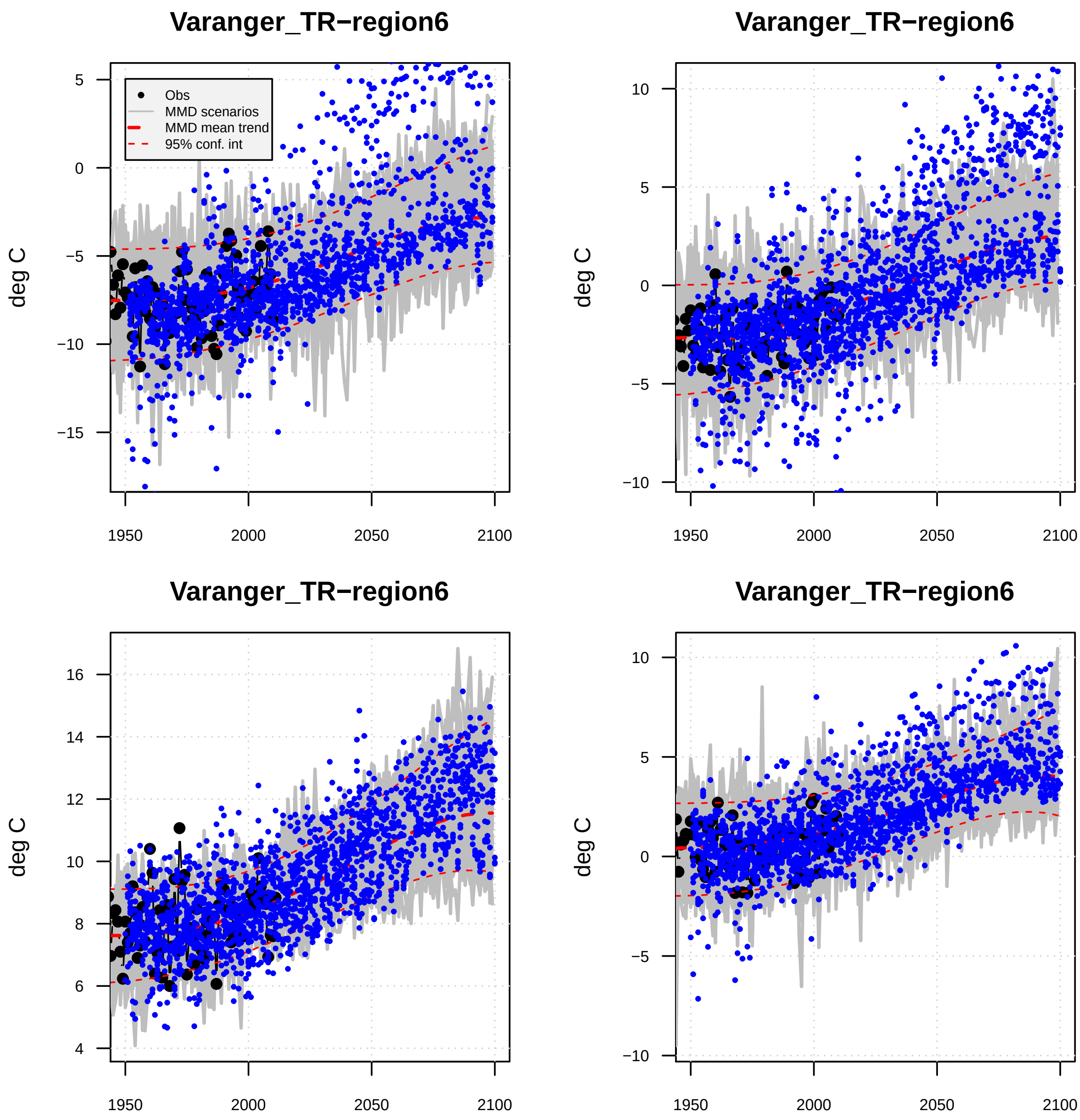

Figure 26: *Same as Figure 22, but for temperature region 6.*

7.3 Additional figures: Annual means for T(2m)

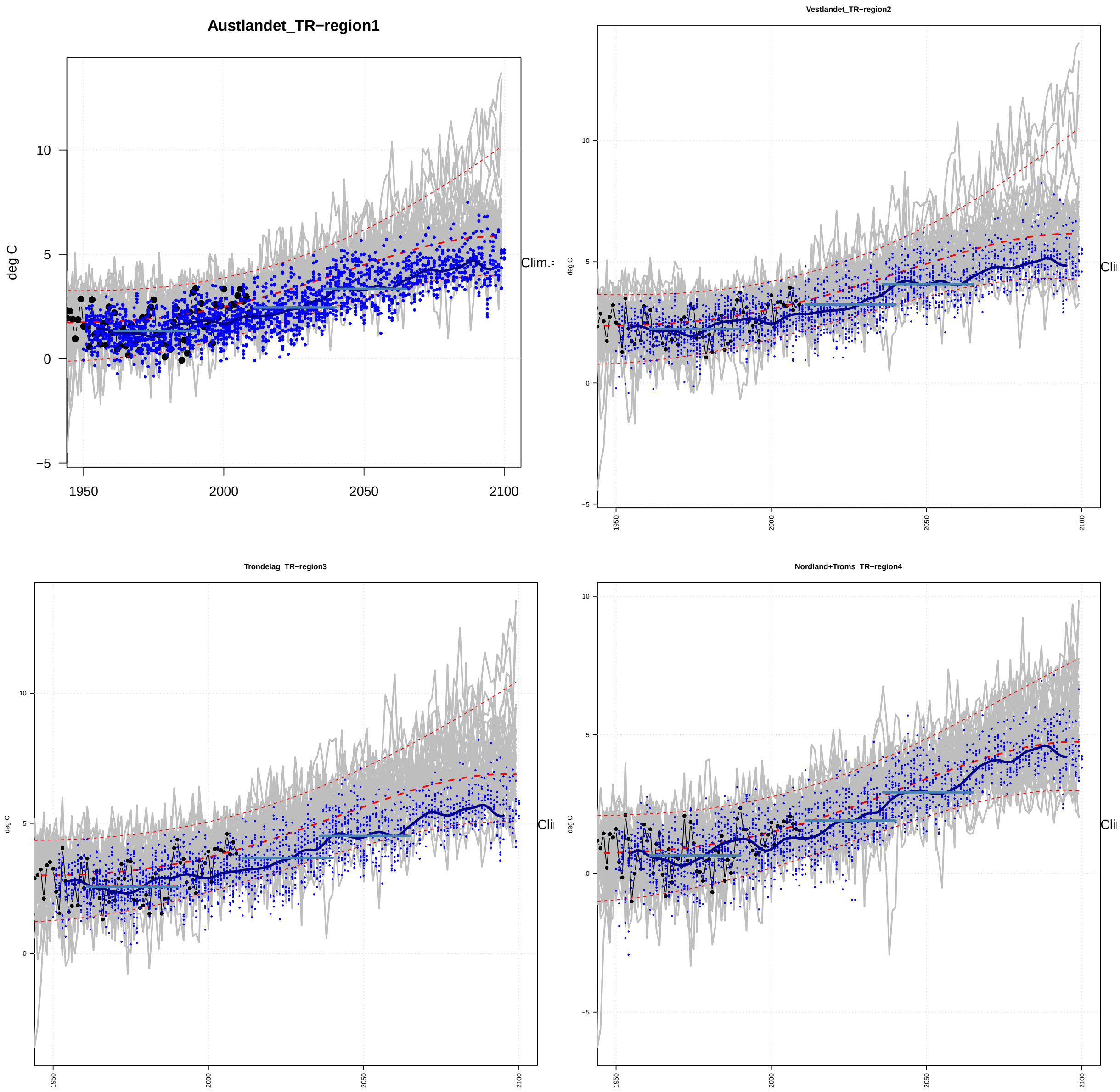

Figure 27: *Annual means for TR 1–4.*

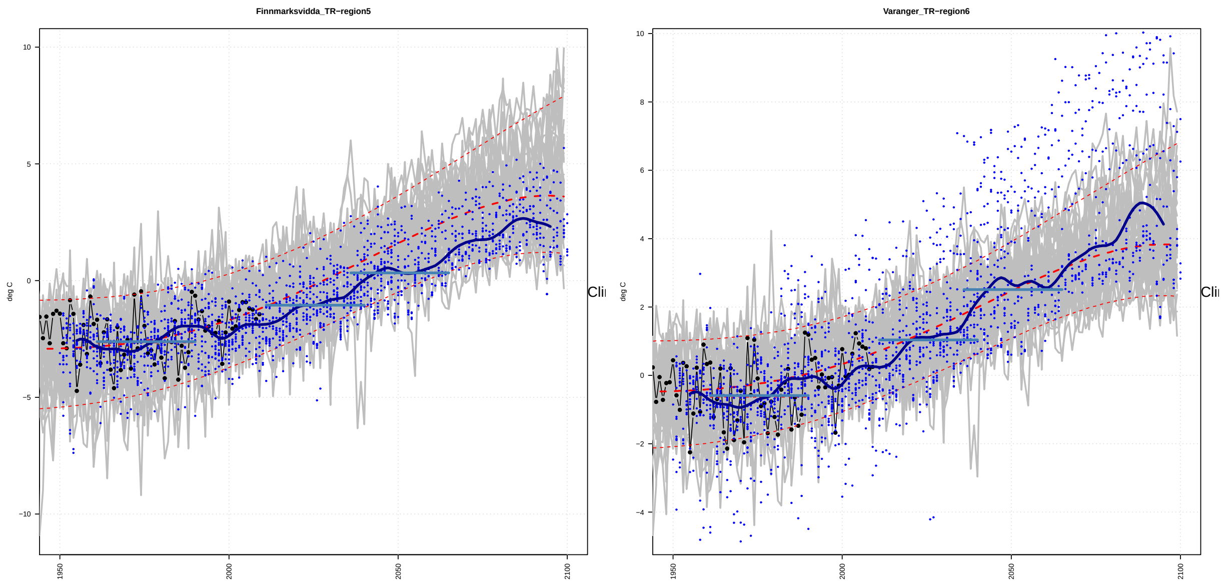

Figure 28: *Annual means for TR 5–6.*

7.4 Additional figures: precip

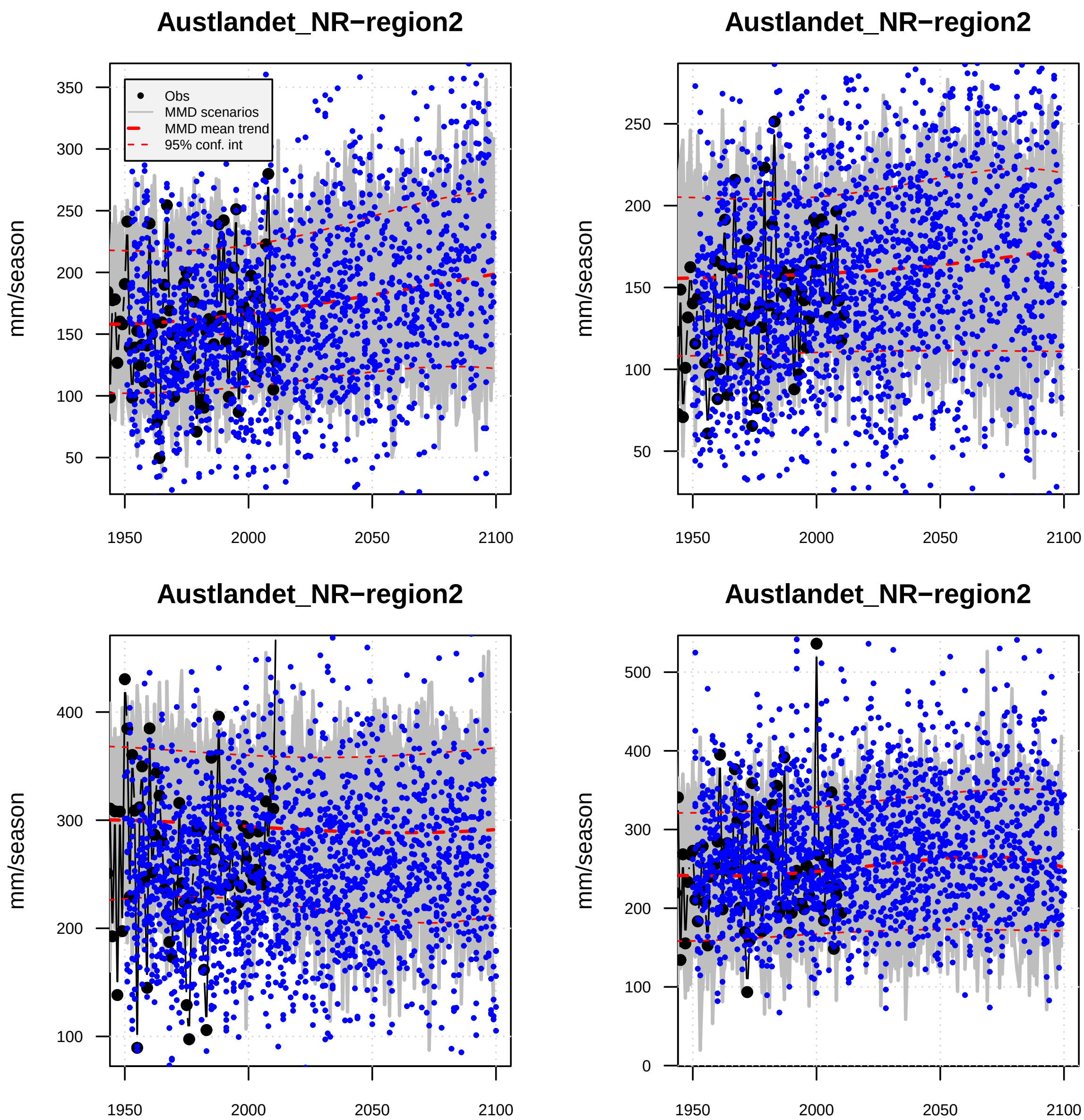

Figure 29: *Plume plots showing the the mean precipitation in precipitation region 2 based on observations (black), ESD results (grey shading), and RCM results (blue symbols) for the four seasons (top left to bottom right DJF, MAM, JJA, and SON). The RCM results have been adjusted to have the same mean for the interval overlapping with the observations, applying the adjustment separately for each calendar month.*

