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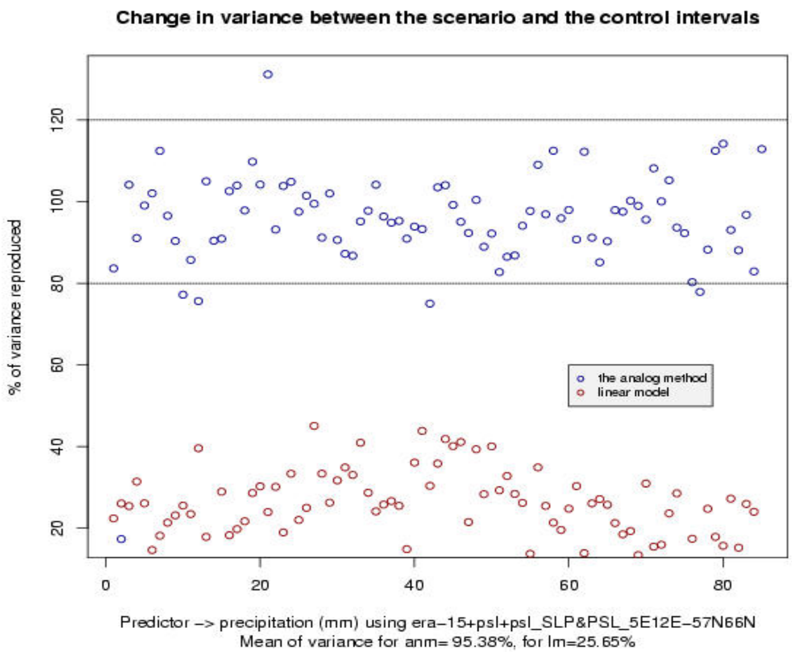
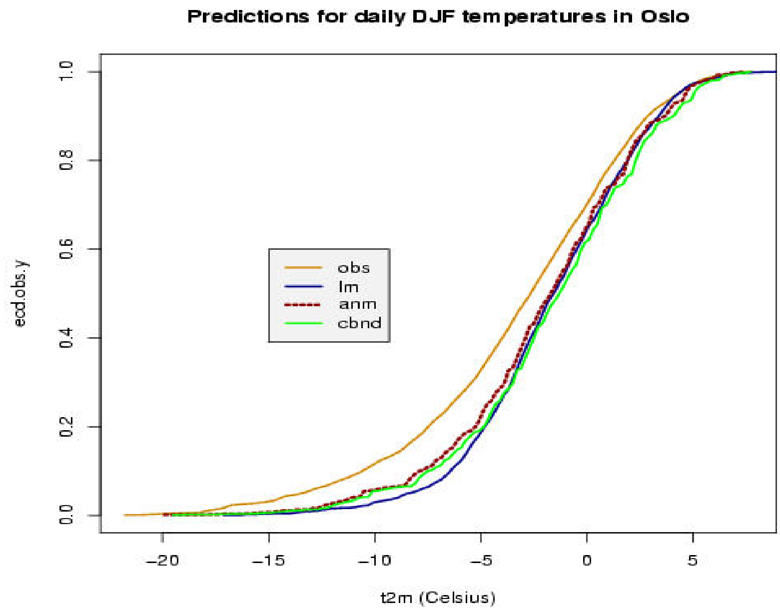
The Analog method applied to downscaling of climate scenarios

Alexandra Imbert

Report 08/03





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The analog method applied to downscaling of climate scenarios

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SUMMARY:

This report is a documentation of statistical analyses performed during a five-month training period at the met.no Climatology Division with the help of R.E. Benestad and I.Hanssen-Bauer.

Downscaling analysis was tested by incorporating the analog method and compared with a linear model. Its performance was studied in terms of correlation and variance levels. Behaviour in the extremes also provided a relevant tool of comparison and was used to make predictions in the future. In the same way to study climate change, two different statistical approaches based on the analog method were implemented.
This was done for daily winter precipitation and temperature for 91 stations mainly located in southern Norway.
The analyses were performed by use of the R-software and an important task was to build a package called anm *to facilitate further studies with the analog method. This package is now freely available from the Internet (URL:http://cran.r-project.org) and a documentation is provided at the end of this report.*

KEYWORDS:

The Analog method; Downscaling; clim.pact; Regional climate change; extreme values; Common EOFs.

SIGNATURES:

....	....………..
Eirik Førland	Øystein Hov
Head of Climate Research Section	Head of the met.no Climatology

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The analog method applied to downscaling of climate scenarios.

By A. Imbert

INSA Engeering Course in Mathematical Modelling *

June 13, 2003

ABSTRACT

Downscaling analysis can be improved by incorporating statistical techniques such as the analog method. This method has the advantage of being more appropriate than the linear model when studying precipitation which is not gaussian. This method has then been developed for analysis of local climate on a daily basis. Tests have been applied to both daily winter precipitation and temperature. The results suggest that precipitation and temperature depend on the weather pattern and that analog methods do skillfully reproduce the variability and the observed amounts, especially for temperature.
Analysis of observed linear trends for 1980-1992 and trends reproduced by the analog model show a very similar behaviour of the two corresponding distributions. The analog method is able to reproduce the tail of the distribution describing extreme values as well as the return values and it can then be used to study future climate.

KEY WORDS: the Analog method Downscaling clim.pact Regional climate change Common EOFs.

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Contents

Introduction

Even if the impacts of climate change are global, its effects on a more concentrated area are also interesting to look at, and for this, downscaling techniques are an important tool of analysis. Indeed, even if General Circulation Models (GCMs) represent the main features of the global atmospheric circulation reasonably well, their performance in reproducing regional climatic details is rather poor. Two types of downscaling are generally considered: dynamical downscaling (*Christensen* et al., 2001) and empirical downscaling (*Beckmann & Buishand*, 2002; *Zorita & von Storch*, 1999; *von Storch* et al., 1993).

The idea of downscaling GCM predictions is to relate the large scale parameters such as upper level winds, geopotential heights, and sea level pressure to historical observations of temperature, precipitation or wind speed for instance. Thus, the local scale information is derived from the larger scale considering that the regional climate is the result of interplay of the overall atmospheric, or oceanic circulation and of regional specifics such as topography, land-sea distribution and land-use.

Statistical methods can also be introduced to increase the performance of these techniques. One approach is to use a linear model as Rasmus E.Benestad proposed it in his study about dynamically downscaled temperature scenarios in southern Norway (*Benestad & Hanssen-Bauer*, 2003). The method has proved to skillfully reproduce observed temperature but is not so appropriate to study variables non normally distributed. Analog methods permit to deal in a better way with this problem and have then commonly been used in downscaling of local climate eg (*van den Dool*, 1995; *Zorita & von Storch*, 1999). They can indeed be tested on precipitation whose distribution is not gaussian and they also give a good description of the tails of distribution.

Benestad (2001) proposed the use of "common PCAs" (*Flury*, 1988; *Sengupta & Boyle*, 1998; *Barnett*, 1999), also refered to as "common EOFs" in empirical downscaling. In this report, the analog method is applied in a common EOF frame and applied to downscaling, first for daily December-February precipitation and then for daily December-February temperature, by using the `clim.pact`* R-package already developped by Rasmus E.Benestad (*Benestad*, 2003a).

After a general presentation of the Meteorological Institute and a description of the main theoretical concepts, the analog method is tested on 91 stations, mainly in southern Norway, to analyse how good is the fit and how well the method can reproduce observations in the extremes. The method is then applied to empirical downscaling and a comparison is drawn with the results based on a linear model presented by Benestad (*Benestad & Hanssen-Bauer*, 2003). Finally, the analog method has been written in order to make it into a R-package called `anm`, now freely available over the Internet (URL http://www.R-project.org/) and for which a documentation is given in the report.

1 General presentation

1.1 The Norwegian Meteorological Institute

The institute provides the public with meteorological services for both civil and military purposes. The institute is to provide services for the authorities, commerce and industry, institutions and the general public for the protection of their interests, for the protection of life and property, for planning and for the protection of the environment.

The official duties of the Norwegian Meteorological Institute include:

- issue weather forecasts
- study the national climatological conditions and produce climatological reports
- provide meteorological observations from Norway, adjacent sea areas, and from the Svalbard area
- carry out research and development in support of the institute's operational functions to ensure that the service are of the highest possible standard
- make available the results of its work
- provide special services for the public and private interests on a commercial basis
- participate in international meteorological co-operation.

*Available from the CRAN Internet site (http://cran.r-project.org/)

1.2 Vision and basic functions

The vision is that the institute is to be a centre of excellence on meteorological conditions relevant for Norway, and the results of its competence are to be used as a tool to the general public, the authorities, commerce and industry in their decision making process on a short term basis and for the future.
The main goals are that

- The institute shall provide meteorological services that in content and quality meet the requirements of society. In order to meet both present and future requirements, the institute is to carry out relevant research and development activities.
- The institute's activities shall, on all levels, from the collection of observations to the final forecasting product, be based on an effective and modern atmospheric and ocean forecasting system.
- The institute shall provide expertise on climate conditions on the global and the national scale and shall at any time be able to provide climatological information for monitoring and planning purposes, and as input to the formulation of national climate policies.

The main activities of the institute are therefore associated with core activities financed by the Government, as well as with commercial services.

Core Activities

- **Observations**: Operation, data collection and the transmission of national and international observational data
- **Research and development** financed by the Government: development and improvement of operational models, tasks related to environmental emergency services, and general climate research
- **Weather forecasting**: Analyses, prognoses, general forecasts and warnings, emergency preparedness
- **Climatological services**: Observations, databases and general climatological information

Commercial Services

- **Products and services tailored to fit customers' requirements**
- **Services for aviation**
- **Commercial climatological services**: Specialised weather and climatological information, climatological data, statistics and environmental data from the Continental Shelf
- **Commissions and reports**: Atmosphere and sea impact analyses, transport models of marine pollution and air pollution, quantitative precipitation calculations, regional and local climatology, calculations of extremes and application of climatological data.

1.2.1 International Co-operation

The work of the Norwegian Meteorological Institute depend on extensive international co-operation. International exchange of data, technology, knowledge and methodology is required. The atmosphere knows no national boundaries, and to prepare forecasts, the institute needs access to observational data from all over the world. This is particularly important for the 7-10 day weather forecasts.

Common international measurement techniques and standards can only be achieved through international co-operation. High capacity communication and data handling systems for the exchange of data and products are the result of extensive co-operative activities.

Norway is a member of the World Meteorological Organization (WMO), the European Centre for Medium Range Weather Forecasts (ECMWF), and the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT). The institute is actively involved in the work of these organisations.
The European meteorological institutes have also entered into a number of formal and informal co-operative agreements in order to exploit common resources to the benefit of all. One example is ECOMET, an economic interest grouping of the meteorological services.
Another is EUMETNET, a network for co-operation with defined subject areas for a more cost-effective exploitation of these resources.

1.2.2 Climatology Division

The Climatology Division is responsible for the Norwegian Meteorological Institute's climatological services. It is headed by Mr. Øystein Hov.
The database in which the data are stored is the basis for the climatological service. Society makes use of the data in various ways, and the main users are those who deal with water resource management, hydroelectric power and energy supply, transport and communications, planning, maritime and offshore activities, insurance, building and construction, sports and leisure events.

The Climatology Division produces a wide range of climatological reports, such as estimates and analyses of extreme values, studies of local climate, analyses based on existing data-material and special measurement projects where new data are related statistically to reference data.
Climatological research includes analyses and prognoses for mean and extreme weather conditions, and how these vary with time and space. The aim is to gain more knowledge about the processes that cause variations in the climate, and to investigate the possible long-term effect of man's activities.

2 Presentation of the method

2.1 EOF

In climatology, Principal Component Analysis (PCA) received the name of Empirical Orthogonal Functions (EOF) Analysis (*Lorenz*, 1956).

The EOF analysis has been employed to phenological and climatological data from two aspects which are data compression and outlier detection. EOFs consist in orthogonal spatial patterns that can be thought of as empirically derived basis functions and are used to identify patterns of simultaneous variation (*von Storch & Zwiers*, 1999).

Among the existing statistical downscaling techniques, the analog method appears to be one of the simplest to implement. The idea is to search archives of climatological data closely resembling current observations and assume that the future evolution of the climate will be similar to the flows that followed the historical analogs.

The analog method has the advantage of being reliable both for normally and nonnormally distributed local variables. Moreover, it produces the right level of variablity of the local variables and preserves the spatial covariance between them. To obtain matches between currently observed and historical fields as accuratly as possible, several fields should be considered. Thus, not only heights and temperature fields but also sea level pressure (SLP) need to be taken into account.

A problem associated with this method is the need for sufficiently long observations, so that a reasonable analog of the large-scale circulation always can be found.
Due to the number of degrees of freedom of the large-scale atmospheric circulation, it has been pointed out that on a global basis and for prediction purposes several thousands years would be needed (*Zorita & von Storch*, 1999). However, many of these degrees of freedom represent just background noise that can be previously filtered out, for instance, by a standard empirical orthogonal function (EOF) analysis (*Lorenz*, 1956; *Preisendorfer*, 1988). In downscaling applications the area of interest is not global but normally covers a continent or an ocean basin, which, as a result, reduces the degrees of freedom of the problem.

2.2 The analog concept

The analog method consists in associating the local variables observed with the most similar large-scale circulation pattern in a pool of historical observations. To achieve this comparison, minimum distances can be used.
Thus, if n is the number of EOFs taking into account and $x_k(t)$ the amplitude of the kth EOF pattern at time t, then the pattern of coordinates z_k has its analog defined as the circulation at time step t that

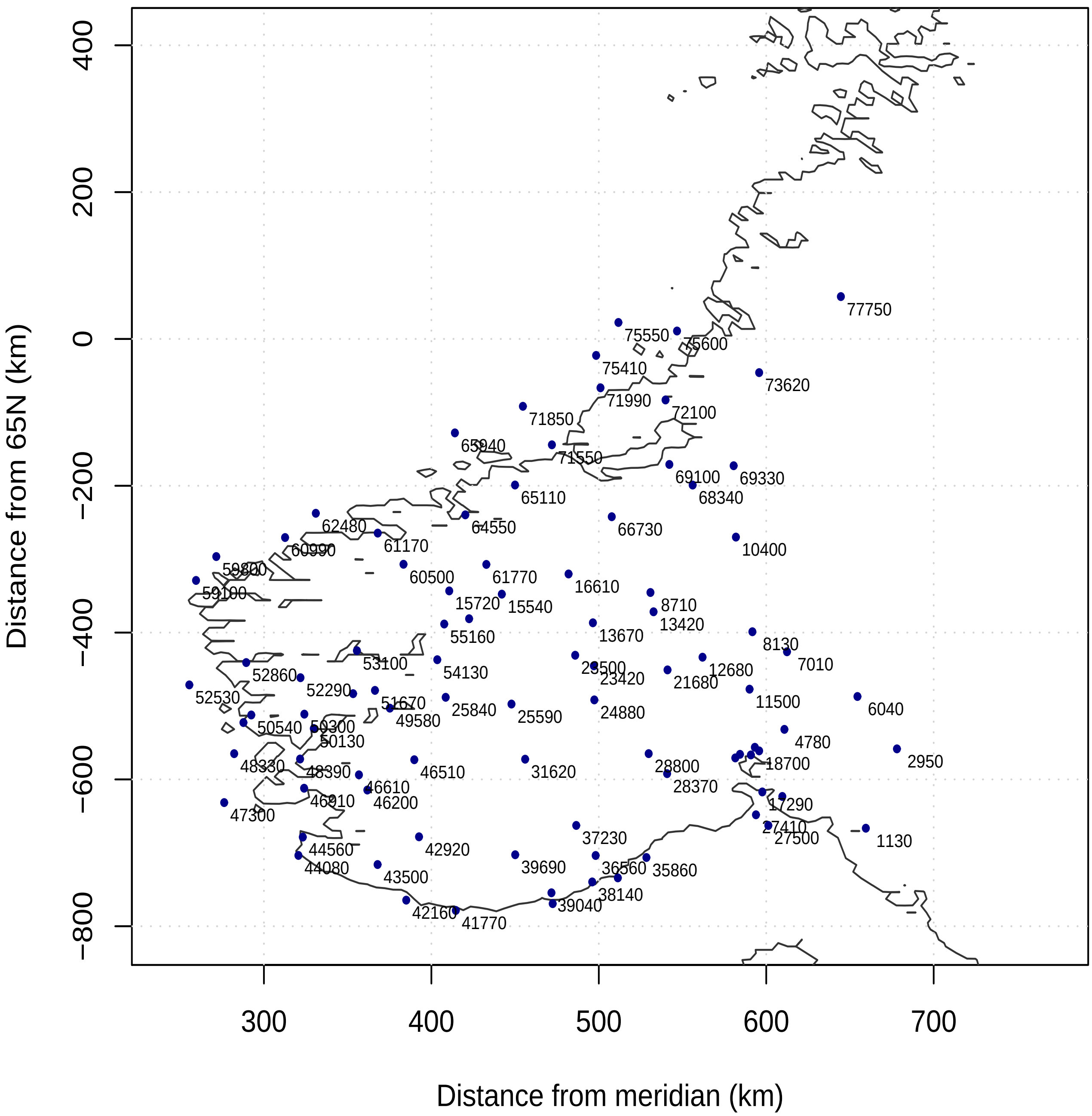


Figure 1. Location of the meteorological stations in southern Norway

minimizes the distance in EOF space:

$$d(t) = \sum_{k=1,n} [z_k - x_k(t)]^2.$$

A cross-validation was also carried out to improve the fitting of the process, the technique consisting in omitting at each step one observation of the predictand. The data is then divided into a set of size $n-1$ and the remaining value. In that way, the cross-validation procedure uses all n observations of the predictand to evaluate the prediction (*Wilks*, 1995).

To check the performance of the method, it can be determined which observation in the historical dataset is the closest to the observation at time t. Statistical tests can then be used to compare the two predictions returned by both tests. Correlation and Root Mean-Squared Error (rmse) provide two common measures of comparison which are implemented in the routine *predict.anm* (*Appendix*).

2.2.1 Predictors

The applications of downscaling techniques vary widely with respect to regions, spatial and temporal scales and the type of both predictors and predictands. Different parameters have then to be taken into account as they play a role and influence the analysis.
The first of them is the number of Principal Components (PC) that should be retained without discarding important information carried in the original data.
It is indeed generally not useful to include all of the predictor variables as they would not permit to significantly increase the results but would slow the computing of analysis. However, there is not a clear criterion to decide how many of them are sufficient to produce a good prediction model. This problem can be partly solved by implementing a stepwise algorithm in which, at each step, the most important predictor variable is included. In the end, the algorithm selects the model which gets the lowest rmse.
Another parameter to consider is the geographical location of the region on which downscaling procedure has focused on. If, for instance, the study lies on the region defined by 16°E-31°E and 64°N-73°N spatial coordinates, the best matches should be expected for northern Norway as around Tromsø.

