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Predictability of seasonal precipitation in the Nordic region

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ABSTRACT

Predictability of seasonal precipitation in the Nordic countries (Denmark, Finland, Iceland, Norway and Sweden) is investigated using a nine-member ensemble of atmospheric general circulation model simulations with prescribed sea-surface temperature from October 1950 until March 1999. The simulations and corresponding observations from 65 stations in the Nordic countries are used to identify large-scale patterns of seasonal precipitation, the predictability of which is investigated. Subsequently, the identified large-scale patterns are used in a statistical downscaling of the model simulated precipitation. The downscaling, which is of the model output statistics type, yields seasonal predictions for the individual stations. The model simulations of precipitation are compared to predictions of precipitation directly from observed sea-surface temperature using a statistical prediction method and no dynamic model. The two different methods give consistent results. It is demonstrated that seasonal precipitation in the Nordic region contains a weak predictable signal in several seasons. The most skilful predictions can be made in spring, especially in the April–June season when precipitation appears to be influenced both by tropical and North Atlantic sea surface temperature. In particular, the North Atlantic Oscillation in winter appears to influence the North Atlantic sea-surface temperature in spring, which in turn has an effect on precipitation in Scandinavia.

1. Introduction

Seasonal forecasting is largely based on the notion that the seasonally averaged atmospheric circulation is modulated by slowly varying boundary conditions for the atmosphere, most notably varying sea-surface temperature (SST) (Palmer and Anderson, 1994; Shukla, 1998; Goddard et al., 2001). The effect that El Niño conditions have on global seasonal climate is a prime example of the influence that tropical SST can have on the atmospheric circulation (Diaz et al., 2001). In the extratropics the influence of SST anomalies on the atmospheric circulation is less clear. The internal variability of the extratropical atmosphere, i.e. variability which is not a result of external forcing, is believed to contribute much more to the total variability than is the case in the tropics (Rowell, 1998).

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One way to study the influence that SST variability has on atmospheric variability, is to simulate the atmospheric circulation using an atmospheric general circulation model (GCM) forced by prescribed observed SST. If the model simulation agrees with observations (not necessarily perfectly, but to an extent where coincidental agreement can be ruled out with high confidence) then there is reason to believe that SST variability has a deterministic influence on the atmospheric circulation. Such a result can be further substantiated through the use of ensembles of model simulations where the individual simulations in the ensemble differ only by their initial conditions. Consequently, the spread between the simulations in the ensemble is a result of the internal variability of the model atmosphere [see the special DSP/PROVOST issue, vol. 126 (No. 567) of the *Quarterly Journal of the Royal Meteorological Society*].

In the extratropics, where the internal variability is relatively high, detection of statistically significant model simulation skill requires relatively long time series of model simulations and observations. One of the hardest variables to simulate and predict is extratropical precipitation, and one of the regions where seasonal predictability is notoriously low is northern Europe. Nevertheless, the extent to which seasonal precipitation is predictable in northern Europe is of general interest.

The interest in seasonal predictability for European climate dates back at least to the study of Ratcliffe and Murray (1970), who related mean sea-level pressure patterns over Europe to preceding SST anomalies in the Labrador Sea. More recent statistical studies have related European surface air temperature and precipitation to principal components of North Atlantic SST (Colman and Davey, 1999); also European seasonal climate variability has been related to the state of the El Niño/Southern Oscillation (ENSO) (Fraedrich and Mueller, 1992; van Oldenborgh et al., 2000). Modelling studies also indicate an influence of ENSO on North Atlantic/European atmospheric circulation (May and Bengtsson, 1998; Feddersen, 2000).

The recent publication of the Nordklim dataset (Tuomenvirta et al., 2001) of monthly mean values of precipitation, temperature and a number of other variables for selected climate stations in the Nordic countries (Denmark, Finland, Iceland, Norway and Sweden) as well as access to a recently completed ensemble of long model simulations of monthly precipitation enable us to make a detailed systematic study of predictability of seasonal precipitation in the Nordic region, both at regional scale and for individual stations. In order to increase confidence in predictability estimates that are based on model simulated precipitation, statistical relations are identified between SST and observed seasonal precipitation.

The paper is organized as follows. A brief description is given in section 2 of the model simulations and the observed precipitation data. Section 3 introduces the method for estimating whether or not large-scale patterns of seasonal precipitation are predictable. Results of the predictability analysis applied to model simulated precipitation are also shown in section 3, while results of the predictability analysis applied to seasonal precipitation that is specified statistically from SST are presented in section 4. The origin of predictability for seasonal precipitation in the Nordic region is discussed in section 5. A method for statistical downscaling of seasonal precipitation is introduced in section 6, and predictive skill scores (in terms of correlations between downscaled and observed precipitation anomalies) are presented for the individual stations. Finally, conclusions are presented in section 7.

2. Model and observed precipitation data

The dynamical model is a climate version (cycle 12d) of the Meteo-France Arpege atmospheric GCM (Doblas-Reyes et al., 2000). Nine long AMIP-type simulations were made where the model was forced by observed SST from October 1950 until March 1999. The quasi-global SST was taken from the Reynolds historical reconstructed SST dataset from 1950–1990 (Smith et al., 1996) and from the Reynolds optimally interpolated SST dataset from 1991–1999 (Reynolds and Smith, 1994). The model horizontal resolution was T42 with 31 vertical levels.

The observations of precipitation were taken from the Nordklim climate dataset (available at http://www.smhi.se/hfa_coord/nordklim/nkds.htm), which includes monthly values of precipitation for a number of stations in the Nordic countries during the period 1890–1999. For the few months in which observations are missing between 1950 and 1999, monthly climatological values were used instead.

3. Interannual variability and skill of model simulated large-scale patterns of precipitation

The model output is available on a Gaussian grid, while the observed precipitation is available at 65 irregularly scattered stations (Fig. 1). Thus, a direct comparison between model output and observations may not give the best estimate of the skill of the model. Instead, we attempt to identify large-scale patterns of precipitation for both model output and observations and validate the time evolution of these large-scale patterns. Several methods exist that can be used to identify large-scale patterns (Bretherton et al., 1992). Here we are particularly interested in patterns that are well simulated by the model, i.e. patterns for which the cross-covariance is high between model output and observations (Ward and Navarra, 1997).

