Downscaling of GCM forecasts to streamflow over Scandinavia

Patrik Nilsson, Cintia B. Uvo, Willem A. Landman and Tinh D. Nguyen

ABSTRACT

A seasonal forecasting technique to produce probabilistic and deterministic streamflow forecasts for 23 basins in Norway and northern Sweden is developed in this work. Large scale circulation and moisture fields, forecasted by the ECHAM4.5 model 4 months in advance, are used to forecast spring flows. The technique includes model output statistics (MOS) based on a non-linear Neural Network (NN) approach. Results show that streamflow forecasts from Global Circulation Model (GCM) predictions, for the Scandinavia region are viable and highest skill values were found for basins located in south-western Norway. The physical interpretation of the forecasting skill is that stations close to the Norwegian coast are directly exposed to prevailing winds from the Atlantic Ocean, which constitute the principal source of predictive information from the atmosphere on the seasonal timescale.

Key words | downscaling, forecasting, general circulation model, model output statistic, neural networks

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INTRODUCTION

The seasonal predictability of streamflow in Scandinavia has emerged over the most recent decade due to the deregulation and privatization of the electricity market in the 1990s. Streamflow is the key information for hydropower production and e.g. in Norway up to 99% of the electricity generated is hydroelectricity (EIA 2004). Global circulation models (GCMs) have been used worldwide in seasonal forecasting and show skill at global scales (e.g. Palmer and Anderson 1994). However, GCMs are not skilful in simulating the great variability on the local scale that the streamflow imply (Xu 1999) as GCMs do not have the temporal and spatial resolution which is necessary for the detailed estimation of local climate, and for the consideration of the interaction between climatological and hydrological systems. To assess the effect of large-scale circulations on local parameters a downscaling method is needed.

Seasonal climate forecasting is essentially based on the opinion that the slowly evolving sea surface temperature (SST) anomalies influence seasonal mean weather conditions (Palmer & Anderson 1994; Goddard *et al.* 2001). Variability in SST provides the main source of atmospheric predictability at seasonal time-scales. Therefore, estimation of the evolution of SST anomalies, which are often relatively predictable, and subsequently employing them as input to an atmospheric GCM, potentially provides the means of generating forecasts of seasonal average weather (Graham *et al.* 2000). Streamflow is affected by precipitation, temperature, temperature gradient and anomalies, evapotranspiration, changes in soil water storage, vegetation cover and soil surface characteristics, among others. From these factors, only precipitation and temperature are explicitly simulated by GCMs. None of the other factors are predicted and they impress a non-linear characteristic to the relation climate–streamflow (e.g. Cannon & Whitfield 2001). Consequently, a non-linear downscaling model is preferred.

A variety of models have been used in downscaling studies. In general, models used to downscale large scale GCM variables to streamflow or precipitation in Scandinavia have

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been linear. Feddersen (2003) applied a linear model output statistics (MOS) approach to downscale GCM simulated precipitation in the Scandinavian countries. It is demonstrated that the predictive skill is found in the AMJ season and possible also weak signals in other seasons. A multiple linear regression model has been used to downscale large scale climate GCM variables to seasonal precipitation in southern Scandinavia (Linderson *et al.* 2004). The model is skillful for all seasons in reproducing the variability of the mean precipitation. Hellström *et al.* (2001) also developed a skilful multiple linear regression model for downscaling of monthly precipitation based on GCM variables.

Other well-known downscaling approaches used worldwide are canonical correlation analysis (CCA) (Landman and Goddard 2005), polynormal regression (Hewitson 1994) and neural network (NN) (Cannon & Whitfield 2001). In Crane & Hewitson (1998) non-linear NN is used in a downscaling procedure to derive precipitation from GCM geopotential height and specific humidity data and this downscaling procedure effectively captured the monthly precipitation totals in the Susquehanna basin in the USA.