2.2.2 Predictand

The test of the analog model was made for 91 stations in Norway. A list of the locations, including position and elevation is given in Table 1 and Figure 1 shows a map of the same locations.

3 Results

3.1 Scatterplots

Before implementing the analog method, it may be informative to look at the repartition of wet and dry days by drawing scatter plots as it is presented in Figures 2 and 3. In these graphs, rainy days appear in blue whereas dry days are represented by red solid circles.

The number of data points (daily observations) falling into box (i, j) is $n(i, j)$, and the corresponding number of wet and dry days is $n_w(i, j)$ and $n_d(i, j)$ respectively. One necessary criterion is that the boxes are sufficiently large to give robust statistics on the data distribution. Contour lines have also been added to the plots by evaluating a Kriging surface over the grid (from *R-package 'spatial'*).

The plots are shown for different EOF dimensions in Figure 2 and for different stations in Figure 3(a)-(d), using the two first PCs as a reference.

The scatter plots suggest a weak clustering of dry days with respect to the SLP-based EOFs. A vector of factors "wet" and "dry" was constructed according to whether the daily precipitation was non-zero or greater than zero. A multiple regression was carried out between the vector of factors and the PCs, and a summary of the regression model was used to identify the PCs that were most important. Another method to select the right number of PCs was to used a stepwise algorithm which was implemented in the routine *step.anm* (*Appendix*) presented in section 2.2.1.

This is illustrated by figure 4 where the evolution of the correlation coefficient (right axis) as well as of the rmse (left axis) are plotted versus the steps of the algorithm. The aim is to select a model among

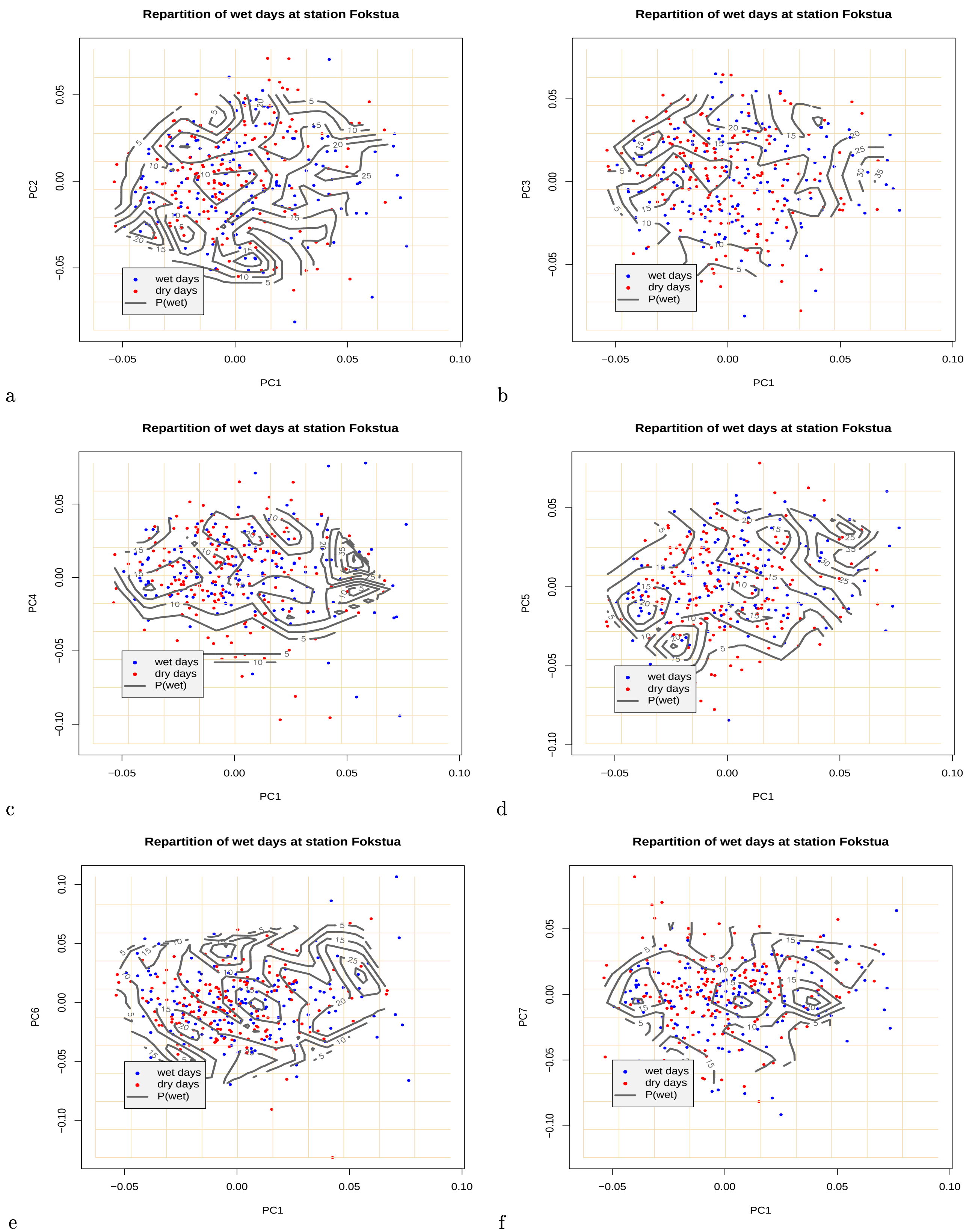


Figure 2. Probablity patterns of wet days at Fokstua in different EOF spaces. Contour: unit in percentage. The first PC is plotted versus (a) PC2, (b) PC3, (c) PC4, (d) PC5, (e) PC6, (f) PC7.

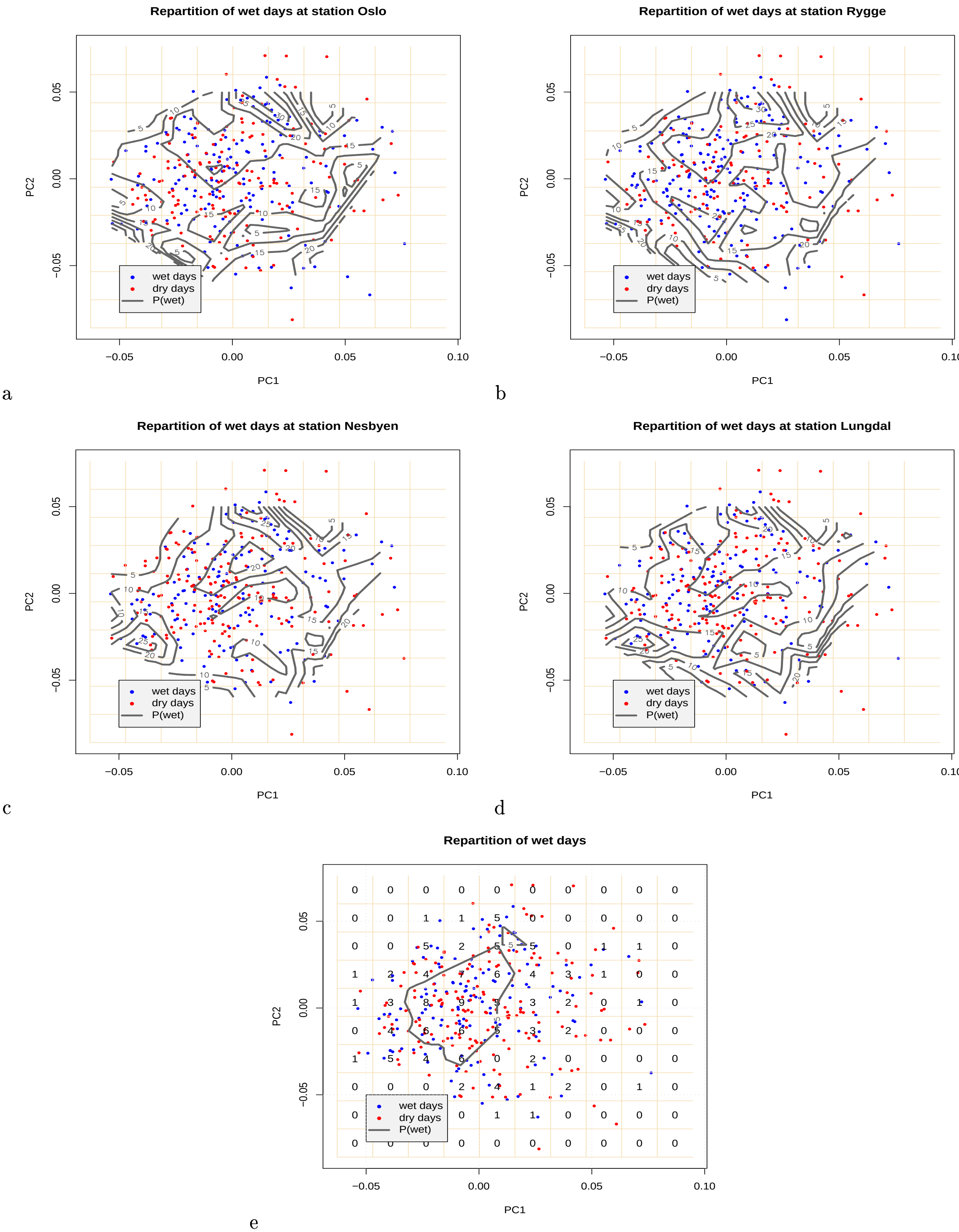


Figure 3. Probability patterns of wet days in (a) Oslo (b) Rygge (c) Nesbyen (d) Lungdal. (e) A Scatterplot based on an equal number of wet and dry days in Lungdal with contour lines using a Kriging surface (unit in percentage).

TABLE 1. A presentation of the meteorological stations. The columns list the longitude (°E), latitude (°N) and altitude (m. a.s.l).

n	location	station	lon	lat	alt
1	Røros	10400	11.38	62.57	628.00
2	Prestebakke	1130	11.54	58.99	157.00
3	Østre	11500	10.87	60.70	264.00
4	Lillehammer	12680	10.48	61.09	114.00
5	Venabu	13420	10.11	61.65	930.00
6	Skåbu	13670	9.38	61.52	890.00
7	Gjeilo	15540	8.45	61.87	378.00
8	Bråtå	15720	7.86	61.91	712.00
9	Fokstua	16610	9.29	62.11	386.00
10	Rygge	17150	10.79	59.38	205.00
11	Jeløy	17290	10.59	59.44	12.00
12	Oslo	18700	10.72	59.94	380.00
13	Tryvasshøgda	18960	10.69	59.99	528.00
14	Fornebu	19400	10.62	59.89	10.00
15	Dønski	19480	10.50	59.90	59.00
16	Asker	19710	10.44	59.86	163.00
17	Vest−torpa	21680	10.04	60.94	542.00
18	Fagernes	23420	9.24	60.99	365.00
19	Løken	23500	9.07	61.12	525.00
20	Nesbyen	24880	9.12	60.57	70.00
21	Geilo	25590	8.20	60.52	353.00
22	Finse	25840	7.50	60.60	1224.00
23	Måkerøy	27410	10.44	59.16	43.00
24	Færder	27500	10.53	59.03	6.00
25	Kongsberg	28370	9.65	59.66	168.00
26	Lungdal	28800	9.52	59.91	142.00
27	Magnor	2950	12.21	59.97	154.00
28	Moesstrand	31620	8.18	59.84	388.00
29	Lyngør	35860	9.15	58.63	4.00
30	Torungen	36200	8.79	58.38	12.00
31	Nelaug	36560	8.63	58.66	142.00
32	Tveitsund	37230	8.52	59.03	124.00
33	Landvik	38140	8.52	58.33	6.00
34	Kjevik	39040	8.07	58.20	23.00
35	Oksøy	39100	8.05	58.07	9.00
36	Byglandsfjord	39690	7.80	58.67	212.00
37	Lindesnes	41770	7.05	57.98	13.00
38	Lista	42160	6.57	58.11	14.00
39	Sirdal	42920	6.85	58.89	242.00
40	Ualand	43500	6.35	58.55	196.00
41	Obrestad	44080	5.56	58.66	24.00
42	Sola	44560	5.64	58.88	312.00
43	Suldal	46200	6.42	59.46	58.00
44	Midtlæger	46510	6.99	59.83	1079.00

the first eight predictor variables representing rainfall at station Bergen. The graph suggests that the minimum rmse (12.25) is obtained at step seven with a good correlation (0.43), which leads to keep the first seven predictors for further analysis.

The previous plots have not taken into account the possible disproportion between the number of wet and dry days during winter which can influence the results. However, if we refer to the total number of wet days as N_{wet} (depicted in each subgrid) and to the total number of dry days as N_d, it appears that N_{wet} is far greater than N_d. In Sirdal for instance, rainy days are three times more frequent than days without precipitation ($N_d = 389$ and $N_{wet} = 785$).

To avoid biases caused by many more wet days, scatter plots based on an equal number of wet and dry days were realized. Samples of wet days were generated by selecting 100 different combinations of $N = \min(N_w, N_d)$ days. The analysis was then repeated 100 times, taking the average number of $p(i,j) = n.w(i,j)/n(i,j)$. The results are shown for Sirdal in Figure 3(e) which suggests that there is not a specific repartition of rainy and dry days.

TABLE 1 continued...

n	location	station	lon	lat	alt
45	Sauda	46610	6.36	59.65	240.00
46	Nedre	46910	5.75	59.48	64.00
47	Utsira	47300	4.88	59.31	55.00
48	Gardermoen	4780	11.08	60.21	202.00
49	Slåtterøy	48330	5.07	59.91	15.00
50	Upsangervatn	48390	5.77	59.84	60.00
51	Eidfjord	49580	6.86	60.47	165
52	Omastrand	50130	5.98	60.22	2.00
53	Kvamskogen	50300	5.91	60.39	210.00
54	Flesland	50500	5.23	60.29	48.00
55	Bergen	50540	5.33	60.38	23.00
56	Voss	51590	6.50	60.65	30.00
57	Reimegrend	51670	6.74	60.69	590.00
58	Modalen	52290	5.95	60.84	114.00
59	Hellisøy	52530	4.71	60.75	20.00
60	Takle	52860	5.38	61.03	38
61	Vangsnes	53100	6.65	61.17	51.00
62	Lærdal	54130	7.52	61.06	36.00
63	Fortun	55160	7.70	61.50	27.00
64	Sognefjell	55290	8.00	61.57	1413.00
65	Kråkenes	59100	4.99	62.03	41.00
66	Svinøy	59800	5.27	62.33	38.00
67	Flisa	6040	12.02	60.61	184.00
68	Tafjord	60500	7.42	62.23	52.00
69	Vigra	60990	6.12	62.56	106.00
70	Hjelvik	61170	7.21	62.62	21.00
71	Lesjaskog	61770	8.37	62.23	621.00
72	Ona	62480	6.54	62.86	13.00
73	Tingvoll	64550	8.30	62.84	69.00
74	Vinjeoera	65110	9.00	63.21	229.00
75	Sula	65940	8.47	63.85	5.00
76	Berkaak	66730	10.02	62.82	231.00
77	Selbu	68340	11.12	63.21	117.00
78	Vaernes	69100	10.94	63.46	23.00
79	Meråker	69330	11.70	63.44	145.00
80	Rena	7010	11.44	61.16	240.00
81	Ørland	71550	9.60	63.70	10.00
82	Halten	71850	9.41	64.17	16.00
83	Buholmråsa	71990	10.45	64.40	18.00
84	Namdalseid	72100	11.20	64.25	86.00
85	Harran	73620	12.51	64.59	118.00
86	Nordøyan	75410	10.55	64.80	33.00
87	Sklinna	75550	11.00	65.20	23.00
88	Leka	75600	11.70	65.10	47.00
89	Susendal	77750	14.02	65.52	265.00
90	Evenstad	8130	11.14	61.41	255.00
91	Sørnesset	8710	10.15	61.89	739.00

3.2 The analog method

3.2.1 Data description

To check the quality of the analog method, it has been tried to reconstruct the time series of the December-February (DJF) daily temperature and rainfall in Norway in the period 1980-1992. Two large-scale variables are used in the testing, the SLP field and the temperature field, the second one being particularly adapted to study daily temperature. These common EOFs were produced by Rasmus E. Benestad with the *clim.pact* R-package.

3.2.2 Precipitation

Table 3 gives the rmse and correlation coefficients between daily December-February rainfall observations and predictions in southern Norway.
The results point to poor correlations for most of the stations. This is significant of oneof the weaknesses of the method which does not optimize the Pearson correlation, contrary to a linear model.
However, the table also provides information about the skill of the two approaches to reproduce variability. This time, the analog method reveals to be the most appropriate as the percentages of variance reproduced range from 74% to 114% and are close to 100% in most of the cases whereas the linear model

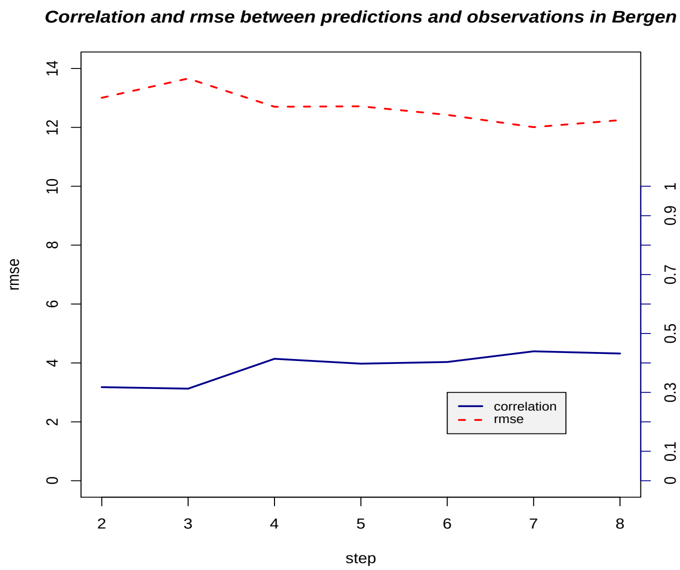
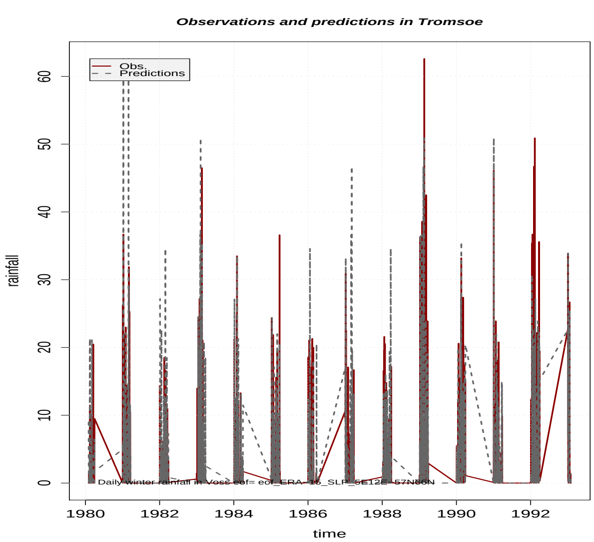


Figure 4. Selection of the predictor variables using a stepwise algorithm for rainfall in Bergen.



