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Seasonal Forecasting for Norway: an assessment

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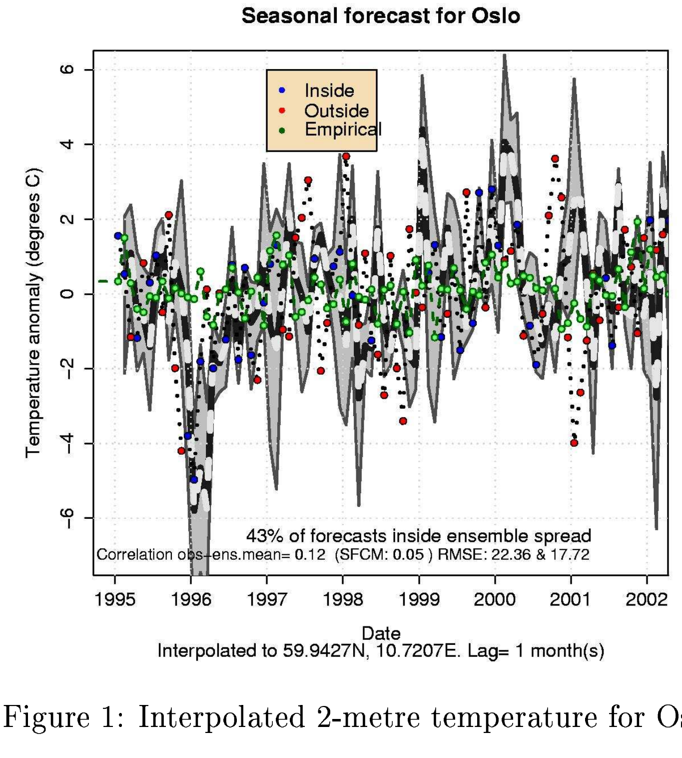

Figure 1: Interpolated 2-metre temperature for Oslo.

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Abstract

A brief review of seasonal forecasting studies relevant to the Scandinavian region is presented. Seasonal forecast products from the European Centre for Medium-Range Weather Forecasts (ECMWF) have been evaluated against interpolated 2-meter temperature for Oslo. The assessment suggests a small but positive anomalous correlation coef£cient, indicative of some skill of statistical signi£cance at the 5% level. The assessment was compared with ECMWF's own veri£cation, showing a good agreement. Seasonal forecasts from ECMWF were compared with simple empirical-statistical model results from the Norwegian Meteorological Institute, the latter indicating similar, albeit slightly lower, correlation.

Additional external seasonal forecasting resources are also presented. Some examples of how seasonal forecasts may be presented are also given.

Keywords

Seasonal forecasting, ECMWF products, empirical models, evaluation.

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1 Introduction

Reliable seasonal forecasts are valuable (*Førland* et al., 1999), and a number of various studies have attempted to identify precursory signals that may be utilised in seasonal forecasting. 'Modern' seasonal forecasting, based on scienti£c methods and climate models, initially had a focus on the Tropics and the El Niño Southern Oscillation (ENSO) phenomenon in particular, as the associated regional anomalies tend to have well-de£ned structures and a degree of persistence. The higher latitudes are associated with stronger high-frequency 'noise' and was conceived to be more dif£cult due to stronger non-linear effects (the Coriolis force, presence of strong fronts, effects of ice and snow, etc). The large-scale wind patterns and rainfall in certain regions of the tropics are strongly determined by the sea surface temperature (SST) and are not sensitive to initial (previous) conditions of the atmosphere (*Shukla*, 1998). The lack of sensitive dependence on the initial conditions provides a scienti£c basis for long-range forecasting of tropical climate variations. *Shukla* (1998) suggests that the latitudinal dependence of the rotational force and solar heating give rise to the unique large-scale tropical circulation structure which is stable for a given SST structure. After an El Niño onset, the growth and maturation for the following 6–9 months seem to be predictable.

Here, the the term '*predictor*' is the input ($\mathbf{X}(\mathbf{t})$ or x) and '*predictand*' is the forecast variable (e.g. y in $y(t+1) = \mathcal{F}[\mathbf{X}(\mathbf{t})]$). This report gives a brief summary of some previous work, following a quasi-chronological order, and presents an evaluation of the ECMWF seasonal forecasts for Europe and the Nordic region.

2 A brief review of literature on seasonal forecasting

2.1 Early attempts

Attempts to make long-term forecasts at the Norwegian Meteorological Institute can be traced back to *Evjen* (1956) who explored the persistence in sea level pressure (SLP) through lagged correlations and lagged regressions in terms of empirical-statistical monthly forecasts. Here both predictors as well as predictand were SLP from station series. He looked at a selection of stations (Vardø in Norway and Stykkisholmur in Iceland) and found month-to-month lagged correlations r_{xy} in the range 0.27–0.54 (the respective number of pairs were $n =$ 81 & 26). For the summer months (x/y is May/June, June/July, July/August, and August/September) at Vardø *Evjen* (1956) derived the following lagged regression equation for SLP: $y + 0.09 = 0.25 \times (x + 0.53)$, and $r_{xy} = 0.48$, for $n = 60$).