Linear combinations ("modes") of each of the two fields that are associated with maximal cross-covariance are determined by singular value decomposition (SVD) of the cross-covariance matrix of model output and observations. SVD allows us to expand the model simulated precipitation anomalies $\boldsymbol{x}(t)$ and the

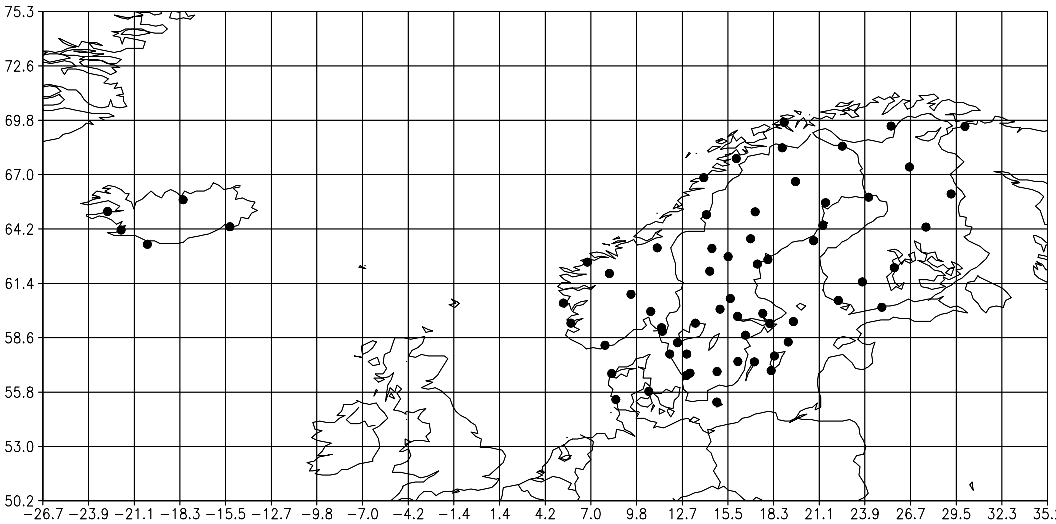

Fig. 1. Location of precipitation observing stations and Gaussian model grid corresponding to a T42 spectral truncation.

observed precipitation anomalies $\boldsymbol{y}(t)$ in terms of singular vectors $\boldsymbol{g}_j$ and $\boldsymbol{h}_j$ as

$$\boldsymbol{x}(t) = \sum_{j=1}^{N} u_j(t)\boldsymbol{g}_j$$

$$\boldsymbol{y}(t) = \sum_{j=1}^{N} v_j(t)\boldsymbol{h}_j$$

where N is the number of years of simulated and observed precipitation. We shall use the singular vectors of the SVD as our large-scale patterns. The singular values of the SVD are equal to the covariance explained by each pair of patterns. The squared covariance explained by the first N SVD modes is equal to the sum of the N largest singular values squared. Thus it is customary to give the squared covariance fraction that is explained by each SVD mode, together with plots of the patterns and time series (analogous to the fraction of explained variance resulting from EOF and principal-component analyses). See Bretherton et al. (1992) for details.

As an example, consider the AMJ season for which correlation patterns of the first SVD mode are shown in Fig. 2. The corresponding time series $u_1(t)$ and $v_1(t)$, obtained by projection of the simulated and observed anomaly fields onto the respective singular vectors, are shown in Fig. 3. The patterns in Fig. 2 are obtained as correlations between $u_1(t)$ and observed and ensemble mean of model simulated precipitation, respectively. The analysed model simulated precipitation field covers the region 25°W–35°E, 50°N–75°N, and the observed precipitation comprises seasonal values at the 65 selected stations in the Nordic countries. A comparison between the model pattern and the pattern of observations in Fig. 2 shows that the model pattern appears to be shifted southwards over Scandinavia, thus indicating that the direct model output is likely to show poor agreement with the observed precipitation for stations located in the area where the model and observed patterns have opposite signs.

However, the relatively high correlation in time ($r = 0.60$) between the SVD time series for the first mode of the observed precipitation and for the first mode of the ensemble mean of the model simulated precipitation (Fig. 3) suggests that the model is capable of simulating some of the observed interannual variability. However, one has to be careful with the significance of correlations between SVD time series, because the SVD modes will include random variability ("noise") in the two fields that happens by chance to have a high covariance (Cherry, 1996). Hence, a test of statistical significance is required of the SVD modes before the predictive skill of the model is discussed.

Alternatively, the contribution from noise to the SVD time series can be reduced substantially by using a cross-validation technique to calculate the time series: For each year the SVD patterns are calculated for model simulated and observed precipitation time series that do not include values for that

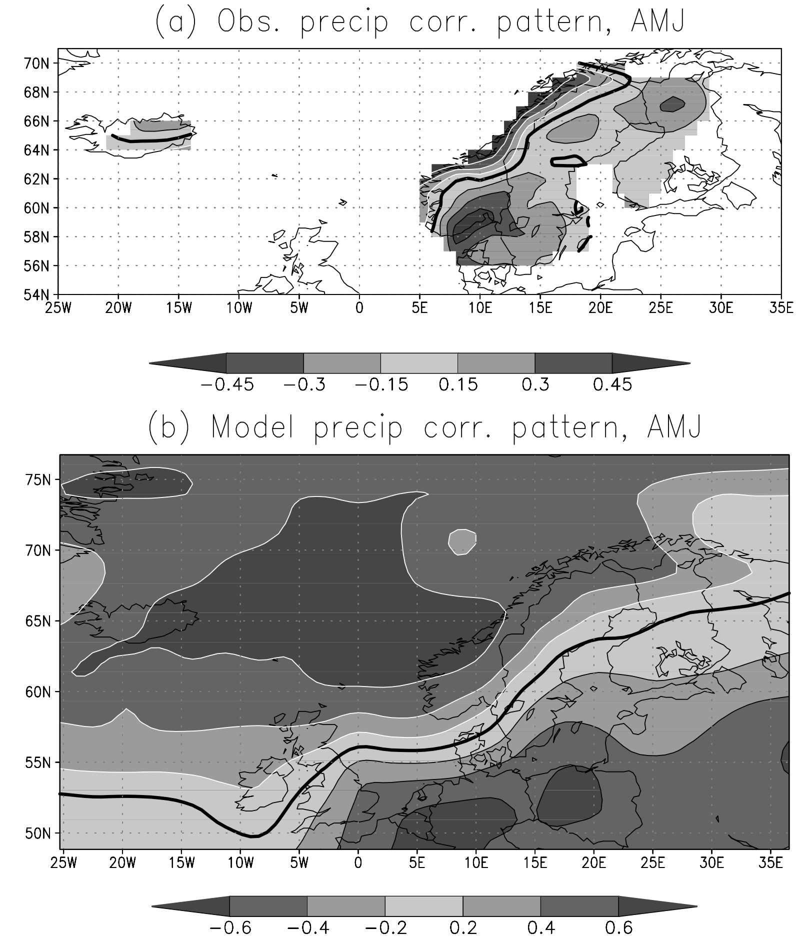

Fig. 2. Correlation patterns of the leading mode of an SVD analysis between model simulated and observed seasonal precipitation in the AMJ season, 1951–1998. The squared covariance fraction SCF = 46.4% for the first SVD mode. (a) Pattern of observed precipitation (correlations at stations interpolated onto a regular 1° × 1° grid); (b) model pattern (ensemble mean). White contours are used for positive correlations; black contours for negative correlations.

particular year. (Data for neighbouring years would have to be excluded as well if the data were autocorrelated; however, the year-to-year autocorrelation is in general small for seasonal precipitation in the Nordic region.) Cross-validated SVD time series are then obtained by projecting the fields of model simulated and observed precipitation for the year in question onto the calculated singular vectors.