The objective of this work is to investigate the seasonal predictability of streamflow over Scandinavia through the use of a downscaling method, linking large scale circulation and moisture fields, as forecasted from the ECHAM4.5 GCM, to streamflow. CCA (Barnett & Preisendorfer 1987) is used to find the most suitable predictors for streamflow. A MOS is applied to relate winter season (JFM) predictors as forecasted by the GCM in December, to melting season (MJ) streamflow using a non-linear NN model. The average May–June streamflow predictand was chosen for being representative of the discharge resultant from the spring melting in the investigated basins. The expected skill values are higher over most near-costal or island locations, as GCM forecasts are run with prescribed observed SST, which should influence significantly, and preferentially, the costal and island regions (Johansson *et al.* 1998). Higher skill is consequently expected on the Norwegian west coast where also hydropower production is higher and therefore streamflow forecast is of large importance.

The winter climate in the studied region (Norway and northern Sweden) is affected by terrain features. The most significant feature on the Scandinavian Peninsula is the Scandinavian mountains which extend along the Swedish and Norwegian boarder (Figure 1). The climate is mainly influenced by the westerly winds from the Atlantic (Hellström *et al.* 2001) and the mountains force the air to rise, causing the air to cool and causing precipitation on the western side of the Scandinavian mountain range. The eastward continental air masses of the Eurasian continent also have an effect on the

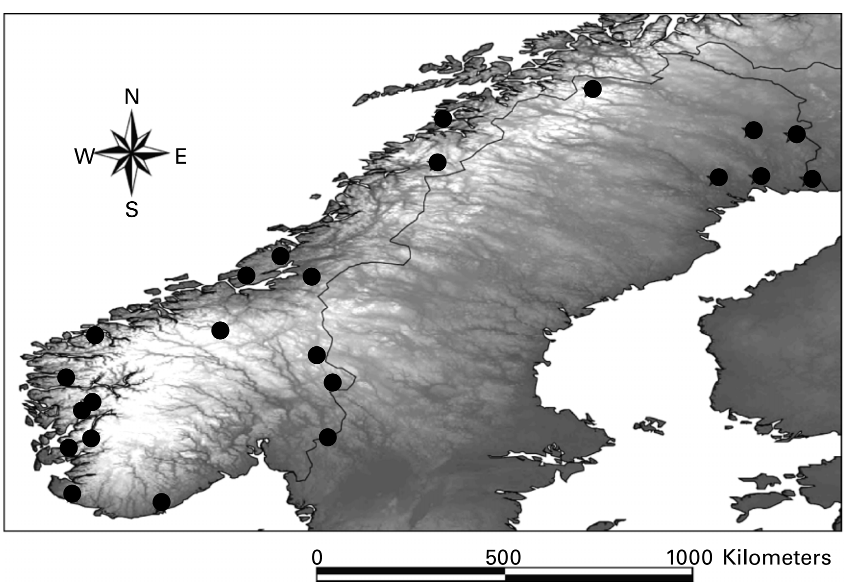

Figure 1 | Topography map showing the Scandinavian mountain range, which extends along the Norwegian and Swedish boarder. The gauging stations are marked with stars. Brighter areas are higher in elevation (Patrik Nilsson).

Scandinavian climate, especially on the parts of Scandinavia located on the east side of the Scandinavian mountain range (Ångström 1974) as they collect moisture from the Baltic Sea and precipitate it over land.

The streamflow forecasts are performed with a total lead-time of four months as the GCM is forced by persisting December SST anomalies through the JFM forecast season (imposing a 1-month lead-time) and the MOS related JFM forecasted from the GCM to May-June streamflow.

The forecasts, in this study, are performed both probabilistically and deterministically. Deterministic forecasting was carried out by using GCM ensemble means, as input to MOS. Probabilistic forecasting is made by using each of the ensemble members as input to MOS.