In the winter 1982–1983 a record-strong El Niño event took place which was not detected before it already was in a mature phase because aerosols from the El Chichón eruption (Mexico 17.3°N,1982 March–April) interfered with satellite observations. The weather around the world showed an unusual behaviour, which surprised meteorologists until the realisation that an El Niño was taking place (*Canby*, 1984). Despite early attempts, it was the objective to forecast El Niño events that probably provided the strongest impetus for modern seasonal forecasting. There were two types of approaches to the prediction problem: statistically based schemes and dynamical models. In some cases, a hybrid model, a combination of the two, was adopted.

2.1.1 empirical-statistical models

Barnett & Preisendorfer (1987) had used Canonical Correlation Analysis (CCA) to explore the potentials for seasonal forecasting over the United States, but seasonal prediction of ENSO has also utilised empirical-statistical models (*Barnston & Ropelewski*, 1992; *Barnston*, 1995; *van den Dool*, 1995; *Zhang & Pan*, 1995; *Jiang* et al., 1995; *Penland & Sardeshmukh*, 1995) and served as a benchmarking of the various schemes. *Førland & Nordli* (1993) examined autocorrelations in temperature and precipitation series from Norwegian climate stations. They found a signi£cant degree of persistence in late winter (Jan/Feb $r_{xy} \approx 0.5$–0.6, Fig 3.3) and summer (Jul/Aug $r_{xy} \approx 0.4$–0.5, Fig 3.8) temperature along the coast of southern Norway and southeastern part of the country respectively. The highest persistence in precipitation was found near the west coast of Norway (e.g. Jan/Feb $r_{xy} \approx 0.3$–0.4, Fig 4.1b). *Johansson* et al. (1998) analysed a number of meteorological £elds (surface air temperature, local SST, northern hemispheric 700-hPa geopotential height, and quasi global SST) in order to identify the level and origin of seasonal forecast skill for surface air temperature in Northern Europe. The most skillful forecasts were, according to this study, for the winter season with a weaker secondary peak in skill during summer, and the geopotential heights gave the best scores. *Sutton & Allen* (1997) suggested that there may be predictability on decadal scales associated with propagating anomalies in the North Atlantic. *Colman & Davey* (1999) applied a statistical scheme to predict the July–August precipitation, surface temperature and pressure over Europe from January–February SSTs in the North Atlantic. They suggest that the minimum and maximum July–August temperature over much of northwest Europe is predictable using a lagged linear regression with anonaly correlation coef£cient (ACC) in the range 0.4–0.7. The July–August rainfall and pressure were found to be less predictable. Predicted warm summers were associated with the movement of high SST anomalies across the North Atlantic from the east coast of the USA to the northwest of Europe during spring months. The predicted cold summers, on the other hand, tended to follow low spring-time SST in the vicinity of the British isles. A coherence analysis between winter SST and summer temperatures was strongest at 7–8 year time scales.

Vautard et al. (1999) explored space-time principal components (multichannel singular spectrum analysis, MSSA) in empirical-statistical prediction schemes for North American surface temperatures. They proposed using so-called linear error in probability space (LEPS) as well as correlation as a measure of skill. When they compared the MSSA method with similar predictions based on CCA, they found the predictions derived from MSSA to be marginally superior, possibly due to the non-seasonal nature of the MSSA model and over-£tting problems inherent to CCA. The CCA model may produce spurious negative correlations over large areas. The overall skill was found signi£cant for winter, spring and summer predictions, but close to zero during autumn.

Martis et al. (2002) reported strong relationships for up to 4 months lag between El Niño Southern Oscillation (ENSO) and October–January rainfall on the leeward islands Aruba, Curecao, and Bonaire. Analysis of the circulation suggested that the main factors in¤uencing the precipitation are the upper-level divergence, vorticity and lower-level veering of the trade winds.

Lloyd-Huges & Saunders (2002) explored ENSO teleconnections to European spring precipitation. They found strongest ENSO links across the central European region (45°N–55°N, 5°W–35°E). They suggested using the F-distributed *Chow test statistics* for evaluating the model because stability in time is fundamental to the utility of empirical forecast schemes. This statistic gives the ratio of the sum of squares from the full regression to the sum of squares from two adjacent subsets. They reported 14–18% improvement over climatology when utilising the ENSO teleconnections in a lagged linear multiple regression scheme.

Kharin & Zwiers (2003) explored different methodologies for optimising the predictive skill for an empirical-statistical scheme for making probability forecasts, using 700-hPa temperature and 500-hPa height as predictors.

Colman & Davey (2003) used a statistical scheme involving a combination of CCA, nearest neighbour regression (combined multi-method forecast scheme) and SST to forecast global SST. They found it hard to beat persistence in the extra-tropics. The combined multi-method scheme was an improvement to simpler individual schemes.

Mo (2003) proposed that a method termed 'ensemble canonical correlation', using global SST and SLP, surface temperature and soil moisture as predictors respectively to forecast the mean surface temperature over the United States at 1–2 seasons lead. Their forecasts were the weighted average of these individual forecasts. The use an ensemble mean is an improvement to the individual forecasts, which tend to have skill over different parts of the globe.