The calculation of cross-validated SVD time series only makes sense if the individual modes are separable, i.e. for the SVD analyses that are made in the cross-validation procedure, the first mode (i.e. the mode associated with the highest singular value) should correspond to the same pair of spatial patterns (singular vectors) throughout the cross-validation. Likewise, the secondary modes of the SVD analyses should correspond to specific pairs of spatial patterns. If, for example, exclusion of one year in the SVD analysis that led to the leading mode patterns in Fig. 2 would result in a completely different pair of leading mode patterns, corresponding to, e.g., the second mode patterns of the original SVD analysis, then modes 1 and 2 would not be separable, and the cross-validated time series would correspond to neither mode 1 nor mode 2. This mixing of the modes typically happens when there is little difference between the corresponding singular values.

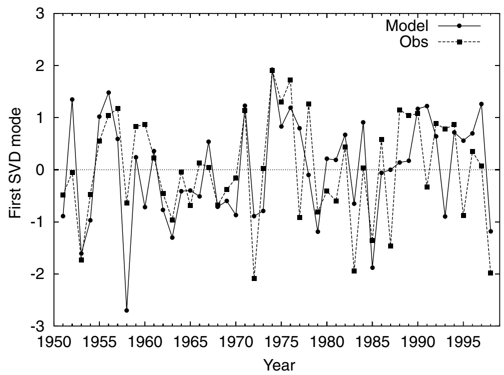

Fig. 3. Standardized model (ensemble mean; solid line) and observational (dashed line) time series of the first SVD mode for AMJ precipitation. Correlation = 0.60.

Table 1. *Correlations between cross-validated SVD time series for model simulated and observed seasonal precipitation in the Nordic region*[a]

Season	Mode 1	Mode 2
DJF	0.12	**0.27****
JFM	0.11	–
FMA	0.16	–
MAM	0.19	–
AMJ	**0.30***	–
MJJ	0.13	**0.31***
JJA	–	–
JAS	–	**0.26****
ASO	0.14	–
SON	0.10	−0.08
OND	0.10	–
NDJ	−0.30	–

[a]Correlations that are significant at the 5%(*) and 10%(**) levels are printed in bold. Correlations are not shown for SVD modes that are not separable from other SVD modes.

Correlations between the first two cross-validated SVD time series are given in Table 1. When there is no entry, the SVD mode was not separable from the other SVD modes. Statistical significance of the correlations were estimated using a one-sided *t*-test. Significance at the 5% and 10% levels is indicated in the table.

It is evident from the correlations in Table 1 that the model predictive skill is very moderate for large-scale patterns of precipitation in the Nordic region. For the leading SVD mode a significant correlation is only found for the AMJ season.

Even for the seasons in which correlations are tested significant, there is still a slight possibility that the correlation is a result of chance. In order to establish further confidence in the model predictive skill we shall make use of the ensemble of model simulations. The availability of an ensemble allows us to test whether the model output contains a deterministic climate signal, or whether the model output is better described as the result of a purely stochastic process ("noise").

Firstly, for the AMJ season, it is noted that the correlations between the cross-validated SVD time series for observed precipitation and for each of the nine individual simulations for the first mode are smaller (correlations found to lie between −0.39 and 0.25) than the correlation between the cross-validated SVD time series for observed precipitation and the ensemble mean (correlation 0.30, given in Table 1). This is consistent with the notion that taking the ensemble mean averages out the noise, leaving more of the predictable signal.

Secondly, it was tested whether averaging over the ensemble members (i.e. taking the ensemble mean) will reduce the climate noise and thereby increase the signal-to-noise ratio, regardless of the relation between model output and observations. That is, the proportion of the total variance explained by an ensemble mean time series that contains a genuine climate signal is expected to exceed the proportion of the total variance explained by an ensemble mean time series that does not contain a climate signal.

The statistical test for the existence of a climate signal in the model simulation ensemble is based on a Monte Carlo resampling approach. All values in the SVD ensemble time series were resampled 500 times to form random SVD ensemble time series, and each time the variance was calculated of the ensemble mean of the resampled SVD time series. An estimate of the significance level for existence of a climate signal (i.e. the probability that a stronger signal would appear by chance) is then given by the number of times that the variance of the randomly generated SVD ensemble mean time series exceeded the variance of the real SVD ensemble mean time series divided by the total number of times the SVD ensemble time series was resampled.

For the first SVD mode in AMJ only a weakly significant signal could be detected in the ensemble of simulated precipitation (significance level estimated to 16%). For the remaining seasons for which significant correlations were found between the cross-validated SVD time series, the climate signals were more significant than for the AMJ season.

It is somewhat unexpected that the climate signal is so relatively weak in AMJ, which is the season in which the ensemble mean of the first SVD mode correlates best with observations (Table 1). The strength of the common signal in the model simulations can also be expressed in terms of a correlation coefficient. If the observations are replaced by one of the ensemble members, and the SVD analysis is applied to this ensemble member and the mean of the remaining ensemble members, then a "perfect-model" cross-validated correlation can be obtained. One would expect the perfect-model correlation to exceed the correlation between model and observations, but here the perfect-model correlations were found to be less (they varied between -0.16 and 0.20, depending on which member was acting as "observation"). This seemingly contradictory result can be due to either (i) the higher correlation between observations and model results being a result of chance given the relatively small ensemble size, or (ii) the fact that the model is not perfect, especially when it is taken into consideration that grid box model output is verified against point observations. For a non-perfect model it is possible to overestimate the internal variability, and as a consequence the time series for the individual ensemble members can be more noisy than the time series for the observations, and so the perfect-model correlations can be lower than the correlations between the SVD time series for the model simulated and observed precipitation.

The significance levels indicated in Table 1 reflect the magnitude of the corresponding correlations. Among a large collection of correlations some of the correlations are likely to test significant by chance. Thus, a test for significance should also include a test for the significance of the number of individual significant correlations, the so-called problem of multiplicity (Wilks, 1995, pp. 151–157). However, here we shall simply use the individual significance levels as indicators of potentially interesting cases to be studied in more detail in the following and return to the problem of multiplicity at the end of section 6.