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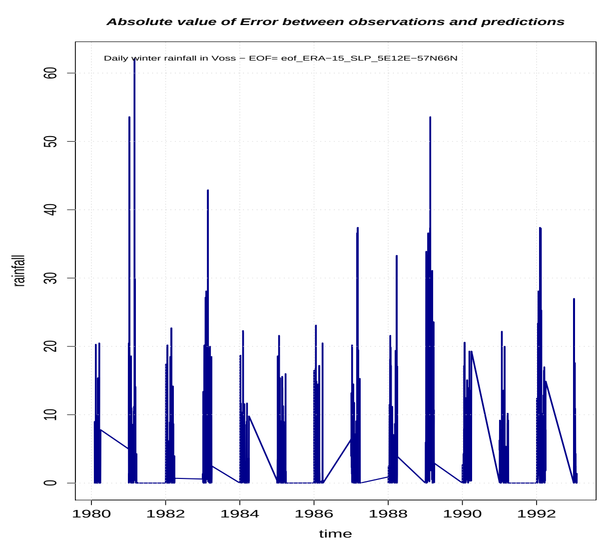

b

Figure 5. Results of the Analog method for daily winter rainfall in Voss using the SLP field and 5E16E-57N66N region for downscaling. (a) Comparison between daily winter rainfall and predictions by the analog method. (b) Absolute error between observations and predictions.

is not able to restitute more than 45% of the observed variability.
Thus, this study already suggests that none of the two techniques is better than another but that their performance depends on the criterium taking into account.

The analog method can also be generalized by introducing different weights on the EOF coordinates (*Zorita & von Storch*, 1999). Each of them was then weighted by its eigenvalue and the results are summarized in the two columns *rmse.w* and *r.anm.w*. They suggest that the fit between predictions and observations has been improved with the introduction of weights, especially for the stations located on the south-western coast, which is not surprising as it corresponds to the region where downscaling was

TABLE 2. Comparison of the standard analog method with a weighted version and a linear model. The columns list the Pearson correlation coefficient for the three models (resp. r.anm, r.anm.w and r.lm), the rmse with and without weights (resp.rmse and rmse.w), as well as the percentage of variance reproduced between observations and predictions with the analog model (var.anm) and a linear model (var.lm). The study was on daily DJF precipitations (mm). Downscaling was derived using the SLP field covering the 5°E 12°E-57°N 66°N region.

n	station	location	r.anm	rmse	r.anm.w	rmse.w	r.lm	var.anm	var.lm
1	10400	Røros	0.14	3.23	0.13	3.31	0.34	77.88	11.44
2	1130	Prestebakke	0.22	6.61	0.25	6.67	0.50	88.25	24.75
3	11500	Østre	0.10	3.76	0.07	3.86	0.42	80.27	17.41
4	12680	Lillehammer	0.29	3.68	0.32	3.55	0.51	99.60	25.88
5	13420	Venabu	0.15	3.90	0.16	3.73	0.42	112.47	17.87
6	13670	Skåbu	0.19	3.93	0.27	3.62	0.40	114.17	15.69
7	15540	Gjeilo	0.23	4.03	0.10	4.57	0.34	112.87	11.86
8	15720	Bråtå	0.40	5.90	0.38	5.98	0.52	93.05	27.23
9	16610	Fokstua	0.21	2.36	0.20	2.42	0.39	88.07	15.22
10	17150	Rygge	0.33	4.80	0.26	5.05	0.51	96.76	25.93
11	17290	Jeløy	0.28	5.73	0.17	6.35	0.47	88.64	21.81
12	18700	Oslo	0.27	3.81	0.24	4.02	0.47	74.48	22.07
13	18960	Tryvasshøgda	0.25	8.10	0.17	8.88	0.49	82.91	24.02
14	19400	Fornebu	0.26	4.14	0.20	4.35	0.47	83.64	22.40
15	19480	Dønski	0.31	5.38	0.24	5.78	0.51	87.34	26.05
16	19710	Asker	0.32	6.58	0.27	7.08	0.56	91.08	31.41
17	21680	Vest-torpa	0.25	5.19	0.15	5.49	0.51	99.05	26.09
18	23420	Fagernes	0.12	3.82	0.21	3.53	0.38	102.03	14.65
19	23500	Løken	0.18	3.81	0.27	3.44	0.43	112.43	18.15
20	24880	Nesbyen	0.31	2.03	0.31	2.05	0.48	90.36	23.14
21	25590	Geilo	0.34	3.97	0.35	3.75	0.48	85.72	23.46
22	25840	Finse	0.56	5.52	0.54	5.71	0.63	75.62	39.59
23	27410	Måkerøy	0.17	6.69	0.13	6.58	0.42	104.98	17.87
24	27500	Færder	0.25	5.29	0.15	5.40	0.48	105.24	23.40
25	28370	Kongsberg	0.29	5.46	0.23	5.73	0.51	90.41	25.60
26	28800	Lungdal	0.40	3.42	0.40	3.44	0.54	90.90	28.94
27	2950	Magnor	0.17	4.78	0.19	4.63	0.43	102.56	18.29
28	31620	Moesstrand	0.39	4.17	0.44	3.98	0.54	88.28	29.52
29	35860	Lyngør	0.18	7.31	0.17	7.35	0.44	103.97	19.78
30	36200	Torungen	0.18	8.22	0.15	8.29	0.47	97.85	21.70
31	36560	Nelaug	0.29	9.98	0.32	9.37	0.53	109.78	28.61
32	37230	Tveitsund	0.40	5.19	0.35	5.33	0.55	104.18	30.26
33	38140	Landvik	0.27	9.33	0.23	8.81	0.49	131.18	23.96
34	39040	Kjevik	0.33	8.24	0.33	8.32	0.55	93.16	30.12
35	39100	Oksøy	0.22	8.73	0.21	8.52	0.44	103.84	18.97
36	39690	Byglandsfjord	0.39	8.62	0.40	8.34	0.58	104.85	33.34
37	41770	Lindesnes	0.27	7.51	0.25	7.62	0.47	97.54	22.02
38	42160	Lista	0.26	7.55	0.29	7.19	0.50	101.46	24.99
39	42920	Sirdal	0.56	10.28	0.60	9.50	0.67	99.47	45.05
40	43500	Ualand	0.32	15.84	0.42	14.56	0.58	91.18	33.36
41	44080	Obrestad	0.27	8.02	0.23	8.27	0.51	101.99	26.26
42	44560	Sola	0.33	6.48	0.35	6.45	0.56	90.61	31.71
43	46200	Suldal	0.35	15.94	0.35	16.02	0.59	87.22	34.88
44	46510	Midtlæger	0.31	4.93	0.23	5.12	0.57	86.74	33.05
45	46610	Sauda	0.45	13.65	0.50	12.91	0.64	95.15	40.94

derived. The increase in the correlation is then statistically significant for stations such as `Omastrand`, `Flesland`, `Voss`, `Modalen`, `Hellisøy`, `Takle`, `Lærdal`, `Vangsnes` or `Kråkenes`. At the same time, the rmse has decreased, which makes the generalized version of the analog method quite interesting.

Figure 5(a) shows a comparison between observations and predictions from the analog model in Voss and Figure 5(b) gives the corresponding absolute error. The correlation was estimated to 0.55 and the rmse was 7.46 (Table 3). Although the analog model overestimates the precipitation peaks, it successfully reproduces the observations. For climate analysis and future scenarios, however, the exact timing is less important than the statistical properties such as distributions.

One advantage the analog method has to linear regression-based models is that the shape of the distribution is in principal conserved. The tails of the distributions are of great interest for studies of extreme weather events and that is why a general extreme value (GEV) distribution (*R-package evd*) and a general Pareto distribution (GPD) (*Imbert*, 2002) were used to model the extreme distributions.

Figure 6 shows that winter rainfall observations and predictions fit equally well to the GPD and that their distributions vary similarly.

TABLE 3 continued...

n	station	location	r.anm	rmse	r.anm.w	rmse.w	r.lm	var.anm	var.lm
46	46910	Nedre	0.28	15.35	0.29	15.24	0.54	97.76	28.68
47	47300	Utsira	0.31	6.35	0.23	6.56	0.49	104.14	24.12
48	4780	Gardermoen	0.30	5.00	0.26	5.15	0.51	96.35	25.79
49	48330	Slåtterøy	0.29	7.75	0.29	7.90	0.52	94.85	26.64
50	48390	Upsangervatn	0.23	13.37	0.24	13.39	0.5	95.27	25.48
51	49580	Eidfjord	0.36	15.77	0.38	15.31	0.59	90.91	34.86
52	50130	Omastrand	0.36	18.21	0.41	17.26	0.60	93.88	36.07
53	50300	Kvamskogen	0.52	15.73	0.56	14.74	0.66	93.26	43.83
54	50500	Flesland	0.27	9.45	0.36	9.25	0.55	75.02	30.38
55	50540	Bergen	0.42	12.39	0.43	12.25	0.60	103.49	35.82
56	51590	Voss	0.47	8.30	0.55	7.46	0.65	104.03	41.84
57	51670	Reimegrend	0.45	12.19	0.48	12.15	0.63	99.20	40.11
58	52290	Modalen	0.37	20.70	0.46	18.69	0.64	95.05	41.11
59	52530	Hellisøy	0.23	6.07	0.30	5.88	0.46	92.32	21.49
60	52860	Takle	0.41	22.16	0.48	20.80	0.63	100.42	39.34
61	53100	Vangsnes	0.20	10.18	0.26	9.80	0.53	88.94	28.33
62	54130	Lærdal	0.39	6.17	0.46	5.78	0.54	82.75	29.28
63	55160	Fortun	0.42	7.47	0.43	7.21	0.57	86.49	32.78
64	55290	Sognefjell	0.46	3.67	0.32	4.27	0.53	86.82	28.39
65	59100	Kråkenes	0.25	7.08	0.30	7.07	0.51	94.09	26.20
66	59800	Svinøy	0.16	4.69	0.19	4.65	0.37	97.7	13.72
67	6040	Flisa	0.20	3.15	0.21	3.29	0.44	88.1	19.71
68	60500	Tafjord	0.44	7.96	0.45	7.67	0.59	109.02	34.90
69	60990	Vigra	0.42	7.17	0.34	7.52	0.5	96.9	25.47
70	61170	Hjelvik	0.39	9.64	0.35	9.91	0.54	105.91	29.09
71	61770	Lesjaskog	0.25	7.70	0.28	7.49	0.46	112.47	21.35
72	62480	Ona	0.36	9.18	0.31	9.26	0.44	95.92	19.56
73	64550	Tingvoll	0.36	8.01	0.33	7.94	0.5	97.95	24.73
74	65110	Vinjeoera	0.38	9.70	0.43	8.95	0.55	90.73	30.31
75	65940	Sula	0.21	7.93	0.21	7.90	0.41	96.71	16.52
76	66730	Berkaak	0.29	5.42	0.27	5.25	0.49	112.21	23.88
77	68340	Selbu	0.40	4.27	0.33	4.35	0.51	91.16	26.08
78	69100	Vaernes	0.33	4.86	0.33	4.80	0.52	85.14	27.12
79	69330	Meråker	0.34	6.88	0.32	7.13	0.51	90.29	25.74
80	7010	Rena	0.17	4.93	0.15	4.94	0.46	97.91	21.25
81	71550	Ørland	0.19	6.95	0.22	6.62	0.43	97.53	18.50
82	71850	Halten	0.13	5.55	0.23	5.10	0.44	100.22	19.30
83	71990	Buholmråsa	0.20	5.43	0.23	5.12	0.37	98.96	13.41
84	72100	Namdalseid	0.45	7.32	0.43	7.36	0.56	94.48	31.12
85	73620	Harran	0.36	9.13	0.40	8.99	0.56	95.58	30.95
86	75410	Nordøyan	0.18	5.49	0.19	5.65	0.39	108.16	15.47
87	75550	Sklinna	0.16	5.99	0.16	6.05	0.40	100.06	15.95
88	75600	Leka	0.25	8.86	0.25	8.75	0.49	105.24	23.62
89	77750	Susendal	0.41	8.08	0.40	8.95	0.51	74.14	26.17
90	8130	Evenstad	0.31	4.87	0.21	5.11	0.53	93.64	28.56
91	8710	Sørnesset	0.12	3.60	0.22	3.43	0.34	92.27	11.54

The return value plots have also the same unbounded shape which is characteristic of an infinite limit for extrapolation (*Coles*, 1999).

When considering all these results, it is important to keep in mind that the length of the test period was short and that, as a consequence, the results may not be robust.

3.2.3 Temperature

The analysis was carried out for the temperature records from the same stations as in Table 1 but on temperature predictors. The results for the December-February season are depicted in Table 3 and suggest that there is a good match between the observations and the time series reproduced with the analog method.

Both the correlation and the percentage of variance reproduced by the model suggest indeed that the method is able to skillfully describe the observations.

Some stations however get poor Pearson coefficients with both approaches (Prestebakke, Asker, Finse, Moesstrand, Sirdal, Midtlæger, Upsangervatn, Eidfjord, Hellisøy, Kråkenes, Flisa, Tafjord, Ona, Vinjøera, Selbu, Namdalseid, Nordøyan, Leka, Evenstad, Sørnesset), which Benestad accounted for *low data quality or a weak relationship between the large-scale features and local temperature.*

What is interesting to note is that, even for these stations, the analog method unlike the linear model is able to reproduce the variance levels.

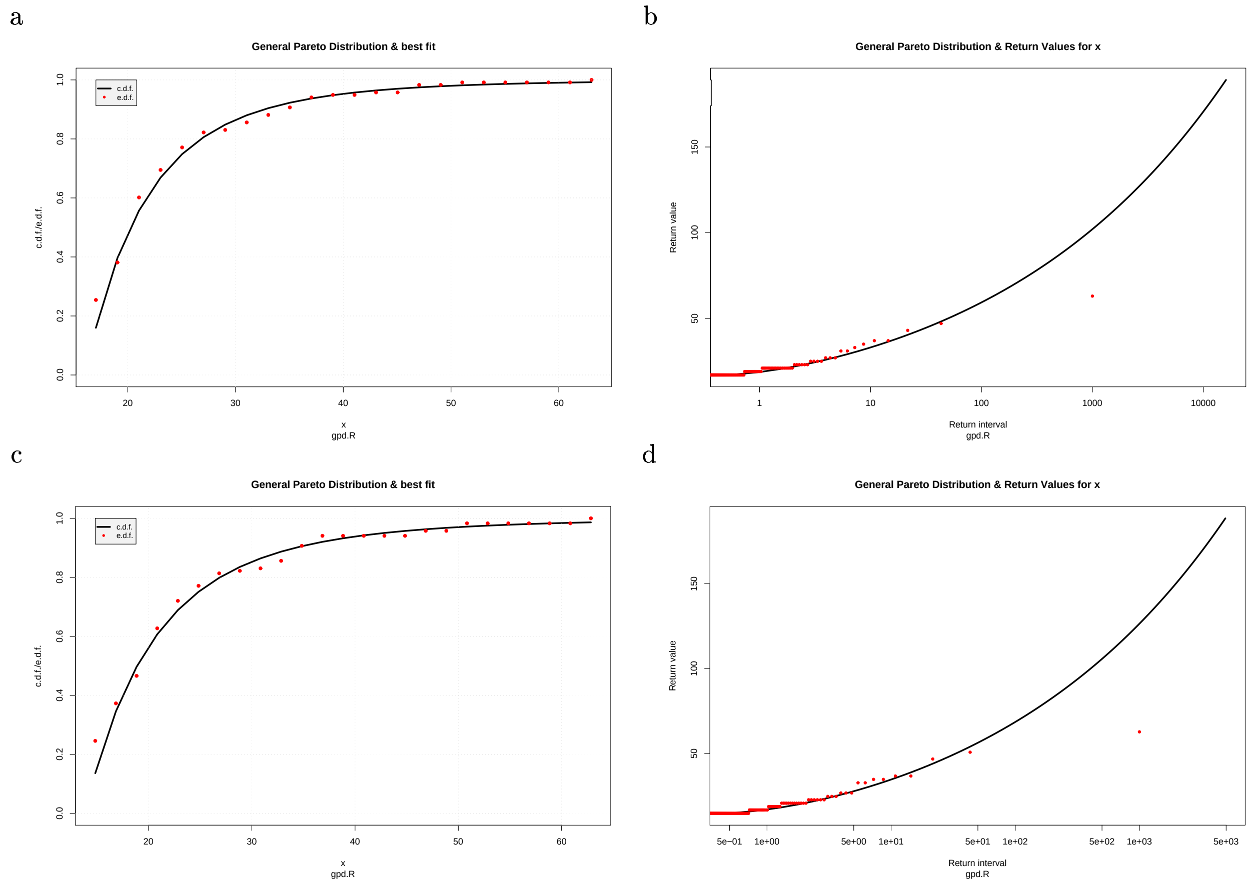

Figure 6. A comparison between daily December-February rainfall observations and predictions from the analog method at station Voss. Generalized Pareto Distribution for (a) observations, (c) predictions. Return value plots for (b) observations, (d) predictions.

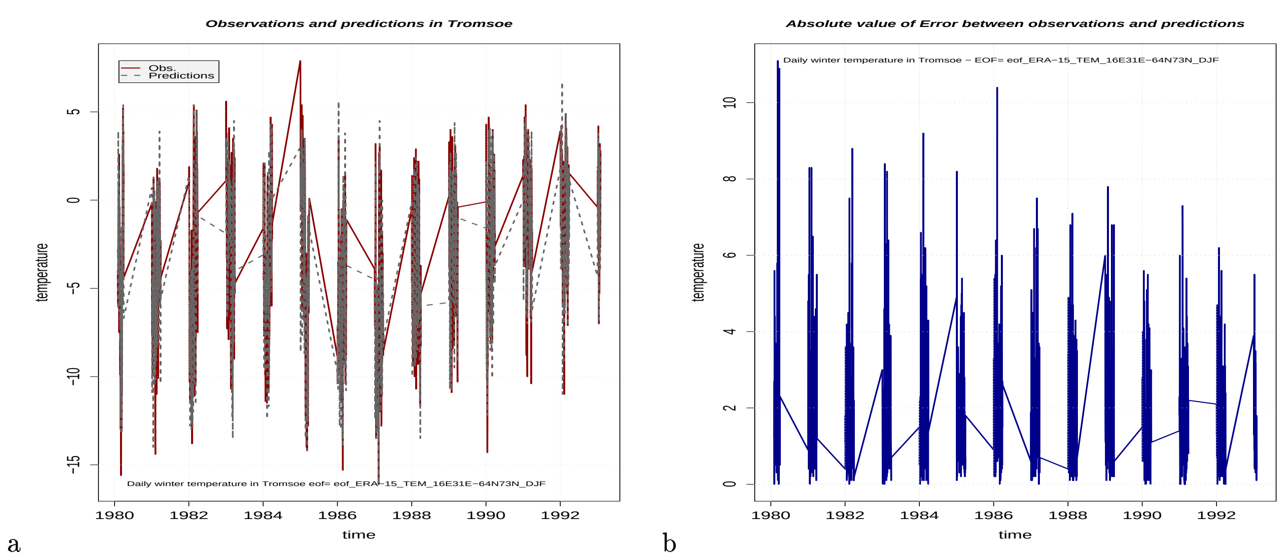

Figure 7. Results of the Analog method for daily winter temperature in Tromsoe using 7 PCs. Downscaling was applied to the 16°E 31°E-64°N 73°N region with a temperature field.(a) Comparison between predictions and observations.(b) Absolute error between observations and predictions.