Blender et al. (2003) used linear regression to predict monthly mean temperature in regions of England, Germany and Scandinavia, using monthly mean teleconnection indices, North Atlantic SST, and European climate variables as predictors. A parallel study was conducted with data from a 600-year integration with the ECHAM/HOPE AOGCM. They found high skill for February–March (ACC=0.6) and August–September, with somewhat lower scores for the simulations (ACC ≈ 0.5) and a different seasonal dependency for skill.

van Oldenborgh et al. (2003) compared empirical-statistical models with 'dynamical forecasts' from European Centre Medium-Range Weather Forecast (ECMWF) Atmosphere-Ocean General Circulation Model (AOGCM). They suggested that the dynamical ECMWF models show better skill in 2-meter temperature forecasts over sea and the tropical land areas than the statistical scheme based on persistence and lagged regression. Their evaluation did not encompass northern Europe, as they claim that much of the seasonal climate variability in mid-latitudes is unpredictable and that seasonal predictability of precipitation is mainly based on ENSO teleconnections (the skill is higher during strong El Niño and La Niña events than during neutral conditions). *van Oldenborgh* et al. (2003) also proposed that some of the errors from the AOGCM may be corrected for by a downscaling technique.

2.1.2 Dynamical models

The prediction of ENSO pioneered the use of coupled ocean-atmosphere models (*McCreary & Anderson*, 1991; *McCreary*, 1983; *McCreary & Anderson*, 1984; *Zebiak & Cane*, 1987; *Kirtman* et al., 1995; *Ji* et al., 1994; *Ji & Leetmaa*, 1995; *Zebiak & Cane*, 1995). Many of the early coupled models were so-called 'hybrid models' where one component consisted of a dynamical/thermodynamical model (e.g. the 'Zebiak model') and one part (often the atmosphere) of a statistical model (*Barnett* et al., 1993, 1995; *Balmaseda* et al., 1994). A review of the prospects for seasonal forecasting in general was presented in *Palmer & Anderson* (1994), *Barnston* et al. (1994), *Latif* et al. (1994), and *Anderson* (1995). There have been several studies on the predictability on seasonal time scales: *Eckert & Latif* (1997) and *Moore & Kleeman* (1997) used AOGCMs to study the effect of high-frequency weather noise on the ENSO onset.

Krishnamurti et al. (1999) and *Yun* et al. (2003) explored the use of multi-model 'superensembles' (AMIP data set), and found that the superensemble outperformed all individual model forecasts for multi-seasonal, medium-range weather, and hurricane forecasts. They used multiple regression to preform a collective bias removal (a kind of weighted averaging) and showed that the superensemble had higher skill than forecasts based solely on ensemble averaging. *Palmer* et al. (2000) explored seasonal prediction in multi-model ensembles based on the results from the PROVOST project.

Mo & Strauss (2002) examined the added value in combining a statistical scheme to correct for errors in the past performance of a AOGCM (COLA) and found that such an approach removes the systematic structural (distortion) errors.

Feddersen (2003) evaluated seasonal forecasts for precipitation for the Nordic region and reported marginal skill. The most skillful predictions can be made in spring (April–June) and the SST in both tropical Paci£c and Indian oceans and the North Atlantic may have some in¤uence. The in¤uence of the North Atlantic Oscillation (NAO) on the spring-time temperature may also have an effect on the Scandinavian precipitation.

2.1.3 The influence of snow

Hawkins et al. (2002) suggested a link between the North American snow-cover and the North American Monsoon system. They suggest that the areal extent of monthly and seasonal snow cover over North America is correlated with precipitation totals, precipitation frequency and severe weather associated with North American Monsoon.

Kumar & Yang (2003) found a systematic in¤uence of snow variability on the atmospheric winter mean on extra-tropical latitudes in the Northern Hemisphere, and they suggested that cause for the variability in the lower troposphere was related to the dependence of surface albedo on snow depth amount.

Ueda et al. (2003) studied the role of snow-cover for the subsequent season's weather, and its relevance to seasonal and inter-annual variations of atmospheric circulation.

2.1.4 The influence of the stratosphere

Thompson et al. (2002) suggested that a dynamical coupling between the stratospheric and tropospheric circulation may result in the potential predictability for extreme cold events throughout the Northern Hemisphere both on month-to-month and winter-to-winter time scales. They proposed that a substantial weakening of the wintertime polar vortex tends to be followed by low surface temperatures and an increased probability of extreme cold events over North America, northern Europe and eastern Asia. These anomalies may persist for up to $\sim$2 months. Furthermore, the easterly phase of the quasi-biennial oscillation (QBO) appears to bias the probability to more frequent cold events and vice versa.

Baldwin et al. (2003) used an empirical-statistical model to explore the skill of forecasts beyond 10 days lead of the monthly-mean Arctic Oscillation (AO). They found precursory signals in the lower stratospheric circulation anomalies that were most skillful during boreal winter. They proposed that these anomalies may affect the troposphere by affecting the upper tropospheric waves and hence inducing surface pressure changes.

2.1.5 Seasonal forecasting and the Norwegian Meteorological Institute

The large number of recent papers related to seasonal prediction suggest growing interest and activity around seasonal prediction. There has been some activity on the seasonal prediction problem at the Norwegian Meteorological Institute where *Benestad* (2002, 2001b, 1999) explored various empirical-statistical seasonal prediction strategies for the Nordic countries. However, this work has not yet been part of a network or been coordinated with other weather/climate major centres. Recently, the World Meteorological Organisation (WMO) in a note (SSP/RA VI.SRO/44 'Operational Provision of Long-Range Forecast (LRF) products for Region VI, Geneva, 12 November 2003) informs about plans to establish a system for LRF based on four centres: ECMWF, Mètèo-France, Moscow and the UK Met Of£ce, starting from January 2004.