4. Interannual variability and skill of statistically predicted large-scale patterns of precipitation

The role of the atmospheric GCM in the previous section was to act as a "black box" that transforms global SST variations (in a nonlinear way) to variations in precipitation. The GCM adds what, for practical purposes, can be regarded as a stochastic element to the transformation from SST to precipitation. The use of an ensemble of simulations makes it possible to estimate a signal-to-noise ratio, and thus to assess the uncertainty that is associated with a prediction.

An alternative to using the GCM is statistically to predict, or specify, seasonal precipitation patterns directly from the SST without use of a dynamical model. If variations in SST drive variations in precipitation then linear statistical prediction of precipitation from SST should yield a first-order estimate of the predictive skill. If the relation between SST variations and seasonal precipitation is highly nonlinear then the skill estimate may be poor, but if the internal variability of the atmosphere is high, as a result of the chaotic dynamics of the atmosphere in the Atlantic/European region, then predictability may be detected more easily without the internal variability generated by a dynamical model.

Seasonal precipitation in the Nordic region is, in the following, specified from SST using the same methodology as in the previous section. That is, an SVD analysis is applied to seasonal SST anomalies and observed precipitation anomalies, and the resulting precipitation patterns and associated time series are cross-validated. Similar statistical methods have been widely used to make seasonal forecasts of precipitation and surface air temperature (Barnston, 1994; Barnston and Smith, 1996; Johansson et al., 1998).

A slight problem arises if we want to compare predictive skill of the purely statistical method with that of the GCM simulations. The model simulated seasonal precipitation (in, e.g., AMJ) is based on prescribed SST from the same season (AMJ). As the model atmosphere has no influence on the prescribed SST, the model simulations can be used to obtain an estimate of the atmospheric predictability that is caused by variations in SST anomalies.

However, in the real world extratropics, the atmosphere has an influence on SST anomalies (Frankignoul, 1985), so we can not just use a statistical specification of seasonal precipitation based on SST from the same season to estimate predictability. In order to make sure that the correlations we obtain between statistically specified and observed precipitation are estimates of predictive skill, the SST must lead the precipitation, unless we are certain that the SST is not affected by the state of the atmosphere in the region in which we are trying to make predictions.

In a direct comparison of predictive skill the GCM-based approach will thus have an advantage over the purely statistical approach when the latter is based on SST that leads the precipitation. In order to make a fair comparison between the two methods additional model experiments would be needed. The SST would have to be predicted in advance, either statistically, e.g. by persisting anomalies, or dynamically, using a coupled ocean/atmosphere model.

However, here our main interest is to investigate only whether or not interannual variation in precipitation in the Nordic region is forced by variation in SST, and so for the statistical predictions we will treat local, North Atlantic SST and tropical SST separately. We shall assume that the extratropical atmosphere has very little influence on tropical SST, and so we allow precipitation in the Nordic region to be "predicted" from concurrent tropical SST. Predictions that are based on extratropical SST should, however, include a lead time so as to avoid ambiguity in the results caused by the atmosphere possibly forcing the SST.

The results of the statistical specification of precipitation in the Nordic region are summarized in Table 2. Statistically significant correlations are found in the spring seasons FMA to MJJ, most notably in AMJ when both tropical and North Atlantic SST seem to have a predictable influence on seasonal precipitation. Statistical significance levels are estimated from a one-sided *t*-test.

Table 2. *Correlations between cross-validated SVD time series for the first SVD mode for SST and observed seasonal precipitation in the Nordic region*[a]

Season	Tropical SST	North Atlantic SST
DJF	0.14	−0.24
JFM	0.21	–
FMA	**0.32****	–
MAM	**0.25*****	–
AMJ	**0.41***	**0.48***
MJJ	**0.36****	0.20
JJA	0.10	0.12
JAS	–	−0.10
ASO	−0.33	–
SON	–	0.12
OND	0.04	0.22
NDJ	–	0.09

[a]Correlations that are significant at 1, 5 and 10% levels, are printed in bold and denoted *, ** and ***, respectively. Correlations are not given when the first SVD mode is not separable from other SVD modes. Specifications of precipitation are based on tropical SST from the same season and North Atlantic SST from the preceeding season. NB: Correlation for AMJ based on North Atlantic SST is for the second SVD mode.

5. Origin of predictive skill

In order to locate which parts of the ocean have a predictable impact on precipitation in the Nordic region, it is informative to inspect the correlation in time between SST and the time series of the identified large-scale patterns of precipitation.

For the statistical specification of seasonal precipitation directly from SST we find four dominant SST patterns that are statistically linked to seasonal precipitation in the Nordic region.

(1) An all-tropical SST anomaly (except for the western Pacific) which is associated with anomalous precipitation in almost all of Scandinavia in the seasons JFM to MJJ: above-normal tropical SST is associated with above normal precipitation in Scandinavia, and vice versa (AMJ example in Fig. 4).

(2) An NAO-like pattern in North Atlantic SST (Wallace et al., 1990) that is associated with a precipitation anomaly dipole in Scandinavia in the seasons AMJ to JJA: an SST anomaly pattern corresponding to a positive NAO index in winter is associated with below normal precipitation in southern Scandinavia and above normal precipitation in western, northern and eastern Scandinavia in spring and early summer, and vice versa (AMJ example in Fig. 5).

(3) A North Atlantic SST anomaly, especially in the eastern part, which is associated with a precipitation anomaly dipole in Scandinavia in the seasons SON to NDJ: Above-normal North Atlantic SST in summer is associated with above-normal precipitation in northwestern Norway and below-normal precipitation in the rest of Scandinavia in autumn, and vice versa (OND example in Fig. 6).

(4) An ENSO-like SST anomaly which is associated with a weak precipitation pattern in Scandinavia in the DJF season: Warm ENSO events are associated with above-normal precipitation in southern and northern Scandinavia and below-normal precipitation in central and eastern Scandinavia, and vice versa (Fig. 7).