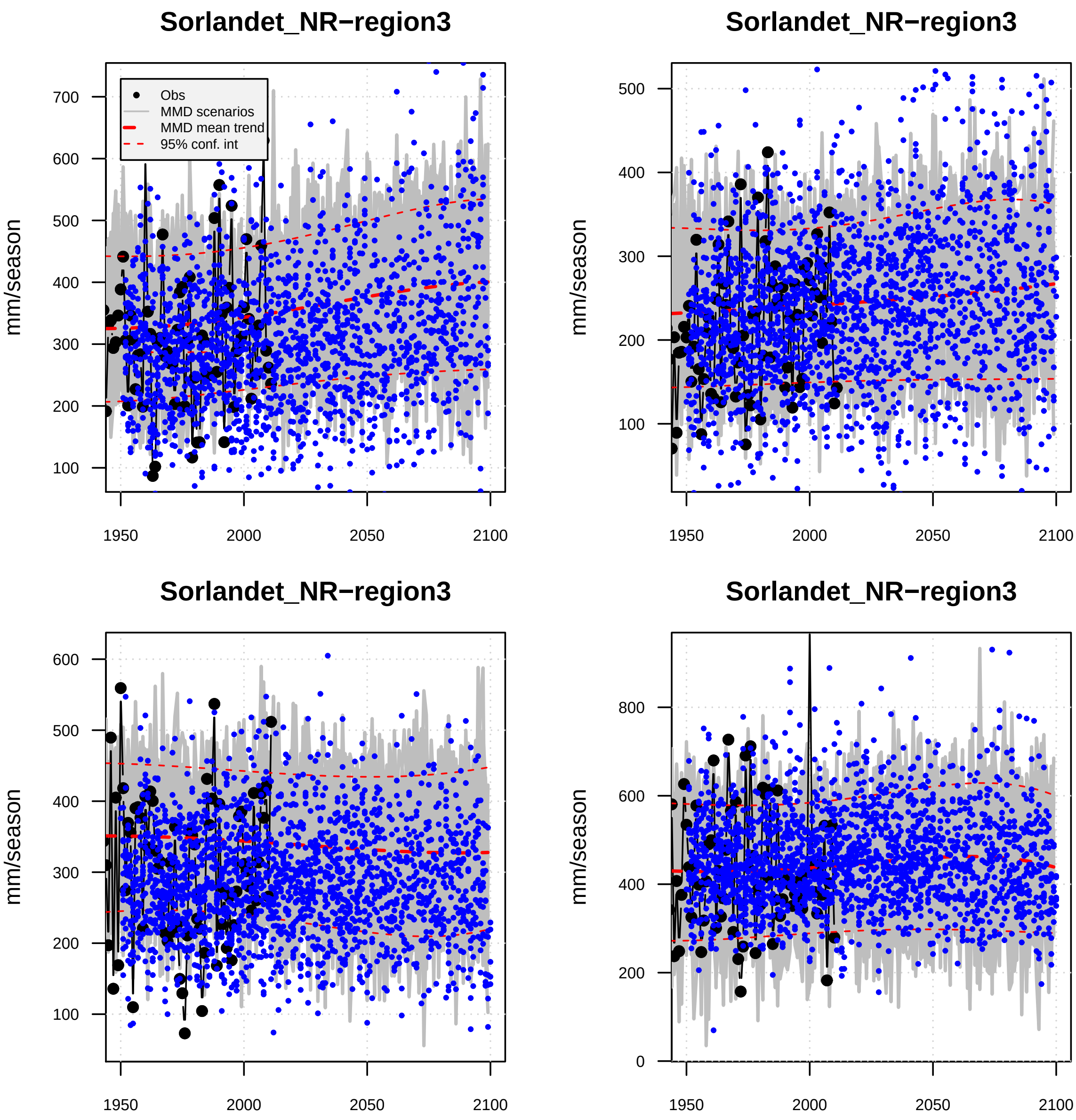

Figure 30: *Same as Figure 7, but for precipitation region 3.*

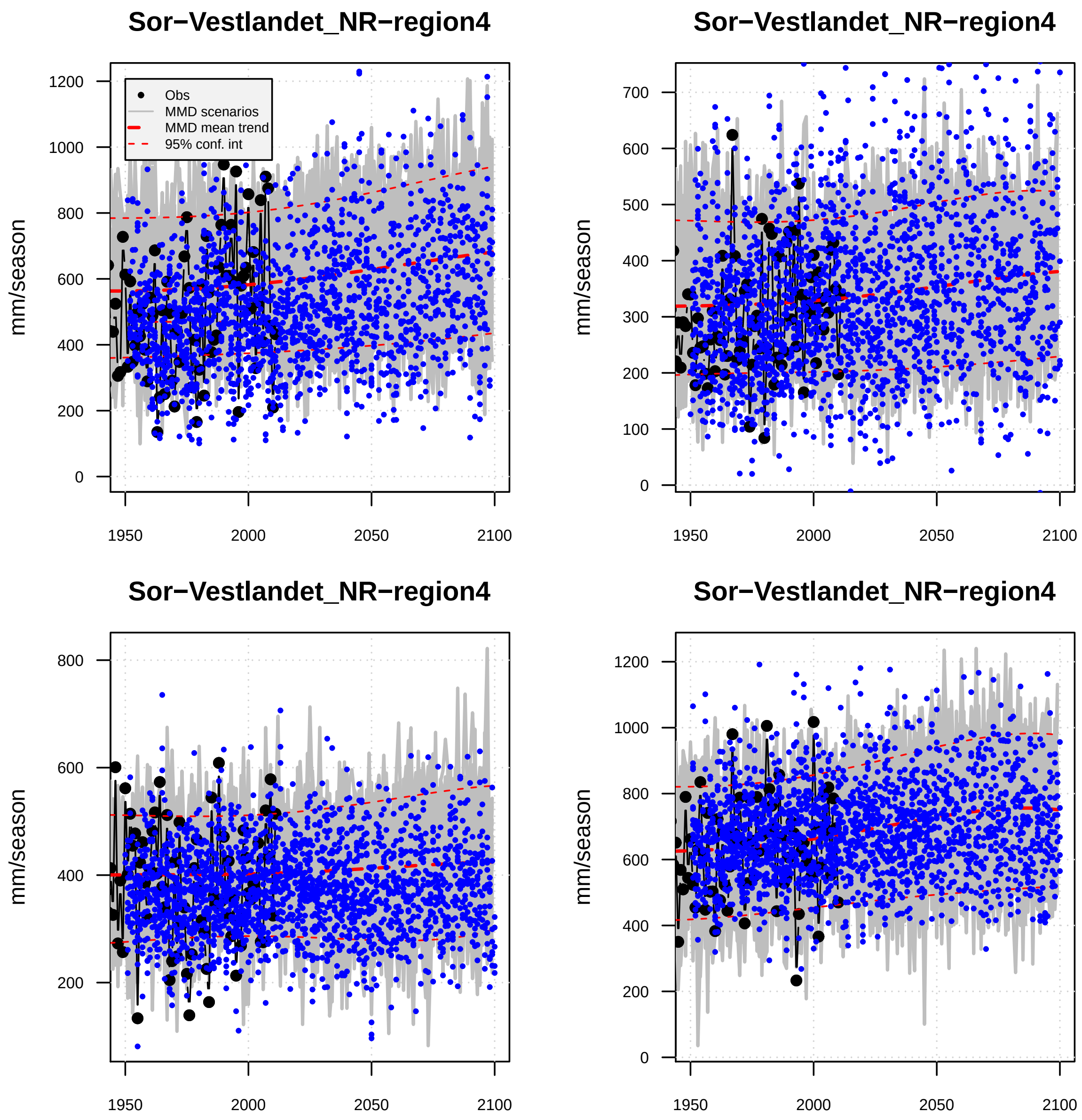

Figure 31: *Same as Figure 7, but for precipitation region 4.*

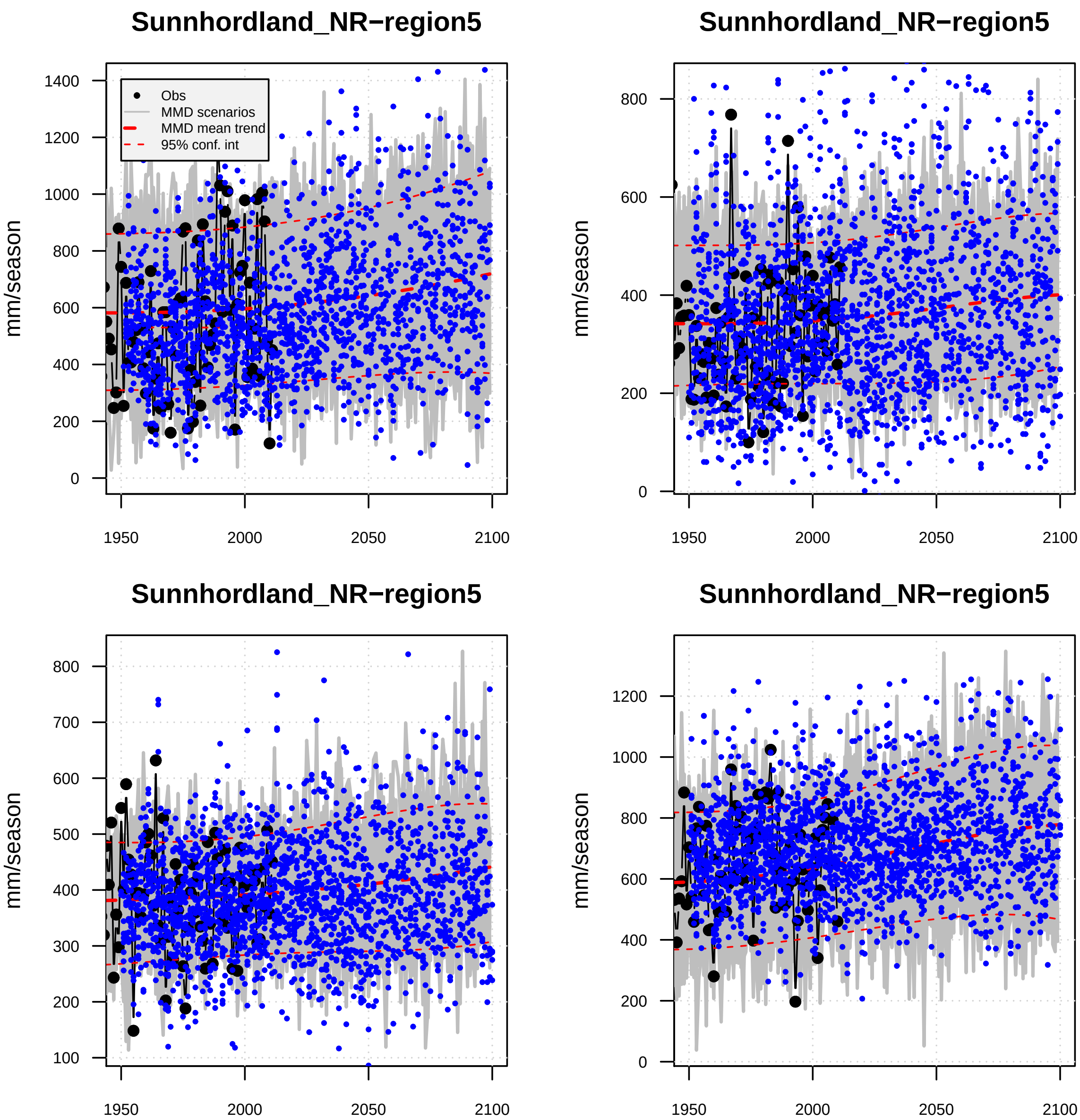

Figure 32: *Same as Figure 7, but for precipitation region 5.*

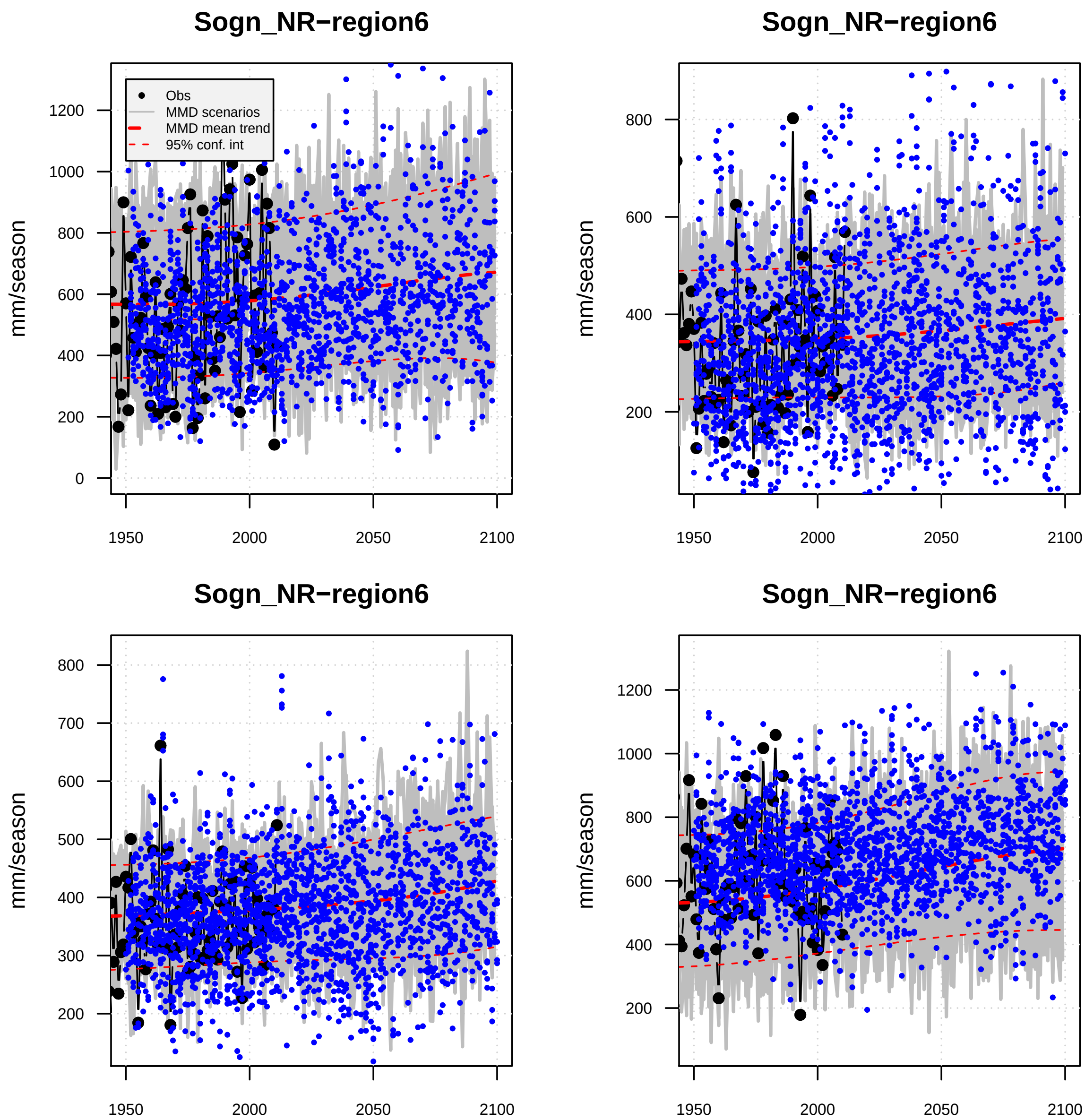

Figure 33: *Same as Figure 7, but for precipitation region 6.*

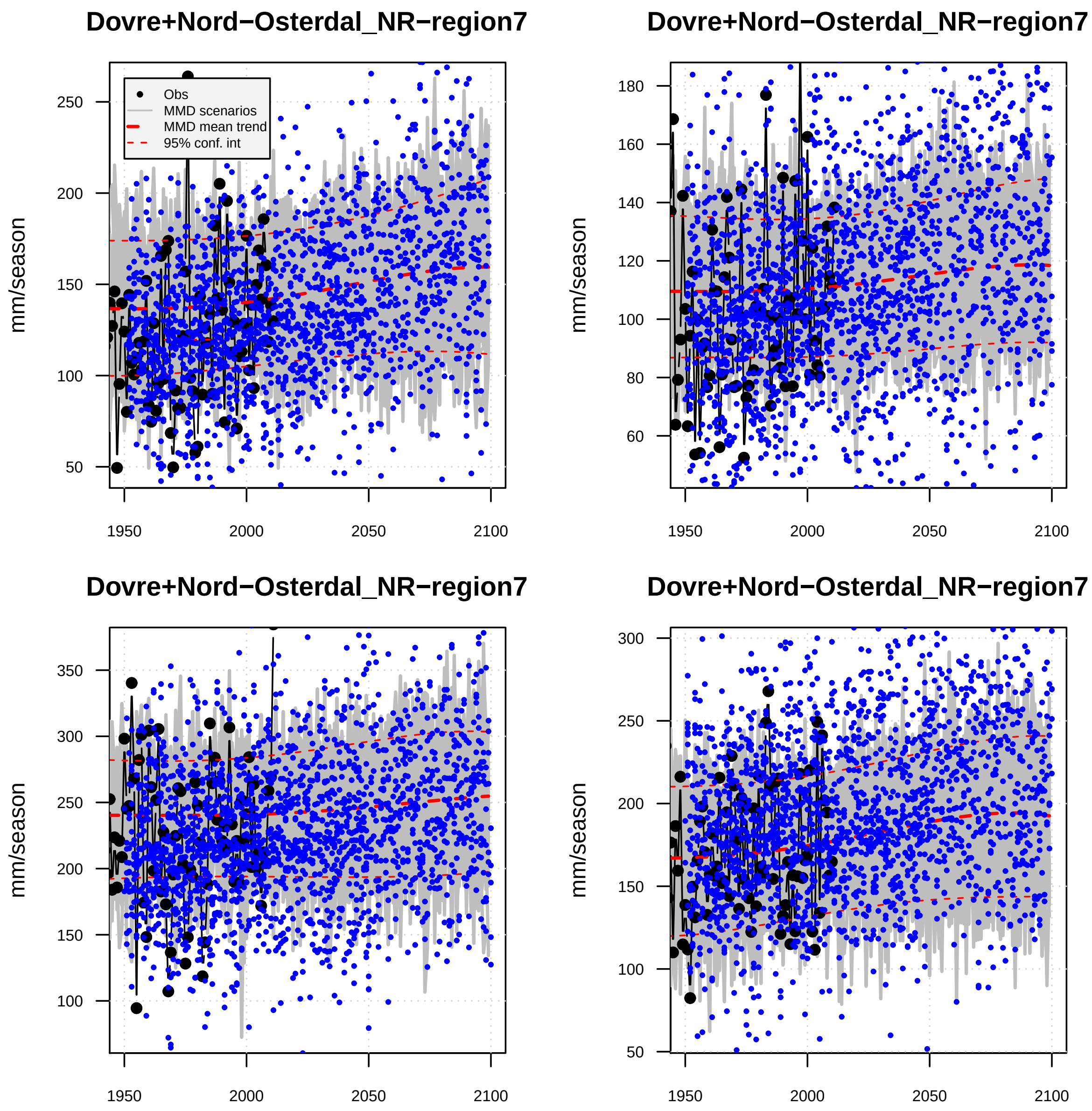

Figure 34: *Same as Figure 7, but for precipitation region 7.*