The likelihood of a anthropogenic climate change (*Houghton* et al., 2001) makes good seasonal forecasts more essential. If severe events, such as the exceptionally wet autumn 2000 (November: 564mm at Bjørnholt near Oslo which was 470% of the 1961–90 climatology) (*Benestad & Melsom*, 2002) or dry August–September 2002 (August 71mm = 60% and September 51mm = 40% at Bjørnholt) become more commonplace, or if heat waves such as in the summer of 2003 in Europe (*Schär* et al., 2004) become more frequent, then it is important for societies to be prepared. Furthermore, progress in climate change research and seasonal forecasting can lead to mutual synergy effects. One example is the impact research on seasonal forecasting on coupled atmosphere-ocean modelling.

3 Data & Methods

Seasonal forecasts in the form of gridded £elds of monthly means of forecast means were retrieved from ECMWF. Each forecast comprised of an ensemble of £ve members. These data were compared to monthly means of daily means of 2-meter temperature for the interval September 1994–August 2002. All data were retrieved as GRIB £les and converted to netCDF format in order to read the data into the `R` environment for further analysis.

Climatological values were estimated from each ensemble run and for the ERA40 control, and anomalies were derived by subtracting the respective climatological values from the £elds of each member/analysis (hence the climatology may vary slightly among the members). In this context, a '£eld' is a time series of 2D maps (a 3-dimensional matrix holding gridded data: $\mathbf{X}(\mathbf{t}, \mathbf{y}, \mathbf{x})$).

Anomalous correlation coef£cients (ACC) were estimated for the entire ensemble by concatenating the anomalies of the individual ensemble members along the time axis and correlating this combined set with a corresponding £eld of EC analysis of similar length by repeating the same £eld 5 times (along the time axis).

4 Results

Figure 2 presents an evaluation of the ECMWF seasonal forecasts done at ECMWF and for all of Europe, and these graphics were obtained from the URL: http://www.ecmwf.int/. This evaluation indicates some skill at 2–4 month lead (positive ACC), but the scores are not very high for 2m temperature (a), precipitation (b) or SLP (c). The evaluation does not give any indication of whether some European locations are associated with higher degree of predictability than others. The relatively high ACC score for the SST predictions (d) are interesting, and brings up the question whether these can be used with e.g. a statistical downscaling technique to provide improved seasonal forecasts (*Benestad & Tveito*, 2002).

Figure 3 shows a set of evaluation results obtained at the Norwegian Meteorological Institute. The correlations analysis was applied to anomalies for all calendar months with monthly (as opposed to 3-monthly) values and for one-month lead predictions. The evaluations shown in both Figure 2 and Figure 3 involve only a few degrees of freedom, and are subject to uncertainties due to sampling ¤uctuations. Although the map of correlation scores in Figure 3a indicates highest scores over the North Sea, the regional dependency of skill remains somewhat uncertain due to the short lengths of the series. The time series shown in Figure 3b–c present (bilinearly) interpolated values for the location of Oslo. Empirical-statistical based forecasts are also shown (green), and both ACC and root mean square error (RMSE) (*Wilks*, 1995) are presented. Figure 3b shows the results with no further statistical processing, whereas a MOS is applied to Figure 3c, where the low correlation results in a dramatic reduction of the amplitude (variability) of the ECMWF forecasts. The ACC scores are nevertheless roughly in line with those reported by ECMWF and shown in Figure 2 and with *van Oldenborgh* et al. (2003). A comparison between the distribution of the analysis (also interpolated) and the ECMWF members and ensemble mean (Figure 3d) suggest a realistic range and roughly similar distributions. The fact that the ensemble mean (red) follows the observations and individual ensemble members so closely is due to a high correlation among the members (which may have implications for the degrees of freedom and the signi£cance associated with the correlation analysis, as the different members are not independent of each other). The high inter-member correlation may suggest that there is a strong precursory signal and that there is a great potential for seasonal forecasting (assuming the forecast model gives a good representation of the real world).

The empirical-statistical model forecasts shown in Figure 3 gave slightly lower ACC, but higher RMSE scores than the ECMWF seasonal prognosis. Figure 4 shows how the ACC scores from the empirical-statistical model varies with lead time (also referred to as ’lag’). The highest scores were obtained for 0-lag and one month’s lead time, as expected, but were generally low for longer lead times. Since this evaluation only involved SLP, it doesn’t rule out the possibility of predictability for longer lead times based on other parameters (e.g. SST, sea-ice, stratospheric conditions).