TABLE 3. Comparison of the standard analog method with a weighted version and a linear model. The columns list the Pearson correlation coefficient for the three models (resp. r.anm, r.anm.w and r.lm), the rmse with and without weights (resp.rmse and rmse.w), as well as the percentage of variance reproduced between observations and predictions with the analog model (var.anm) and a linear model (var.lm). The study was on daily DJF temperatures (°C). Downscaling was derived using the temperature field covering the 4°E 14°E-58°N 64°N region.

n	station	location	r.anm	rmse	r.anm.w	rmse.w	r.lm	var.anm	var.lm
1	10400	Røros	0.71	6.42	0.78	5.61	0.84	84.76	70.22
2	1130	Prestebakke	0.40	3.64	0.85	3.16	0.58	83.31	33.26
3	11500	Østre	0.69	4.40	0.83	3.77	0.83	87.25	69.6
4	12680	Lillehammer	0.74	4.18	0.80	3.87	0.84	83.69	70.61
5	13420	Venabu	0.7	3.58	0.77	3.31	0.84	78.47	69.90
6	13670	Skåbu	0.61	3.85	0.78	3.47	0.76	82.89	58.30
7	15540	Gjeilo	0.72	6.80	0.78	6.16	0.83	93.67	69.19
8	15720	Bråtå	0.72	4.80	0.79	4.37	0.83	81.71	69.40
9	16610	Fokstua	0.75	3.42	0.83	3.05	0.86	80.09	74.67
10	17150	Rygge	0.74	3.90	0.83	3.50	0.84	78.93	70.10
11	17290	Jeløy	0.76	3.17	0.87	2.68	0.85	78.33	72.21
12	18700	Oslo	0.73	3.45	0.83	3.09	0.84	79.12	69.93
13	18960	Tryvasshøgda	0.73	2.88	0.84	2.60	0.84	77.34	71.07
14	19400	Fornebu	0.73	3.75	0.81	3.41	0.82	80.13	68.03
15	19480	Dønski	0.69	4.08	0.77	3.77	0.81	79.86	65.27
16	19710	Asker	0.06	3.54	0.82	3.09	0.15	87.58	2.27
17	21680	Vest-torpa	0.70	4.58	0.73	4.21	0.85	94.76	72.46
18	23420	Fagernes	0.68	5.58	0.75	5.13	0.8	86.74	64.11
19	23500	Løken	0.65	5.84	0.72	5.24	0.82	93.06	66.77
20	24880	Nesbyen	0.68	6.29	0.72	5.78	0.79	83.55	61.91
21	25590	Geilo	0.70	4.48	0.80	3.97	0.83	82.86	69.17
22	25840	Finse	0.22	4.42	0.80	3.72	0.32	80.09	10.35
23	27410	Måkerøy	0.56	3.23	0.86	2.78	0.70	81.71	49.60
24	27500	Færder	0.74	2.60	0.89	2.16	0.83	74.77	69.36
25	28370	Kongsberg	0.69	4.81	0.77	4.41	0.82	80.94	66.71
26	28800	Lungdal	0.69	5.12	0.77	4.64	0.82	82.67	67.63
27	2950	Magnor	0.73	4.74	0.78	4.43	0.84	80.18	71.37
28	31620	Moesstrand	0.18	3.60	0.82	3.19	0.36	85.08	13.18
29	35860	Lyngør	0.73	2.82	0.87	2.39	0.83	74.94	69.01
30	36200	Torungen	0.73	2.67	0.88	2.22	0.84	74.49	70.15
31	36560	Nelaug	0.57	3.98	0.82	3.52	0.73	79.48	52.84
32	37230	Tveitsund	0.69	4.18	0.83	3.6	0.82	80.04	67.7
33	38140	Landvik	0.68	3.82	0.81	3.37	0.83	85.80	69.21
34	39040	Kjevik	0.72	3.54	0.83	3.10	0.83	78.43	69.11
35	39100	Oksøy	0.74	2.50	0.89	2.04	0.85	76.06	71.58
36	39690	Byglandsfjord	0.69	3.58	0.82	3.15	0.82	77.20	67.34
37	41770	Lindesnes	0.75	2.23	0.91	1.79	0.85	73.16	71.49
38	42160	Lista	0.75	2.35	0.90	1.92	0.85	75.37	72.25
39	42920	Sirdal	0.14	4.67	0.78	4.17	0.26	81.01	6.71
40	43500	Ualand	0.73	2.81	0.85	2.39	0.84	76.57	71.00
41	44080	Obrestad	0.78	2.43	0.89	1.98	0.87	77.34	76.24
42	44560	Sola	0.75	2.58	0.87	2.18	0.86	75.97	73.37
43	46200	Suldal	0.69	3.91	0.78	3.51	0.82	84.93	66.55
44	46510	Midtlæger	0.36	2.89	0.83	2.61	0.56	90.94	31.47
45	46610	Sauda	0.70	3.56	0.78	3.24	0.83	81.83	68.62

These remarks go along with what has already been noted for rainfalls and so reinforce the fact that the two approaches are complementary and should be considered simultaneously.

Table 3 also presents the results for the weigthed version of the analog method (columns *r.anm.w* and *rmse.w*). As for rainfalls, the weights were assigned to the eigenvalue of each EOF. The results give evidence for a significant improvement of the previous model. Not only is the rmse lower but also the correlation coefficients have increased significantly. For many stations (41 out of 91 i.e 45%), the results evidence an even better fit than the linear model, which is particularly relevant for the stations previously quoted. *

An illustration of the performance of the analog method is given in Figure 7. The second graph shows that the time series of observations and analogs vary coherently. The method is able to reproduce the trend and the different oscillations of temperature with a reasonable error (Figure 7(b)).

*Prestebakke, Asker, Finse, Moesstrand, Sirdal, Midtlæger, Upsangervatn, Eidfjord, Hellisøy, Kråkenes, Flisa, Tafjord, Ona, Vinjøera, Selbu, Namdalseid, Nordøyan, Leka, Evenstad, Sørnesset.

TABLE 3 continued...

n	station	location	r.anm	rmse	r.anm.w	rmse.w	r.lm	var.anm	var.lm
46	46910	Nedre	0.73	2.91	0.84	2.43	0.85	79.99	73.00
47	47300	Utsira	0.75	1.70	0.90	1.40	0.86	73.39	74.20
48	4780	Gardermoen	0.72	4.33	0.82	3.85	0.83	79.91	68.07
49	48330	Slåtterøy	0.74	1.75	0.88	1.46	0.86	75.85	74.80
50	48390	Upsangervatn	0.16	2.47	0.86	2.13	0.16	94.77	2.45
51	49580	Eidfjord	0.18	3.00	0.78	2.65	0.24	84.83	5.71
52	50130	Omastrand	0.71	2.37	0.83	2.04	0.84	79.42	69.82
53	50300	Kvamskogen	0.73	3.11	0.83	2.71	0.85	79.68	71.78
54	50500	Flesland	0.76	2.27	0.88	1.88	0.87	76.2	75.29
55	50540	Bergen	0.76	2.28	0.86	1.93	0.87	79.66	76.49
56	51590	Voss	0.74	4.60	0.80	4.09	0.84	80.57	70.43
57	51670	Reimegrend	0.54	3.64	0.81	3.2	0.74	87.49	55.06
58	52290	Modalen	0.71	3.44	0.79	3.13	0.83	86.08	69.06
59	52530	Hellisøy	0.11	1.73	0.89	1.46	0.07	89.44	0.48
60	52860	Takle	0.76	2.19	0.86	1.94	0.87	78.97	75.62
61	53100	Vangsnes	0.61	2.50	0.81	2.18	0.77	83.59	59.82
62	54130	Lærdal	0.71	3.83	0.78	3.46	0.82	83.16	66.79
63	55160	Fortun	0.74	3.92	0.82	3.5	0.82	81.55	67.83
64	55290	Sognefjell	0.78	3.37	0.85	2.86	0.89	82.7	78.49
65	59100	Kråkenes	0.14	1.67	0.87	1.44	0.22	99.09	4.85
66	59800	Svinøy	0.79	1.56	0.87	1.37	0.89	80.73	79.53
67	6040	Flisa	0.49	5.54	0.80	4.91	0.67	82.43	45.5
68	60500	Tafjord	0.18	3.19	0.75	2.98	0.35	94.27	11.92
69	60990	Vigra	0.78	1.88	0.85	1.68	0.88	82.58	77.68
70	61170	Hjelvik	0.76	2.55	0.83	2.32	0.87	82.29	75.37
71	61770	Lesjaskog	0.72	5.83	0.78	5.16	0.83	80.85	69.68
72	62480	Ona	0.10	1.64	0.88	1.38	0.16	85.91	2.55
73	64550	Tingvoll	0.70	3.49	0.76	3.23	0.82	84.51	67.92
74	65110	Vinjeoera	0.11	3.39	0.79	2.99	0.21	89.38	4.54
75	65940	Sula	0.52	1.77	0.86	1.64	0.71	83.12	50.59
76	66730	Berkaak	0.70	3.91	0.77	3.47	0.86	84.22	73.93
77	68340	Selbu	0.23	3.75	0.83	3.22	0.37	81.91	13.65
78	69100	Vaernes	0.74	3.89	0.82	3.44	0.85	78.86	71.45
79	69330	Meråker	0.72	4.89	0.81	4.26	0.83	80.06	69.42
80	7010	Rena	0.71	5.85	0.79	5.20	0.82	81.33	67.04
81	71550	Ørland	0.77	2.56	0.84	2.31	0.86	78.09	74.56
82	71850	Halten	0.75	1.91	0.84	1.82	0.85	76.98	72.6
83	71990	Buholmråsa	0.79	2.35	0.84	2.28	0.86	78.56	74.76
84	72100	Namdalseid	0.07	4.24	0.81	3.78	0.13	102.70	1.75
85	73620	Harran	0.69	5.43	0.76	5.04	0.83	81.32	69.52
86	75410	Nordøyan	0.21	2.24	0.82	2.24	0.22	102.43	4.62
87	75550	Sklinna	0.75	2.27	0.80	2.24	0.85	79.58	72.60
88	75600	Leka	0.35	3.05	0.79	2.96	0.55	80.18	30.48
89	77750	Susendal	0.68	6.46	0.72	6.24	0.81	80.76	65.81
90	8130	Evenstad	0.32	5.73	0.74	5.28	0.44	79.38	19.11
91	8710	Sørnesset	0.19	5.72	0.76	5.17	0.32	83.6	10.31

Figure 8 shows a comparison between the empirical distribution functions ($e.d.f$) of the observations and of the corresponding predictions. It reveals a very good fit to GPD for both distributions using the 90th percentile as a threshold. Even more than for rainfall (see paragraph 3.2.2), they show very similar behaviours.

The same remarks apply when considering a GEV model. The resulting return values for both observations and predictions can then be seen in Figure 9 which provides graphical diagnostics such as a quantile plot, a density plot and a return level plot. In Figure 9, predictions appear in blue whereas observations are in black. Both the density and the quantile plot suggest that the quality of the GEV is not very good when fitting predictions and observations. This can be accounted for by the fact that the tests were based on only 39 values, which is quite poor.

However, the comparison of the return level plots (Figure 8) shows that the shape for observations and predictions is the same. It is bounded shape, which is significant of a negative shape parameter for a GEV distribution and suggest that extrapolation to any level will lead to a finite limit (*Coles*, 1999).

Thus, both GEV and GPD lead to evidence a similarity between the prediction and observation-based return values and this suggest that the analog method is able to reproduce the distributions of the observations, even in the extremes.

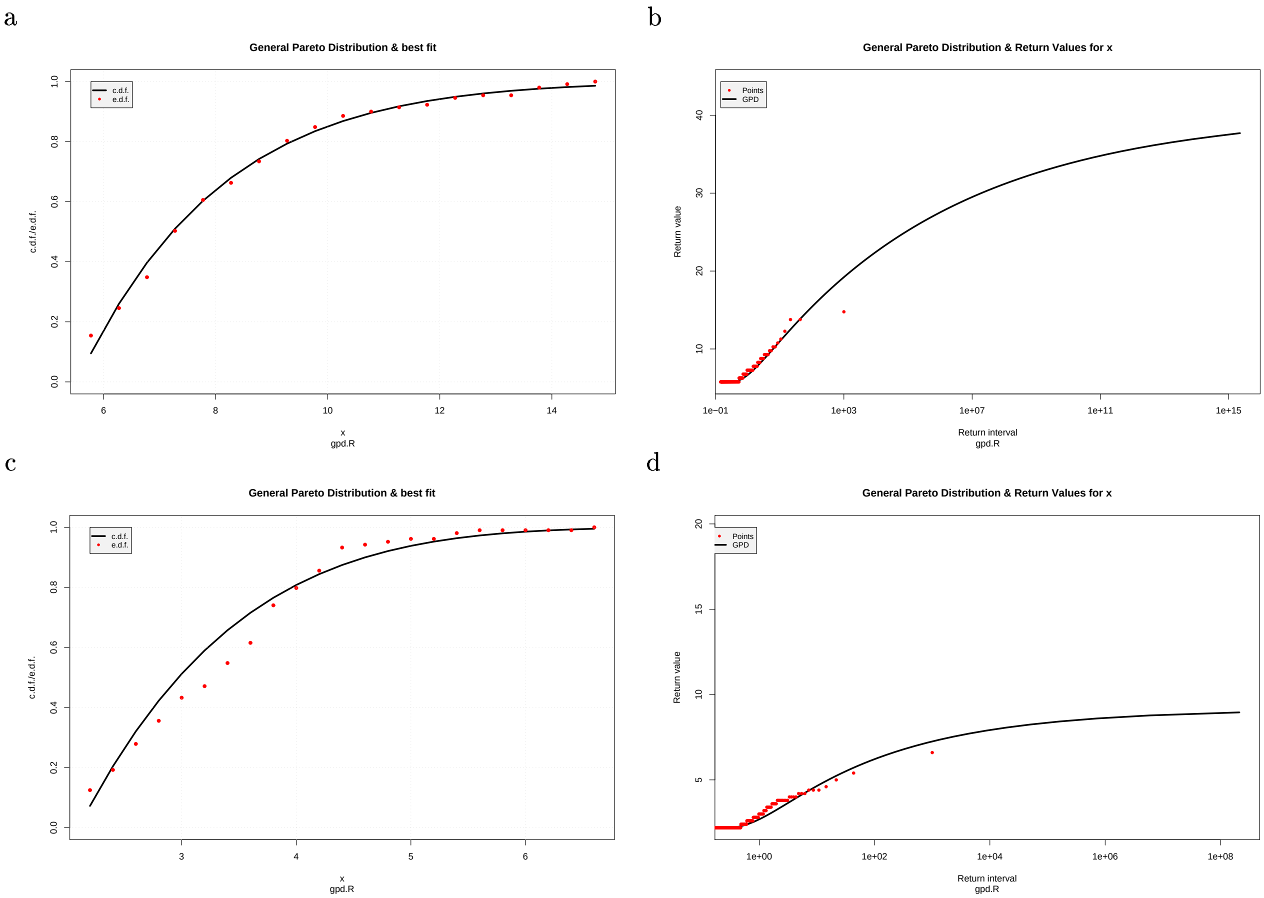

Figure 8. A comparison between extreme distributions for daily December-February absolute minimum temperature observations and predictions from the analog method at station Tromsoe. Generalized Pareto Distribution for (a) observations, (b) predictions. Return value plots for (c) observations, (d) predictions.

4 Downscaling

One advantage of downscaling techniques is that they can be used to provide local information for the study of climate change. Here, the downscaling was based on the same common EOF framework that has been evaluated and tested by Benestad for a linear model *(Benestad, 2002, 2003c,b)*. The analog method has proved to be able to reproduce skillfully observations, even in the extremes, and it is then interesting to compare downscaled results when using the two statistical approaches. This is done by numerical tests and by fitting predictions to GEV and GPD distributions.
The different tables produced are presented in the appendix.