The SST pattern in Fig. 5 closely resembles the "footprint" of the winter NAO (in its positive phase) (Czaja and Frankignoul, 2002). The precipitation

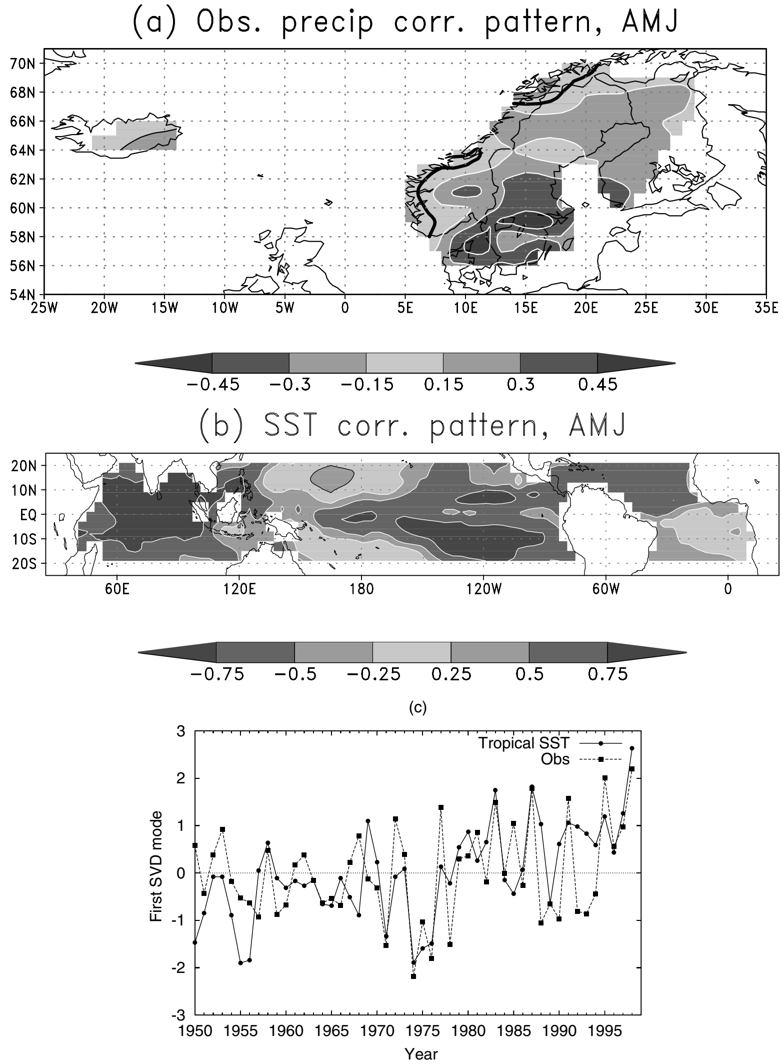

Fig. 4. Correlation patterns and time series for the first mode of an SVD analysis between tropical SST and observed seasonal precipitation in the AMJ season, 1951–1998. The squared covariance fraction SCF = 68.7% for the first SVD mode. (a) Observed precipitation pattern; (b) SST pattern; (c) standardized time series for the first SVD mode. White contours are used for positive correlations; black contours for negative correlations.

patterns in the Nordic region in spring are closely related to the atmospheric circulation. Figure 8 shows the AMJ mean sea-level pressure (MSLP) correlation pattern associated with the SST and precipitation correlation patterns in Fig. 5. The MSLP pattern is obtained by correlating the MSLP field in the North Atlantic/European region with the SVD time series for precipitation. The correlation pattern in Fig. 8 shows that the pattern of negative precipitation anomalies in southern Scandinavia and positive precipitation anomalies in northern Scandinavia and, in particular, in western Norway in AMJ (Fig. 5) is associated with positive MSLP anomalies in southern Scandinavia, centered southwest of Denmark, and negative MSLP anomalies in northern Scandinavia.

The MSLP pattern shown in Fig. 8 is not an NAO-like pattern, but we hypothesize that the state of the winter NAO is a source of precipitation predictability

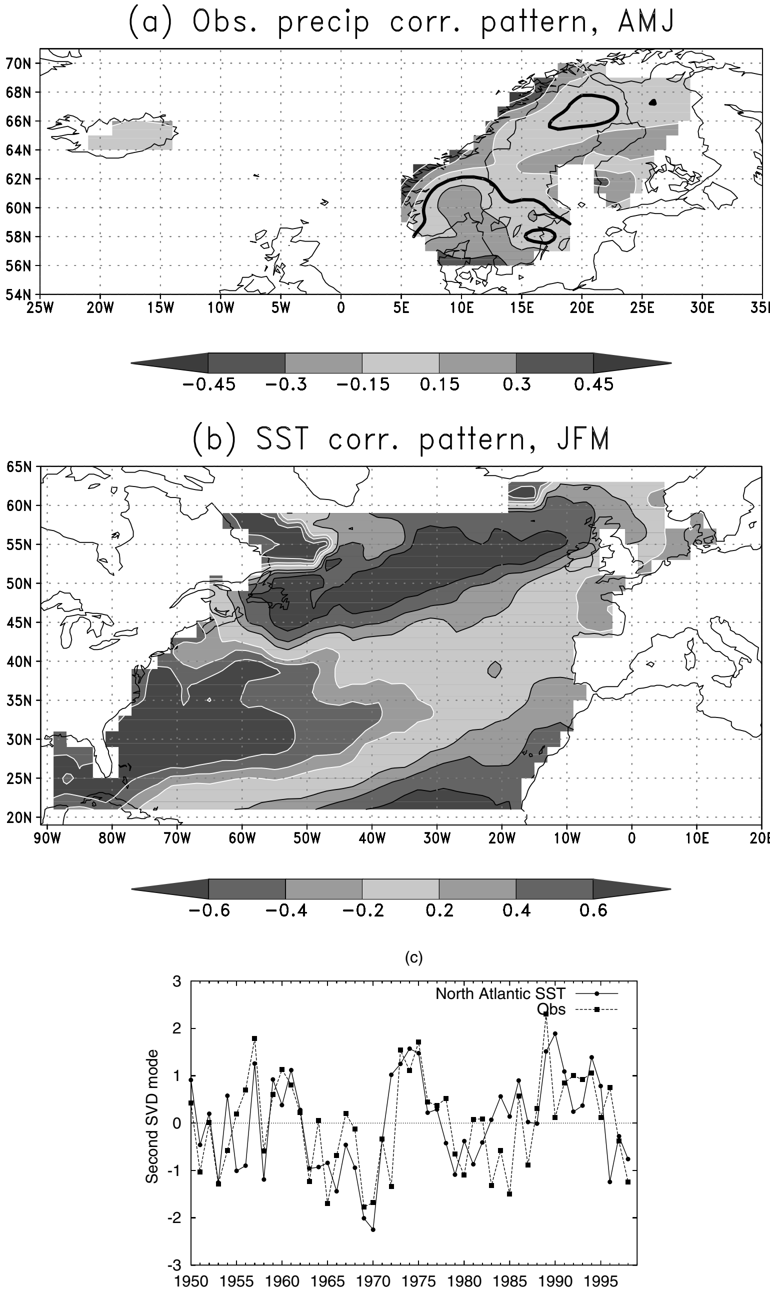

Fig. 5. Correlation patterns and time series for the second mode of an SVD analysis between North Atlantic SST and observed seasonal precipitation in the AMJ season, 1951–1998. The squared covariance fraction SCF = 25.8% for the second SVD mode. (a) Observed precipitation pattern; (b) SST pattern; (c) standardized time series for the second SVD mode. White contours are used for positive correlations; black contours for negative correlations.