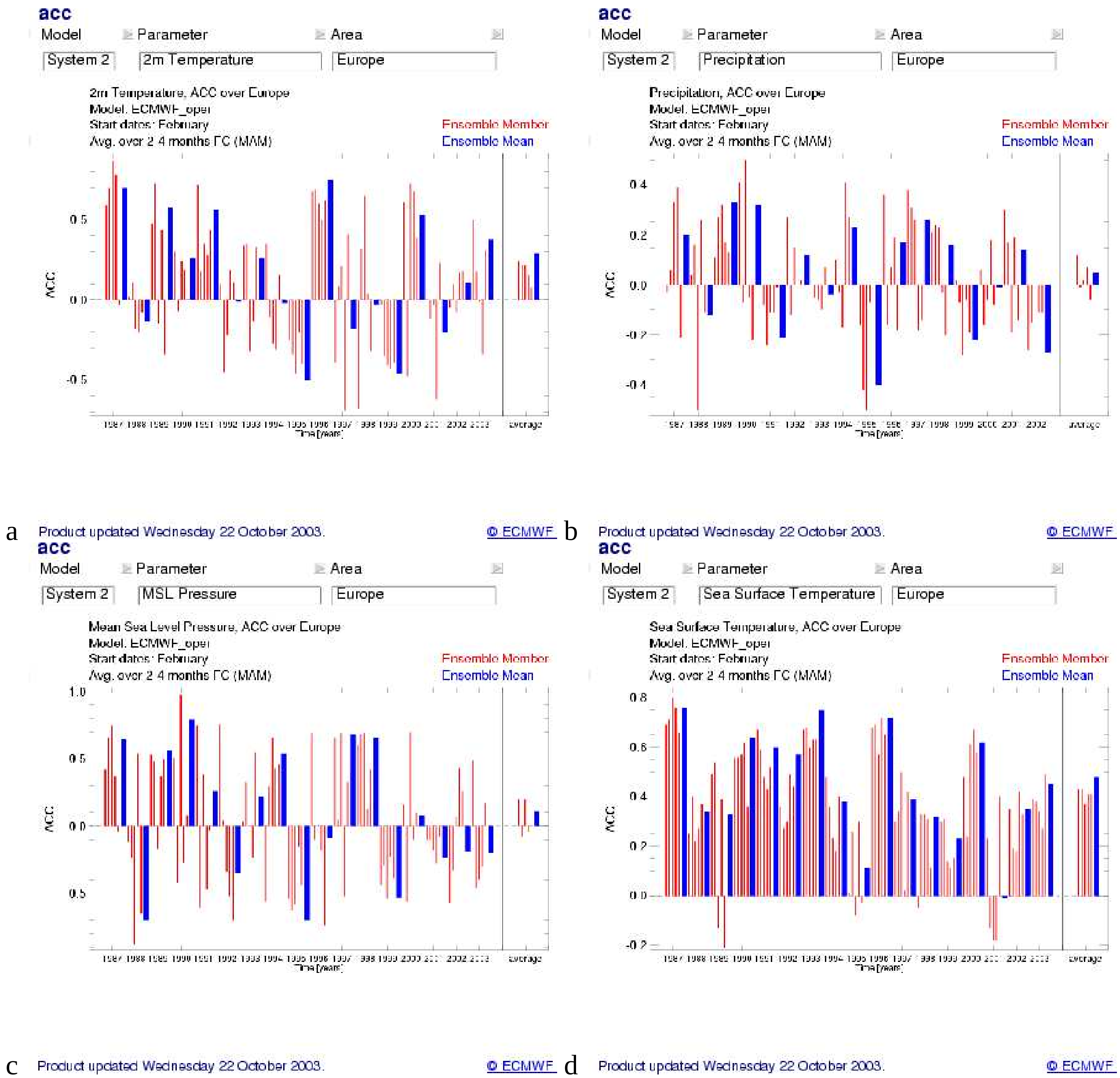


Figure 2: Validation (1987–2003) performed by ECMWF for the entire European region (aggregated) based on anomalous correlation coef£cient. The validation was for 3-monthly anomalous means and a lead time of 1 month.