4.1 Precipitation

Table 4 (*Appendix*) gives a summary of the performance of the analog method (`r` and `var`) and shows some results on local climate change in southern Norway for the DJF season (95 quantile).
Column 6 lists the percentage of the variance accounted for by the multiple regression. This gives an indication on how well the empirical downscaling can reproduce the December-February precipitation using the two different model approaches: linear and analog. The linear model then shows a better fit than the analog method, which can once more be accounted for by the fact that it is made in a way to optimize correlation in terms of the Pearson correlation.
On the other hand, the analog model yields more realistic variance levels (column 11). The ratio of variance between the control and the scenario periods ($\mathrm{var}(\mathrm{T}_{sce})/\mathrm{var}(\mathrm{T}_{ctl})$) ranges between 0.79 and 1.31, and is close to 1 for all the stations, indicating that the method reproduces skillfully the variance. Figure 10 makes it very clear. The blue circles which give the changes in variance for the analog method

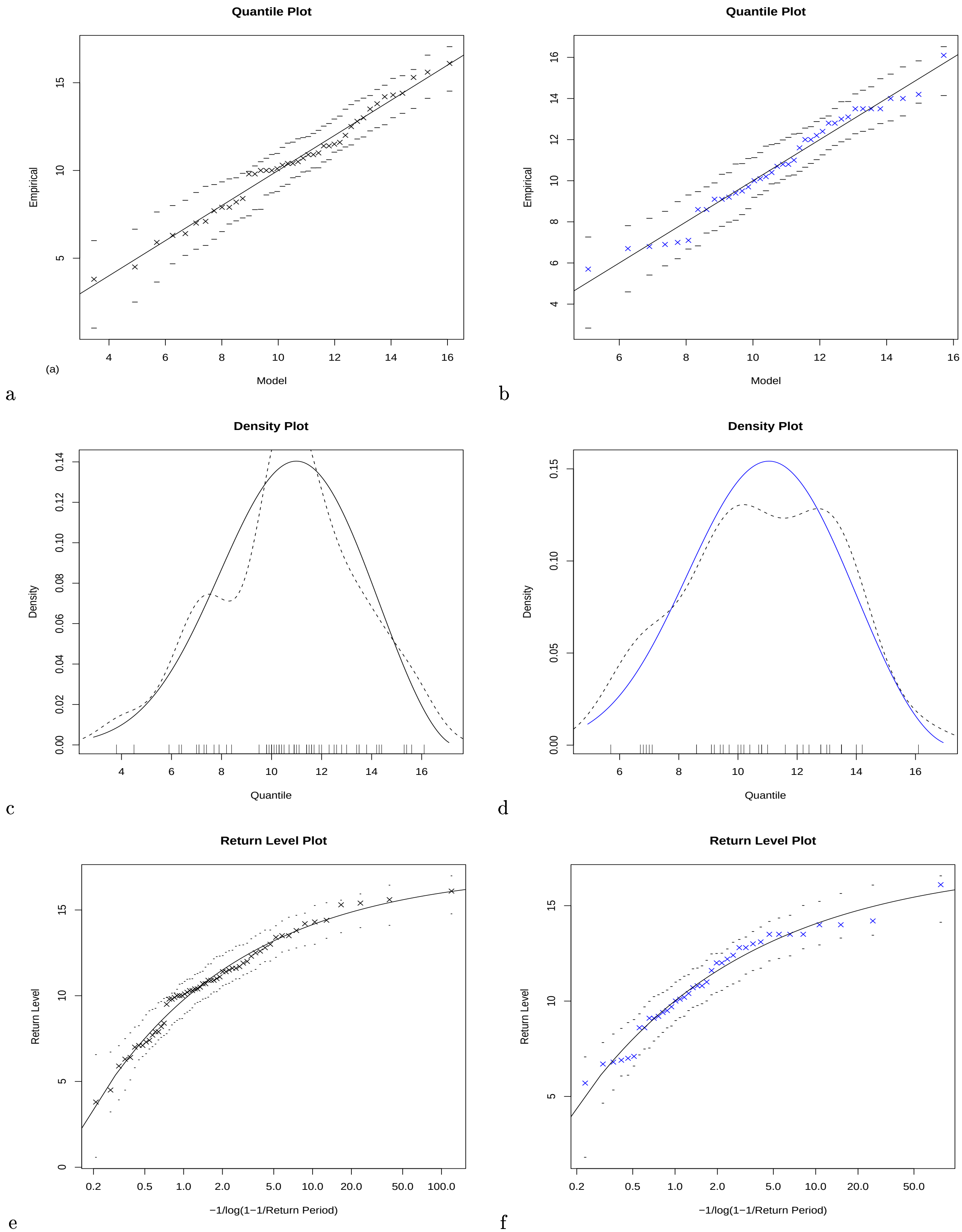

Figure 9. A comparison between GEV distributions for absolute minimum daily winter temperature and predictions in Tromsoe. (a) Quantile plot for observations. (b) Quantile plot for predictions. (c) Density for observations. (d) Density for predictions. (e) Return level plot for observations. (f) Return level plot for predictions. Observations appear in black whereas predictions are on blue.

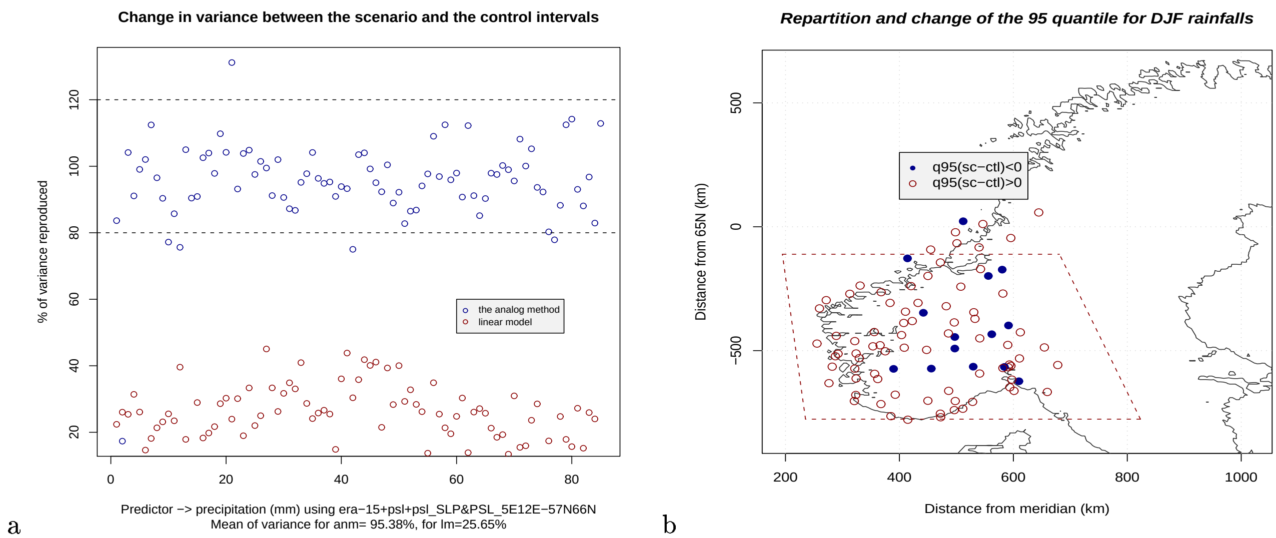

Figure 10. (a) Comparison of the percentage of variance reproduced by the analog method and a linear model. (b) Geographical repartition of the change in large rainfalls between a control period (ctl) and a scenario (sc). The study was on daily DJF precipitation (mm) in southern Norway.

appear indeed included in a 80%-120% tube, for all the station except one.
On the contrary, the red circles suggest that the linear model reproduces very poorly the variance levels.

Thus, the two methods have different strengths and weaknesses and the choice of one method rather than the other will depend on what is expected from the analysis.

From the results listed in column 9, it appears that the average amount of precipitation ($\Delta rr = mean(sc) - mean(ctl)$) generally increases from the control period to the scenario, the trend being negative for only 23% of the stations. This general increase is also suggested when looking at the changes in the extremes as it is illustrated in figure 10(b). No obvious pattern can be drawn from the comparison of the 95 percentile for the control and the scenario periods (respectively noted `q95ctl` and `q95sc`). 26 stations experiment an increase in the largest amount of rainfalls, as for `Prestebakke, Byglandsfjord, Ualand` or `Takle` for instance, whereas 12 stations evidence lower precipitations.

4.2 Temperature

A detailed summary of the downscaled scenarios for DJF temperature and using the analog method is presented in Table 6 (*Appendix*). This table can be compared to the one in *Benestad* (2003a) where the downscaling was applied to the same stations but with a linear model.

When comparing the Pearson correlation (R^2), it appears that the two different model approaches generally show a good fit. Here, it is to mention that this coefficient was multiplied by 100 and rounded so that they are presentated like percentages. The linear model shows again an even better fit than the analog method. Stations with a low R^2 (Prestebakke, Skåbu, Asker, Finse, Moesstrand, Sirdal, Midtlæger, Upsangervatn, Eidfjord, Reimegrend, Hellisøy, Kråkenes, Flisa, Tafjord, Ona, Vinjøera, Sula, Selbu, Namdalseid, Nordøyan, Leka, Evenstad, Sørnesset) appear to be the same already pointed out in the paragraph 3.2.3. * It also interesting to note that the percentage of the local variance reproduced by the empirical downscaling is higher than 70% at all the stations, which is what was also obtained by

*low data quality or a weak relationship between the large-scale features and local temperature.

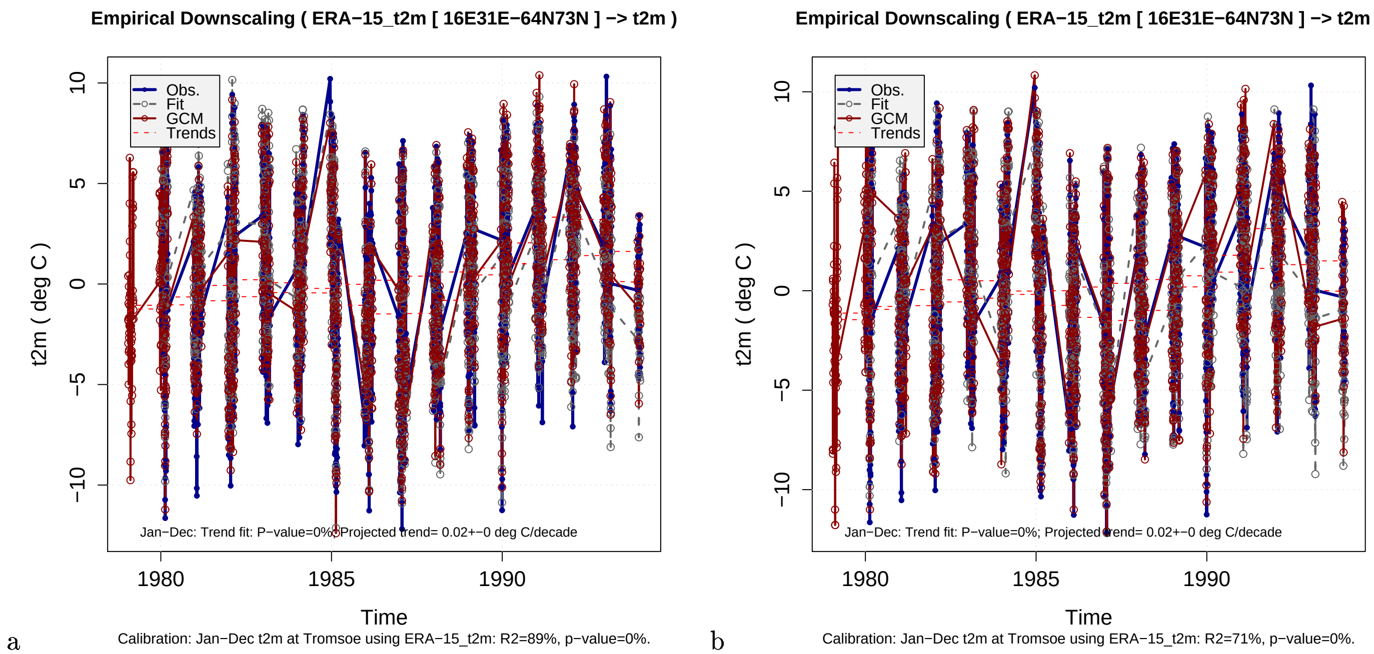

Figure 11. Empirical downscaling for daily winter temperature in Tromsoe.(a) Comparison between observations and predictions using a linear model.(b) Comparison between observations and predictions using the analog model.

Benestad when using a linear model. A proportion of more than 1 (e.g Rygge, Jeløy, Fornebu, Dønski, ...) indicates that the model estimates a variability higher than the one of the control period. With a mean of variance ratios equal to `0.96`, the analog method reveals once again to be a better model than a linear model to reproduce variablity.

However, conclusions are similar for both approaches apply when considering the changes in temperature ranges determined by the quantity $\mathrm{var}(\mathrm{T}_{sce})/\mathrm{var}(\mathrm{T}_{ctl})$. As for the linear model indeed, the results suggest a reduction in the temperature range. This decrease is statistically significant as the `p-value` associated with the Student's test suggests it. The `p-value` is indeed lower than the confidence level, set to 0.05, which reveals that the means in temperature are significantly different from the control period to the scenario.

As for the evolution of the highest and lowest temperatures (respectively represented by the 95 percentile and the 5 percentile), they evidence some differences with Benestad's study. Column 12 gives the difference q95(sc)-q95(ctl) and positive values then indicate an increase in the warmest temperatures. The same applies for the coldest temperatures given by the 5 percentile. It is still true that the minimum temperature increases faster than the maximum temperature but this is the case for less stations than with the linear model and with lower values. The mean for the 95 percentile is `0.57` wheareas it is `0.86` for the 5 percentile and a wilcoxon test reveals that this difference is statistically significant.

An illustration of this is given in Figure 11 in which downscaled results produced by the `clim.pact` package are depicted for the linear model (a) and the analog method (b). Here, ERA-15 temperature field was used to study Tromsø. The regression model successfully describes the local variations with the two approaches.

Analysis of extremes is also provided in Figure 12 and the Generalized Pareto Distributions of the downscaled results for December-February daily temperature in Tromsø were compared for the two statistical approaches. Predictions based on the analog method then appear in the two first graphs at the top whereas predictions from downscaling using a linear model are at the bottom. The distributions as well as the return level plots evidence very similar behaviour and both reveal to have a good fit.

However, for some stations, the analog method appears to reproduce more skillfully the trend of the extreme values than the linear model does. As an illustration of this, a comparison can be drawn between the return level plots for observations and predictions in Alta (Figures 13 and 14). Here indeed,

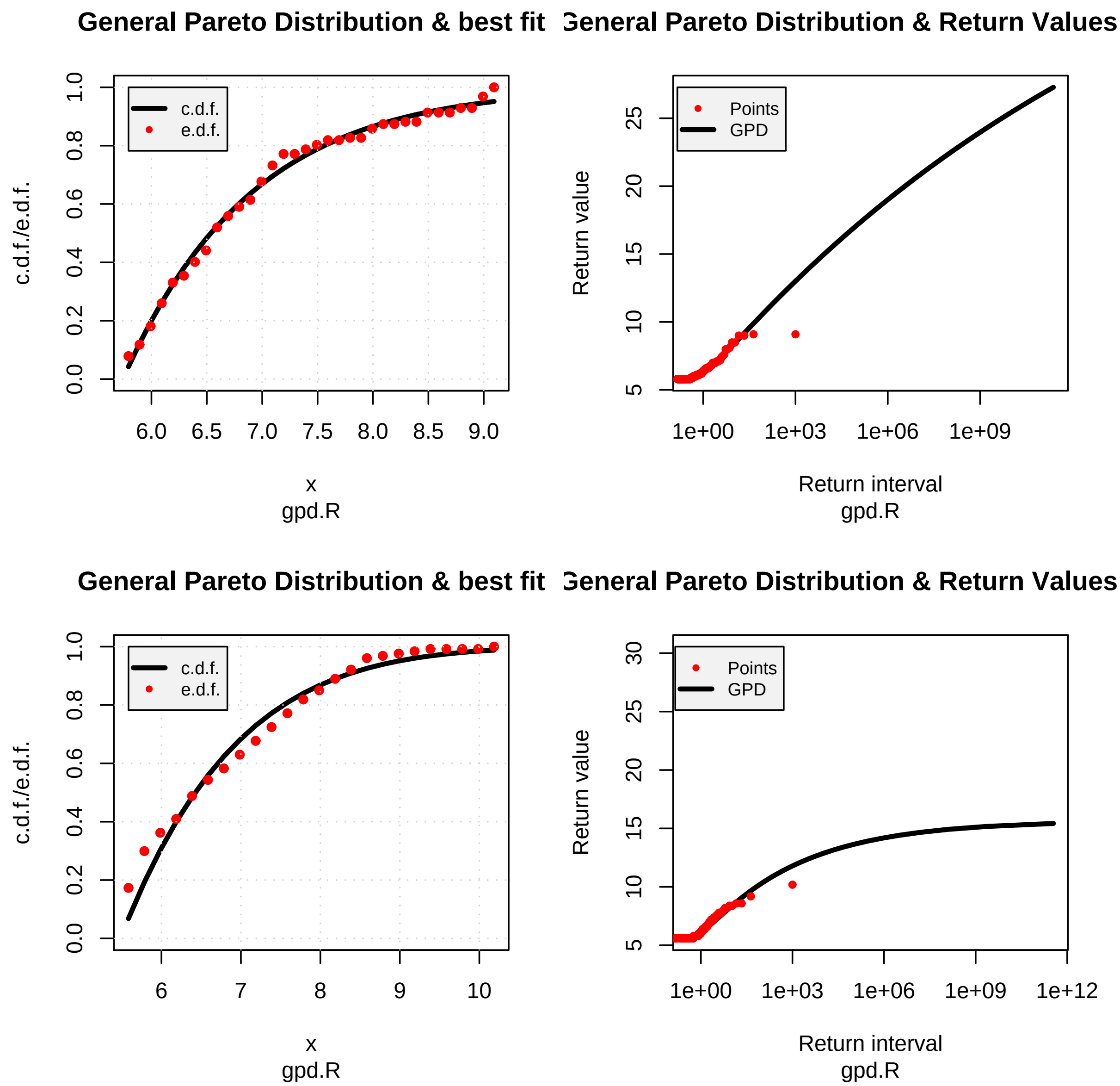

Figure 12. Generalized Pareto Distribution for daily winter absolute minimum temperature predictions in Tromsoe using the analog method (top) and a linear model (bottom).

predictions from downscaling with a linear model is not able anymore to capture the shape of the return value plot for observations, what the analog method can.

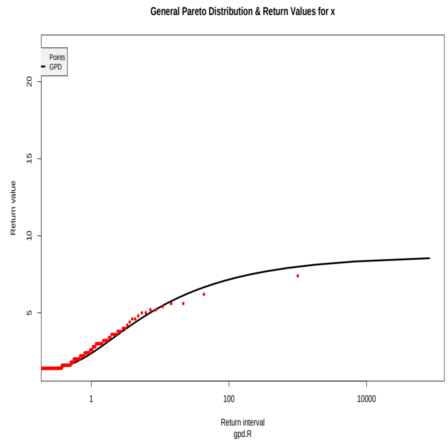

Figure 13. Return level plot for DFJ daily observed temperatures in Alta.