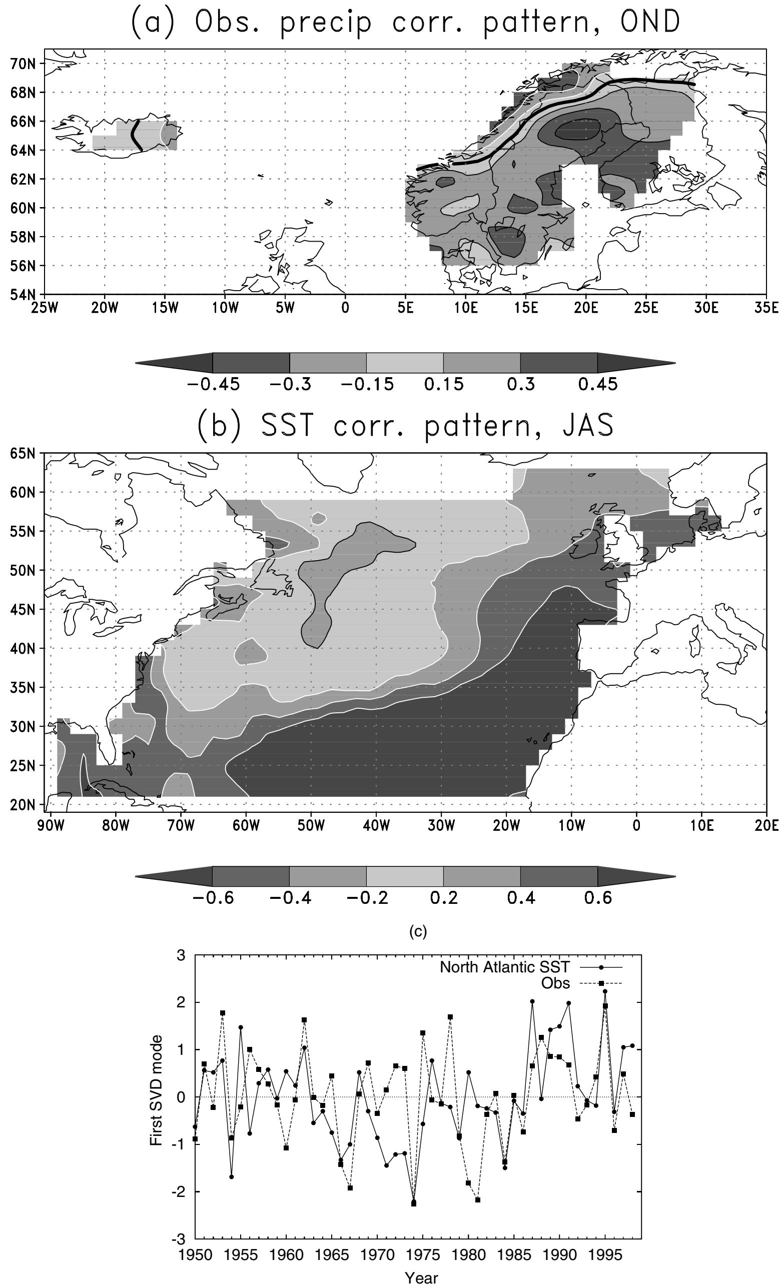

Fig. 6. As in Fig. 5, but for the first SVD mode for the OND season (SCF = 56.5%).

in spring through the forcing of North Atlantic SST in winter, the persistence of the SST from winter to spring and North Atlantic SST forcing of the atmospheric circulation in spring.

The precipitation patterns in Figs. 4a and 5a both show a dipole between southern Scandinavia and western Norway. As the tropical and extropical modes of Atlantic SST (in Figs. 4c and 5c) are almost

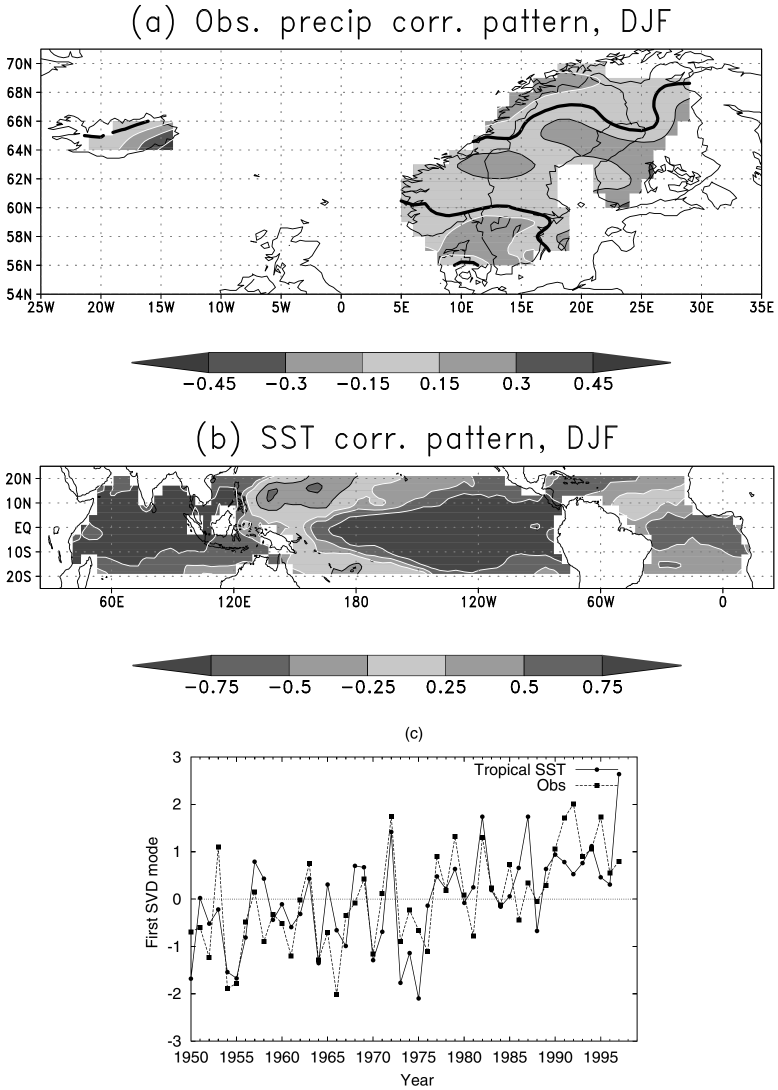

Fig. 7. As in Fig. 4, but for the first SVD mode for the DJF season (SCF = 47.6%). Year in (c) is for December in DJF season.

uncorrelated, it is likely that both tropical and extratropical North Atlantic SST contribute to predictability of precipitation in the Nordic region in the AMJ season.