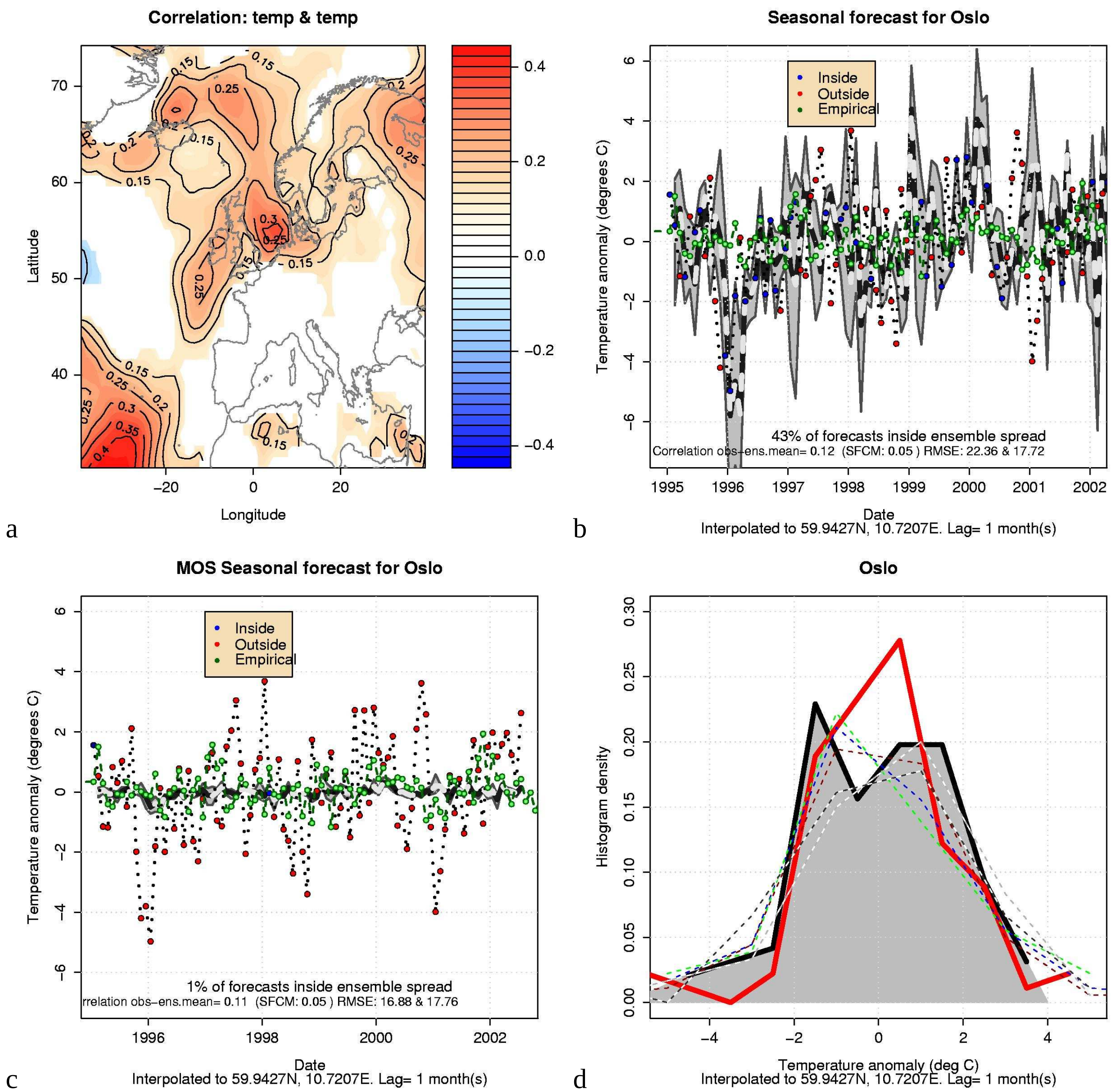
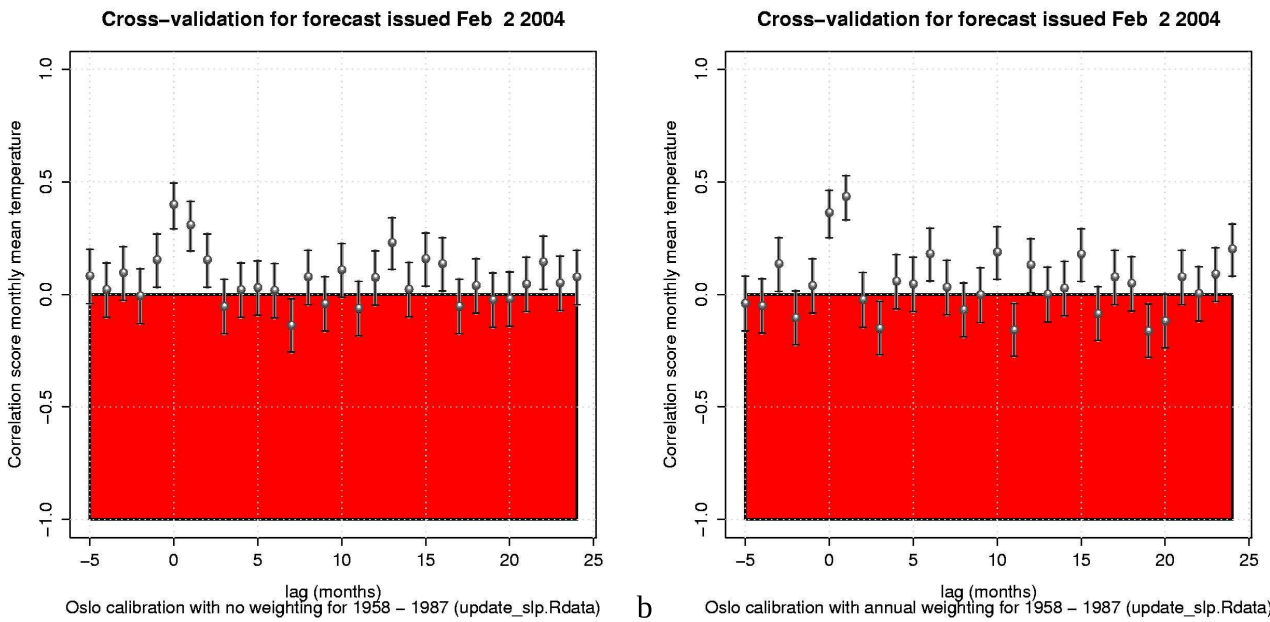


Figure 3: Evaluation of the ECMWF seasonal forecasts carried out at the Norwegian Meteorological Institute. The analysis was applied to one month with one month lag. a) map of ACC for all ensemble members, b) time series representing Oslo, c) Model Output Statistics for Oslo T2m, d) the distribution of T2m. Also shown are results from empirical-statistical forecast model calibrated for Oslo-Blindern. The coloured regions in panel a represent regions where the correlation is signi£cant at the 5% level (default setting for `corField` in the `R`-package `clim.pact`). The evaluation interval was September 1994–August 2002.



a b

Figure 4: Test of a empirical-statistical forecast model calibrated for Oslo-Blindern. ACC shown as a function of lag: a) without annual weights, b) with annual weights. The empirical-statistical model was developed by Benestad and the predictor was SLP.

4.1 Examples of presentation of seasonal forecast products around the world

The National Center for Environmental Prediction (NCEP) and the International Research Institute (IRI) at Coloumbia University, in the United States, also carry out seasonal forecasts on an operational basis (see the appendix for an example), as does the UK Met Of£ce.