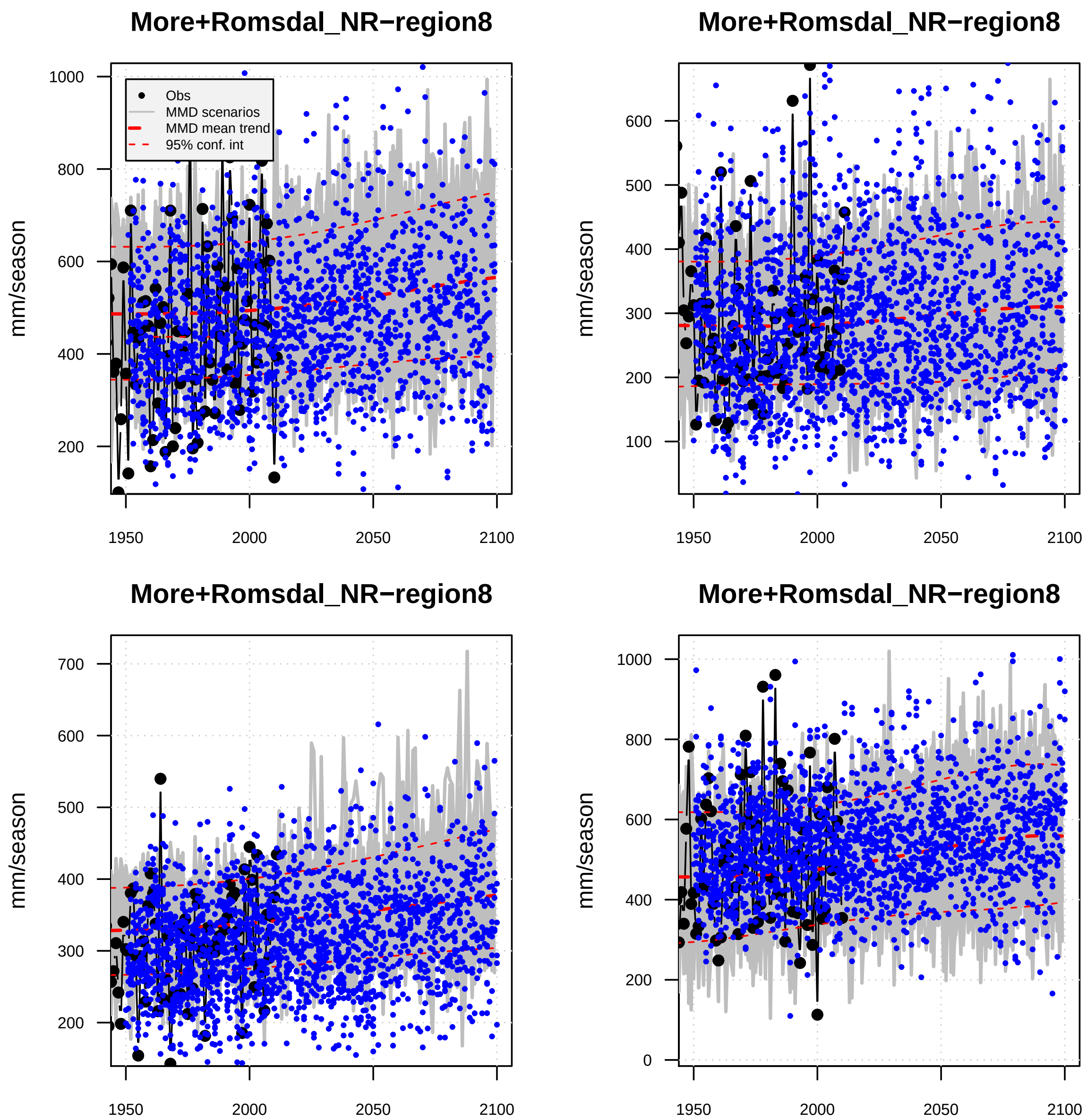

Figure 35: *Same as Figure 7, but for precipitation region 8.*

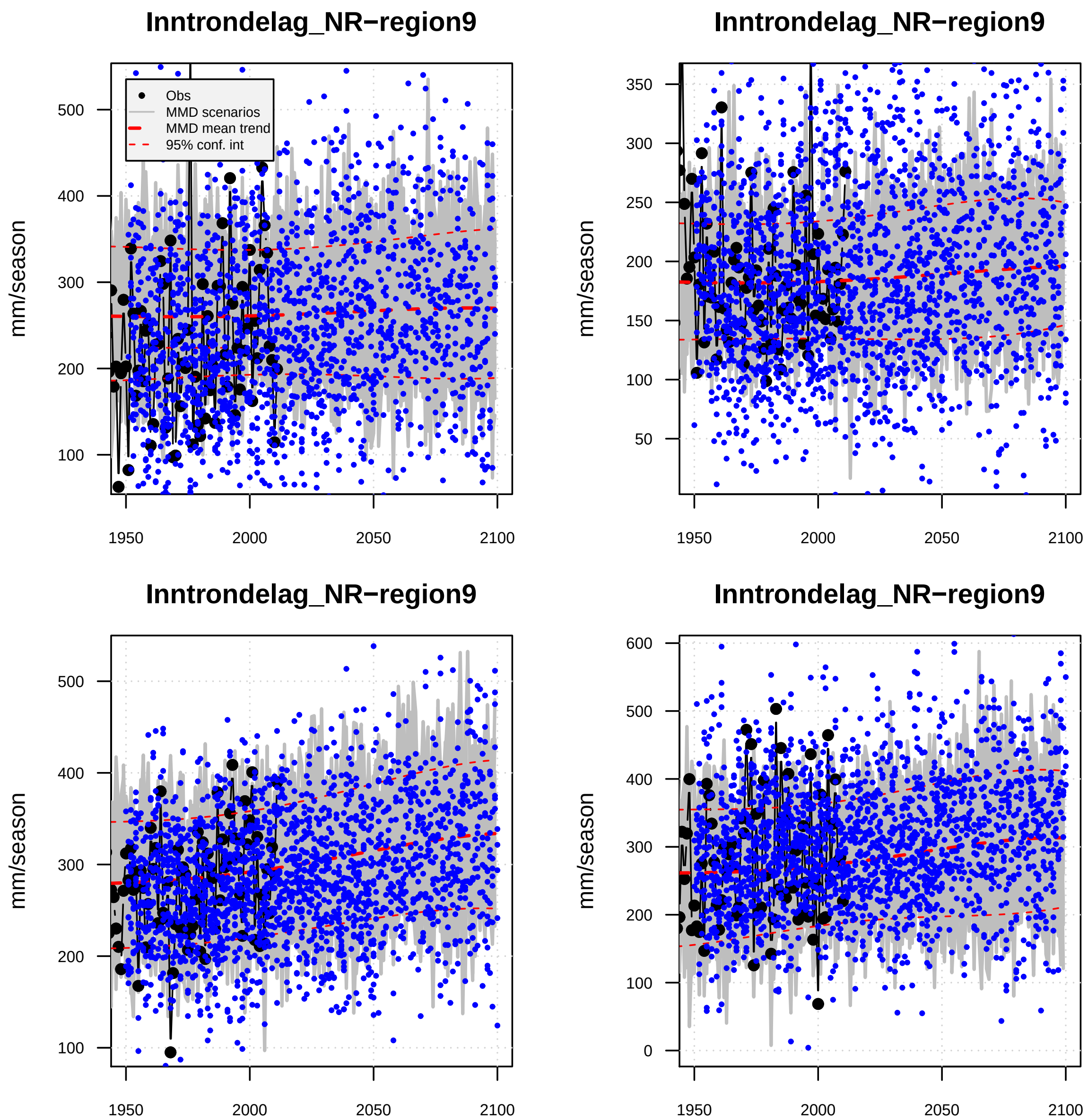

Figure 36: *Same as Figure 7, but for precipitation region 9.*

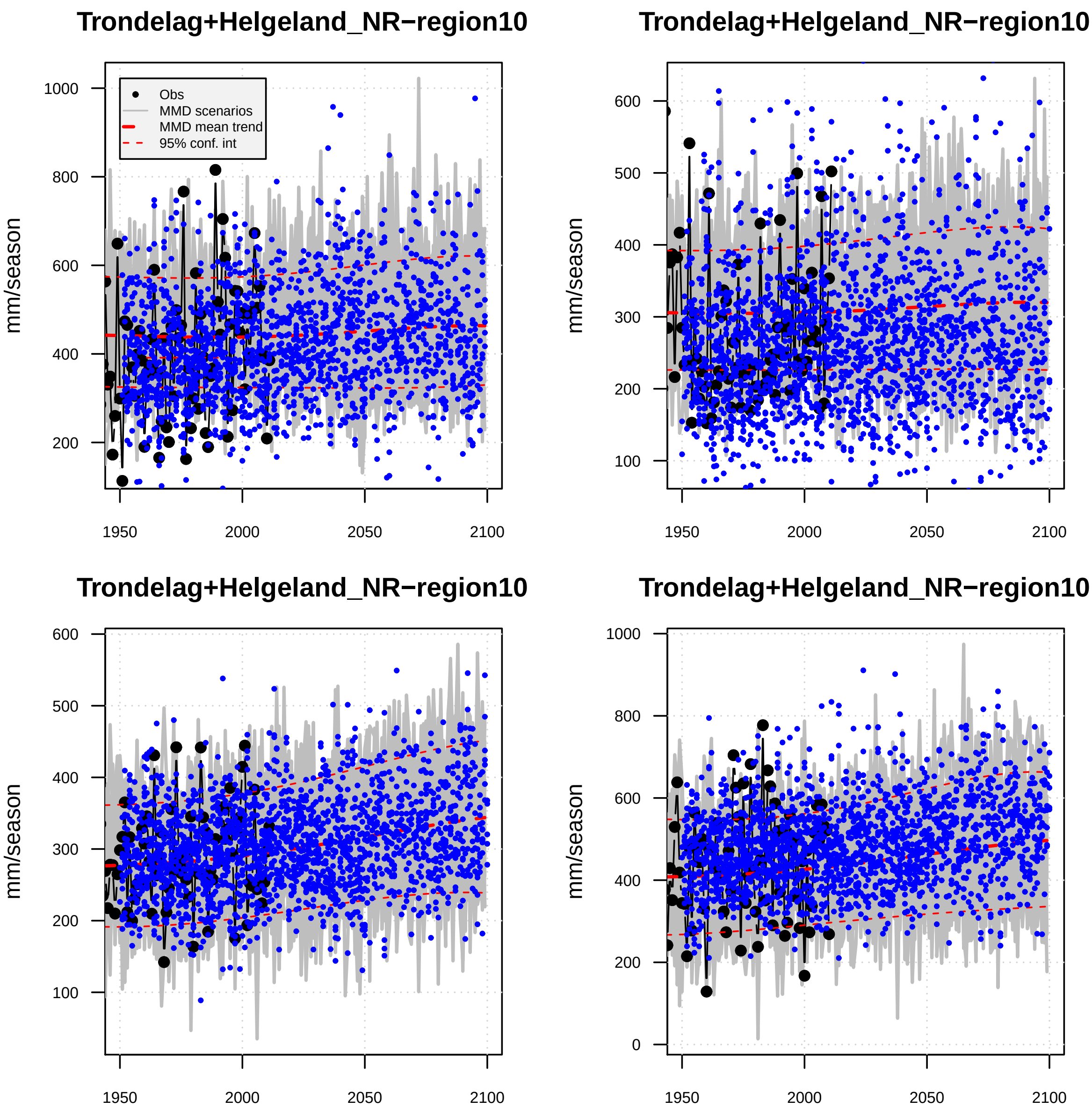

Figure 37: *Same as Figure 7, but for precipitation region 10.*

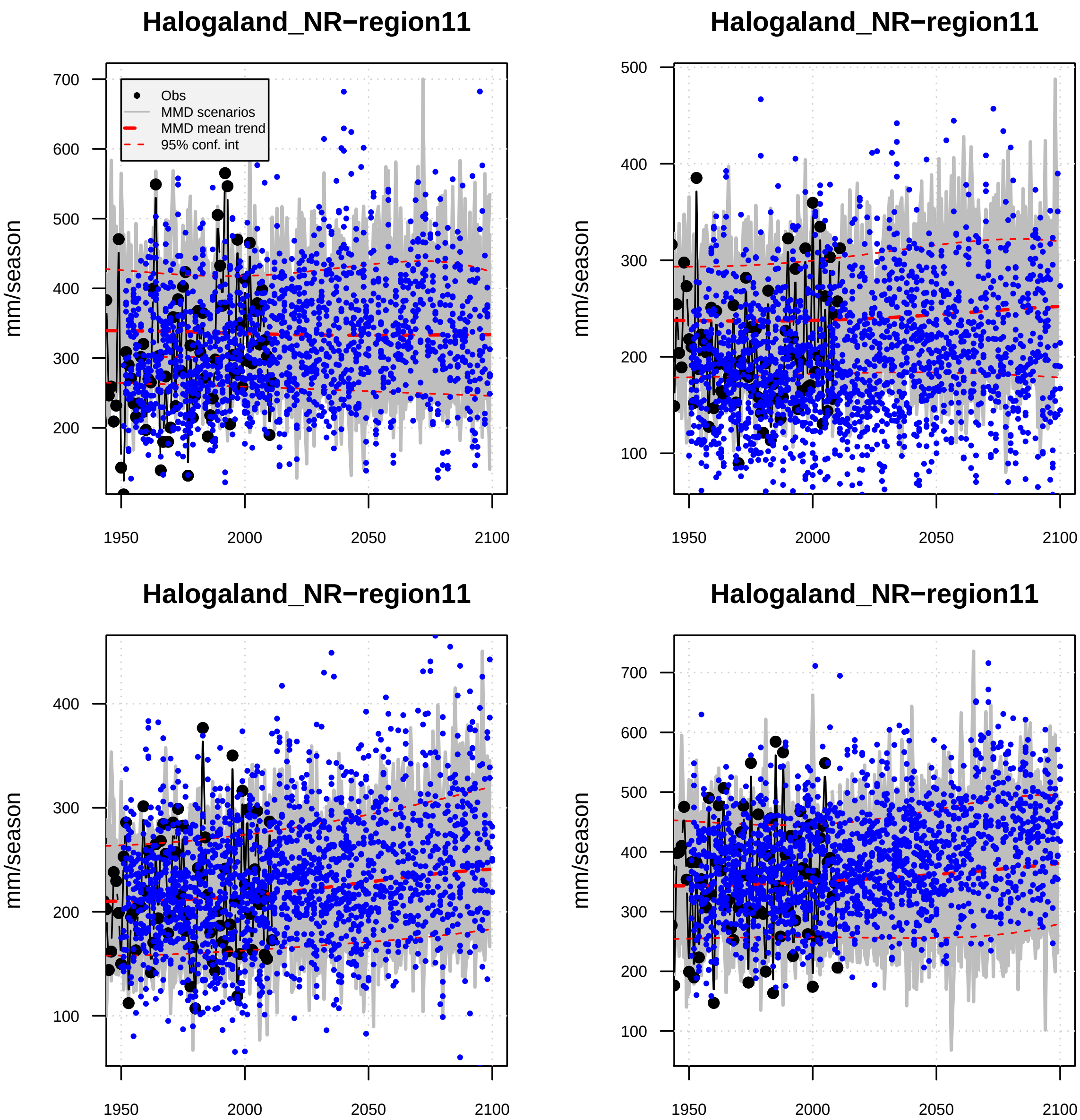

Figure 38: *Same as Figure 7, but for precipitation region 11.*

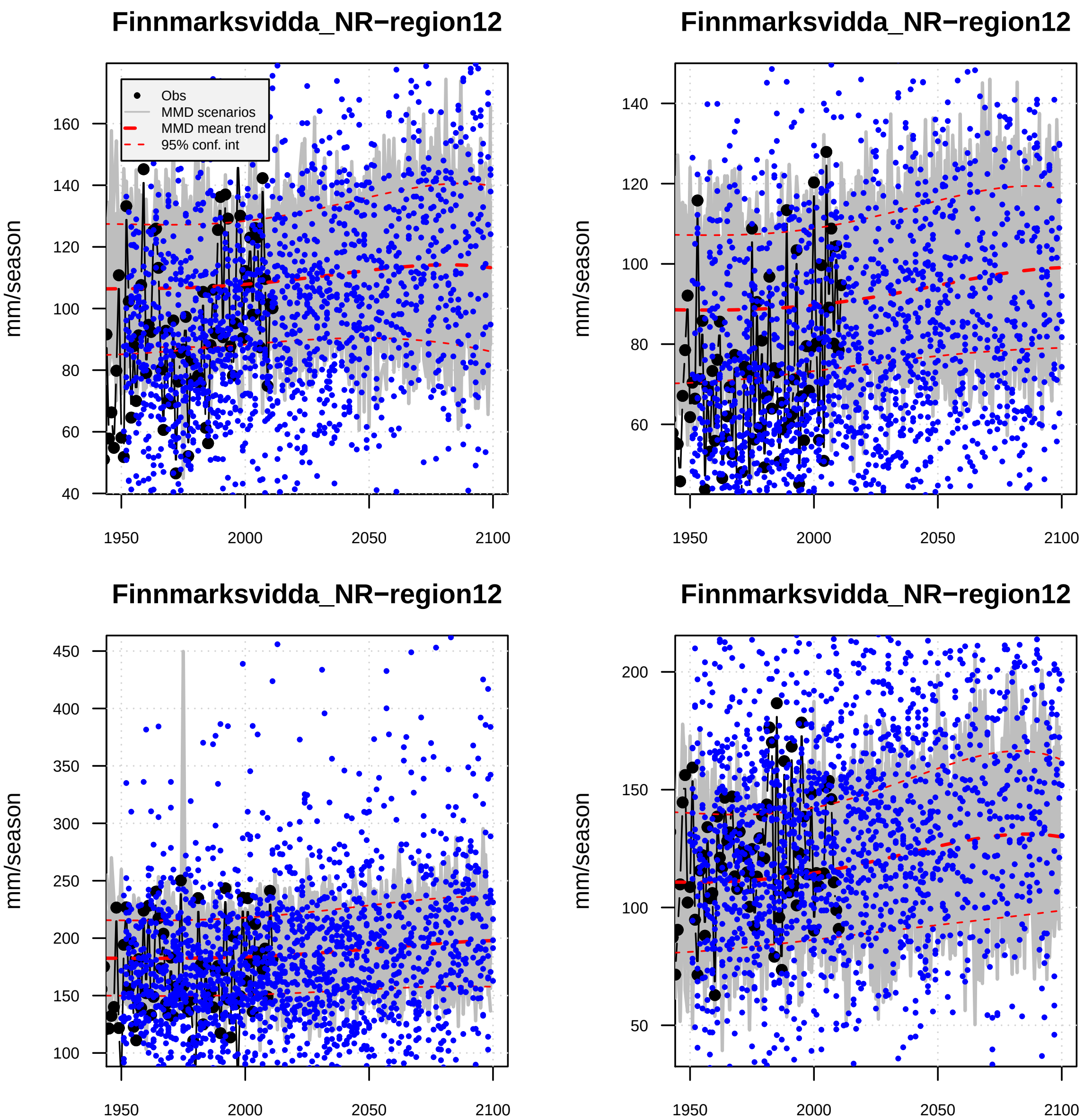

Figure 39: *Same as Figure 7, but for precipitation region 12.*