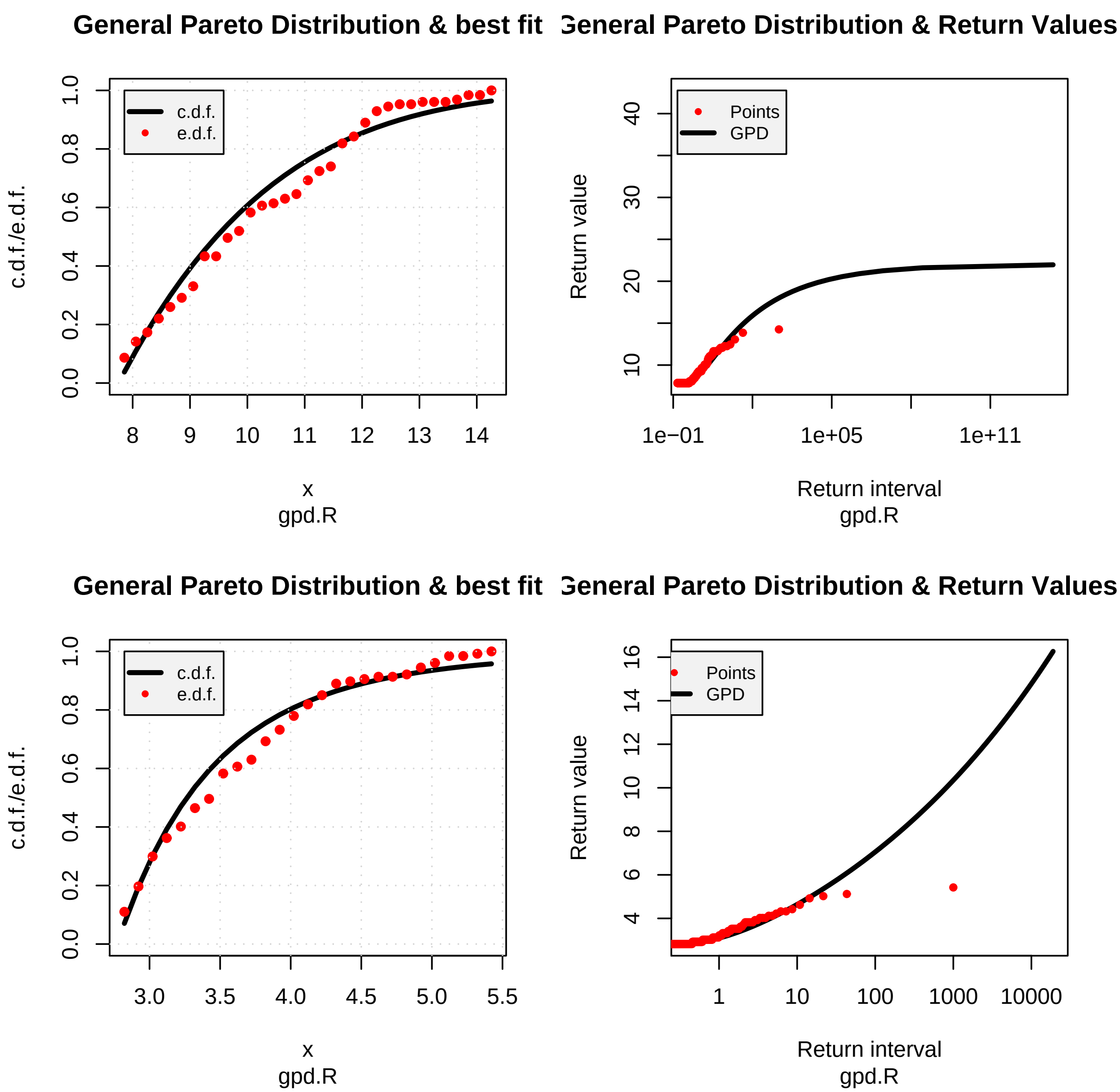

Figure 14. Generalized Pareto Distribution and return value plots for DFJ daily temperature predictionsin Alta, using the analog method (top) and a linear model (bottom).

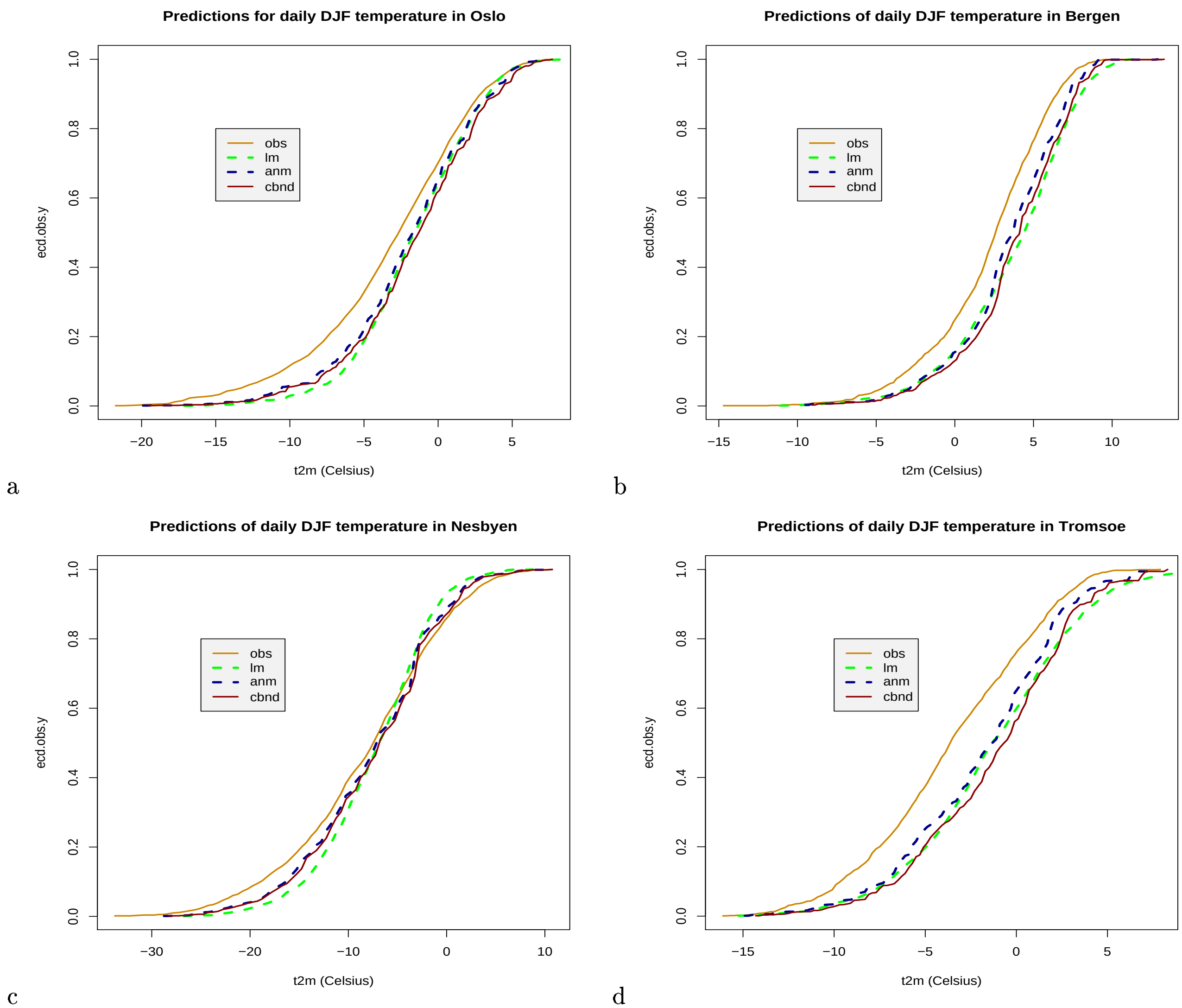

Figure 15. ecd for daily DJF predictions for lm, anm and a combined anm-lm method (cbnd) (a) Oslo, (b)Bergen, (c) Nesbyen, (d) Tromsoe.

4.3 Future prespectives

The previous tables give some evidence of climate change, which many studies have already pointed out (*Houghton* et al., 2001; *Stott* et al., 2001). Changes in the extremes especially are likely to occur and it was shown that temperature especially should increase in the future. This can be taken into account for the previous analysis based on the analog method in order to get more realistic predictions.
To achieve this, two methods can then be thought of. The first of them is to include the whole year in the calibration period. Warming implies indeed that spring (March-May) climatic conditions for instance will get close to March-June period in the next years and this method permits to deals with this problem by looking for analogs in a wider range of climatic patterns.
This way of proceeding can be repeated for autum and winter, the only problem being for summer as no warmer months can be found.
Another method to take into account climate change is to combined the analog method and a linear model, now having in hand the performances of both of them. The idea is to use the trend from the linear model (lm) to scale the predictions from the analog approach. The trend is expressed by the change in mean between the predictions for the scenario and for the control period period. The lm trend, refered

as DT.lm, is then added to anm predictions after removing the anm trend (noted DT.anm), as follows:

$$predictions = anm.predictions - DT.anm + DT.lm$$

A first approach to analyse the results can be to look at the empirical cumulative distribution functions (e.c.d.f) of the linear model (lm) as well as of the anm (anm) and combined methods (cbnd). They are compared in Figure 15, together with the observations.
Four stations from different geographical and meteorological patterns in Norway were used to study daily DJF temperatures: Oslo for southern Norway, Bergen for the western coast, Nesbyen for the inland mountains and Tromsoe for the northern part.
The plot shows that both the analog and the combined methods get close to the observations in the extremes and this, in a better way than the linear model. Future work is planned to analyse more deeply the performance of the combined method and to compare it with the approach consisting in taking the whole year as a calibration period.

Conclusion

The analog method has been presented and applied to daily winter rainfall and temperature, mainly in southern Norway. The results reveal the performance of the technique and its insuffiencies.

The relationships between the observations and the reconstructed time series reveal that the technique is able to reproduce skillfully temperatures but that the results are not so significant when looking at rainfalls. In terms of correlation, the fit is better with a linear model whose main characteristic is to optimize the Pearson coefficient. However, the analog method always proves to be able to return realistic climatic variation and in this respect, presents a relevant advantage to a linear model. In some studies, the variance reproductibility can be a more deciding criterium than the correlation and, in this case, the analog method will then be prefered. One method is then not better than the other, it is the type of the analysis itself which will determine the one to choose.

The study of temperatures and rainfalls in the extremes also suggest the good performance of the analog model and proves that it can be applied to future climate, keeping in mind its weaknesses and strengths. Statistical approaches based on the analog method have then been thought of to deal in a better way with this. Two of them have already been developpped, one using the whole year as a calibration period and the other one using the trend from a linear model. Future work is planned to analyse more deeply the results.

However, what was suggested by all the results is that predicting values requires to consider several model approaches in order to get a more realistic description of the observed series and to anticipate correctly future changes.

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References

Barnett, T.P., 1999. Comparison of Near-Surface Air Temperature Variability in 11 Coupled Global Climate Models. *Journal of Climate*, **12**, 511–518.

Beckmann, B.-R., & Buishand, T.A., 2002. Statistical downscaling relationships for precipitation in the Netherlands and north Germany. *International Journal of Climatology*, **22**, 15–32.

Benestad, R.E., 2001. A comparison between two empirical downscaling strategies. *Int. J. Climatology*, **21**, 1645–1668. DOI 10.1002/joc.703.

Benestad, R.E., 2002. Empirically downscaled temperature scenarios for northern Europe based on a multi-model ensemble. *Climate Research*, **21**, 105–125.

Benestad, R.E., 2003a. *clim.pact-V.1.0*. KLIMA 04/03. The Norwegian Meteorological Institute, PO Box 43 Blindern, 0313 Oslo, Norway.

Benestad, R.E., 2003b. *A first-order evaluation of climate outlooks based on the IPCC A2 and B2 SRES emission scenarios*. KLIMA 03/03. The Norwegian Meteorological Institute, PO Box 43 Blindern, 0313 Oslo, Norway.

Benestad, R.E., 2003c. *Past and future trends in the occurrence of wet and dry periods*. KLIMA 02/03. The Norwegian Meteorological Institute, PO Box 43 Blindern, 0313 Oslo, Norway.

Benestad, R.E., & Hanssen-Bauer, I., 2003. *Empirical-based refinement of dynamically downscaled temperature scenarios in southern Norway*. KLIMA 07/03. The Norwegian Meteorological Institute, PO Box 43 Blindern, 0313 Oslo, Norway.

Christensen, J.H., Risnen, J., Iversen, T., Bjørge, D., Christensen, O. B., & Rummukainen., 2001. A synthesis of regional climate change simulations - A Scandinavian perspective. *Geophys. Res. Lett.*, **28**(6), 1003.

Coles, Stuart., 1999 (June). *Extreme value theory and applications*. Notes from a couse on EVT and applications presented at the 44th Reunião Annual da RBRAS e 8th SEAGRO, at Bucato, São Paulo, Brazil, 26-30 July, 1999. URL: http://www.maths.lancs.ac.uk/~coless.

Flury, B., 1988. *Common Principal Components and Related Multivariate Models*. Wiley Series in Probability and Mathematical Statistics. New York: Wiley.

Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., van der Linden, P.J., Dai, X., Maskell, K., & Johnson, C.A., 2001. *Climate Change 2001: The Scientific Basis*. Contribution of Working Group I to the Third Assessment Report of IPCC. International Panel on Climate Change, (Available from www.ipcc.ch).

Imbert, A., 2002. *Application of extreme values to study climate change*. KLIMA 16/02. met.no, PO Box 43 Blindern, 0313 Oslo, Norway.

Lorenz, E.N., 1956. *Empirical Orthogonal Functions and Statistical Weather Prediction*. Sci. rep. 1. Department of Meteorology, MIT.

Preisendorfer, R.W., 1988. *Principal Component Analysis in Meteorology and Oceanology*. Amsterdam: Elsevier Science Press.

Sengupta, S., & Boyle, J. S., 1998. Using Common Principal Components in Comparing GCM Simulations. *Journal of Climate*, **11**, 816–830.

Stott, P.A., Tett, S.F.B., Jones, G.S., Allen, M.R., Ingram, W.J., & Mitchell, J.F.B., 2001. Attribution of twentieth century temperature change to natural and anthropogenic causes. *Climate Dynamics*, **17**, 1–21.

van den Dool, H.M., 1995. Constructed Analogue Prediction of the East Central Tropical Pacific through Spring 1996. *NOAA: Experimental Long-Lead Forecast Bulletin*, **4**, 41–43.

von Storch, H., & Zwiers, F.W., 1999. *Statistical Analysis in Climate Research*. Cambridge, UK: Cambridge University Press.

von Storch, H., Zorita, E., & Cubasch, U., 1993. Downscaling of Global Climate Change Estimates to Regional Scales: An Application to Iberian Rainfall in Wintertime. *Journal of Climate*, **6**, 1161–1171.

Wilks, D.S., 1995. *Statistical Methods in the Atmospheric Sciences*. Orlando, Florida, USA: Academic Press.

Zorita, E., & von Storch, H., 1999. The Analog Method as a Simple Statistical Downscaling Technique: Comparison with More Complicated Methods. *Journal of Climate*, **12**, 2474–2489.

Appendix

TABLE 4. A summary of the downscaled scenarios for the different stations in DJF season. The downscaling was applied on precipitations (mm) using the analog method as a statistical approach. The columns list the longitude (°E), latitude (°N), altitude (m. a.s.l), the variance accounted for by the multiple regression (%), estimated precipitation change (°C) and the 95 percentile for both the control period and the scenario period.

	location	station	lon	lat	alt	r2	rr.chng	var	q95ctl	q95sc
1	Røros	10400.00	11.38	62.57	628.00	5.00	0.09	1.14	−0.63	9.37
2	Prestebakke	1130.00	11.54	58.99	157.00	5.00	0.65	1.12	−3.41	27.39
3	Østre	11500.00	10.87	60.70	264.00	3.00	0.28	1.31	−0.06	12.84
4	Lillehammer	12680.00	10.48	61.09	114.00	15.00	−0.06	0.86	−1.17	13.83
5	Venabu	13420.00	10.11	61.65	930.00	6.00	0.00	0.99	−0.91	14.99
6	Skåbu	13670.00	9.38	61.52	890.00	3.00	−0.20	0.96	−0.41	12.89
7	Gjeilo	15540.00	8.45	61.87	378.00	3.00	0.04	0.85	0.25	5.25
8	Bråtå	15720.00	7.86	61.91	712.00	21.00	0.60	1.15	−0.52	17.68
9	Fokstua	16610.00	9.29	62.11	386.00	4.00	0.07	1.06	−0.48	6.02
10	Rygge	17150.00	10.79	59.38	205.00	14.00	0.41	1.04	−3.03	20.17
11	JelØy	17290.00	10.59	59.44	12.00	6.00	0.21	0.99	−1.43	19.57
12	Oslo	18700.00	10.72	59.94	380.00	13.00	0.73	1.24	−1.97	23.03
13	Tryvasshøgda	18960.00	10.69	59.99	528.00	8.00	0.72	1.19	−1.64	27.56
14	Fornebu	19400.00	10.62	59.89	10.00	12.00	0.34	1.09	−1.47	19.63
15	Dønski	19480.00	10.50	59.90	59.00	16.00	0.54	1.09	−1.88	17.12
16	Asker	19710.00	10.44	59.86	163.00	15.00	0.11	0.98	−1.59	18.41
17	Vest−torpa	21680.00	10.04	60.94	542.00	11.00	0.17	1.14	0.30	12.60
18	Fagernes	23420.00	9.24	60.99	365.00	5.00	−0.31	0.79	−0.62	12.48
19	Løken	23500.00	9.07	61.12	525.00	6.00	−0.29	0.91	−0.61	12.79
20	Nesbyen	24880.00	9.12	60.57	70.00	14.00	−0.03	0.91	−0.67	6.43
21	Geilo	25590.00	8.20	60.52	353.00	13.00	0.11	1.21	−1.52	9.68
22	Finse	25840.00	7.50	60.60	1224.00	28.00	0.19	1.10	−1.49	22.61
23	Måkerøy	27410.00	10.44	59.16	43.00	5.00	0.12	1.05	−1.61	15.89
24	Færder	27500.00	10.53	59.03	6.00	8.00	0.52	1.06	−2.45	19.95
25	Kongsberg	28370.00	9.65	59.66	168.00	12.00	−0.08	0.92	−0.36	14.14
26	Lungdal	28800.00	9.52	59.91	142.00	23.00	−0.06	0.89	−1.32	13.38
27	Magnor	2950.00	12.21	59.97	154.00	2.00	0.32	1.10	−0.65	11.55
28	Moesstrand	31620.00	8.18	59.84	388.00	22.00	−0.06	0.87	−2.26	13.64
29	Lyngør	35860.00	9.15	58.63	4.00	7.00	0.84	1.14	−0.64	18.26
30	Torungen	36200.00	8.79	58.38	12.00	7.00	1.26	1.28	−1.59	23.61
31	Nelaug	36560.00	8.63	58.66	142.00	18.00	0.84	1.29	−2.26	36.64
32	Tveitsund	37230.00	8.52	59.03	124.00	26.00	0.77	1.18	−3.03	29.17
33	Landvik	38140.00	8.52	58.33	6.00	10.00	0.54	1.14	0.07	18.57
34	Kjevik	39040.00	8.07	58.20	23.00	15.00	1.49	1.24	−4.06	37.54
35	Oksøy	39100.00	8.05	58.07	9.00	5.00	1.47	1.27	−1.64	27.86
36	Byglandsfjord	39690.00	7.80	58.67	212.00	24.00	1.62	1.29	−2.85	44.55
37	Lindesnes	41770.00	7.05	57.98	13.00	6.00	0.51	1.03	−2.37	22.63
38	Lista	42160.00	6.57	58.11	14.00	10.00	0.97	1.11	−3.48	25.92
39	Sirdal	42920.00	6.85	58.89	242.00	34.00	1.19	1.12	−7.72	51.78
40	Ualand	43500.00	6.35	58.55	196.00	17.00	2.72	1.24	−5.39	84.11
41	Obrestad	44080.00	5.56	58.66	24.00	10.00	1.17	1.31	−1.92	30.28
42	Sola	44560.00	5.64	58.88	312.00	10.00	0.85	1.27	−2.21	29.29
43	Suldal	46200.00	6.42	59.46	58.00	14.00	1.13	1.09	−1.47	59.03
44	Midtlæger	46510.00	6.99	59.83	1079.00	21.00	−0.17	0.93	0.48	8.48
45	Sauda	46610.00	6.36	59.65	240.00	26.00	1.81	1.16	−4.44	49.56