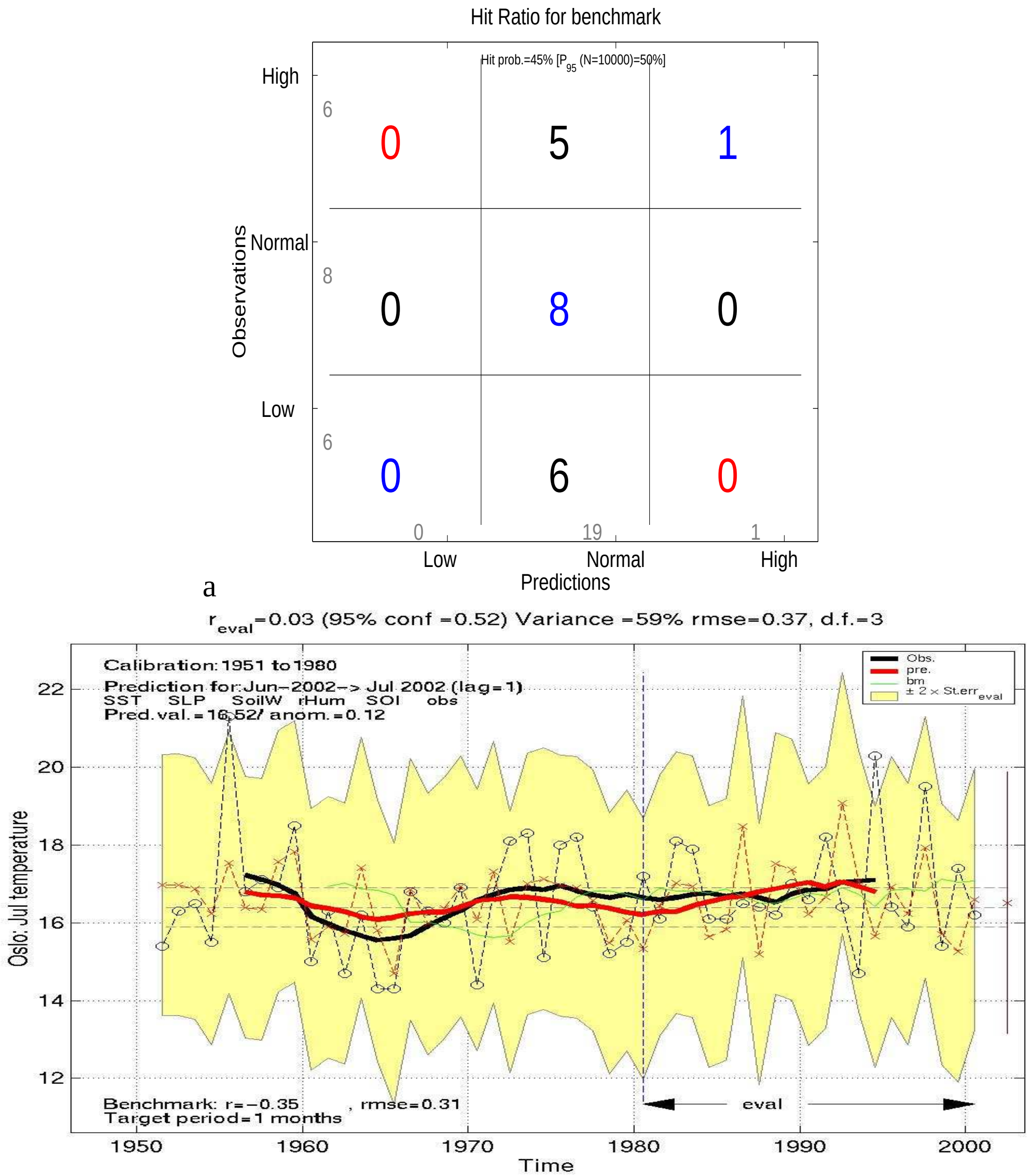
The Bureau of Meteorology (BOM) in Australia disseminates seasonal forecasts (’Seasonal Outlook’) for ENSO, based on a number of different forecast models, and the Experimental Long-lead forecast bulletin (URL: http://grads.iges.org/ellfb/home.html) has provided a forum for operational seasonal forecasts (last issue available on-line was March 2003 with 15 different articles). The Dutch Meteorological Institute (KNMI) Climate Explorer (URL: http://climexp.knmi.nl/) is another resource for empirical seasonal forecasting.

The Danish Meteorological Institute gives updated seasonal forecasts for the temperature in Denmark and southern Greenland (not shown) and present these as probability density functions (pdf). These predictions are derived from ECMWF seasonal forecasts, post-processed through further statistical analysis. This type of preprocessing could involve empirical-statistical downscaling or model output statistics (MOS). There is also some activity on seasonal forecasting at the Swedish Meteorological Hydrological Institute (SMHI), but their products are presently not placed on their home pages.

When presenting seasonal forecasts it is important to show the past performance and skill scores, so that the user can get an idea of how reliable these predictions are. One way to do so is to provide results from evaluations, e.g. in form of a contingency table (Figure 5a). It is also important to show a comparison between predictions made in the past and the actual values in a form of a time series plot, together with the present forecast (e.g. Figure 5b).

Figure 6a shows a series of box-whisker plots for an ensemble of forecasts and past skill. The results presented in this £gure were generated using a random sub-sampling technique to calibrate 100 different empirical-statistical models on different data values. This approach may be one way to deal with observational errors or non-linearities that may corrupt the empirical models. The forecasts from an ensemble of models can be presented as a distribution, here shown as a histogram of values obtained for the prediction (Figure 6b).