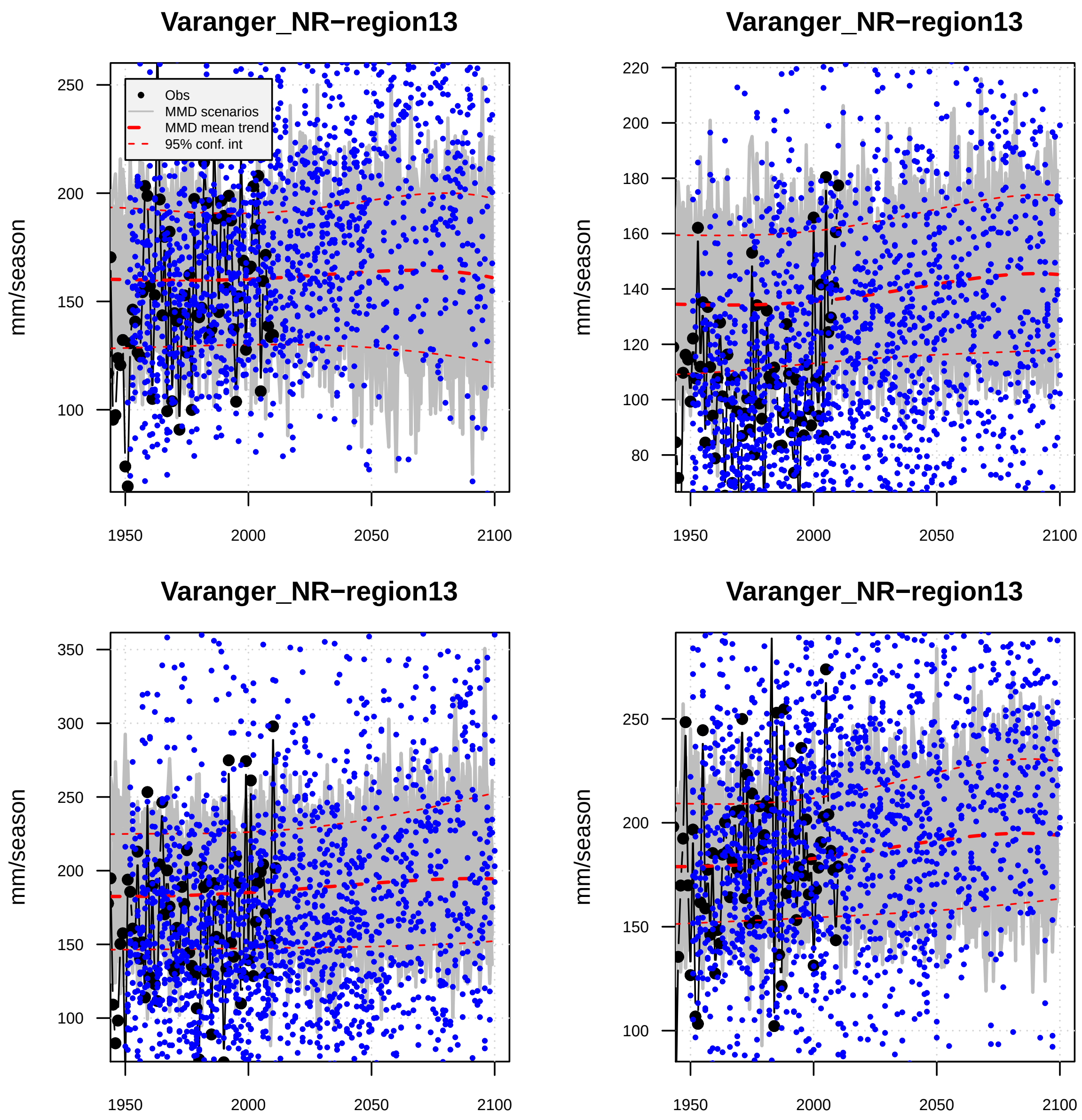

Figure 40: *Same as Figure 7, but for precipitation region 13.*

Additional figures: Annual means for precip

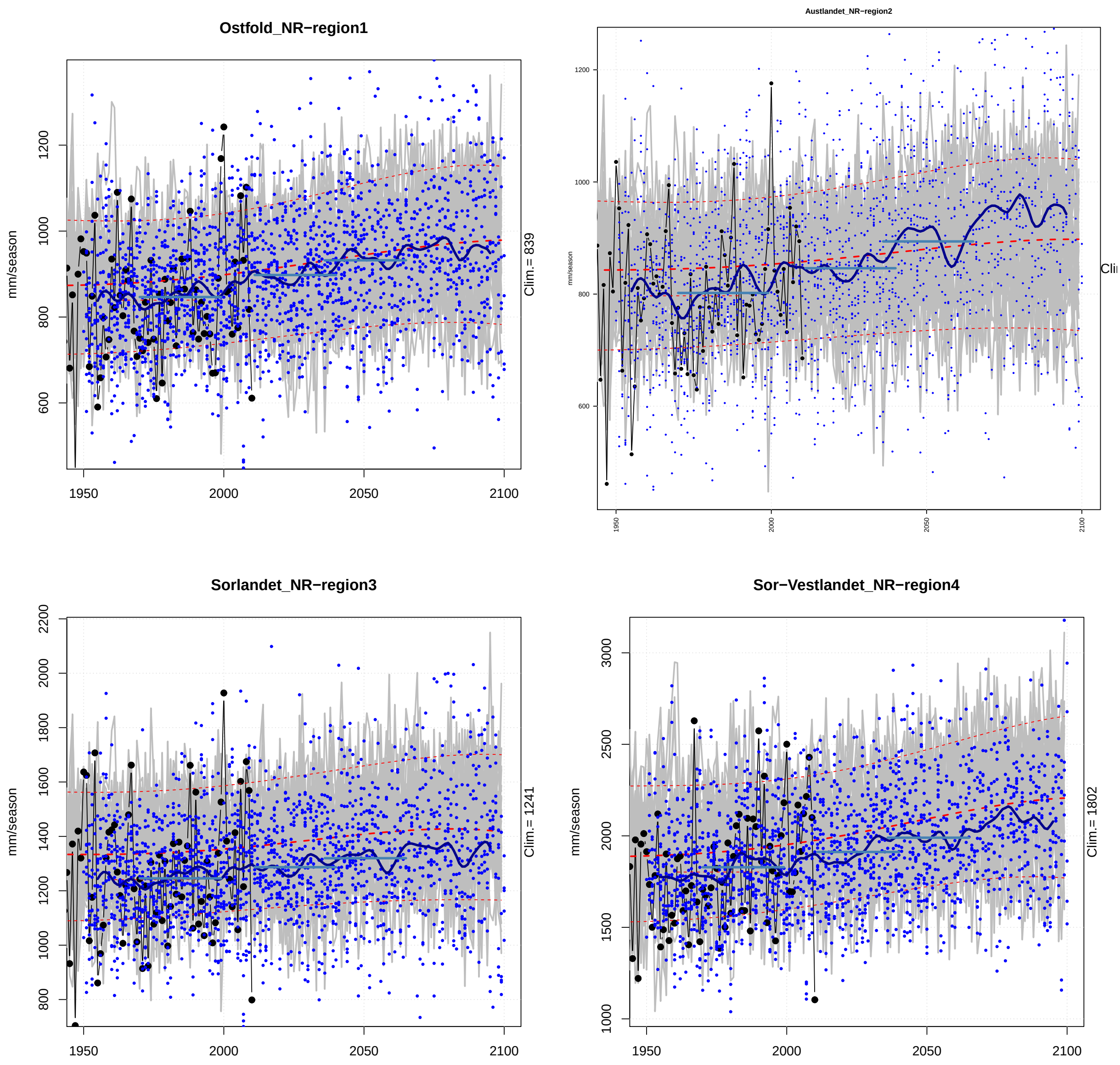

Figure 41: *Annual means for NR 1–4.*

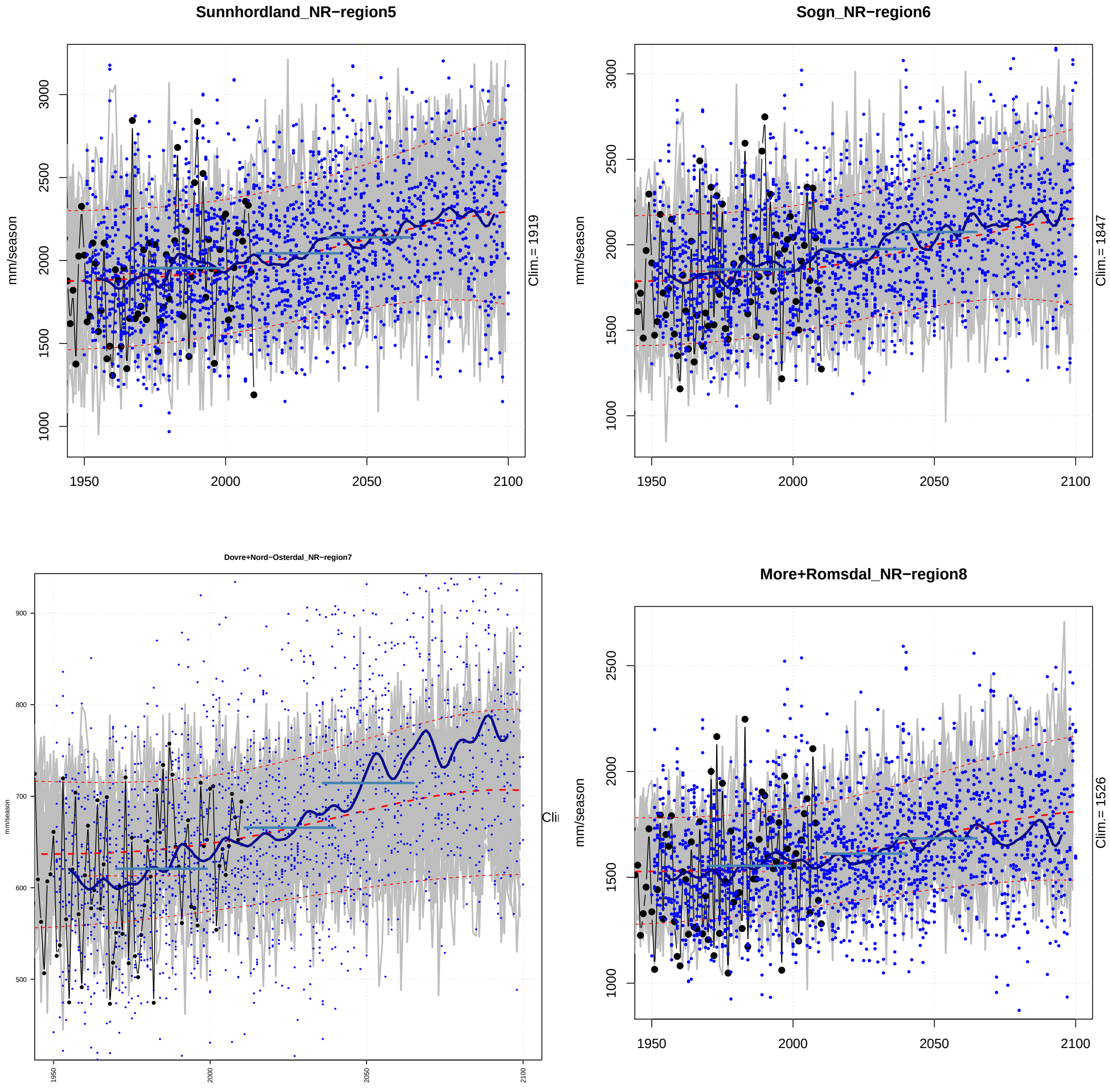

Figure 42: *Annual means for NR 5–8.*

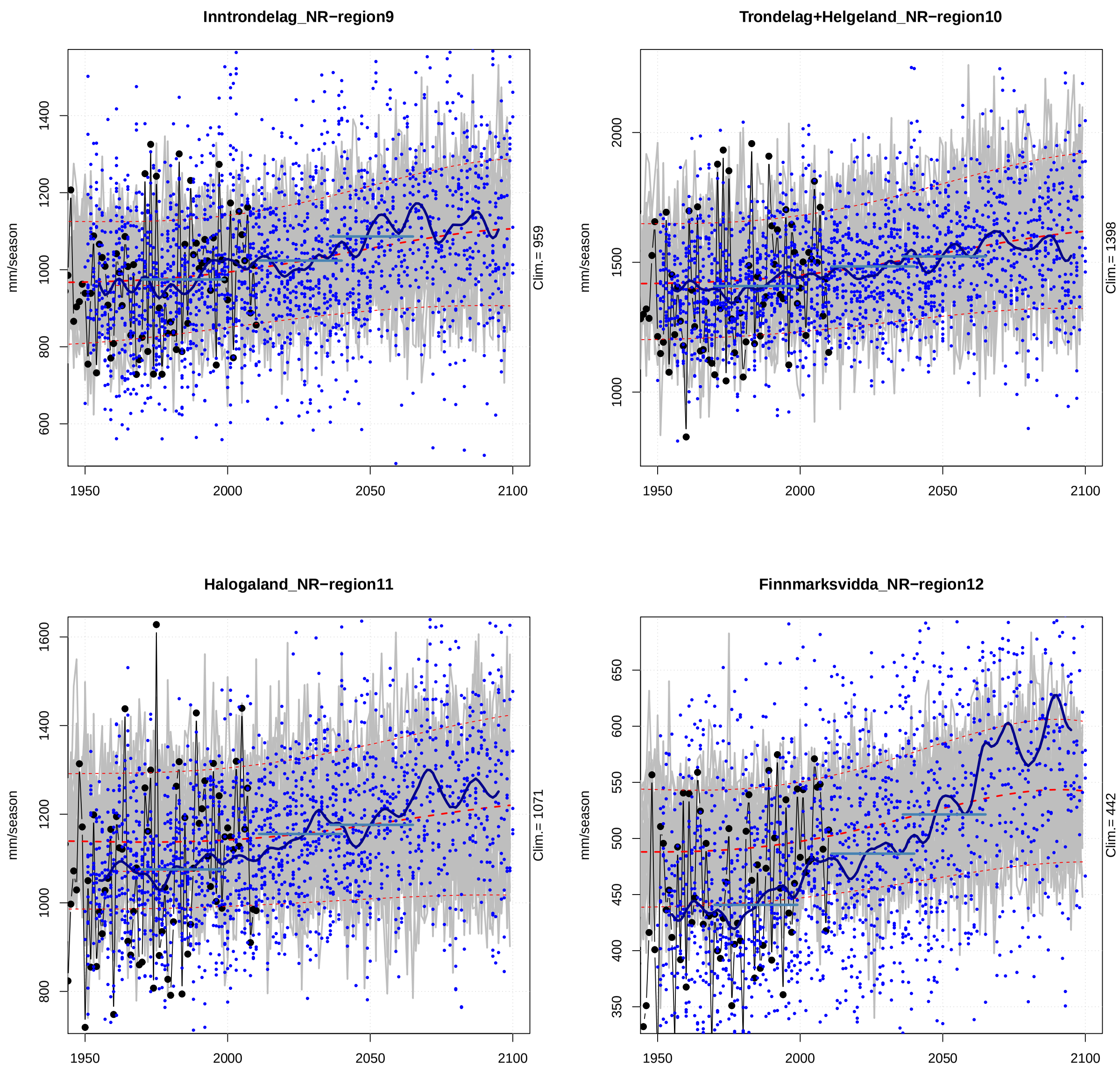

Figure 43: *Annual means for NR 9–12.*

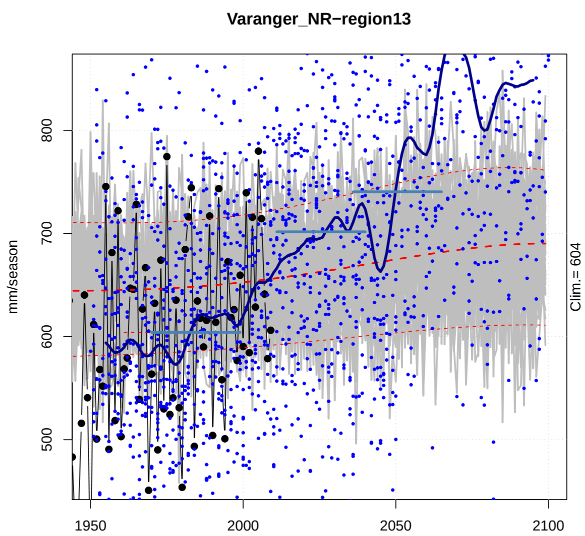

Figure 44: *Annual means for NR 13.*

Appendix

R-scripts `dsStatnett` & `dsStatnett2.R`:

7.4.1 `dsStatnett.R`

```
library(met.no.REB)
library(clim.pact)
library(evd)
library(WriteXLS)
#source("met.no.REB/R/allmyfunctions.R")
#source("clim.pact/R/catFields.R")
#source("clim.pact/R/objDS.R")

#url.rr.tr <- "http://klapp.oslo.dnmi.no/metnopub/production/metno?re=20&ct=text/plain&p=RR&fy=&ty=2011&r_type=GR&r_no=0"

#source("met.no/R/ESD.results.R")
#source("clim.pact/R/objDS.R")
#source("clim.pact/R/ds.R")
#source("clim.pact/R/eof.R")
#source("clim.pact/R/plotEOF.R")
#source("clim.pact/R/plotDS.R")

# Add GEV for extremes.

heatwave.2003 <- function(loc="LANGRES") {
  esd <- ESD.results(loc)
  showall(esd,mon=6:8)
  dev.copy2eps(file="heatwave.eps")
}

coldspell <- function() {
  esd <- ESD.results()
  showall(esd,mon=c(12,1,2),obs.get="KDVH4DS()")
  dev.copy2eps(file="coldsnap.eps")
}

block.max <- function(X) {
  print("block.max: find max value")
  print(dim(X))
  bmax <- apply(X,2,max,na.rm=TRUE)
  print(length(bmax))
  bmax
}

extremes <- function(X,obs,rcm=NULL,ylab="Return level  x -1") {
  print("extremes: Fit GEV:")
  dev.new()
  extr <- fgev(X)
  h <- hist(-obs)
  print(summary(h))
  print("Return value analysis:")
  rl.obs <- rl(extr,main="GEV return value analysis",
               ylab=ylab,xlab="Return interval",
               sub=attr(X,"description"),xlim=c(0.15,50),ylim=c(0,30))
  grid()
  for (i in 1:length(obs)) lines(c(0.10,0.20),rep(obs[i],2),col="red")
  lines(h$density+0.20,h$mids,col="red")
  if (!is.null(rcm)) {
    print("add RCM results")
    print(rcm)
    for (i in 1:length(rcm)) lines(c(0.10,0.17),rep(rcm[i],2),col="darkgreen")
  }
}


esd2xls <- function(region=1,param="TAM") {
```

```
  locations <- list.files(path="STATNETT",pattern=".Rdata")
  dig <- switch(param,"TAM"=1,"RR"=0)
  rt <- switch(param,"TAM"="TR","RR"="NR")
  ele <- switch(param,"TAM"=101,"RR"=601)
  locations <- locations[grep(rt,locations)]
  print(locations)
  reg <- locations[grep(paste(rt,"-region",region,".",sep=""),locations,
                        fixed=TRUE)]
  reg <- substr(reg,1,nchar(reg)-6)
  esd <- ESD.results(reg,path="STATNETT/",case.sens=TRUE,ele=ele)
  obs.get <- paste("obslandsdel(",region,
                   ", param='",param,"', rt='",rt,"')",sep="")
  print(obs.get)
  ESD <- showall(esd,obs.get = obs.get,ele=ele,
                 remove.bad.sd = FALSE)

  print("Save as XLS format")
  ExcelFileName <- paste("ESD4region-",region,"_",param,".xls",sep="")

  gcms <- union(ESD$gcms.sce,c(ESD$gcms.ctl,"obs"))
  yymm <- c( sort(rep(ESD$yy.20c,12)) + (rep(1:12,length(ESD$yy.20c))-0.5)/12,
             sort(rep(ESD$yy.21c,12)) + (rep(1:12,length(ESD$yy.21c))-0.5)/12 )
  yymm.obs <- sort(rep(ESD$obs.station$yy,12)) +
              (rep(1:12,length(ESD$obs.station$yy))-0.5)/12
  N <- length(yymm); M <- length(gcms)
  esd4xls <- matrix(rep(NA,N*M),N,M)
  rownames(esd4xls) <- round(yymm,2); colnames(esd4xls) <- gcms

  print(summary(ESD$obs.station))

  for (i in 1:M) {
    i1 <- is.element(ESD$gcms.ctl,gcms[i])
    if (sum(i1)==1) {
      esd4xls[1:1200,i] <- c(ESD$ctl[i1,,])
      plot(yymm[1:1200],c(ESD$ctl[i1,,]),type="l")
    } else if (gcms[i]=="obs") {
      lines(yymm.obs,c(t(ESD$obs.station$val)),col="red")
      it <- is.element(yymm,yymm.obs)
      esd4xls[it,i] <- c(t(ESD$obs.station$val))
    }
    i2 <- is.element(ESD$gcms.sce,gcms[i])
    if (sum(i2)==1) {
      esd4xls[1201:2400,i] <- c(ESD$sce[i2,,])
    }
  }

  #print(summary(ESD)); stop("HERE")


  write.table(file=ExcelFileName,round(esd4xls,2),sep=", ",quote=FALSE)

#  WriteXLS(esd4xls,
#           file = ExcelFileName,
#           SheetNames = NULL, perl = "perl",
#           verbose = FALSE, Encoding = c("UTF-8", "latin1"),
#           row.names = FALSE,
#           AdjWidth = FALSE, AutoFilter = FALSE, BoldHeaderRow = FALSE,
#           FreezeRow = 0, FreezeCol = 0,
#           envir = parent.frame())
}

extrStatnett <- function(region,interval=2011:2040,param="RR",
                         base.line=NULL,ref=1961:1990,adjust=TRUE) {
  season<-cbind(c(12,1,2),c(3,4,5),c(6,7,8),c(9,10,11))
  locations <- list.files(path="STATNETT",pattern=".Rdata")
  dig <- switch(param,"TAM"=1,"RR"=0)
  rt <- switch(param,"TAM"="TR","RR"="NR")
  ele <- switch(param,"TAM"=101,"RR"=601)
  locations <- locations[grep(rt,locations)]
  print(locations)
```

```
reg <- locations[grep(paste(rt,"-region",region,".",sep=""),locations,
                      fixed=TRUE)]
reg <- substr(reg,1,nchar(reg)-6)
esd <- ESD.results(reg,path="STATNETT/",case.sens=TRUE,ele=ele)
obs.get <- paste("obslandsdel(",region,
                 ", param='",param,"', rt='",rt,"')",sep="")
print(obs.get)
low1 <- rep(NA,5)
attr(low1,'Description') <- c("DJF","MAM","JJA","SON","annual")
low2 <- low1; hig1 <- low1; hig2 <- low1; mval <- low1
low0 <- low1; hig0 <- low1

for (is in 1:5) {
  print("Get the seasonal/annual values")
  dev.new()
  if (is < 5) ESD <- showall(esd,months=season[,is],
                             obs.get = obs.get,ele=ele,
                             remove.bad.sd = FALSE) else
              ESD <- showall(esd,months=1:12,obs.get = obs.get,
                             ele=ele,remove.bad.sd = FALSE)

  mval[is] <- mean(ESD$obs,na.rm=TRUE)
  lines(c(1900,2100),rep(0.6*mval[is],2),lty=2)
  lines(c(1900,2100),rep(1.5*mval[is],2),lty=2)

  para <- switch(as.character(param),"TAM"=".t2m","RR"=".pr")

  if (adjust) {
    obs <- eval(parse(text=obs.get))
    base.line <-  switch(param,
                         "TAM"=colMeans(obs$val[is.element(obs$yy,ref),]),
                         "RR"=colMeans(obs$val[is.element(obs$yy,ref),])*3)
  } else base.line <- NULL
  print("add RCM...")
  addRCM(landsdel=region,param=para,col="pink",season=is,
              base.line=base.line,ref=ref) -> rcm.results
  print(summary(c(rcm.results)))
  print("Got ESD results")
  n0 <- length(obs$val[,1])
  n1 <- length(ESD$ctl[1,1,])
  n2 <- length(ESD$sce[1,1,])
  scl.sea <- switch(param,"TAM"=0.333,"RR"=1.0)
  scl.ann <- switch(param,"TAM"=1.0/12.0,"RR"=1.0)
  if (is==1) {
    # winter
    X0 <- scl.sea*(obs$val[1:(n0-1),12] + obs$val[2:n0,1] +
                   obs$val[2:n0,2])
    X1 <- scl.sea*(ESD$ctl[,12,1:(n1-1)] + ESD$ctl[,1,2:n1] +
                 ESD$ctl[,2,2:n1])
    X2 <- scl.sea*(ESD$sce[,12,1:(n2-1)] + ESD$sce[,1,2:n2] +
                 ESD$sce[,2,2:n2])
    obs$yy <- obs$yy[-1]
    ESD$yy.20c <- ESD$yy.20c[-1]
    ESD$yy.21c <- ESD$yy.21c[-1]
  } else if (is < 5) {
    # other seasons
    X0 <- scl.sea*(obs$val[,season[1,is]] + obs$val[,season[2,is]] +
                   obs$val[,season[3,is]])
    X1 <- scl.sea*(ESD$ctl[,season[1,is],] + ESD$ctl[,season[2,is],] +
                 ESD$ctl[,season[3,is],])
    X2 <- scl.sea*(ESD$sce[,season[1,is],] + ESD$sce[,season[2,is],] +
                 ESD$sce[,season[3,is],])
  } else {
    # annual mean
    X0 <- scl.ann * ( obs$val[,1] + obs$val[,2] + obs$val[,3] +
                      obs$val[,4] + obs$val[,5] + obs$val[,6] +
                      obs$val[,7] + obs$val[,8] + obs$val[,9] +
                      obs$val[,10] + obs$val[,11] + obs$val[,12] )
    X1 <- scl.ann * ( ESD$ctl[,1,] + ESD$ctl[,2,] + ESD$ctl[,3,] +
                      ESD$ctl[,4,] + ESD$ctl[,5,] + ESD$ctl[,6,] +
```

```
                        ESD$ctl[,7,] + ESD$ctl[,8,] + ESD$ctl[,9,] +
                        ESD$ctl[,10,] + ESD$ctl[,11,] + ESD$ctl[,12,] )
      X2 <- scl.ann * ( ESD$sce[,1,] + ESD$sce[,2,] + ESD$sce[,3,] +
                        ESD$sce[,4,] + ESD$sce[,5,] + ESD$sce[,6,] +
                        ESD$sce[,7,] + ESD$sce[,8,] + ESD$sce[,9,] +
                        ESD$sce[,10,] + ESD$sce[,11,] + ESD$sce[,12,] )
    }

    iv <- is.element(ESD$yy.20c,ref)
    vi <- is.element(ESD$yy.21c,interval)
    v0 <- is.element(obs$yy,ref)

    print(c(length(obs$yy),length(X0)))
    lines(obs$yy,X0)
    for (im in 1:length(X1[,1])) lines(ESD$yy.20c[iv],X1[im,iv],lwd=3)
    for (im in 1:length(X2[,1])) lines(ESD$yy.21c[iv],X2[im,iv],lwd=3)

    low0[is] <- pnorm( 0.6*mval[is],mean=mean(X0[v0],na.rm=TRUE),
                       sd=sd(X0[v0],na.rm=TRUE) )

    low1[is] <- pnorm( 0.6*mval[is],mean=mean(X1[,iv],na.rm=TRUE),
                       sd=sd(X1[,iv],na.rm=TRUE) )

    low2[is] <- pnorm( 0.6*mval[is],mean=mean(X2[,iv],na.rm=TRUE),
                       sd=sd(X2[,iv],na.rm=TRUE) )

    hig0[is] <- 1.0 - pnorm( 1.5*mval[is],mean=mean(X0[v0],na.rm=TRUE),
                       sd=sd(X0[v0],na.rm=TRUE) )

    hig1[is] <- 1.0 - pnorm( 1.5*mval[is],mean=mean(X1[,iv],na.rm=TRUE),
                       sd=sd(X1[,iv],na.rm=TRUE) )

    hig2[is] <- 1.0 - pnorm( 1.5*mval[is],mean=mean(X2[,iv],na.rm=TRUE),
                       sd=sd(X2[,iv],na.rm=TRUE) )

    #print(dim(X1)); print(summary(c(X1))); print( 0.6*mval[is])
    #low1[is] <-
    #  round(100*sum(X1[,iv] < 0.6*mval[is],is.na=TRUE)/
    #        sum(is.finite(X1[,iv])),2)
    #low2[is] <-
    #  round(100*sum(X2[,vi] < 0.6*mval[is],is.na=TRUE)/
    #        sum(is.finite(X2[,vi])),2)
    #hig1[is] <-
    #  round(100*sum(X1[,iv] > 1.5*mval[is],is.na=TRUE)/
    #        sum(is.finite(X1[,iv])),2)
    #hig2[is] <-
    #  round(100*sum(X2[,vi] > 1.5*mval[is],is.na=TRUE)/
    #        sum(is.finite(X2[,vi])),2)
    #low0[is] <-
    #  round(100*sum(X0 < 0.6*mval[is],is.na=TRUE)/sum(is.finite(X0)),2)
    #hig0[is] <-
    #  round(100*sum(X0 > 1.5*mval[is],is.na=TRUE)/sum(is.finite(X0)),2)
  }
  low0[is.na(low0)] <- 0; hig0[is.na(hig0)] <- 0
  low1[is.na(low1)] <- 0; hig1[is.na(hig1)] <- 0
  low2[is.na(low2)] <- 0; hig2[is.na(hig2)] <- 0

  #print(c(low1,low2,hig1,hig2)); stop("HERE")

  results <- list(low1=low1,low2=low2,hig1=hig1,hig2=hig2,
                  low0=low0,hig0=hig0,mval=mval)
  invisible(results)
}

exceedancetable <- function(interval=2011:2040,param="RR",
                            base.line=NULL,ref=1970:1999,adjust=TRUE) {
  tab.low0 <- matrix(rep(NA,5*13),5,13)
  obs <- obslandsdel(1,param="RR",rt="NR")
  rownames(tab.low0) <- c("DJF","MAM","JJA","SON","annual")
  colnames(tab.low0) <- paste("region",1:13)
```

```
  tab.hig0 <- tab.low0; tab.mval=tab.low0
  tab.low1 <- tab.low0; tab.hig1 <- tab.low0
  tab.low2 <- tab.low0; tab.hig2 <- tab.low0
  attr(tab.low0,'interval') <- range(obs$yy)
  attr(tab.hig0,'interval') <- range(obs$yy)
  attr(tab.low1,'interval') <- range(ref)
  attr(tab.hig1,'interval') <- range(ref)
  attr(tab.low2,'interval') <- range(interval)
  attr(tab.hig2,'interval') <- range(interval)
  for (ireg in 1:13) {
    extrStatnett(ireg,interval=interval,param=param,
                 base.line=base.line,ref=ref,adjust=adjust) -> results
    tab.low0[,ireg] <- results$low0
    tab.hig0[,ireg] <- results$hig0
    tab.low1[,ireg] <- results$low1
    tab.hig1[,ireg] <- results$hig1
    tab.low2[,ireg] <- results$low2
    tab.hig2[,ireg] <- results$hig2
    tab.mval[,ireg] <- results$mval
    while (dev.cur()>1) dev.off()
  }
  print("----------------------------------------------")
  #print(range(interval))
  #print("Obs: % < 0.6 mean:")
  #print(tab.low0)
  #print("Obs: % > 1.5 mean:")
  #print(tab.hig0)
  #print("CTL: % < 0.6 mean:")
  #print(tab.low1)
  #print("CTL: % > 1.5 mean:")
  #print(tab.hig1)
  #print("SCE: % < 0.6 mean:")
  #print(tab.low2)
  #print("SCE: % > 1.5 mean:")
  #print(tab.hig2)

  tables <- list(tab.low0=tab.low0,tab.hig0=tab.hig0,
                 tab.low1=tab.low1,tab.hig1=tab.hig1,
                 tab.low2=tab.low2,tab.hig2=tab.hig2,tab.mval=tab.mval)
  invisible(tables)
}

# Read data from RCM:

addRCM <- function(landsdel,param="t2m",col="blue",season=0,
                   filter=FALSE,test=FALSE,base.line=NULL,ref=1961:1990,
                   lty=0,plot=TRUE) {
  if (season > 4) season <- 0
  print(paste("addRCM:",season,landsdel,param,col))
  tr <- switch(param,"t2m"="_tr","pr"="_nr",".t2m"="_tr",".pr"="_nr")
  RCMs <- list.files(pattern=paste("landsdeler_",landsdel,tr,sep=""))
  for (i in 1:length(RCMs)) {
    print(RCMs[i])
    load(RCMs[i])
    rcms <- names(landsdel)
    print(rcms)
    rcms <- rcms[grep(param,rcms)]
    print(rcms)
    N.rcms <- length(rcms)
    nt <- 150
    season.area.mean.all <- matrix(rep(NA,nt*N.rcms),N.rcms,nt)
    for (ii in 1:N.rcms) {
      print(rcms[ii])
      cline <- paste("areamean <- landsdel$",rcms[ii],"$areamean",sep="")
      eval(parse(text=cline))
      cline <- paste("years <- landsdel$",rcms[ii],"$yymm",sep="")
      eval(parse(text=cline))
      cline <- paste("months <- landsdel$",rcms[ii],"$months",sep="")
      eval(parse(text=cline))
      #years <- trunc(rcm.xtr$yymm)
```

```
print(years[1:3])
if (trunc(years[1]) < trunc(years[2])) years <- years + 1/12
#print(years[1:3])
year.stats <- table(trunc(years))
no.mon.yr <- as.numeric(year.stats)
incompl.yr <- no.mon.yr < 12
year <- as.numeric(rownames(year.stats))
#print(year.stats)
if (sum(incompl.yr)>0) {
  print(paste("Incomplete years:",year[incompl.yr]))
  year <- year[!incompl.yr]
}
ny <- length(year)
monthlydata <- matrix(rep(NA,ny*12),ny,12)
#print(table(months)); print(table(trunc(years)))
for (im in 1:12) {
  i1 <- is.element(year,trunc(years))
  i2 <- is.element(trunc(years),year) & is.element(trunc(months),im)
  #print(paste("im loop:",im,length(i1),length(i2),sum(i1),sum(i2)))
  #print(dim(monthlydata))
  monthlydata[i1,im] <- areamean[i2]
}
monthlydata[abs(monthlydata)>9999] <- NA
dec <- c(monthlydata[1:(ny-1),im],NA)
janfeb <- rbind(rep(NA,2),monthlydata[2:ny,1:2])
winter <- rowMeans(cbind(dec,janfeb))
spring <- rowMeans(monthlydata[,3:5])
summer <- rowMeans(monthlydata[,6:8])
autumn <- rowMeans(monthlydata[,9:11])
annual <- rowMeans(monthlydata)

if (param==".pr") {
# Convert from 'mm/day' to 'mm/month'
  winter <- winter * 90; spring <- spring * 90
  summer <- summer * 90; autumn <- autumn * 90
  annual <- annual * 360
  const <- sum(base.line)/3  # base-line are given as 3-month means
} else const <- mean(base.line)


if (!is.null(base.line)) {
  if (length(base.line)!=12)
    stop("base.line must be a 12-element vector")
  annual <- annual - mean(annual[is.element(year,ref)]) + const
  winter <- winter - mean(winter[is.element(year,ref)]) +
                         mean(base.line[c(1,2,12)])
  spring <- spring - mean(spring[is.element(year,ref)]) +
                         mean(base.line[3:5])
  summer <- summer - mean(summer[is.element(year,ref)]) +
                         mean(base.line[6:8])
  autumn <- autumn - mean(autumn[is.element(year,ref)]) +
                         mean(base.line[9:11])
}

#image(monthlydata); x11()
#print(c(length(year),length(annual),length(winter),NA,dim(monthlydata)))

if (test) {
  plot(years,areamean,type="l",main="addRCM: test")
  lines(year,annual,lwd=3)
  lines(year,winter,lwd=2,col="blue")
  lines(year,spring,lwd=2,col="green")
  lines(year,summer,lwd=2,col="darkgreen")
  lines(year,autumn,lwd=2,col="red")
  grid()
  stop()
}

season.area.mean <- switch(as.character(season),
                        "0"=annual,
```

```
                              "1"=winter,"2"=spring,"3"=summer,"4"=autumn)
      print(paste("stdv=",sd(season.area.mean,na.rm=TRUE)));
      print(summary(season.area.mean))

      if (plot) {
        if (!filter) {
          points(year,season.area.mean,col=col,lty=3,pch=19,cex=0.4)
          if (lty>0) lines(year,season.area.mean,col=col,lty=3)
        } else {
          points(year,gauss.filt(season.area.mean,30),
                 col=col,lty=3,pch=19,cex=0.4)
          if (lty>0) lines(year,gauss.filt(season.area.mean,30),
                         col=col,lty=3)
        }
      }

      if (season==1) year <- year+1
      ii1 <- is.element(1951:2100,year)
      ii2 <- is.element(year,1951:2100)
      print(paste("addRCM: check. ii=",ii,"ii1:",sum(ii1),"ii2:",sum(ii2),
                  "RCM:",rcms[ii]))
      season.area.mean.all[ii,ii1] <- season.area.mean[ii2]
    }
  }
  #print(season); print(season.area.mean.all[,10])
  #x11(); image(season.area.mean.all)
  #x11(); plot(season.area.mean.all[,10],main="season.area.mean.all[,1]"); stop()
  attr(season.area.mean.all,"year") <- 1951:2100
  attr(season.area.mean.all,"season") <- season
  attr(season.area.mean.all,"RCM") <- rcms
  invisible(season.area.mean.all)
}

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))
    x11()
    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))

   x11()
   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)
}



computeStatnett <- function(ds=TRUE,param="TAM",rt="TR",exclude=NULL,
                            scen="sresa1b",start=1,stans=NULL) {

  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")

  # tidligere URL
  #url <- paste("http://klapp.oslo.dnmi.no/metnopub/production/metno?re=20&ct=text/plain&p=",
  #                     param,"&fy=1900&r_type=",rt,sep="")
  # REB 16.02.2011

  if (param=="TAM")
    url <-paste("http://klapp.oslo.dnmi.no/metnopub/production/",
              "metno?re=20&ct=text/plain&p=",param,"&fy=1900&r_type=",rt,sep="") else
```

```
  if (param=="RR")
    url <- paste("http://klapp.oslo.dnmi.no/metnopub/production/metno?re=20&",
                 "ct=text/plain&p=RR&fy=&ty=2011&r_type=",rt,sep="")

  print(url)
  region.curve <- read.table(url,header=TRUE)
#  regions <- as.numeric(rownames(table(region.curve$region_no)))
  regions <- as.numeric(rownames(table(region.curve$regionid)))
  if (is.null(stans)) stans <- length(regions)

  for (i in regions[start:stans]) {
    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","6"="Varanger",
                                     "5"="Finnmarksvidda") else

    if (rt=="NR") location <- switch(as.character(i),
                                     "0"="Heile_landet","2"="Austlandet","1"="Ostfold",
                                     "3"="Sorlandet","4"="Sor-Vestlandet","5"="Sunnhordland",
                                     "6"="Sogn","8"="More+Romsdal","7"="Dovre+Nord-Osterdal",
                                     "9"="Inntrondelag","10"="Trondelag+Helgeland",
                                     "11"="Halogaland",
                                     "13"="Varanger","12"="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)
    iextract <- is.element(region.curve$regionid,i) & is.element(region.curve$month,1:12)

    #print(summary(region.curve)); print(sum(iextract))
    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)

    #load("ERA40_prec_mon.Rdata")
    #corField(pre,obs,mon=1)
    #save(file="test.Rdata",pre,obs)
    #stop("FORCED STOP HERE")

    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,LINPACK=TRUE,
#            do.a1b=TRUE,do.rcm=0,qc=FALSE,station=obs,predictand = "Statnett",
#            path="/home/rasmusb/data/ipcc_FoAR/GCMs/",op.path="STATNETT",
#            lon=lon,lat=lat,scen=scen,stop.on.poor.perf=TRUE,lsave=TRUE,exclude=exclude)
```

```
    if (ds) ds.one(ele=ele,cmons=1:12,silent=FALSE,LINPACK=TRUE,
            do.a1b=TRUE,do.rcm=0,qc=FALSE,station=obs,predictand = "StatnettII",
            path="GCMs/",op.path="STATNETT",
            lon=lon,lat=lat,scen=scen,stop.on.poor.perf=FALSE,lsave=TRUE,exclude=exclude)

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

showStatnett <- function(location="unspecified",ele=101,method="rowMeans",
                         plot=TRUE,verbose=FALSE,obs=NULL) {
    print(paste("showStatnett: location=",location))
    snett <- ESD.results(station=location,ele=ele,predictand="Statnett",obs=obs,
                         path="STATNETT/",case.sens=TRUE,verbose=verbose)

    #print(summary(snett))
    if (is.null(snett$N1)) snett$N1 <- length(snett$scen.files.20c)
    if (is.null(snett$N2)) snett$N2 <- length(snett$scen.files.21c)

    if (plot) {
      par(cex.axis=1,las=1,mfrow=c(1,1),mar=c(5, 4, 4, 2) + 0.1)
      plotESD.box(snett)
      dev.copy2eps(file=paste("Fig_",location,"-boxplot.eps",sep=""))
      plotESD.plume(snett,method=method) -> plume
    }
    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$val)",sep="")))
      if (plot) {
        points(obs$yy,obs.hdd,pch=19)
        lines(obs$yy,obs.hdd,lwd=2,lty=2)
      }
    }

    invisible(snett)
}

nou.fig <- function(path="~/elephanta_disk/rasmusb/STATNETT/",
                    location="unspecified",ele=101,method="rowSums",
                    verbose=FALSE,years=2071:2100) {
  sesong <- c("Vinter","Var","Sommer","Host","Ar")
  season <- c("winter.sce","spring.sce","summer.sce","autumn.sce","annual.sce")
  cmons <- matrix(c(12,1,2, 3:5, 6:8, 9:11),3,4)
  locations <- list.files(path=path,pattern=".Rdata")
  filter <- switch(as.character(ele),"101"="TR-","601"="NR-")
  elemcode <- switch(as.character(ele),"101"="31","601"="17")