The relation between tropical SST and seasonal precipitation in Scandinavia (Fig. 4) is consistent with the analysis of van Oldenborgh et al. (2000), who found a positive correlation between SST in the Niño-3 region in boreal winter and seasonal precipitation in spring in north-western Europe, including the southern part of Scandinavia, i.e. below-normal precipitation in spring is statistically linked to cold ENSO events.

The SST correlation patterns (not shown) that are associated with the leading SVD modes between model simulated and observed precipitation are found to be weaker than the SST patterns that are shown in Figs. 4–7, but do in general agree with those patterns, thus confirming the results obtained by the SVD analyses between SST and observed precipitation.

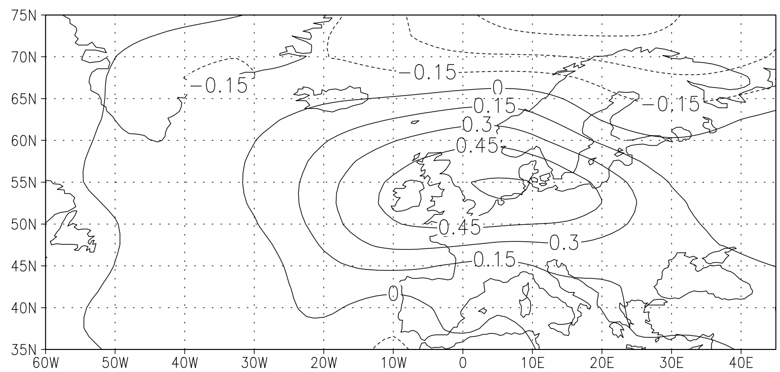

Fig. 8. Mean sea level pressure (MSLP) correlation pattern associated with the North Atlantic SST and Nordic precipitation patterns and time series shown in Fig. 5 for the AMJ season.

A postive trend from 1975 onwards is observed in both central tropical Pacific SST and Scandinavian precipitation (Fig. 7c). The trend in Scandinavian precipitation is closely related to a trend from the mid-seventies in the NAO which coincides with (but is not necessarily physically related to) a trend, or jump, in ENSO. Whether global warming contributes to the trend in Scandinavian precipitation (Hanssen-Bauer and Førland, 2000) is an open question, but the trend certainly appears to contribute significantly to the predictive skill. The correlation between the cross-validated SVD time series drops from 0.14 (Table 2) to less than 0 when the linear trend is removed from the SVD time series.

6. Statistical downscaling and predictive skill for individual stations

The analysis of the large-scale patterns of precipitation has demonstrated the likely existence of predictive skill, at least for the AMJ season. In the following it is shown how the large-scale prediction can be statistically downscaled in order to provide forecasts for the individual stations. Using the model output directly from the grid boxes that are closest to the observing stations generally gives poor predictions, even when the model output is corrected for a possible constant bias. Instead, a model output statistics (MOS) approach is applied to downscale model simulated rainfall. That is, precipitation at the observing stations is specified by linear regression on the first few SVD model simulation time series (Feddersen et al., 1999). Similarly, the observed precipitation can be specified by linear regression on the first few SVD time series from the SVD analysis of SST and observed precipitation.

Predictive skill scores of the MOS downscaled model output and the purely statistical predictions are estimated using cross-validation. That is, precipitation is specified for each year, using only data from the remaining years for the SVD analysis and for finding a regression equation. The SVD analysis is applied to observed precipitation and the ensemble mean of the model simulated precipitation (or tropical or North Atlantic SST). The ensemble mean is also used to derive the regression equation for the MOS downscaling. The predictive skill of the downscaling and of the purely statistical predictions is expressed in terms of a mean anomaly correlation where the statistical moments are averaged separately before calculation of the correlation (Déqué and Royer, 1992). The results are listed in Table 3. Statistical significance of the mean anomaly correlations is tested using a Monte Carlo resampling test.

The predictive skill for the individual stations is expressed in terms of correlation in time between the downscaled model precipitation anomaly and the observed precipitation anomaly. Figures 9 and 10 show the skill scores for the two most predictable seasons, AMJ and NDJ.

The number of SVD time series to include in the downscaling is chosen simply by requiring that the "explained" squared covariance should be at least 80% of the total squared covariance. This choice leads to inclusion of between three and six SVD time series.

The cross-validated correlation skill scores for the individual stations are moderate, generally less than 0.5, even for the most skilful seasons. For the NDJ season (Fig. 10) a small part of the predictive skill can

Table 3. *Mean anomaly correlations for statistically downscaled dynamical predictions of precipitation and for statistical predictions based on tropical SST from the same season and for North Atlantic SST from the preceeding three-monthly season*[a]

Season	Predictor		
	Model precipitation	Tropical SST	North Atlantic SST
DJF	0.10	0.10	0.06
DJF	0.10	0.10	0.06
JFM	0.02	0.14	**0.16*****
FMA	−0.17	**0.15*****	0.05
MAM	0.09	0.06	−0.12
AMJ	**0.15***	**0.11****	**0.18***
MJJ	0.02	**0.13*****	**0.15***
JJA	−0.02	−0.01	0.06
JAS	−0.02	−0.16	−0.19
ASO	−0.10	−0.10	−0.14
SON	−0.05	0.10	0.00
OND	0.07	**0.19*****	0.12
NDJ	0.06	**0.22***	**0.18****

[a]Correlations that are significant at 1, 5 and 10% levels are printed in bold and denoted *, ** and ***, respectively.

be attributed to trends in the precipitation during the 1951–1998 period.

6.1. Statistical significance of the predictive skill

Only a few of the mean anomaly correlations in Table 3 were found to be statistically significant. For example, for the statistical downscaling of model simulated precipitation statistical significance was only achieved for the AMJ season. However, in a test for statistical significance we also have to take into account that this result was obtained by searching for significant correlations among predictions for twelve different seasons, and so the chance that "random" predictions test significant at, say, a 1% level for any one of the seasons is considerably higher than 1%. This problem of multiplicity (Wilks, 1995, pp. 151–157), closely related to the problem of field significance (Livezey and Chen, 1983), was not taken into account in the estimates of significance levels that are listed in Table 3. In order to do that, an additional Monte Carlo type significance test was applied to find the probability that the mean anomaly correlation skill