TABLE 4 continued...

	location	station	lon	lat	alt	r2	rr.chng	var	q95ctl	q95sc
46	Nedre	46910.00	5.75	59.48	64.00	9.00	1.37	1.04	−2.72	44.58
47	Utsira	47300.00	4.88	59.31	55.00	8.00	0.52	1.22	−2.68	28.62
48	Gardermoen	4780.00	11.08	60.21	202.00	13.00	0.51	1.11	−0.99	15.01
49	Slåtterøy	48330.00	5.07	59.91	15.00	7.00	1.03	1.19	−1.64	29.06
50	Upsangervatn	48390.00	5.77	59.84	60.00	4.00	0.72	1.10	−0.39	54.81
51	Eidfjord	49580.00	6.86	60.47	165.00	15.00	0.49	1.17	−1.50	52.90
52	Omastrand	50130.00	5.98	60.22	2.00	13.00	1.58	1.13	−1.15	70.75
53	Kvamskogen	50300.00	5.91	60.39	210.00	30.00	1.33	1.12	−6.19	67.81
54	Flesland	50500.00	5.23	60.29	48.00	13.00	0.60	1.18	−1.90	21.80
55	Bergen	50540.00	5.33	60.38	23.00	16.00	1.35	1.18	−3.78	42.02
56	Voss	51590.00	6.50	60.65	30.00	23.00	0.74	1.14	−2.78	31.12
57	Reimegrend	51670.00	6.74	60.69	590.00	19.00	1.12	1.14	−3.39	49.91
58	Modalen	52290.00	5.95	60.84	114.00	23.00	3.04	1.17	−0.83	66.37
59	Hellisøy	52530.00	4.71	60.75	20.00	4.00	0.22	1.27	−1.03	16.77
60	Takle	52860.00	5.38	61.03	38.00	17.00	2.72	1.15	−2.31	93.39
61	Vangsnes	53100.00	6.65	61.17	51.00	2.00	1.04	1.14	1.20	27.80
62	Lærdal	54130.00	7.52	61.06	36.00	14.00	0.47	1.15	−0.75	17.25
63	Fortun	55160.00	7.70	61.50	27.00	16.00	0.99	1.20	−0.53	26.27
64	Sognefjell	55290.00	8.00	61.57	1413.00	16.00	−0.10	1.04	−1.11	11.19
65	Kråkenes	59100.00	4.99	62.03	41.00	15.00	0.49	1.22	0.84	16.04
66	Svinøy	59800.00	5.27	62.33	38.00	2.00	0.59	1.47	−0.26	17.57
67	Flisa	6040.00	12.02	60.61	184.00	7.00	0.34	1.30	−0.64	8.80
68	Tafjord	60500.00	7.42	62.23	52.00	26.00	−0.06	1.07	−0.24	23.06
69	Vigra	60990.00	6.12	62.56	106.00	13.00	0.38	1.33	−1.12	19.38
70	Hjelvik	61170.00	7.21	62.62	21.00	13.00	0.38	1.11	0.53	36.43
71	Lesjaskog	61770.00	8.37	62.23	621.00	10.00	−0.24	0.85	1.19	14.99
72	Ona	62480.00	6.54	62.86	13.00	7.00	0.94	1.30	0.68	27.98
73	Tingvoll	64550.00	8.30	62.84	69.00	15.00	−0.08	1.07	1.61	22.51
74	Vinjeoera	65110.00	9.00	63.21	229.00	13.00	−0.23	1.09	−0.30	40.30
75	Sula	65940.00	8.47	63.85	5.00	4.00	0.21	1.17	1.17	18.77
76	Berkaak	66730.00	10.02	62.82	231.00	19.00	−0.26	0.85	0.53	7.53
77	Selbu	68340.00	11.12	63.21	117.00	13.00	−0.26	0.96	−0.11	7.89
78	Vaernes	69100.00	10.94	63.46	23.00	13.00	0.08	1.08	−0.18	18.12
79	Meråker	69330.00	11.70	63.44	145.00	7.00	−0.08	0.98	0.24	16.55
80	Rena	7010.00	11.44	61.16	240.00	9.00	0.47	1.18	−0.24	13.86
81	Ørland	71550.00	9.60	63.70	10.00	6.00	0.17	1.21	−0.15	27.85
82	Halten	71850.00	9.41	64.17	16.00	6.00	−0.02	1.02	1.27	14.17
83	Buholmråsa	71990.00	10.45	64.40	18.00	2.00	0.20	1.04	1.58	14.38
84	Namdalseid	72100.00	11.20	64.25	86.00	14.00	0.02	1.04	1.36	19.86
85	Harran	73620.00	12.51	64.59	118.00	14.00	−0.08	0.99	0.88	20.08
86	Nordøyan	75410.00	10.55	64.80	33.00	2.00	0.27	1.14	0.84	15.84
87	Sklinna	75550.00	11.00	65.20	23.00	2.00	−0.01	0.92	0.88	12.68
88	Leka	75600.00	11.70	65.10	47.00	7.00	−0.19	0.99	1.69	17.19
89	Susendal	77750.00	14.02	65.52	265.00	24.00	−0.35	1.14	−1.06	22.04
90	Evenstad	8130.00	11.14	61.41	255.00	14.00	−0.15	0.83	−1.61	25.89
91	Sørnesset	8710.00	10.15	61.89	739.00	1.00	0.24	1.15	−0.53	10.97

TABLE 5. A comparison between the performance of the analog method (anm) and the linear model (lm). The columns list the Pearson correlation coefficient and the proportional change in variance between the scenario and the control intervals. The analysis was on December-February daily temperature for stations in southern Norway.

n	station	location	r.anm	r.lm	var.anm	var.lm
1	10400	Røros	0.71	0.84	84.76	70.22
2	1130	Prestebakke	0.40	0.58	83.31	33.26
3	11500	Østre	0.69	0.83	87.25	69.60
4	12680	Lillehammer	0.74	0.84	83.69	70.61
5	13420	Venabu	0.70	0.84	78.47	69.90
6	13670	Skåbu	0.61	0.76	82.89	58.30
7	15540	Gjeilo	0.72	0.83	93.67	69.19
8	15720	Bråtå	0.72	0.83	81.71	69.40
9	16610	Fokstua	0.75	0.86	80.09	74.67
10	17150	Rygge	0.74	0.84	78.93	70.10
11	17290	Jeløy	0.76	0.85	78.33	72.21
12	18700	Oslo	0.73	0.84	79.12	69.93
13	18960	Tryvasshøgda	0.73	0.84	77.34	71.07
14	19400	Fornebu	0.73	0.82	80.13	68.03
15	19480	Dønski	0.69	0.81	79.86	65.27
16	19710	Asker	0.06	0.15	87.58	2.27
17	21680	Vest-torpa	0.70	0.85	94.76	72.46
18	23420	Fagernes	0.68	0.8	86.74	64.11
19	23500	Løken	0.65	0.82	93.06	66.77
20	24880	Nesbyen	0.68	0.79	83.55	61.91
21	25590	Geilo	0.70	0.83	82.86	69.17
22	25840	Finse	0.22	0.32	80.09	10.35
23	27410	Måkerøy	0.56	0.70	81.71	49.6
24	27500	Færder	0.74	0.83	74.77	69.36
25	28370	Kongsberg	0.69	0.82	80.94	66.71
26	28800	Lungdal	0.69	0.82	82.67	67.63
27	2950	Magnor	0.73	0.84	80.18	71.37
28	31620	Moesstrand	0.18	0.36	85.08	13.18
29	35860	Lyngør	0.73	0.83	74.94	69.01
30	36200	Torungen	0.73	0.84	74.49	70.15
31	36560	Nelaug	0.57	0.73	79.48	52.84
32	37230	Tveitsund	0.69	0.82	80.04	67.7
33	38140	Landvik	0.68	0.83	85.80	69.21
34	39040	Kjevik	0.72	0.83	78.43	69.11
35	39100	Oksøy	0.74	0.85	76.06	71.58
36	39690	Byglandsfjord	0.69	0.82	77.20	67.34
37	41770	Lindesnes	0.75	0.85	73.16	71.49
38	42160	Lista	0.75	0.85	75.37	72.25
39	42920	Sirdal	0.14	0.26	81.01	6.71
40	43500	Ualand	0.73	0.84	76.57	71.00
41	44080	Obrestad	0.78	0.87	77.34	76.24
42	44560	Sola	0.75	0.86	75.97	73.37
43	46200	Suldal	0.69	0.82	84.93	66.55
44	46510	Midtlæger	0.36	0.56	90.94	31.47
45	46610	Sauda	0.70	0.83	81.83	68.62

TABLE 5 continued...

n	station	location	r.anm	r.lm	var.anm	var.lm
46	46910	Nedre	0.73	0.85	79.99	73.00
47	47300	Utsira	0.75	0.86	73.39	74.20
48	4780	Gardermoen	0.72	0.83	79.91	68.07
49	48330	Slåtterøy	0.74	0.86	75.85	74.8
50	48390	Upsangervatn	0.16	0.16	94.77	2.45
51	49580	Eidfjord	0.18	0.24	84.83	5.71
52	50130	Omastrand	0.71	0.84	79.42	69.82
53	50300	Kvamskogen	0.73	0.85	79.68	71.78
54	50500	Flesland	0.76	0.87	76.2	75.29
55	50540	Bergen	0.76	0.87	79.66	76.49
56	51590	Voss	0.74	0.84	80.57	70.43
57	51670	Reimegrend	0.54	0.74	87.49	55.06
58	52290	Modalen	0.71	0.83	86.08	69.06
59	52530	Hellisøy	0.11	0.07	89.44	0.48
60	52860	Takle	0.76	0.87	78.97	75.62
61	53100	Vangsnes	0.61	0.77	83.59	59.82
62	54130	Lærdal	0.71	0.82	83.16	66.79
63	55160	Fortun	0.74	0.82	81.55	67.83
64	55290	Sognefjell	0.78	0.89	82.7	78.49
65	59100	Kråkenes	0.14	0.22	99.09	4.85
66	59800	Svinøy	0.79	0.89	80.73	79.53
67	6040	Flisa	0.49	0.67	82.43	45.50
68	60500	Tafjord	0.18	0.35	94.27	11.92
69	60990	Vigra	0.78	0.88	82.58	77.68
70	61170	Hjelvik	0.76	0.87	82.29	75.37
71	61770	Lesjaskog	0.72	0.83	80.85	69.68
72	62480	Ona	0.1	0.16	85.91	2.55
73	64550	Tingvoll	0.70	0.82	84.51	67.92
74	65110	Vinjeoera	0.11	0.21	89.38	4.54
75	65940	Sula	0.52	0.71	83.12	50.59
76	66730	Berkaak	0.70	0.86	84.22	73.93
77	68340	Selbu	0.23	0.37	81.91	13.65
78	69100	Vaernes	0.74	0.85	78.86	71.45
79	69330	Meråker	0.72	0.83	80.06	69.42
80	7010	Rena	0.71	0.82	81.33	67.04
81	71550	Ørland	0.77	0.86	78.09	74.56
82	71850	Halten	0.75	0.85	76.98	72.6
83	71990	Buholmråsa	0.79	0.86	78.56	74.76
84	72100	Namdalseid	0.07	0.13	102.7	1.75
85	73620	Harran	0.69	0.83	81.32	69.52
86	75410	Nordøyan	0.21	0.22	102.43	4.62
87	75550	Sklinna	0.75	0.85	79.58	72.6
88	75600	Leka	0.35	0.55	80.18	30.48
89	77750	Susendal	0.68	0.81	80.76	65.81
90	8130	Evenstad	0.32	0.44	79.38	19.11
91	8710	Sørnesset	0.19	0.32	83.6	10.31

TABLE 6. A summary of the downscaled scenarios for the different stations in DJF season. The downscaling was applied on temperature using the analog method as a statistical approach. The columns list the longitude (°E), latitude (°N), altitude (m. a.s.l), the variance accounted for by the multiple regression (%), estimated temperature change (°C), corresponding t-test, the proportional change in variance between the scenario and the control intervals, and the estimated change in the 95 and 5 percentiles (°C).

	location	station	lon	lat	alt	R2	p.val	t.chng	t.test	var	q95	q05
1	Røros	10400	11.38	62.57	628.00	62.00	0	0.57	0.01	1.05	0.88	0.92
2	Prestebakke	1130	11.54	58.99	157.00	19.00	0	0.47	0.00	1.01	0.60	1.30
3	Østre	11500	10.87	60.70	264.00	58.00	0	0.83	0.00	0.98	0.08	0.37
4	Lillehammer	12680	10.48	61.09	114.00	56.00	0	0.71	0.00	0.99	0.63	1.05
5	Venabu	13420	10.11	61.65	930.00	55.00	0	0.67	0.00	0.94	0.28	0.87
6	Skåbu	13670	9.38	61.52	890.00	40.00	0	0.74	0.00	0.95	0.50	0.96
7	Gjeilo	15540	8.45	61.87	378.00	56.00	0	0.71	0.00	1.05	1.54	−0.68
8	Bråtå	15720	7.86	61.91	712.00	58.00	0	0.96	0.00	0.96	0.78	0.61
9	Fokstua	16610	9.29	62.11	386.00	60.00	0	0.91	0.00	0.99	0.54	0.67
10	Rygge	17150	10.79	59.38	205.00	59.00	0	1.14	0.00	0.98	1.02	1.85
11	Jeløy	17290	10.59	59.44	12.00	68.00	0	1.11	0.00	0.95	0.32	0.77
12	Oslo	18700	10.72	59.94	380.00	63.00	0	0.98	0.00	1.01	1.45	1.04
13	Tryvasshøgda	18960	10.69	59.99	528.00	60.00	0	0.90	0.00	0.89	0.23	1.17
14	Fornebu	19400	10.62	59.89	10.00	62.00	0	1.01	0.00	0.96	0.32	1.20
15	Dønski	19480	10.50	59.90	59.00	57.00	0	1.02	0.00	0.96	0.32	0.98
16	Asker	19710	10.44	59.86	163.00	2.00	0	−0.19	0.28	0.96	−1.02	0.00
17	Vest−torpa	21680	10.04	60.94	542.00	54.00	0	0.62	0.00	0.98	−0.93	1.45
18	Fagernes	23420	9.24	60.99	365.00	51.00	0	0.85	0.00	0.98	0.62	1.95
19	Løken	23500	9.07	61.12	525.00	55.00	0	0.86	0.00	0.94	0.46	0.69
20	Nesbyen	24880	9.12	60.57	70.00	50.00	0	1.06	0.00	0.99	0.77	0.61
21	Geilo	25590	8.20	60.52	353.00	55.00	0	0.84	0.00	0.99	0.93	0.69
22	Finse	25840	7.50	60.60	1224.00	7.00	0	0.12	0.50	1.01	0.21	0.08
23	Måkerøy	27410	10.44	59.16	43.00	37.00	0	0.57	0.00	1.03	1.11	0.22
24	Færder	27500	10.53	59.03	6.00	64.00	0	0.86	0.00	0.96	0.65	0.29
25	Kongsberg	28370	9.65	59.66	168.00	58.00	0	1.05	0.00	1.02	1.26	0.71
26	Lungdal	28800	9.52	59.91	142.00	57.00	0	0.84	0.00	0.97	0.12	0.81
27	Magnor	2950	12.21	59.97	154.00	62.00	0	1.26	0.00	0.90	0.97	1.10
28	Moesstrand	31620	8.18	59.84	388.00	6.00	0	0.60	0.00	0.97	0.62	0.80
29	Lyngør	35860	9.15	58.63	4.00	60.00	0	0.82	0.00	0.93	0.26	0.57
30	Torungen	36200	8.79	58.38	12.00	59.00	0	0.73	0.00	0.94	0.59	0.55
31	Nelaug	36560	8.63	58.66	142.00	36.00	0	1.03	0.00	0.97	1.13	1.68
32	Tveitsund	37230	8.52	59.03	124.00	54.00	0	1.13	0.00	0.91	0.97	1.24
33	Landvik	38140	8.52	58.33	6.00	50.00	0	0.85	0.00	0.85	0.24	0.88
34	Kjevik	39040	8.07	58.20	23.00	52.00	0	0.76	0.00	0.96	0.44	0.36
35	Oksøy	39100	8.05	58.07	9.00	57.00	0	0.68	0.00	0.95	0.53	0.46
36	Byglandsfjord	39690	7.80	58.67	212.00	53.00	0	0.97	0.00	0.87	1.00	1.57
37	Lindesnes	41770	7.05	57.98	13.00	58.00	0	1.65	0.00	0.89	0.56	0.28
38	Lista	42160	6.57	58.11	14.00	60.00	0	0.74	0.00	0.97	0.77	0.06
39	Sirdal	42920	6.85	58.89	242.00	5.00	0	−0.06	0.68	0.98	−0.13	0.13
40	Ualand	43500	6.35	58.55	196.00	54.00	0	0.71	0.00	0.94	0.42	0.20
41	Obrestad	44080	5.56	58.66	24.00	61.00	0	0.81	0.00	0.97	0.44	0.99
42	Sola	44560	5.64	58.88	312.00	57.00	0	0.71	0.00	0.93	0.50	0.71
43	Suldal	46200	6.42	59.46	58.00	47.00	0	0.79	0.00	0.88	0.07	1.67
44	Midtlæger	46510	6.99	59.83	1079.00	25.00	0	0.43	0.00	1.01	0.00	0.47
45	Sauda	46610	6.36	59.65	240.00	50.00	0	0.76	0.00	0.88	0.50	2.07

TABLE 6 continued...