  xoffs <- switch(as.character(ele),"101"=0.1,"601"=-0.3)
  ylab <- switch(as.character(ele),"101"="grader C","601"="%")
  if (ele==101) ylim <- c(0,10) else ylim <- c(-30,60)
  locations <- locations[grep(filter,locations)]
  N <- length(locations); regions <- rep(NA,N)
  result <- list(name="ESD",path=path,ele=ele,years=years)
  print(locations)
  for (i in 1:N) {
    uscr <- instring("_",locations[i])-1
    print(substr(locations[i],1,uscr[1]))
    snett <- ESD.results(station=substr(locations[i],1,uscr[1]),ele=ele,
                         predictand="Statnett",obs=obs,
                         path=path,case.sens=TRUE,verbose=verbose)
    i1 <- instring(filter,locations[i]) + 9; i2 <- nchar(locations[i])-6
    regions[i] <- as.numeric(substr(locations[i],i1,i2))
    print(locations[i])
    print(paste(i1,", ",i2,", ", substr(locations[i],i1,i2),
                " -> result$reg.",regions[i]," <- plotESD.box(snett,years=years)",sep=""))
    eval(parse(text=paste("result$reg.",regions[i],
                 " <- plotESD.box(snett,years=years)",sep="")))
```

```
  }

  print(locations)
  jeh.a1 <- as.matrix(read.table(paste("~/data/HA2v1/Table4_2071-2100_",
                                      elemcode,".txt",sep=""),header=TRUE))
  jeh.a2 <- as.matrix(read.table(paste("~/data/HB2v1/Table4_2071-2100_",
                                      elemcode,".txt",sep=""),header=TRUE))
  jeh.a3 <- as.matrix(read.table(paste("~/data/MB2v1/Table4_2071-2100_",
                                      elemcode,".txt",sep=""),header=TRUE))
  jeh.a4 <- as.matrix(read.table(paste("~/data/MB2v2/Table4_2071-2100_",
                                      elemcode,".txt",sep=""),header=TRUE))
  jeh.b1 <- as.matrix(read.table(paste("~/data/HA2v1/Table4_1961-1990_",
                                      elemcode,".txt",sep=""),header=TRUE))
  jeh.b2 <- as.matrix(read.table(paste("~/data/HB2v1/Table4_1961-1990_",
                                      elemcode,".txt",sep=""),header=TRUE))
  jeh.b3 <- as.matrix(read.table(paste("~/data/MB2v1/Table4_1961-1990_",
                                      elemcode,".txt",sep=""),header=TRUE))
  jeh.b4 <- as.matrix(read.table(paste("~/data/MB2v2/Table4_1961-1990_",
                                      elemcode,".txt",sep=""),header=TRUE))

  #print(dim(jeh.a1)); print(rowMeans(jeh.a1)); print(colMeans(jeh.a1))

  #print(summary(c(jeh.a1[,4:(N+3)])))

  x11()
  par(mfrow=c(5,1),mar=c(2,4,1,1),cex.axis=0.8)
  for (i in 1:5) {
    if (i < 5) im <- is.element(jeh.a1[,3],cmons[,i]) else im <- is.finite(jeh.a1[,3])
#    print(table(jeh.a1[im,3]))
    sce <- matrix(rep(NA,N*60),N,60)
    for (ii in 1:N) {
      reg <-  eval(parse(text=paste("result$reg.",ii,sep="")))
      #print(summary(reg)); print(dim(sce))
      n <- length( eval(parse(text=paste("reg$",season[i],sep=""))))
      #print(n); print(paste("reg$",season[i],sep="")); print(summary(reg))
      sce[ii,1:n] <- eval(parse(text=paste("reg$",season[i],sep="")))
    }
    save(file="test.Rdata",sce)
#    boxplot(as.data.frame(t(sce)),col="grey",lwd=1,range=0,outline=FALSE,
#            main=sesong[i],ylim=c(0,6))
    plot(c(0.5,N+0.5),ylim,type="n",xlim=c(0.5,N+0.5),ylim=ylim,xlab="region",ylab=ylab)
    text(N+xoffs,0.95*ylim[2],sesong[i],pos=4)
    for (ii in 1:N) {
      rect(ii-0.15,quantile(sce[ii,],0.10,na.rm=TRUE),ii+0.15,
           quantile(sce[ii,],0.90,na.rm=TRUE),
           col="grey")
      lines(ii+c(-0.15,0.15),rep(mean(sce[ii,],na.rm=TRUE),2),lwd=2)

      print(paste("Region",ii,sesong[i]," q_0.1=",
                 round(quantile(sce[ii,],0.10,na.rm=TRUE),2),
                 "mean=",round(mean(sce[ii,],na.rm=TRUE),2)," q_0.9=",
                 round(quantile(sce[ii,],0.90,na.rm=TRUE),2)))
      if (ele==101) {
        print(round(c(mean(jeh.a1[im,3+ii])-mean(jeh.b1[im,3+ii]),
                     mean(jeh.a2[im,3+ii])-mean(jeh.b2[im,3+ii]),
               mean(jeh.a3[im,3+ii])-mean(jeh.b3[im,3+ii]),
                     mean(jeh.a4[im,3+ii])-mean(jeh.b4[im,3+ii])),2))
        points(ii-0.15,mean(jeh.a1[im,3+ii])-mean(jeh.b1[im,3+ii]),
               pch=18,col="red",cex=1.1)
        points(ii-0.15,mean(jeh.a1[im,3+ii])-mean(jeh.b1[im,3+ii]),
               pch=23,cex=1.1)
        points(ii-0.1,mean(jeh.a2[im,3+ii])-mean(jeh.b2[im,3+ii]),
               pch=15,col="red",cex=1.1)
        points(ii-0.1,mean(jeh.a2[im,3+ii])-mean(jeh.b2[im,3+ii]),
               pch=22,cex=1.1)
        points(ii-0.2,mean(jeh.a3[im,3+ii])-mean(jeh.b3[im,3+ii]),
               pch=15,col="green",cex=1.1)
        points(ii-0.2,mean(jeh.a3[im,3+ii])-mean(jeh.b3[im,3+ii]),
               pch=22,cex=1.1)
        points(ii+0.15,mean(jeh.a4[im,3+ii])-mean(jeh.b4[im,3+ii]),
```

```
               pch=15,col="blue",cex=1.1)
        points(ii+0.15,mean(jeh.a4[im,3+ii])-mean(jeh.b4[im,3+ii]),
               pch=22,cex=1.1)
    } else {
        points(ii-0.15,100*( mean(jeh.a1[im,3+ii])-
                             mean(jeh.b1[im,3+ii]) )/mean(jeh.b1[im,3+ii]),
               pch=18,col="red",cex=1.1)
        points(ii-0.15,100*( mean(jeh.a1[im,3+ii])
                             -mean(jeh.b1[im,3+ii]) )/mean(jeh.b1[im,3+ii]),
               pch=23,cex=1.1)
        points(ii-0.1,100*( mean(jeh.a2[im,3+ii])-
                            mean(jeh.b2[im,3+ii]) )/mean(jeh.b2[im,3+ii]),
               pch=15,col="red",cex=1.1)
        points(ii-0.1,100*( mean(jeh.a2[im,3+ii])-
                            mean(jeh.b2[im,3+ii]) )/mean(jeh.b2[im,3+ii]),
               pch=22,cex=1.1)
        points(ii-0.2,100*( mean(jeh.a3[im,3+ii])-
                            mean(jeh.b3[im,3+ii]) )/mean(jeh.b3[im,3+ii]),
               pch=15,col="green",cex=1.1)
        points(ii-0.2,100*( mean(jeh.a3[im,3+ii])-
                            mean(jeh.b3[im,3+ii]) )/mean(jeh.b3[im,3+ii]),
               pch=22,cex=1.1)
        points(ii+0.15,100*( mean(jeh.a4[im,3+ii])-
                             mean(jeh.b4[im,3+ii]) )/mean(jeh.b4[im,3+ii]),
               pch=15,col="blue",cex=1.1)
        points(ii+0.15,100*( mean(jeh.a4[im,3+ii])-
                             mean(jeh.b4[im,3+ii]) )/mean(jeh.b4[im,3+ii]),
               pch=22,cex=1.1)
    }
    }
    grid()
  }
#   symbols with fill colours to be used for highlighted scenarioes
  modl <- c('MB2v1','HA2v1','HB2v1','MB2v2')
  pchs <- c(22     ,23     ,22     ,22     )
  cols <- c("green","red"  ,"red"  ,"blue" )

# Legend to highlighted scenarios
  legend(0.5,ylim[2],modl,
         pch=pchs,pt.bg=cols,
         col='black',pt.cex=1.15,
         ncol=2,bg="grey95",cex=1.*par("cex"))

    dev.copy2eps(file=paste("dsStatnett-nou-",ele,".eps",sep=""))
}

nou.fig2 <- function(station=c("Vestlandet","Sogn"),ele=c(101,601)) {
  for (i in 1:length(station)) avisPlot(station=station[i],ele=ele[i],path="STATNETT/",
                                        case.sens=TRUE,google.earth=FALSE)
  for (i in 1:length(station)) {
    esd <- ESD.results(station=station[i],ele=ele[i],path="STATNETT/",case.sens=TRUE)
    plotESD.box(esd)
    dev.copy2eps(file=paste("dsStatnett-nou-fig2-",station[i],ele[i],".eps",sep=""))
  }
}

nou.fig3 <- function(station="Austlandet",ele=101) {
  esd.a1b <- ESD.results(station=station,ele=ele,path="STATNETT/",case.sens=TRUE)
  esd.a2 <- ESD.results(station=station,ele=ele,path="STATNETT/",scen="sresa2",case.sens=TRUE)
#  esd.b1 <- ESD.results(station=station,ele=ele,path="STATNETT/",scen="sresb1",case.sens=TRUE)
  plotESD.pdf(esd.a1b)
  plotESD.pdf(esd.a2,col=c("grey","red"),add=TRUE)
#  plotESD.hist(esd.b1,col=c("grey","darkgreen"),add=TRUE)
  legend(10,0.4,c("20C3M   ","SRESA1b   ","SRESA2   "),col=c("grey","blue","red"),
         bg="grey95",lty=1,lwd=3,cex=0.7)
  dev.copy2eps(file="dsStatnett-nou-fig3.eps")
}


finalStatnett <- function(ele=101,inflation=FALSE,period=2010:2040,
```

```
                        addRCM=TRUE,ref=1961:1990,adjust=TRUE) {
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,200*5); dim(M) <- c(200,5); Q1 <- M; Q2 <- M; S <- M
t <- 1900:2099; nt <- length(t)
m <- rep(NA,nt*5); dim(m) <- c(nt,5); q1 <- m; q2 <- m; m.0 <- m; s <- m
trend <- rep(NA,200*5); dim(trend) <- c(200,5)
print(locations)
n <- length(locations)
sce.2000.2040 <- rep(NA,n*5); dim(sce.2000.2040) <- c(n,5)
sce.0.2000.2040 <- sce.2000.2040
rcm.spread <- rep("NA",150*6); dim(rcm.spread) <- c(150,6)
rcm.median <- rep("NA",150*6); dim(rcm.median) <- c(150,6)
RCM.spread <- rep(NA,150*15*n); dim(RCM.spread) <- c(150,3,5,n)
rcm.ts <- rep(NA,150*16); dim(rcm.ts) <- c(150,16);
rcm.sd <- rep(NA,150*6); dim(rcm.sd) <- c(150,6);
colnames(rcm.ts) <- c("Year","DJF.q05","DJF.ave","DJF.q95",
                      "MAM.q05","MAM.ave","MAM.q95",
                      "JJA.q05","JJA.ave","JJA.q95",
                      "SON.q05","SON.ave","SON.q95",
                      "ANN.q05","ANN.ave","ANN.q95")
clim <- rep(NA,5*n); dim(clim) <- c(n,5)

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

print("finalStatnett: loop through locations")
locs <- rep("?",n)
for (i in 1:n) {
  dot <- instring(".",locations[i])
  ireg <- as.numeric(substr(locations[i],dot[length(dot)]-1,dot[length(dot)]-1))
  ireg10 <- as.numeric(substr(locations[i],dot[length(dot)]-2,dot[length(dot)]-1))
  if (!is.na(ireg10)) ireg <- ireg10
  #print(ireg); stop()
  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),mar=c(5, 4, 4, 2) + 0.1)
  plot(c(1900,2100),range(statnett$sce,na.rm=TRUE),type="n",main=locs[i])
  grid()
  N <- length(statnett$scen.files.21c)
  z <- rep(NA,200*N*5); dim(z) <- c(200,N,5)

  X <- obs$yy
  Y0 <- matrix(rep(NA,length(X)*5),length(X),5)
  for (igcm in 1:N) {
    for (is in 1:5) {
      if (is.element(is,2:4)) {
        y1 <- statnett$ctl[igcm,seasons[,is],]
        y2 <- statnett$sce[igcm,seasons[,is],]
        y0 <- obs$val[,seasons[,is]]
        y0.clim <- obs$val[is.element(obs$yy,1961:1990),seasons[,is]]
      } else if (is==1) {
        y1 <- rbind( statnett$ctl[igcm,12,1:99],
                    statnett$ctl[igcm,1:2,2:100])
        y1 <- cbind(rep(NA,3),y1)
        y2 <- rbind( statnett$sce[igcm,12,1:99],
                     statnett$sce[igcm,1:2,2:100])
        y2 <- cbind(rep(NA,3),y2)
        y0 <- cbind(obs$val[-length(obs$yy),12],
                     obs$val[-1,1:2])
        y0 <- rbind(rep(NA,3),y0)
        print("summary(y0)"); print(summary(c(y0)))
```

```
      y0.clim <- colMeans(obs$val[is.element(obs$yy,1961:1990),seasons[,is]])
      #print(is); print(colMeans(y0))
    } else if (is==5) {
      y1 <- statnett$ctl[igcm,,]
      y2 <- statnett$sce[igcm,,]
      y0 <- obs$val
      y0.clim <- colMeans(obs$val[is.element(obs$yy,1961:1990),])
    }

    Y1 <- switch(as.character(ele),"101"=colMeans(y1),
                                   "601"=colSums(y1))
    Y2 <- switch(as.character(ele),"101"=colMeans(y2),
                                   "601"=colSums(y2))
    Y0[,is] <- switch(as.character(ele),"101"=rowMeans(y0),
                                        "601"=rowSums(y0))
    if (is==1) {
      print("is=1:"); print(summary(c(y0)))
      print(summary(Y0[,is]))
      print(summary(rowMeans(y0)))
      print("---")
    }
    clim[i,is] <- switch(as.character(ele),"101"=mean(y0.clim,na.rm=TRUE),
                                           "601"=sum(y0.clim,na.rm=TRUE))
    base.line <- colMeans(obs$val[is.element(obs$yy,1961:1990),])
    if (ele==601) base.line <- base.line * 3 # 3-month-means
    obs$unit <- switch(as.character(ele),"101"="deg C",
                                         "601"="mm/season")
    #print("HERE2")
    x <- statnett$yy.21c
    if (adjust) {
      match1 <- is.element(x,X)
      match2 <- is.element(X,x)
      offset <- round( mean(Y0[match2,is],na.rm=TRUE) -
                       mean(Y2[match1],na.rm=TRUE),2 )
      print(paste("offset=",offset,"is=",is,sum(match1),sum(match2)))
      Y1   <- Y1 + offset
      Y2   <- Y2 + offset
    } else base.line <- NULL
    if (ele==601) { Y1[Y1 < 0] <- 0;  Y2[Y2 < 0] <- 0}
    #print(dim(z)); print(length(Y1));print(length(Y2))
    z[,igcm,is] <- c(Y1,Y2)
    if (is<5) lines(1900:2099,z[,igcm,is] - mean(Y1,na.rm=TRUE),col=cols[is],lwd=2)
    print(paste("z[,igcm,is]=",is)); print(summary(z[,igcm,is]))
    print(summary(Y2)); print(summary(Y0[,is]))
  }
}

image(z[,,1])

for (is in 1:5) {
  print(paste("HERE4",is))
  for (it in 1:200) {
    M[it,is] <-  median(z[it,,is],na.rm=TRUE)
    S[it,is] <-  sd(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))
print("summary(c(z[,,is]))");print(summary(c(z[,,is])))

# Predicted trends.

print("M[,is]:")
print(summary(M[,is])); print(is)
calm <- data.frame(y=M[,is],t=t)
cals <- data.frame(y=S[,is],t=t)
calq1 <- data.frame(y=Q1[,is],t=t)
calq2 <- data.frame(y=Q2[,is],t=t)
trendM  <- lm(y  ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5),data=calm)
trendS  <- lm(y  ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5),data=cals)
```

```
  trendQ1 <- lm(y ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5),data=calq1)
  trendQ2 <- lm(y ~ t + I(t^2) + I(t^3)+ I(t^4) + I(t^5),data=calq2)
  #print(sum(is.finite(t)))

  #print(dim(m)); print(length(predict(trendM,newdata=calm)))
  m[,is]  <- round(predict(trendM,newdata=calm),2)
  s[,is]  <- round(predict(trendS,newdata=calm),2)
  q1[,is] <- round(predict(trendQ1,newdata=calq1),2)
  q2[,is] <- round(predict(trendQ2,newdata=calq2),2)
  }

#print("HERE6")
par(cex.axis=1,las=1,mfrow=c(2,2),cex.axis=0.7,mar=c(2, 4, 3, 2) + 0.1)

for (is in 1:5) {
  #if (is < 5) plot.rcm <- TRUE else plot.rcm <- FALSE
  plot.rcm <- TRUE
  if (is == 5) {
    dev.copy2eps(file=paste("Fig_",locs[i],".eps",sep=""))
    dev.off()
    plot(c(1950,2100),range(c(z[,,is]),na.rm=TRUE),type="n",
         main=locs[i],ylab=obs$unit,xlab="")

    grid()
    for (igcm in 1:N) lines(1900:2099,z[,igcm,is],lwd=2,col="grey")
    lines(X, Y0[,is],type="b")
    points(X,Y0[,is], pch=19)
    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(1961,1990),rep(clim[i,is],2),lty=2,lwd=1,col="red")
    if (ele==101) mtext(paste("Clim.=",round(clim[i,is],1)),side=4) else
                  mtext(paste("Clim.=",round(clim[i,is])),side=4)
  } else {
    plot(c(1950,2100),range(c(z[,,is]),na.rm=TRUE),type="n",
         main=locs[i],ylab=obs$unit,xlab="")

    grid()
    for (igcm in 1:N) lines(1900:2099,z[,igcm,is],lwd=2,col="grey")
    lines(X, Y0[,is],type="b")
    points(X,Y0[,is], pch=19)
    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(1961,1990),rep(clim[i,is],2),lty=2,lwd=1,col="red")
  }

  if (addRCM) {
      param <- switch(as.character(ele),"101"=".t2m","601"=".pr")

      #print(dim(RCM.spread)); print(dim(rcm.spread)); stop("check addRCM")

      addRCM(landsdel=ireg,param=param,col="blue",season=is,
             base.line=base.line,ref=ref,plot=plot.rcm) -> rcm.stat
       #print("HERE7")
      #print(dim(rcm.stat)); print(dim(rcm.spread))
      #print(summary(c(rcm.stat))); print(attr(rcm.stat,'year')); stop()

      rcm.ts[,1] <- attr(rcm.stat,'year')
      rcm.sd[,1] <- attr(rcm.stat,'year')
      rcm.ts[,3*(is-1)+2] <- round( apply(rcm.stat,2,quantile,0.05,na.rm=TRUE), dig)
      rcm.ts[,3*(is-1)+3] <- round( apply(rcm.stat,2,median,na.rm=TRUE), dig)
      rcm.ts[,3*(is-1)+4] <- round( apply(rcm.stat,2,quantile,0.95,na.rm=TRUE), dig)
      rcm.sd[,is+1] <- round( apply(rcm.stat,2,sd,na.rm=TRUE), dig)

      for (it.rcm in 1:length(rcm.spread[,1])) {
         rcm.spread[it.rcm,1] <- paste(attr(rcm.stat,'year')[it.rcm]," & ")
         rcm.median[it.rcm,1] <- paste(attr(rcm.stat,'year')[it.rcm]," & ")
```

```
          rcm.spread[it.rcm,is+1] <-
            paste(round(quantile(rcm.stat[,it.rcm],0.05,na.rm=TRUE),dig),
                  " -- ",
                  round(quantile(rcm.stat[,it.rcm],0.95,na.rm=TRUE),dig),
                  " & ",sep="")
          rcm.median[it.rcm,is+1] <- round(median(rcm.stat[,it.rcm],na.rm=TRUE),dig)

          RCM.spread[it.rcm,1,is,ireg] <-
            round(quantile(rcm.stat[,it.rcm],0.05,na.rm=TRUE),dig)
          RCM.spread[it.rcm,2,is,ireg] <-
            round(median(rcm.stat[,it.rcm],na.rm=TRUE),dig)
          RCM.spread[it.rcm,3,is,ireg] <-
            round(quantile(rcm.stat[,it.rcm],0.95,na.rm=TRUE),dig)
        }
       if (is==5) {
         lines(1951:2100,gauss.filt(RCM.spread[,2,is,ireg],10),lwd=3,col="darkblue")
         if (ele==101) iii <- is.element(1951:2100,1961:1990) else
                       iii <- is.element(1951:2100,1970:1999)
         print(length(iii)); print(length(1951:2100)); print(table(iii));
         print(range((1951:2100)[iii]))
         lines(range((1951:2100)[iii]),
               rep(mean(RCM.spread[iii,2,is,ireg]),2),lwd=3,col="steelblue")
         iii <- is.element(1951:2100,2011:2040)
         lines(range((1951:2100)[iii]),
               rep(mean(RCM.spread[iii,2,is,ireg]),2),lwd=3,col="steelblue")
         iii <- is.element(1951:2100,2036:2065)
         lines(range((1951:2100)[iii]),
               rep(mean(RCM.spread[iii,2,is,ireg]),2),lwd=3,col="steelblue")
       }
       #print("HERE8")
       if (sum(is.finite(RCM.spread[,,is,ireg]))<100) {
         print(c(is,ireg)); print(summary(RCM.spread[,1,is,ireg]));
         print(summary(RCM.spread[,2,is,ireg]));
         print(summary(c(rcm.stat)))
         print(dim(RCM.spread)); print(dim(rcm.spread)); stop("check addRCM")
       }
       attr(RCM.spread,'year') <- attr(rcm.stat,'year')
       save(file="RCM.spread.rda",RCM.spread)
       #print("HERE9")
   }


#    if ( (ele==101) & (is<5) ) {
#          axis(side=4,at=seq(-15,15,by=1)+clim[i,is],
#          labels=seq(-15,15,by=1),las=0,col="grey40",cex=0.7)
#    } else {
#          axis(side=4,at=seq(-1500,1500,by=100)+clim[i,is],
#          labels=seq(-1500,1500,by=100),las=0,col="grey40",cex=0.7)
#    }

   if (is==1) {
     legend(1950,max(c(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_am_",locs[i],".eps",sep=""))

  write.table(rcm.ts,file=paste("res_ENSEMBLE_",locs[i],"_",
                         ele,".txt",sep=""),
              quote=FALSE,row.names = FALSE,sep="\t")

  write.table(rcm.sd,file=paste("sd_ENSEMBLE_",locs[i],"_",
                         ele,".txt",sep=""),
              quote=FALSE,row.names = 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],
                     ANN.q05=q1[,5],ANN.ave=m[,5],ANN.q95=q2[,5])
  esd.sd <- data.frame(Year=t,
                       DJF.sd=s[,1],MAM.sd=s[,2],JJA.sd=s[,3],SON.sd=s[,4],ANN.sd=s[,5])
  write.table(scen,file=paste("res_ESD_",locs[i],"_",ele,".txt",sep=""),
              quote=FALSE,sep="\t")
  write.table(esd.sd,file=paste("sd_ESD_",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)
}


newPlot <- function(ele=101,list=NULL,norsk=TRUE) {
  pattern <- switch(as.character(ele),"101"="_TR-","601"="_NR-")
  if (is.null(list)) {
    list <- list.files(pattern="Statnett",path="STATNETT/")
    list <- list[grep(pattern,list)]
  }
  for (station in list) {
    esd <- avisPlot(station=station,ele=ele,path="STATNETT/",
                    predictand="Statnett",verbose=TRUE,case.sens=TRUE,
                    norsk=norsk,google.earth=FALSE)
  }
}




statnett.obs <- function(location,ele=101,predictand="Statnett") {
  print(paste("statnett.obs:",location))
  method <- switch(as.character(ele),"101"="rowMeans","601"="rowSums")
  obs.name <- paste("STATNETT/",substr(location,nchar(predictand)+1,nchar(location)-3),
                    ".Rdata",sep="")
  load(obs.name)
  invisible(obs)
}

finalPlot2 <- function(path="STATNETT/",predictand="Statnett",ele=101) {
  locations <- list.files(path=path,pattern=predictand)
  regtype <- switch(as.character(ele),"101"="TR","601"="NR")
  locations <- locations[grep(regtype,locations)]
  if (ele==101) locations <- locations[-grep("+",locations,fixed=TRUE)]
  for (i in 1:length(locations)) {
    obs.get <- paste("statnett.obs('",locations[i],"',ele=",ele,",predictand=predictand)",sep="")
    esd <- finalPlot(path="STATNETT/",predictand=predictand,ele=101,station=locations[i],obs.get=obs.get)
    #print(summary(esd))
    n <- length(esd$gcms.sce)+2
    M <- matrix(rep(NA,n*200*12),200*12,n)
    #print(dim(M))
    #print(length(rep(1901:2100,12)))
    M[,1] <- sort(rep(1901:2100,12))
    M[,2] <- rep(1:12,200)
    for (ii in 3:n) {
```

```
      iii <- is.element(esd$gcms.ctl,esd$gcms.sce[ii-2])
      if (sum(iii)==1) M[1:1200,ii] <- c(esd$ctl[iii,,])
      M[1201:2400,ii] <- c(esd$sce[ii-2,,])
    }
    colnames(M) <- c("year","month",esd$gcms.sce)
    #plot(c(esd$sce[i-2,,]))
    write.table(file=paste("ESD-",locations[i],".txt",sep=""),round(M,2))
  }
}
```