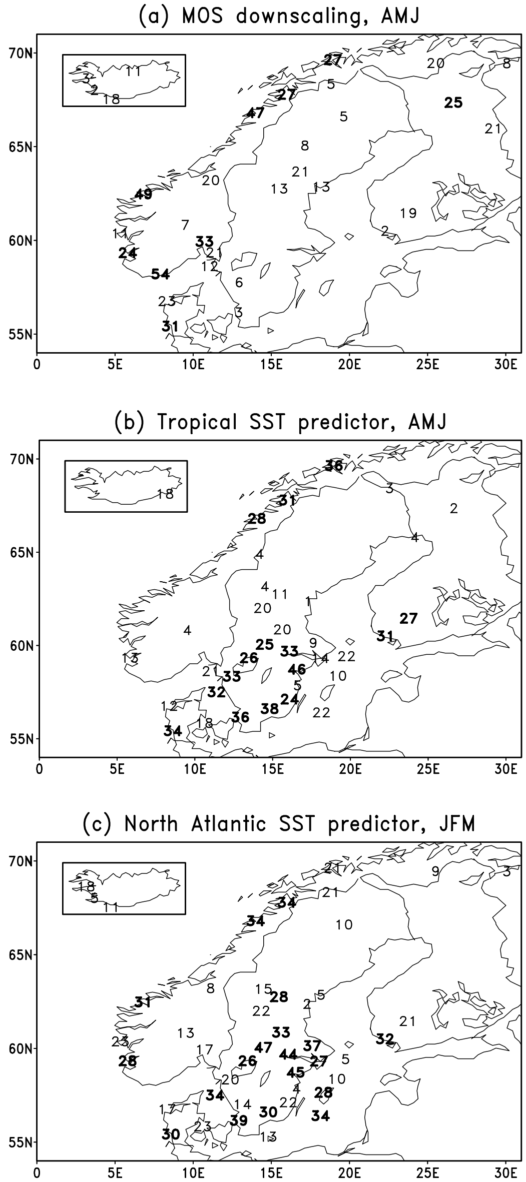

Fig. 9. Cross-validated correlation skill scores in % for precipitation in the AMJ season (1951–1998) for the individual Nordic stations. Only positive correlations are shown. Correlations that are statistically significant at a 10% level (according to a *t*-test) are printed in bold. Skill scores are shown for (a) statistically downscaled model output, (b) statistical "predictions" based on tropical SST from the same season, (c) statistical predictions based on North Atlantic SST from the preceding season.

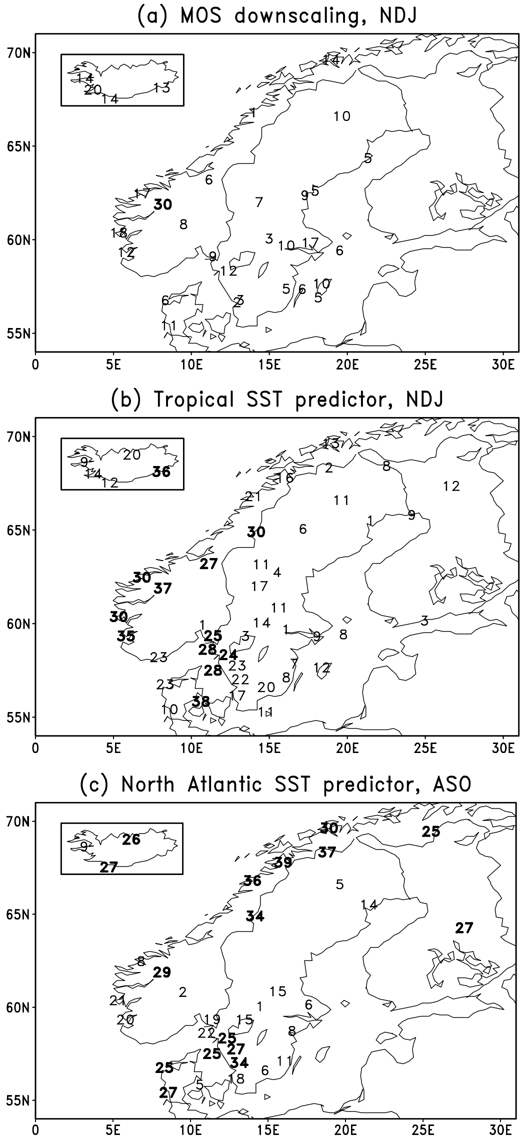

Fig. 10. As in Fig. 9, but for the NDJ season.

of a random prediction from any season exceeds that of the actual AMJ mean anomaly correlation.

It was found that the chance of achieving a 1% significance level for one of the seasons is approximately 10%, while the chance of achieving a 5% significance level is almost 40%. However, we have reason to believe that at least the AMJ result reflects real predictability, because the statistical predictions based on SST and no dynamical model also indicate the relatively high skill in AMJ. An estimation of the level of significance for rejection of the null hypothesis that higher correlations than those found in AMJ for two different prediction methods are a result of pure chance was found using yet another Monte Carlo resampling test.

It was found that it is very unlikely (probability less than 1%) to achieve individual significance levels of 1% by chance for both downscaled model simulated precipitation and statistically predicted precipitation. Thus, there is good reason to believe that the AMJ predictability is real. For NDJ the probability was similarly estimated to be less than 10% that the weak predictability is a result of chance.

7. Conclusions

It has been demonstrated that seasonal precipitation in the Nordic region almost certainly contains a predictable signal in the AMJ season and possibly also weak signals in other seasons. This conclusion is supported by analyses of observed and model simulated precipitation (from a nine-member ensemble of integrations of the Arpege GCM forced by observed SST from 1950–1999) and by statistical prediction of precipitation from observed SST for the same 50-yr period. The predictability is generally low, with the best of the predictive skill obtained in spring, in the AMJ season. In order to detect the predictive signal in the dynamical model output it is essential to have an ensemble of model simulations, as this enables us to average out noise by considering the ensemble mean. SST variability has weaker high frequency variability than precipitation in the Nordic region, and so detection of predictable signals is somewhat easier when seasonal precipitation is predicted statistically from SST.

The origin of the predictive skill has also been studied. Tropical SST appears to have a weak but significant influence on seasonal precipitation in the Nordic region in winter and spring, but the highest predictability appears to be associated with North Atlantic SST in spring. It was found that the SST pattern very closely resembles that associated with the North Atlantic Oscillation in winter. SST anomalies associated with this pattern are fairly persistent from winter to spring, and so it is hypothesized that the North Atlantic SST in spring forces the atmospheric circulation such that after a winter dominated by the positive (negative) phase of the NAO, reduced (increased) amounts of precipitation are likely in southern Scandinavia in spring, while increased (reduced) amounts of precipitation are likely in the rest of Scandinavia, particularly in western Norway, in spring.

In this paper predictability was first demonstrated for large-scale patterns of precipitation in the Nordic region. Subsequently, it was shown how the large-scale variability could be statistically downscaled to make predictions for the individual climate stations, and the results were compared with results from a statistical specification of precipitation directly from observed SST. It would be interesting to compare with the skill that could be obtained using dynamical downscaling, i.e. using a high-resolution regional climate model nested into the global dynamical model. In any case, it still remains to be seen whether practical use can be made of seasonal precipitation forecasts in the Nordic region.

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