	location	station	lon	lat	alt	R2	p.val	t.chng	t.test	var	q95	q05
46	Nedre	46910	5.75	59.48	64.00	54.00	0	0.80	0.00	0.99	0.65	0.87
47	Utsira	47300	4.88	59.31	55.00	58.00	0	0.53	0.00	0.97	0.47	0.36
48	Gardermoen	4780	11.08	60.21	202.00	62.00	0	1.21	0.00	0.93	0.45	1.40
49	Slåtterøy	48330	5.07	59.91	15.00	54.00	0	0.52	0.00	0.93	0.56	0.65
50	Upsangervatn	48390	5.77	59.84	60.00	2.00	0	−0.03	0.75	1.09	0.99	−0.25
51	Eidfjord	49580	6.86	60.47	165.00	4.00	0	0.07	0.48	1.01	0.27	0.27
52	Omastrand	50130	5.98	60.22	2.00	53.00	0	0.73	0.00	1.01	0.67	0.84
53	Kvamskogen	50300	5.91	60.39	210.00	57.00	0	0.88	0.00	0.94	0.55	1.21
54	Flesland	50500	5.23	60.29	48.00	58.00	0	0.76	0.00	0.98	0.62	0.58
55	Bergen	50540	5.33	60.38	23.00	55.00	0	0.69	0.00	1.00	0.54	0.73
56	Voss	51590	6.50	60.65	30.00	59.00	0	1.12	0.00	0.83	0.95	2.76
57	Reimegrend	51670	6.74	60.69	590.00	32.00	0	0.41	0.00	1.03	0.64	0.55
58	Modalen	52290	5.95	60.84	114.00	49.00	0	1.03	0.00	0.82	0.29	2.79
59	Hellisøy	52530	4.71	60.75	20.00	4.00	0	0.18	0.01	0.91	0.19	0.10
60	Takle	52860	5.38	61.03	38.00	58.00	0	0.74	0.00	0.98	0.50	0.58
61	Vangsnes	53100	6.65	61.17	51.00	44.00	0	0.54	0.00	1.04	0.74	0.14
62	Lærdal	54130	7.52	61.06	36.00	53.00	0	0.74	0.00	0.94	0.35	1.13
63	Fortun	55160	7.70	61.50	27.00	61.00	0	0.92	0.00	0.84	0.50	2.01
64	Sognefjell	55290	8.00	61.57	1413.00	60.00	0	0.96	0.00	1.10	1.19	−0.12
65	Kråkenes	59100	4.99	62.03	41.00	8.00	0	0.12	0.13	1.10	0.85	0.21
66	Svinøy	59800	5.27	62.33	38.00	54.00	0	0.58	0.00	0.96	0.53	0.28
67	Flisa	6040	12.02	60.61	184.00	35.00	0	1.30	0.00	0.94	0.29	1.57
68	Tafjord	60500	7.42	62.23	52.00	10.00	0	0.08	0.49	1.05	0.15	−0.22
69	Vigra	60990	6.12	62.56	106.00	55.00	0	0.66	0.00	0.99	1.00	0.30
70	Hjelvik	61170	7.21	62.62	21.00	60.00	0	0.82	0.00	1.08	0.91	1.01
71	Lesjaskog	61770	8.37	62.23	621.00	54.00	0	1.01	0.00	0.99	0.98	2.17
72	Ona	62480	6.54	62.86	13.00	2.00	0	0.03	0.73	1.09	−0.09	0.28
73	Tingvoll	64550	8.30	62.84	69.00	54.00	0	0.77	0.00	1.01	1.28	1.52
74	Vinjeoera	65110	9.00	63.21	229.00	2.00	0	−0.10	0.48	1.05	−0.01	−0.28
75	Sula	65940	8.47	63.85	5.00	26.00	0	0.60	0.00	0.96	0.62	0.49
76	Berkaak	66730	10.02	62.82	231.00	55.00	0	0.83	0.00	1.07	0.89	0.92
77	Selbu	68340	11.12	63.21	117.00	7.00	0	0.38	0.03	1.07	0.43	0.12
78	Vaernes	69100	10.94	63.46	23.00	64.00	0	1.09	0.00	0.89	0.79	1.96
79	Meråker	69330	11.70	63.44	145.00	58.00	0	0.96	0.00	0.96	0.92	1.33
80	Rena	7010	11.44	61.16	240.00	60.00	0	1.16	0.00	1.00	0.80	1.30
81	Ørland	71550	9.60	63.70	10.00	63.00	0	0.87	0.00	0.85	0.62	1.69
82	Halten	71850	9.41	64.17	16.00	60.00	0	0.84	0.00	0.81	0.51	0.90
83	Buholmråsa	71990	10.45	64.40	18.00	66.00	0	1.15	0.00	0.77	0.70	1.46
84	Namdalseid	72100	11.20	64.25	86.00	0.00	10.33	0.24	0.01	0.94	0.23	0.54
85	Harran	73620	12.51	64.59	118.00	56.00	0	1.31	0.00	0.86	0.55	3.77
86	Nordøyan	75410	10.55	64.80	33.00	4.00	0	−0.11	0.24	0.97	−0.19	0.04
87	Sklinna	75550	11.00	65.20	23.00	68.00	0	1.09	0.00	0.74	0.63	1.53
88	Leka	75600	11.70	65.10	47.00	15.00	0	0.88	0.00	0.96	0.68	0.76
89	Susendal	77750	14.02	65.52	265.00	63.00	0	1.82	0.00	0.86	0.70	2.15
90	Evenstad	8130	11.14	61.41	255.00	15.00	0	0.71	0.00	1.08	1.53	1.84
91	Sørnesset	8710	10.15	61.89	739.00	5.00	0	0.23	0.16	1.20	0.91	−1.95

R documentation

of all in 'anm/man'

April 11, 2003

R topics documented:

`anm` *The Analog method*

Description

anm is used to compute the analog method.

Usage

```
anm(formula,data,weights=NULL,cross.valid=NULL)
```

Arguments

`formula`	a symbolic description of the model to be fit.
`data`	the data.frame containing the variables in the model.
`weights`	an optional matrix of weights to be used in the fitting process.
`cross.valid`	an optional matrix of booleans. If not specified, a cross validation is used in the fitting process.

Details

Models for *anm* are specified symbolically. A typical model has the form *predictand terms* where *terms* is a series of predictors whose specification can be of the for *first + second*. anm calls the lower level function [clim.pact]anm.fit.

Value

An object of class "anm". An object of class "anm" is a list containing the following components:

`coefficients`	a vector containing the values for the principal components corresponding to the maximum among observations.
`contrasts`	(not used).
`call`	the matched call.
`terms`	the terms object used.
`model`	the model frame used.
`x`	the matrix used for predictors.
`y`	the predictand.
`weights`	the matrix of weights.
`cross.valid`	equals to True if the cross.validation will be used for the fitting process.
`data`	the input data.frame.

Author(s)

Alexandra Imbert

References

URL http://www.R-project.org/

See Also

linkpredict.anm, linkstepANM

Examples

```
library(survival)
library(clim.pact)
data(temp.era)
data(susendal)
y<-susendal$V6 # temperatures
X<- eof$PC[,c(1,2)]
calibration <- c(susendal$V4>1979 & susendal$V4<1990 & (susendal$V3==1 | susendal$V3==2 | susendal$V3=
evaluation <- c((susendal$V4>1990 & susendal$V4<1993 | susendal$V4==1990) & (susendal$V3==1 | susendal
y.calib <- y[calibration]
y.eval <- y[evaluation]
eof.calib <- c(eof$yy>1979 & eof$yy<1990)
eof.eval <- c(eof$yy> 1990 & eof$yy<1993| eof$yy==1990)
period <- c(calibration, evaluation)
y.period <- y[(susendal$V4>1979 & susendal$V4<1993) & (susendal$V3==1 | susendal$V3==2 | susendal$V3==
test.data <-data.frame(y=y.period,
                       X1=X[eof$yy< 1993 & eof$yy> 1979,1],
```

```
                    X2=X[eof$yy< 1993 & eof$yy> 1979,2],
                    yy=eof$yy[eof.calib | eof.eval],
                    mm=eof$mm[eof.calib | eof.eval],
                    dd=eof$dd[eof.calib | eof.eval])
anm(y ~ X1 + X2,data=test.data)
```

`anm.fit` *Support function for anm*

Description

Basic computing engine called by anm to implement the analog method. This should usually not be used directly.

Usage

```
anm.fit(x, y, tol = 1e-07, ...)
```

Arguments

`x`	design matrix of dimension n * p.
`y`	vector of observations of length n.
`tol`	if equal to 1, information is printed during the running of step.
`cross.valid`	tolerance for the qr decomposition. Default is 1e-7.
`...`	currently disregarded.

Value

A list with components

`coefficients`	vector containing the highest value among observations and the values of the predictors at this date.
`residuals`	n vector.
`fitted.values`	n vector.
`effects`	n vector.
`rank`	integer, giving the rank.
`df.residual`	degrees of freedom of residuals.
`qr`	the QR decomposition, see qr.

Author(s)

Alexandra Imbert

References

URL `http://www.R-project.org/`

See Also

anm, predict.anm

`eof` *Daily common EOF.*

Description

See [clim.pact]EOF

`plotANM` *Plot Diagnostics for an anm Object.*

Description

Three plots are provided: a plot of the minimum distances versus time, a plot comparing the analogs from [clim.pact]EOF and observations and a plot of errors versus time.

Usage

```
plotANM(x,tmp,station,eof.file,leps)
```

Arguments

`x`	the anm object inheriting from anm routine and for which prediction is desired.
`tmp`	True if the analysis is on temperature, False if on precipitation.
`station`	the name of the station.
`eof.file`	string giving the name of the eof file used for the study.
`leps`	if true, postscripts are created for the plots.

Author(s)

Alexandra Imbert

See Also

anm, stepANM, predict.anm, print.anm

Examples

```
library(survival)
library(clim.pact)
data(temp.era)
data(susendal)
y<-susendal$V6 # temperatures
X<- eof$PC[,c(1,2)]
calibration <- c(susendal$V4>1979 & susendal$V4<1990 & (susendal$V3==1 | susendal$V3==2 | susendal$V3=
evaluation <- c((susendal$V4>1990 & susendal$V4<1993 | susendal$V4==1990) & (susendal$V3==1 | susendal
y.calib <- y[calibration]
y.eval <- y[evaluation]
eof.calib <- c(eof$yy>1979 & eof$yy<1990)
eof.eval <- c(eof$yy> 1990 & eof$yy<1993| eof$yy==1990)
```

```
period <- c(calibration, evaluation)
y.period <- y[(susendal$V4>1979 & susendal$V4<1993) & (susendal$V3==1 | susendal$V3==2 | susendal$V3==
test.data <-data.frame(y=y.period,
                       X1=X[eof$yy< 1993 & eof$yy> 1979,1],
                       X2=X[eof$yy< 1993 & eof$yy> 1979,2],
                       yy=eof$yy[eof.calib | eof.eval],
                       mm=eof$mm[eof.calib | eof.eval],
                       dd=eof$dd[eof.calib | eof.eval])
test.anm<-anm(y ~ X1 + X2,data=test.data)
plotANM(test.anm,TRUE,"Susendal","eof_ERA-15_TEM_16E31E-64N73N_DJF",FALSE)
```

`predict.anm` *Predict method for anm objects.*

Description

Returns the predicted values based on the anm object.

Usage

```
predict.anm(object,newdata=NULL,se.fit=FALSE, ...)
```

Arguments

`object`	the anm object inheriting from anm routine.
`newdata`	an optional independant data. If specified, only the vector of predictions is returned.
`se.fit`	if false, only the vector of predictions is returned.
`...`	further arguments passed to or from other methods.

Value

A list with components

`problem.dimension`	the number of predictor variables.
`period.length`	the time period.
`d.min`	the vector of minimum distances.
`date.min`	the vector containing the dates corresponding to the minimum distances.
`analog`	the vector of predictions.
`maxi.anlg`	monthly maxima values of predictions.
`mini.anlg`	monthly minima values of predictions.
`error`	vector of errors between predictions and observations at each date.
`correlation`	correlation coefficient between predictions and observations.
`rmse`	root mean square errors between predictions and observations.

Author(s)

R.E. Benestad and Alexandra Imbert

References

URL http://www.R-project.org/

See Also

anm, stepANM

Examples

```
library(survival)
library(clim.pact)
data(temp.era)
data(susendal)
y<-susendal$V6 # temperatures
X<- eof$PC[,c(1,2)]
calibration <- c(susendal$V4>1979 & susendal$V4<1990 & (susendal$V3==1 | susendal$V3==2 | susendal$V3=
evaluation <- c((susendal$V4>1990 & susendal$V4<1993 | susendal$V4==1990) & (susendal$V3==1 | susendal
y.calib <- y[calibration]
y.eval <- y[evaluation]
eof.calib <- c(eof$yy>1979 & eof$yy<1990)
eof.eval <- c(eof$yy> 1990 & eof$yy<1993| eof$yy==1990)
period <- c(calibration, evaluation)
y.period <- y[(susendal$V4>1979 & susendal$V4<1993) & (susendal$V3==1 | susendal$V3==2 | susendal$V3==
test.data <-data.frame(y=y.period,
                       X1=X[eof$yy< 1993 & eof$yy> 1979,1],
                       X2=X[eof$yy< 1993 & eof$yy> 1979,2],
                       yy=eof$yy[eof.calib | eof.eval],
                       mm=eof$mm[eof.calib | eof.eval],
                       dd=eof$dd[eof.calib | eof.eval])
test.anm<-anm(y ~ X1 + X2,data=test.data)
res <- predict.anm(test.anm)
```

---

print.anm *Print some components of an anm object.*

Description

Prints the coefficients of an anm object.

Usage

```
print.anm(x, digits = max(3, getOption("digits") - 3), ...)
```

Arguments

x	the anm object.
digits	the vector defining the format of printing.
...	currently disregarded.

Author(s)

Alexandra Imbert

References

URL http://www.R-project.org/

See Also

anm, predict.anm

Examples

```
library(survival)
library(clim.pact)
data(susendal)
data(temp.era)
y<-susendal$V6 # temperatures
X<- eof$PC[,c(1,2)]
calibration <- c(susendal$V4>1979 & susendal$V4<1990 & (susendal$V3==1 | susendal$V3==2 | susendal$V3=
evaluation <- c((susendal$V4>1990 & susendal$V4<1993 | susendal$V4==1990) & (susendal$V3==1 | susendal
y.calib <- y[calibration]
y.eval <- y[evaluation]
eof.calib <- c(eof$yy>1979 & eof$yy<1990)
eof.eval <- c(eof$yy> 1990 & eof$yy<1993| eof$yy==1990)
period <- c(calibration, evaluation)
y.period <- y[(susendal$V4>1979 & susendal$V4<1993) & (susendal$V3==1 | susendal$V3==2 | susendal$V3==
test.data <-data.frame(y=y.period,
                       X1=X[eof$yy< 1993 & eof$yy> 1979,1],
                       X2=X[eof$yy< 1993 & eof$yy> 1979,2],
                       yy=eof$yy[eof.calib | eof.eval],
                       mm=eof$mm[eof.calib | eof.eval],
                       dd=eof$dd[eof.calib | eof.eval])
test.anm<-anm(y ~ X1 + X2,data=test.data)
print.anm(test.anm)
```

---

stepANM — *Choose a model by the analog method in a stepwise algorithm*

Description

Performs the analog method step by step to select a model and plots on the same graph both correlation and rmse at each step.

Usage

```
stepANM(anm.obj,trace=1,steps=8)
```

Arguments

anm.obj	the anm object inheriting from anm routine.
trace	if equal to 1, information is printed during the running of the stepwise algorithm.
steps	maximum number of steps, forced to the number of predictor variables if *steps* exceeds it.

Value

A list with components

`Call`	the matched call.
`PC`	the predictor variables selected.
`anm.obj`	the anm object selected.
`coefficients`	the coeffecients of the anm object.
`step.min`	the number of steps which returns the minimum rmse.
`model`	the model corresponding to the minimum rmse.
`Rmse`	the minimum root mean square error.
`correlation`	the correlation between predictions and observations for the selected model.

Note

The running of the stepwise algorithm can be quite slow especially if the number of steps specified in the *steps* argument is high.

Author(s)

Alexandra Imbert

See Also

anm, predict.anm

Examples

```
library(survival)
library(clim.pact)
data(susendal)
data(temp.era)
y<-susendal$V6 # temperatures
X<- eof$PC[,c(1,2,3)]
calibration <- c(susendal$V4>1979 & susendal$V4<1990 & (susendal$V3==1 | susendal$V3==2 | susendal$V3=
evaluation <- c((susendal$V4>1990 & susendal$V4<1993 | susendal$V4==1990) & (susendal$V3==1 | susendal
y.calib <- y[calibration]
y.eval <- y[evaluation]
eof.calib <- c(eof$yy>1979 & eof$yy<1990)
eof.eval <- c(eof$yy> 1990 & eof$yy<1993| eof$yy==1990)
period <- c(calibration, evaluation)
y.period <- y[(susendal$V4>1979 & susendal$V4<1993) & (susendal$V3==1 | susendal$V3==2 | susendal$V3==
test.data <-data.frame(y=y.period,
                       X1=X[eof$yy< 1993 & eof$yy> 1979,1],
                       X2=X[eof$yy< 1993 & eof$yy> 1979,2],
                       X3=X[eof$yy< 1993 & eof$yy> 1979,3],
                       yy=eof$yy[eof.calib | eof.eval],
                       mm=eof$mm[eof.calib | eof.eval],
                       dd=eof$dd[eof.calib | eof.eval])
test.anm<-anm(formula=y ~ X1 + X2 + X3,data=test.data)
stepANM(test.anm,steps=3)
```

`susendal` *Daily Susendal record.*

Description

A station record of daily mean temperature and daily precipitation from Susendal.

Usage

```
data(susendal)
```

Format

The dataset is a data.frame containing:

V1 station number.

V2 a vector holding day of month.

V3 a vector holding the month.

V4 a vector holding the year.

V5 a vector holding daily precipitation in mm.

V6 a vector holding daily mean temperature in deg C.

Source

The Norwegian Meteorological Institute, Climatology division.

References

The Norwegian Meteorological Institute, P.O. Box 43, 0313 Oslo, Norway (URL http://www.met.no)

`temp.era` *Daily winter common EOF.*

Description

Common EOFs for daily December-February temperature.

Usage

```
data(temp.era)
```

Format

EOF EOF patterns.

W Eigen values.

PC Principal components of common PCA.

n.fld Number of different predictors (see [clim.pact]mixFields).

tot.var Sum of all W squared.

id.t Time labels for the fields (see [clim.pact]catFields) - used in [clim.pact]DS.

id.x Spatial labels for the fields (see [clim.pact]mixFields) - used in [clim.pact]plotEOF.

mon Month (1-12) [season (1-4) for daily data] to extract.

id.lon Spatial labels for the fields (see [clim.pact]mixFields) - used in [clim.pact]plotEOF.

id.lat Spatial labels for the fields (see [clim.pact]mixFields) - used in [clim.pact]plotEOF.

region Describes the region analysed.

tim Time information (usually redundant).

lon Longitudes associated with EOF patterns.

lat Latitudes associated with EOF patterns.

var.eof Fractional variances associated with EOF patterns.

yy years.

mm months.

dd days.

v.name Name of element.

c.mon Month-season information.

f.name File name of original data.

Source

Rasmus E. Benestad rasmus.benestad@met.no.

References

Reference to methodology: R.E. Benestad (2001), "A comparison between two empirical downscaling strategies", Int. J. Climatology, vol 210, pp.1645-1668. [DOI 10.1002/joc.703].

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