7.4.2 dsStatnett2.R

```
source("dsStatnett.R")
do.extr <- FALSE
do.figs <- FALSE
do.tabs <- FALSE
do.3day <- FALSE
do.wetcold <- FALSE
do.wetdry <- TRUE
do.esd2xls <- FALSE
do.wholecountry <- FALSE

#computeStatnett(ds=TRUE,param="TAM",rt="TR",exclude=NULL,
#                scen="sresa1b",start=1,stans=NULL)
#computeStatnett(ds=TRUE,param="RR",rt="NR",exclude=NULL,
#                scen="sresa1b",start=1,stans=NULL)

cmon <- c("-JAN-","-FEB-","-MAR-","-APR-","-MAY-","-JUN-",
          "-JUL-","-AUG-","-SEP-","-OCT-","-NOV-","-DEC-")
cols <- c("red","darkred","blue","darkblue","darkgreen","grey40","cyan",
          "magenta","green","steelblue","brown","pink","wheat","violet")

colddryprob <- function(file="dsStatnett_colddry1.rda",interval=1,
                        t.tr=NULL,p.tr=NULL,plot=FALSE) {
  load(file)
  if (is.null(t.tr)) t.tr <- mean(results$X0,na.rm=TRUE)
  if (is.null(p.tr)) p.tr <- 100
  ct1 <- table(round(results$X1),10*round(results$Y1/10))
  ct2 <- table(round(results$X2),10*round(results$Y2/10))

  if (plot) {
    par(bty="n",col.axis="white")
    plot(c(-15,10),c(0,200),type="n",main="Cold & Dry",
          xlab="winter T(2m) [deg C]",ylab="Autumn precip [%]",
          sub="T(2m): TR3; precip: NR7-9")
    lines(rep(mean(results$X0),2),c(0,200),col="grey",lwd=2)
    lines(c(-15,10),rep(100,2),col="grey",lwd=2)
    grid()
    points(results$X0,results$Y0,pch=19,cex=1.5)
    points(results$X1,results$Y1,col="blue",pch=19,cex=1.5)
    points(results$X2,results$Y2,col="steelblue",pch=19,cex=1.5)
    contour(as.numeric(rownames(ct1)),as.numeric(colnames(ct1)),as.matrix(ct1),
          lwd=2,add=TRUE,col="darkblue")
    contour(as.numeric(rownames(ct2)),as.numeric(colnames(ct2)),as.matrix(ct2),
          lwd=2,add=TRUE,col="lightblue")
    legend(6,25,c("Obs","2011-2040","2036-2065"),pch=19,
          col=c("black","blue","steelblue"),cex=0.8,bg="grey95")
  }
  if (interval==1) {
    #print(t.tr); print(as.numeric(rownames(ct1)))
    #print(p.tr); print(as.numeric(colnames(ct1)))
    n1 <- as.numeric(rownames(ct1)) < t.tr
    n2 <- as.numeric(colnames(ct1)) < p.tr
    #print(c(sum(n1),sum(n2)))
```

```
    prob <- round(100*sum(as.matrix(ct1)[n1,n2])/sum(as.matrix(ct1)),1)
  } else {
    n1 <- as.numeric(rownames(ct2)) < t.tr
    n2 <- as.numeric(colnames(ct2)) < p.tr
    prob <- round(100*sum(as.matrix(ct2)[n1,n2])/sum(as.matrix(ct2)),1)
  }
  prob
}


make.table <- function(period=2011:2040,param="TAM",
                       ref=1961:1990,type=1) {

  varnams <- c("DJF.q05","DJF.ave","DJF.q95","MAM.q05","MAM.ave","MAM.q95",
               "JJA.q05","JJA.ave","JJA.q95","SON.q05","SON.ave","SON.q95",
               "ANN.q05","ANN.ave","ANN.q95")
  rt <- switch(param,"TAM"="TR","RR"="NR")
  nr <- switch(param,"TAM"=6,"RR"=13)
  pref <- switch(as.character(type),"1"="ESD_","2"="ENSEMBLE_")
  tab1 <- rep("",5); tab2 <- tab1; tab3 <- tab1; tab4 <- tab1; tab5 <- tab1
  yrs1 <- paste(min(ref),max(ref),sep="-")
  yrs2 <- paste(min(period),max(period),sep="-")
  dig <- switch(param,"TAM"=1,"RR"=0)


  tab1[1] <- yrs1; tab2[1] <- yrs2;  tab3[1] <- yrs1; tab4[1] <- yrs2;
  for (ir in 1:nr) {
    pattern <- paste(rt,"-region",ir,"_",sep="")
    files <- list.files(pattern=pattern)
    print(pattern)
    files <- files[grep(pref,files)]
    print(files)

    tab1[ir+1] <- paste("Region",ir)
    tab2[ir+1] <- paste("Region",ir)
    tab3[ir+1] <- paste("Region",ir)
    tab4[ir+1] <- paste("Region",ir)
    tab5[ir+1] <- paste("Region",ir)
    res <- read.table(files,header=TRUE)
    std <- read.table(paste("sd",substr(files,4,nchar(files)),sep=""),header=TRUE)
    i1 <- is.element(res$Year,ref)
    i2 <- is.element(res$Year,period)
    j1 <- is.element(std[,1],ref)
    j2 <- is.element(std[,1],period)

    for (is in 1:5) {
      iis <- (is-1)*3
      cl.q1.1 <- paste("q1.1 <- round(mean(res$",varnams[iis+1],"[i1]),dig)",sep="")
      print(cl.q1.1)
      eval(parse(text=cl.q1.1))
      cl.q2.1 <- paste("q2.1 <- round(mean(res$",varnams[iis+3],"[i1]),dig)",sep="")
      print(cl.q2.1)
      eval(parse(text=cl.q2.1))
      cl.q1.2 <- paste("q1.2 <- round(mean(res$",varnams[iis+1],"[i2]),dig)",sep="")
      print(cl.q1.2)
      eval(parse(text=cl.q1.2))
      cl.q2.2 <- paste("q2.2 <- round(mean(res$",varnams[iis+3],"[i2]),dig)",sep="")
      print(cl.q2.2)
      eval(parse(text=cl.q2.2))

      cl.m1 <- paste("m1 <- round(mean(res$",varnams[iis+2],"[i1]),dig)",sep="")
      print(cl.m1)
      eval(parse(text=cl.m1))
      cl.m2 <- paste("m2 <- round(mean(res$",varnams[iis+2],"[i2]),dig)",sep="")
      print(cl.m2)
      eval(parse(text=cl.m2))
      s1 <- round(mean(std[j1,is+1]),dig)
      s2 <- round(mean(std[j2,is+1]),dig)

      d <- switch(param,"TAM"=m2-m1,"RR"=round(100*m2/m1))
```

```
      tab1[ir+1] <- paste(tab1[ir+1]," & ",q1.1," -- ",q2.1,sep="")
      tab2[ir+1] <- paste(tab2[ir+1]," & ",q1.2," -- ",q2.2,sep="")
      tab3[ir+1] <- paste(tab3[ir+1]," & ",m1," (",s1,") ", sep="")
      tab4[ir+1] <- paste(tab4[ir+1]," & ",m2," (",s2,") ", sep="")
      tab5[ir+1] <- paste(tab5[ir+1]," & ",d, sep="")
    }
  }
  tab  <- c(tab1,tab2)
  tabm <- c(tab3,tab4)

  writeLines(tab,con=paste("tab_",param,"_",yrs1,"_",yrs2,"_",type,".txt",sep=""))
  writeLines(tabm,con=paste("tabm_",param,"_",yrs1,"_",yrs2,"_",type,".txt",sep=""))
  writeLines(tab5,con=paste("tabd_",param,"_",yrs1,"_",yrs2,"_",type,".txt",sep=""))


}




if (do.extr) {
  region <- 1
  extrStatnett(region,interval=2011:2040,param="TAM",
             base.line=NULL,ref=1961:1990)

  extrStatnett(region,interval=2036:2065,param="TAM",
             base.line=NULL,ref=1961:1990)
}



if (do.figs) {
finalStatnett(ele=101,period=2011:2040,
              addRCM=TRUE,ref=1961:1990,adjust=TRUE)

finalStatnett(ele=101,period=2036:2065,
              addRCM=TRUE,ref=1961:1990,adjust=TRUE)

finalStatnett(ele=601,period=2011:2040,
              addRCM=TRUE,ref=1970:1999,adjust=TRUE)

finalStatnett(ele=601,period=2036:2065,
              addRCM=TRUE,ref=1970:1999,adjust=TRUE)
}

if (do.tabs) {
make.table(period=2011:2040,param="TAM",ref=1961:1990)
make.table(period=2036:2065,param="TAM",ref=1961:1990)
make.table(period=2011:2040,param="RR",ref=1970:1999)
make.table(period=2036:2065,param="RR",ref=1970:1999)

finalStatnett(ele=101,period=2011:2040,
              addRCM=TRUE,ref=1961:1990,adjust=TRUE)
make.table(period=2011:2040,param="TAM",ref=1961:1990,type=2)
make.table(period=2036:2065,param="TAM",ref=1961:1990,type=2)
finalStatnett(ele=601,period=2011:2040,
              addRCM=TRUE,ref=1970:1999,adjust=TRUE)
make.table(period=2011:2040,param="RR",ref=1970:1999,type=2)
make.table(period=2036:2065,param="RR",ref=1970:1999,type=2)
}

if (do.3day) {
  t2m.era40 <- read.fwf("~/data/GCM.daily/ERA40.asc",skip=6,width=c(3,5,4,3,2,5,2,7),
                        col.names=c("day","mon","year","twelve","slash",
                          "index","colon","t2m"))

  t2m.eraint00 <- read.fwf("~/data/GCM.daily/ERAINT_t2m_00.asc",skip=6,
                          width=c(3,5,4,3,2,5,2,7),
                        col.names=c("day","mon","year","twelve","slash",
```

```
                         "index","colon","t2m"))
t2m.eraint06 <- read.fwf("~/data/GCM.daily/ERAINT_t2m_06.asc",skip=6,
                         width=c(3,5,4,3,2,5,2,7),
                       col.names=c("day","mon","year","twelve","slash",
                         "index","colon","t2m"))
t2m.eraint12 <- read.fwf("~/data/GCM.daily/ERAINT_t2m_12.asc",skip=6,
                         width=c(3,5,4,3,2,5,2,7),
                       col.names=c("day","mon","year","twelve","slash",
                         "index","colon","t2m"))
t2m.eraint18 <- read.fwf("~/data/GCM.daily/ERAINT_t2m_18.asc",skip=6,
                         width=c(3,5,4,3,2,5,2,7),
                       col.names=c("day","mon","year","twelve","slash",
                         "index","colon","t2m"))
x <- ma.filt(t2m.era40$t2m,3)
x2 <- ma.filt(0.25*(t2m.eraint00$t2m + t2m.eraint06$t2m +
                   t2m.eraint12$t2m + t2m.eraint18$t2m),3)
mon <- rep(NA,length(t2m.era40$t2m))
for (im in 1:12) mon[t2m.era40$mon==cmon[im]] <- im
jday <- julday(mon,t2m.era40$day,t2m.era40$year) - julday(12,31,1956)
years <- as.numeric(rownames(table(t2m.era40$year)))
years2 <- as.numeric(rownames(table(t2m.eraint00$year)))
t2m.amn <- years; t2m.amn[] <- NA
t2m.amn2 <- years2; t2m.amn2[] <- NA
for (iy in 1:length(years))
  t2m.amn[iy] <- min(x[is.element(t2m.era40$year,years[iy])])
for (iy in 1:length(years2))
  t2m.amn2[iy] <- min(x2[is.element(t2m.eraint00$year,years2[iy])])

list <-  list.files(path="~/data/GCM.daily/",pattern=".txt",full.names=TRUE)
List <-  list.files(path="~/data/GCM.daily/",pattern=".txt")
Z <- matrix(rep(NA,(2+length(list))*150),(2+length(list)),150)

x11()
plot(years,t2m.amn,xlim=c(1950,2100),type="l",lwd=3,cex=0.5,
     main="3-day annual minimum T(2m)",
     xlab="Year",ylab="Daily mean T(2m) [C]",ylim=c(-25,10))
lines(years2,t2m.amn2,lwd=3,col="grey30")
grid()

j1 <- is.element(1951:2100,years)
j2 <- is.element(years,1951:2100)
Z[1,j1] <- t2m.amn[j2]

j1 <- is.element(1951:2100,years2)
j2 <- is.element(years2,1951:2100)
Z[1,j1] <- t2m.amn2[j2]

for (i in 1:length(list)) {
  List[i] <- substr(List[i],1,nchar(List[i])-4)
  print(List[i])
  t2m.drcm <- read.fwf(list[i],skip=7,width=c(3,5,4,3,2,5,2,7),
                       col.names=c("day","mon","year","twelve","slash",
                         "index","colon","t2m"))
  X <- ma.filt(as.numeric(as.character(t2m.drcm$t2m)),3)
  #print(summary(X))
  Years <- as.numeric(rownames(table(t2m.drcm$year)))
  T2m.amn=Years; T2m.amn[] <- NA
  for (iy in 1:length(Years))
    T2m.amn[iy] <- min(X[is.element(t2m.drcm$year,Years[iy])],na.rm=TRUE)

  i1 <- is.element(Years,years) & is.finite(T2m.amn)
  i2 <- is.element(years,Years) & is.finite(t2m.amn)
  offs <- mean(t2m.amn[i2],na.rm=TRUE) - mean(T2m.amn[i1],na.rm=TRUE)
  T2m.amn <- T2m.amn + offs
  #print(summary(T2m.amn)); print(sum(i1)); print(sum(i2))
  points(Years,T2m.amn,pch=19,cex=0.5,col=cols[i])

  j1 <- is.element(1951:2100,Years)
  j2 <- is.element(Years,1951:2100)
  Z[i+2,j1] <- T2m.amn[j2]
```

```
  }

  print("Confidence limits")
  yrs <- seq(1950,2100,by=10)
  q1 <- yrs; q1[] <- NA; q2 <- q1
  print(dim(Z))
  for (id in 1:length(yrs)) {
    k1 <- is.element(trunc(1951:2100/10),trunc(yrs[id]/10))
    #print(table((1951:2100)[k1])); print(length(k1)); print(id)
    sample <- c(Z[,k1])
    q1[id] <- quantile(sample[is.finite(sample)],0.05,na.rm=TRUE)
    q2[id] <- quantile(sample[is.finite(sample)],0.95,na.rm=TRUE)
  }

  c1 <- data.frame(y=q1,t=yrs-mean(yrs) + 5)
  c2 <- data.frame(y=q2,t=yrs-mean(yrs) + 5)
  print(summary(c1)); print(summary(c2))

#  pq1 <- predict(lm(y ~ t + I(t^2),data=c1),newdata=c1)
#  pq2 <- predict(lm(y ~ t + I(t^2),data=c2),newdata=c2)
  pq1 <- predict(lm(y ~ t,data=c1),newdata=c1)
  pq2 <- predict(lm(y ~ t,data=c2),newdata=c2)
  lines(yrs,pq1,lty=2)
  lines(yrs,pq2,lty=2)
  Z <- t(Z)
  colnames(Z) <- c("ERA40","ERAINT",List)
  rownames(Z) <- 1951:2100
  write.table(file="statnett.3day.annual.min.txt",round(Z,1),quote=FALSE,sep="\t")

  legend(2010,-15,c("ERA40","ERAINT",List),pch=c(26,26,rep(19,length(list))),
         lty=c(1,1,rep(0,length(list))),col=c("black","grey30",cols),
         cex=0.75,ncol=2)
  dev.copy2eps(file="GCM-3-daily-t2m.eps")

# Oslo
  print("Stations")
  stnrs <- c(18700,50540,69100,90450)

  # Combine ERAINT & ERA40, with preferance to ERAINT. Exclude 1957 & 2011
  years3 <- 1958:2010
  t2m.amn3 <- c(t2m.amn[!is.element(years,years2)],t2m.amn2)[-c(1,55)]
  T2m.obs=matrix(rep(years3,4),length(years3),4); T2m.obs[] <- NA
  location <- rep(" ",4)

  for (i in 1:length(stnrs)) {
    obs <- KDVH(stnrs[i])
    print(obs$Location); location[i] <- obs$Location
    X <- ma.filt(obs$TAM,3)
    #print(summary(X))
    for (iy in 1:length(years3))
      T2m.obs[iy,i] <- min(X[is.element(obs$Year,years3[iy])],na.rm=TRUE)
    print(summary(T2m.obs[iy,i]))
  }

  # 10,STOCKHOLM
  # 114,KOEBENHAVN - METEOROLOGISK INSTITUT

  x11()
  par(mfcol=c(2,2))
  for (i in 1:length(stnrs)) {
      plot(t2m.amn3,T2m.obs[,i],main=location[i],xlab="ERA40",ylab=stnrs[i])
      calibrate <- data.frame(y=T2m.obs[,i],x=t2m.amn3)
      fit <- lm(y ~ x, data=calibrate)
      abline(fit,lty=2,col="red")
  }
  dev.copy2eps(file="GCM-3-daily-t2m-ERA40-vs-obs.eps")


  x11()
  par(mfcol=c(2,2))
```

```
  for (i in 1:length(stnrs)) {
      calibrate <- data.frame(y=T2m.obs[,i],x=t2m.amn3)
      pre0 <- data.frame(x=t2m.amn3)
      pre1 <- data.frame(x=pq1)
      pre2 <- data.frame(x=pq2)
      fit <- lm(y ~ x, data=calibrate)
      sub <- paste("T=",round(fit$coefficients[1],2),"+",
                   round(fit$coefficients[2],2)," x mean(ERA40)")
      p0 <- predict(fit,newdata=pre0)
      p1 <- predict(fit,newdata=pre1)
      p2 <- predict(fit,newdata=pre2)
      plot(c(1951,2100),range(T2m.obs[,i],p0,p1,p2,na.rm=TRUE),
           type="n",main=location[i],ylab="T (deg C)",xlab="Year",
           sub=sub)
      grid()
      polygon(c(yrs,reverse(yrs)),
              c(p1,reverse(p2)),col="grey70",border="grey40",lwd=3)
      points(years3,T2m.obs[,i])
      lines(years3,p0)
  }
  dev.copy2eps(file="GCM-3-daily-t2m-obs.eps")

  print("extremes: Fit GEV:")
  x11()
  par(mfcol=c(2,2))
  for (i in 1:length(stnrs)) {
    extr <- fgev(-T2m.obs[,i])
    #h <- hist(-T2m.obs[,i]); print(summary(h))
    print("Return value analysis:")
    rl.obs <- rl(extr,main=location[i],
               xlab="Return interval",ylab="-1 x T (deg C)",
               sub="GEV",,xlim=c(0.15,50),ylim=c(0,30))
    grid()