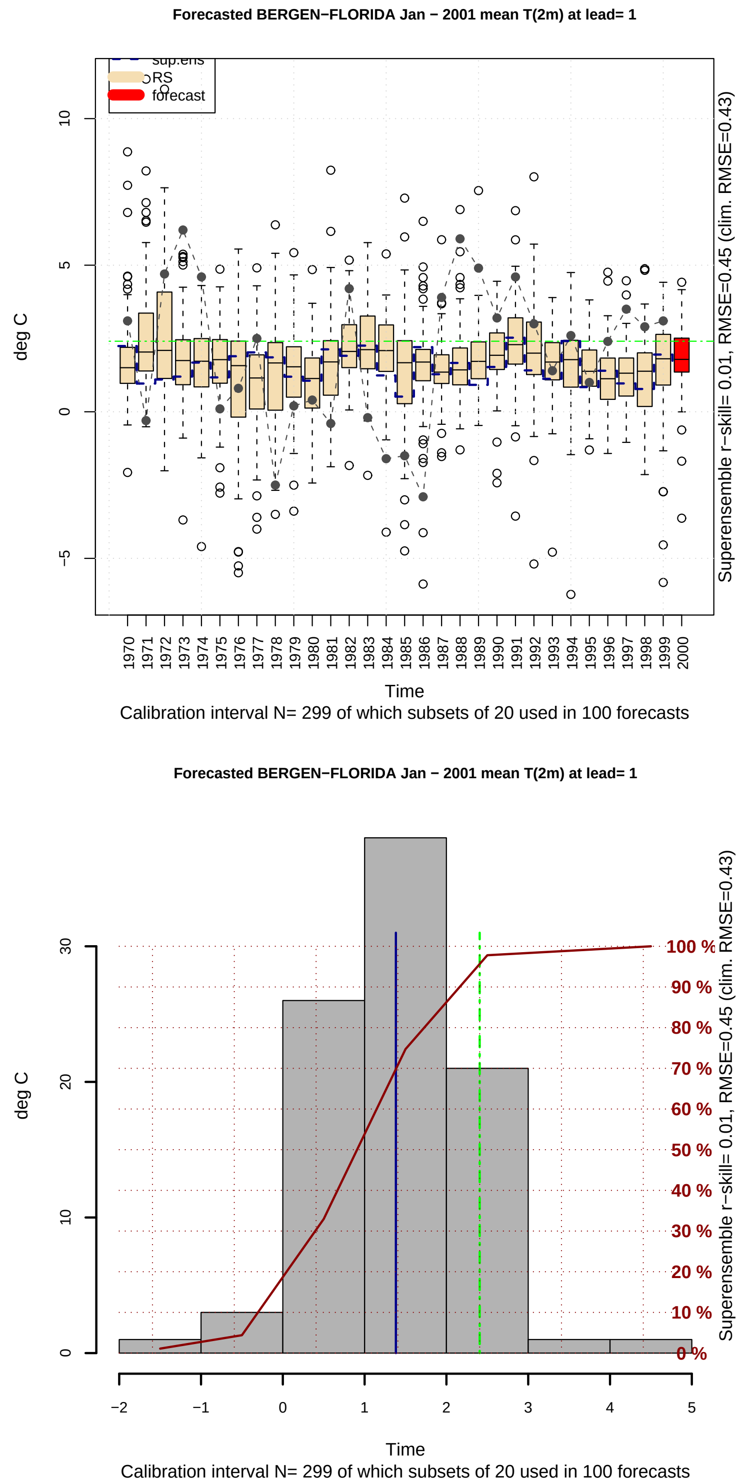
Empirical-statistical downscaling similar to the method proposed by *Benestad* (2001a) can be applied to the SSTs from ECMWF seasonal forecast products (which showed reasonable skill in Figure 2d, using two different data sources for calibration and prediction.



a

b

Figure 5: a) Contingency table example. b) Example of time series plot. From *Benestad* (2002).



a

b

Figure 6: A sample graphic presenting a seasonal forecast. This example is based on a 'random sub-sample' (RS) forecast model, referred to as a 'REM' model by *Benestad* (2002). (`RSFC(eof,"Bergen-Florida",fcst.int=c(1970,2000),lag=1)`)

5 Discussion & Conclusions

A quote from the Danish Meteorological Institute Internet pages: *'Sæsonprognoser er et område i rivende udvikling, og DMI deltager og har deltaget i flere internationale projekter, der søger at forbedre de metoder, der bruges til at lave prognoserne.'* underlines the new impetus on seasonal forecasting and the increased efforts to improve our seasonal forecasting capability. Although the present results suggest only marginal skill over northern Europe, a dedicated research effort is likely to lead to improvements over time, but it is not yet clear whether seasonal forecasting eventually will have practicable skill for northern Europe. Improved observations and longer observational records may provide more accurate initial conditions for AOGCMs as well as leading to better calibration of empirical-statistical models. The studies in the past point toward the use of large ensembles and a weighted combination of the individual members according to their past skills. Downscaling of e.g. forecasted SST may also be a promising approach. A better coordination and compilation of various data sources (from the oceans, cryosphere, stratosphere and of solar activity) may contribute to further progress. Improved data assimilation methods, new advanced numerical modelling schemes, improved knowledge, and growing computational resources/capacities may result in more reliable models in the future.

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6 Appendix