    returtid <- -round(approx(rl.obs$x,rl.obs$y,c(2,10,50))$y,1)
    text(0.2,28,paste("2: ",returtid[1],"C; 10: ",returtid[2],"C; 50: ",
                      returtid[3],"C",sep=""),pos=4,col="darkblue")
  }
  dev.copy2eps(file="GCM-3-daily-t2m-obs-rl.eps")
}



RCM.finnmark <- function(region=6,season=1,ref=1961:1990) {
  cols <- c("black","red","blue","darkgreen","grey","steelblue",
            "brown","cyan","magenta","darkblue","darkred",
            "pink","lightblue","grey30","blue","red")
  pchs <- c(rep(19,9),rep(21,7))
  obs <- obslandsdel(region)
  base.line <- colMeans(obs$val[is.element(obs$yy,ref),])
  addRCM(region,season=season,base.line=base.line,ref=ref,plot=FALSE) -> a
  plot(c(1950,2100),range(a,na.rm=TRUE),type="n",
      main=paste("ENSEMLBE RCMs region",region,"season",season))
  grid()

  ii <- 0
  for (i in 1:length(a[,1])) {
    if (sum( is.finite(a[i,]) )>0) {
      points(1951:2100,a[i,],pch=pchs[i],cex=0.8,col=cols[i])
      lines(1951:2100,a[i,],lty=2,col=cols[i])
      print(substr(attr(a,'RCM'),1,nchar(attr(a,'RCM'))-5)[i])
      print(summary(a[i,]))
    } else{
      print( sum(is.finite(a[i,])) )
      t <- seq(1951,2100,by=10)
      points(t,rep(-23+ii/2,length(t)),pch=19,cex=0.8,col=cols[i])
      lines(range(t),rep(-23+ii/2,2),lty=2,col=cols[i])
      ii <- ii + 1
    }
  }
  legend(2060,-10,
```

```
         substr(attr(a,'RCM'),1,nchar(attr(a,'RCM'))-5),
         col=cols,pch=pchs,lty=2,cex=0.6,bg="grey95")
  dev.copy2eps(file="RCM.finnmark.eps")
}

trender <- function(mon=6:8) {
  for (i in 1:6) {
    obs <- obslandsdel(i)
    plotStation(obs,mon=mon,what="t",l.anom=FALSE)
    dev2bitmap(file=paste("trender_tam_",i,".png",sep=""))
    dev.off()
  }
  for (i in 1:13) {
    obs <- obslandsdel(i,param="RR",rt="NR")
    plotStation(obs,mon=mon,what="t",l.anom=FALSE)
    dev2bitmap(file=paste("trender_rr_",i,".png",sep=""))
    dev.off()
  }
}



if (do.wetcold) {
  print("Wet & Cold: Nouthern Norway")
   tr1  <- showStatnett("Austlandet_TR-region1",ele=101)
   tr2  <- showStatnett("Vestlandet_TR-region2",ele=101)
   nr4 <- showStatnett("Sor-Vestlandet_NR-region4",ele=601)
   nr5 <- showStatnett("Sunnhordland_NR-region5",ele=601)
   nr6 <- showStatnett("Sogn_NR-region6",ele=601)

   load("STATNETT/Austlandet_TR-region1.Rdata")
   obs.tr1 <- obs
   load("STATNETT/Vestlandet_TR-region2.Rdata")
   obs.tr2 <- obs

   load("STATNETT/Sor-Vestlandet_NR-region4.Rdata")
   obs.nr4 <- obs
   load("STATNETT/Sunnhordland_NR-region5.Rdata")
   obs.nr5 <- obs
   load("STATNETT/Sogn_NR-region6.Rdata")
   obs.nr6 <- obs

   print("------------- Read all the data")
   T0 <- (obs.tr1$val + obs.tr1$val)/2
   P0 <- obs.nr4$val+obs.nr5$val+obs.nr6$val
   climP <- mean(colMeans(P0[is.element(obs.nr4$yy,1970:1999),9:11]))
   X0 <- rowMeans(cbind(T0[is.element(obs.tr1$yy,1970:1999),12],
                        T0[is.element(obs.tr1$yy,1971:2000),1:2]))
   Y0 <- 100*rowMeans(cbind(P0[is.element(obs.tr1$yy,1970:1999),9:11]))/climP

   par(bty="n")
   plot(c(-15,10),c(0,200),type="n",main="Cold & Dry",
        xlab="winter T(2m) [deg C]",ylab="Autumn precip [%]",
        sub="T(2m): TR1-2; precip: NR4-6")
   lines(rep(mean(X0),2),c(0,200),col="grey",lwd=2)
   lines(c(-15,10),rep(100,2),col="grey",lwd=2)
   grid()
   points(X0,Y0,pch=19,cex=1)
   X1 <- matrix(rep(NA,30*50),50,30); X2 <- X1; Y1 <- X1; Y2 <- X1

   for (it1 in 1:length(tr1$gcms.sce)) {
   # dim: [gcm,month,year]
     ip4 <- grep(tr1$gcms.sce[it1],nr4$gcms.sce)
     ip5 <- grep(tr1$gcms.sce[it1],nr5$gcms.sce)
     ip6 <- grep(tr1$gcms.sce[it1],nr6$gcms.sce)
     it2 <- grep(tr1$gcms.sce[it1],tr2$gcms.sce)
     if ( (sum(it2)>0) & (sum(ip4)>0) & (sum(ip5)>0) & (sum(ip6)>0) )  {
       T2 <- (tr1$sce[it1,,] + tr2$sce[it2,,])/2
       P2 <- nr4$sce[ip4,,]+nr5$sce[ip5,,]+nr6$sce[ip6,,]
```

```
    #2011--2040
    i.tr.2011.2040 <- is.element(tr1$yy.21c,2011:2040)
    i.tr.2012.2041 <- is.element(tr1$yy.21c,2012:2041)
    i.nr.2011.2040 <- is.element(nr4$yy.21c,2011:2040)
    #2036--2065
    i.tr.2036.2065 <- is.element(tr1$yy.21c,2036:2065)
    i.tr.2037.2066 <- is.element(tr1$yy.21c,2037:2066)
    i.nr.2036.2065 <- is.element(nr4$yy.21c,2036:2065)

    winterT <- colMeans(rbind(T2[12,i.tr.2036.2065],T2[1:2,i.tr.2037.2066]))
    autumnP <- colMeans(rbind(P2[9:11,i.nr.2036.2065]))
    X2[it1,] <- winterT
    Y2[it1,] <- 100*autumnP/climP
    points(X2[it1,],Y2[it1,],col="orange",pch=19,cex=0.5)
    winterT <- colMeans(rbind(T2[12,i.tr.2011.2040],T2[1:2,i.tr.2012.2041]))
    autumnP <- colMeans(rbind(P2[9:11,i.nr.2011.2040]))

    X1[it1,] <- winterT
    Y1[it1,] <- 100*autumnP/climP
    points(X1[it1,],Y1[it1,],col="steelblue",pch=19,cex=0.5)
  }
}
points(X0,Y0,pch=19,cex=1)
ct1 <- table(round(X1),10*round(Y1/10))
ct2 <- table(round(X2),10*round(Y2/10))
contour(as.numeric(rownames(ct1)),as.numeric(colnames(ct1)),as.matrix(ct1),
        lwd=2,add=TRUE,col="darkblue")
contour(as.numeric(rownames(ct2)),as.numeric(colnames(ct2)),as.matrix(ct2),
        lwd=2,add=TRUE,col="red")
legend(6,25,c("Obs","2011-2040","2036-2065"),pch=19,
       col=c("black","blue","orange"),cex=0.8,bg="grey95")
dev.copy2eps(file="dryautumncoldwinterSNorway.eps")
dev.new()

par(bty="n")
results <- list(X0=X0,Y0=Y0,X1=X1,Y1=Y1,X2=X2,Y2=Y2)
save(file="dsStatnett_colddry1.rda",results)

print("Estimate probabilities")

probmatrix <- matrix(rep(NA,9),3,3)
t.tr <- c(-5,-2,0); p.tr <- c(60,100,150)
rownames(probmatrix) <- p.tr
colnames(probmatrix) <- t.tr
probmatrix[1,1] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[1],p.tr=p.tr[1])
probmatrix[1,2] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[2],p.tr=p.tr[1])
probmatrix[1,3] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[3],p.tr=p.tr[1])
probmatrix[2,1] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[1],p.tr=p.tr[2])
probmatrix[2,2] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[2],p.tr=p.tr[2])
probmatrix[2,3] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[3],p.tr=p.tr[2])
probmatrix[3,1] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[1],p.tr=p.tr[3])
probmatrix[3,2] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[2],p.tr=p.tr[3])
probmatrix[3,3] <-
  colddryprob(file="dsStatnett_colddry1.rda",t.tr=t.tr[3],p.tr=p.tr[3])
write.table(file="probmatrix.txt",probmatrix)

print("Wet & Cold: Mid Norway")
tr3  <- showStatnett("Trondelag_TR-region3",ele=101)
nr7 <- showStatnett("Dovre+Nord-Osterdal_NR-region7",ele=601)
nr8 <- showStatnett("More+Romsdal_NR-region8",ele=601)
nr9 <- showStatnett("Inntrondelag_NR-region9",ele=601)
```

```
  load("STATNETT/Trondelag_TR-region3.Rdata")
  obs.tr3 <- obs

  load("STATNETT/Dovre+Nord-Osterdal_NR-region7.Rdata")
  obs.nr7 <- obs
  load("STATNETT/More+Romsdal_NR-region8.Rdata")
  obs.nr8 <- obs
  load("STATNETT/Inntrondelag_NR-region9.Rdata")
  obs.nr9 <- obs

  T0 <- obs.tr3$val
  P0 <- obs.nr7$val+obs.nr8$val+obs.nr9$val
  climP <- mean(colMeans(P0[is.element(obs.nr4$yy,1970:1999),9:11]))
  X0 <- rowMeans(cbind(T0[is.element(obs.tr3$yy,1970:1999),12],
                      T0[is.element(obs.tr3$yy,1971:2000),1:2]))
  Y0 <- 100*rowMeans(cbind(P0[is.element(obs.tr1$yy,1970:1999),9:11]))/climP

  plot(c(-15,10),c(0,200),type="n",main="Cold & Dry",
       xlab="winter T(2m) [deg C]",ylab="Autumn precip [%]",
       sub="T(2m): TR3; precip: NR7-9")
  lines(rep(mean(X0),2),c(0,200),col="grey",lwd=2)
  lines(c(-15,10),rep(100,2),col="grey",lwd=2)
  grid()
  points(X0,Y0,pch=19,cex=1.5)
  X1 <- matrix(rep(NA,30*50),50,30); X2 <- X1; Y1 <- X1; Y2 <- X1

  for (it3 in 1:length(tr3$gcms.sce)) {
  # dim: [gcm,month,year]
    ip4 <- grep(tr3$gcms.sce[it3],nr7$gcms.sce)
    ip5 <- grep(tr3$gcms.sce[it3],nr8$gcms.sce)
    ip6 <- grep(tr3$gcms.sce[it3],nr9$gcms.sce)
    if ( (sum(ip4)>0) & (sum(ip5)>0) & (sum(ip6)>0) )  {
      T2 <- tr3$sce[it3,,]
      P2 <- nr7$sce[ip4,,]+nr8$sce[ip5,,]+nr9$sce[ip6,,]

      #2011--2040
      i.tr.2011.2040 <- is.element(tr3$yy.21c,2011:2040)
      i.tr.2012.2041 <- is.element(tr3$yy.21c,2012:2041)
      i.nr.2011.2040 <- is.element(nr7$yy.21c,2011:2040)
      #2036--2065
      i.tr.2036.2065 <- is.element(tr3$yy.21c,2036:2065)
      i.tr.2037.2066 <- is.element(tr3$yy.21c,2037:2066)
      i.nr.2036.2065 <- is.element(nr7$yy.21c,2036:2065)

      winterT <- colMeans(rbind(T2[12,i.tr.2036.2065],T2[1:2,i.tr.2037.2066]))
      autumnP <- colMeans(rbind(P2[9:11,i.nr.2036.2065]))
      X2[it3,] <- winterT
      Y2[it3,] <- 100*autumnP/climP
      points(X2[it3,],Y2[it3,],col="orange",pch=19,cex=0.5)
      winterT <- colMeans(rbind(T2[12,i.tr.2011.2040],T2[1:2,i.tr.2012.2041]))
      autumnP <- colMeans(rbind(P2[9:11,i.nr.2011.2040]))

      X1[it3,] <- winterT
      Y1[it3,] <- 100*autumnP/climP
      points(X1[it3,],Y1[it3,],col="steelblue",pch=19,cex=0.5)
    }
  }
  points(X0,Y0,pch=19,cex=1)
  ct1 <- table(round(X1),10*round(Y1/10))
  ct2 <- table(round(X2),10*round(Y2/10))
  contour(as.numeric(rownames(ct1)),as.numeric(colnames(ct1)),as.matrix(ct1),
         lwd=2,add=TRUE,col="darkblue")
  contour(as.numeric(rownames(ct2)),as.numeric(colnames(ct2)),as.matrix(ct2),
         lwd=2,add=TRUE,col="red")
  legend(6,25,c("Obs","2011-2040","2036-2065"),pch=19,
        col=c("black","steelblue","orange"),cex=0.8,bg="grey95")
  dev.copy2eps(file="dryautumncoldwinterMNorway.eps")
  results <- list(X0=X0,Y0=Y0,X1=X1,Y1=Y1,X2=X2,Y2=Y2)
  save(file="dsStatnett_colddry2.rda",results)
}
```

```
if (do.wetdry) {
  exceedancetable(interval=2011:2040) -> tables1
  exceedancetable(interval=2036:2065) -> tables2
  data(landsdelmaske)
  par(bty="n",col.axis="white")
#  mycols <- rgb(runif(13),runif(13),runif(13))
  mycols <- rgb(c(1.0,0.5,0.5,1.0,0.8,1.0,0.7,1.0,0.5,0.5,1,0,0.7,1.0),
                c(0.5,1.0,0.5,1.0,0.8,0.5,0.7,1.0,0.5,1.0,1.0,0.7,0.0),
                c(0.5,0.0,1.0,0.0,0.3,1.0,0.7,0.5,0.5,1.0,0.5,1.0,0.5))
  image(landsdelmaske$lon,landsdelmaske$lat,landsdelmaske$nr,
        xlab="",ylab="",col=mycols,main="Autumn")
  for (ir in 1:13) {
    ii <- is.element(landsdelmaske$nr,ir)
    x <- quantile(landsdelmaske$lon.mask[ii],0.70)
    y <- quantile(landsdelmaske$lat.mask[ii],0.25)
    dy <- 0.25
    text(x,y+0*dy,round(tables1$tab.low0[3,ir],2),cex=0.75)
    text(x,y+1*dy,round(tables1$tab.low1[3,ir],2),cex=0.75)
    text(x,y+2*dy,round(tables1$tab.low2[3,ir],2),cex=0.75)
    text(x,y+3*dy,round(tables2$tab.low2[3,ir],2),cex=0.75)
    text(x-4*dy,y+1.5*dy,ir)
  }
  x <- 18; y <- 63
  polygon(c(16,30,30,16,16),
          c(58,58,65,65,58),col="grey70",border="grey60")
  text(x,y+0*dy,"x0",cex=0.75)
  text(x,y+1*dy,"x1",cex=0.75)
  text(x,y+2*dy,"x2",cex=0.75)
  text(x,y+3*dy,"x3",cex=0.75)
  text(x-3*dy,y+1.5*dy,"n")
  legend(21,64.5,c("n=NR","x3=2036-2065","x2=2011-2040",
                 "x1= 1970-1990","x0=observed"),bg="grey80")
  dev.copy2eps(file="dsStatnett2_wetdry.eps")

  print("Precip < 60%")
  print(round(t(tables1$tab.low0),2))
  print(round(t(tables1$tab.low1),2))
  print(round(t(tables1$tab.low2),2))
  print(round(t(tables2$tab.low2),2))
  print("Precip > 150%")
  print(round(t(tables1$tab.hig0),2))
  print(round(t(tables1$tab.hig1),2))
  print(round(t(tables1$tab.hig2),2))
  print(round(t(tables2$tab.hig2),2))
}


if (do.esd2xls) {
  for (i in 1:6) esd2xls(region=i,param="TAM")
  for (i in 1:13) esd2xls(region=i,param="RR")
}

if (do.wholecountry) {
   list <- list.files(pattern="_TAM.xls")
  T2m <- as.matrix(read.table(list[1],header=TRUE,sep=","))
  D <- dim(T2m)
  T2m <- as.numeric(T2m)
  dim(T2m) <- D
  gcms1 <- as.matrix(read.table(list[1],nrows=1,sep=","))
  for (i in 2:length(list)) {
    gcms <- as.matrix(read.table(list[i],nrows=1,sep=","))
    t2m <- as.matrix(read.table(list[i],header=TRUE,sep=","))
    d <- dim(t2m)
    t2m <- as.numeric(t2m)
    dim(t2m) <- d
    print(list[i]); print(dim(t2m)); print(dim(T2m))
    print(class(t2m)); print(class(T2m))
    i1 <- is.element(gcms1,gcms)
    i2 <- is.element(gcms,gcms1)
```

```
    T2m[,i1] <- T2m[,i1] + t2m[,i2]
  }
  T2m <- T2m/length(list)

  list <- list.files(pattern="_RR.xls")
  Rr <- as.matrix(read.table(list[1],header=TRUE,sep=","))
  D <- dim(Rr)
  Rr <- as.numeric(Rr)
  dim(Rr) <- D
  gcms1 <- as.matrix(read.table(list[1],nrows=1,sep=","))
  for (i in 2:length(list)) {
    gcms <- as.matrix(read.table(list[i],nrows=1,sep=","))
    rr <- as.matrix(read.table(list[i],header=TRUE,sep=","))
    d <- dim(rr)
    rr <- as.numeric(rr)
    dim(rr) <- d
    print(list[i]); print(dim(rr)); print(dim(Rr))
    print(class(rr)); print(class(Rr))
    i1 <- is.element(gcms1,gcms)
    i2 <- is.element(gcms,gcms1)
    Rr[,i1] <- Rr[,i1] + rr[,i2]
  }
  Rr <- Rr/length(list)


  rt = "NR"
  url <- paste("http://klapp.oslo.dnmi.no/metnopub/production/metno?re=20&",
               "ct=text/plain&p=RR&fy=&ty=2011&r_type=",rt,sep="")
  region.curve <- read.table(url,header=TRUE)
  nr <- 12; nt <- sum(is.element(region.curve$regionid,1))
  rrmatrix <- matrix(rep(NA,nr*nt),nr,nt)
  for (i in 1:12) {
    rr <- region.curve$region_value[is.element(region.curve$regionid,i)]
    mm <- region.curve$month[is.element(region.curve$regionid,i)]
    ac <- rep(NA,12)
    for (ii in 1:12) {
      ac[ii] <- mean(rr[is.element(mm,ii)],na.rm=TRUE)
      rr[is.element(mm,ii)] <- rr[is.element(mm,ii)] - ac[ii]
    }
    print(round(ac))
    print(summary(rr))
    rrmatrix[i,] <- rr
  }
  print(round(cor(t(rrmatrix)),2))

  plot(stand(gauss.filt(rrmatrix[1,],24)),type="l",
       xlab="",ylab="")
  col <- c("black","darkblue","blue","steelblue","lightgreen","green",
           "darkgreen","brown","darkred","red","wheat","grey")
  for (i in 2:12) lines(stand(gauss.filt(rrmatrix[i,],24)),col=col[i])
}
```