Ensemble members are generated by running GCMs from slightly different initial conditions. The inherent variability of the atmosphere motivates seasonal climate simulations to be expressed probabilistically and the use of ensemble members is a feasible method to estimate the probability distribution of atmospheric states (Branković & Palmer 2000). An ensemble estimates the atmospheric outcomes in a better way than only one GCM outcome, even if, it does not represent the whole range of possible atmospheric states. In addition, errors in the initial conditions as well as deficiencies in the parameterizations and systematic or regime-dependent model errors can be to a large part accounted for through ensemble forecasting (Evans *et al.* 2000). There is inevitable growth in errors of differences between forecasts started from very slightly different initial conditions suggesting that there is no single valid solution but rather a range of possible solutions (Tracton & Kalnay 1993).

This paper is organized as follows: in the following section the study region and the data utilized are described; the next section introduces the methodology for the deterministic and the probabilistic forecasting models; the results of this study are then presented and finally the summary and conclusions which can be drawn from this study.

STUDY REGION AND DATA SETS

The variable to be forecasted is represented by May-June average unregulated streamflow at 17 different gauges in Norway and six in northern Sweden (Figure 1) from 1968 to 2004. It is representative of the streamflow related to the melt of the snow accumulated during winter.

Twelve ensemble members of different GCM variables, including zonal and meridional winds (200, 850 hPa), specific humidity (700, 850 hPa) and geopotential height (200, 850 hPa) are used as predictors. Seasonal averages of each GCM variable and for each ensemble member are calculated. The GCM used in the experiments is the atmospheric ECHAM4.5 (Roeckner *et al.* 1996) run at the International Research Institute for Climate and Society (IRI), Columbia University, New York. The ECHAM4.5 atmospheric dynamics are represented in spectral space with a grid of resolution 2.8125° × 2.7893° (Latitude/Longitude). The domain of the GCM variables was a window extending from 48°N to 76°N and from 25°W to 33°E. The GCM is forced by persisting December SST anomalies through the JFM season, thus imposing a 1-month lead-time.

Both predictor and predictand time series span the period 1968 to 2004. To improve the performance of the NN, all time series were standardized and transformed to the interval −0.9 to 0.9 prior to use, as recommended by Dawson & Wilby (2001). Standardization is done to ensure that all different variables have an equal opportunity to participate in the prediction process (Bartman *et al.* 2003).

METHODOLOGY

The first step in the downscaling technique consisted of CCA pattern analysis to find the most suitable GCM predictor parameters. Then a MOS was applied to relate the predictors to streamflow using a non-linear NN model. The forecasting simulations were done both deterministic, using GCM variables ensemble mean, and probabilistic, using all individual ensemble members separately. The skill of the streamflow forecasts for the 23 Scandinavian basins was verified using the Ranked Probability Skill Score (RPSS) and correlation coefficients.

Canonical correlation analysis (CCA)

The predictor parameters to be used are determined from well-founded hypotheses on the mechanisms which are thought to be responsible for the variability on seasonal timescale (Johansson *et al.* 1998). The diagnostic features of the CCA are used to find these underlying mechanisms. The CCA technique is a step higher in the hierarchy of model complexity than the multiple regression and is used in this study to find the most suitable GCM predictor parameters. The CCA is a statistical model which identifies the linear combination of variables in a predictor field which are most strongly correlated with linear combinations of variables in the predictand fields (von Storch & Zwiers 1999). The diagnostic features of CCA include spatial patterns (or maps). The CCA pattern analysis of JFM GCM ensemble mean variables produces maps (g-map: GCM variables spatial pattern. h-map: streamflow spatial pattern) which show the association between the predictors and the predictands and their respective canonical coefficients. Spatial patterns indicate the association between the GCM large-scale circulation and the streamflow.

Model output statistics (MOS)

MOS (Wilks 1995) is used to relate the GCM quantities to a forecast quantity. It can include directly in the regression equations any influence of specific characteristics, such as systematic errors (Landman & Goddard 2002). For developing a MOS, it is necessary that a set of data consisted of historical records of the predictand (streamflow) as well as archived records of the GCM forecasted variables. The lead-time in MOS forecasts is therefore incorporated in the GCM forecasts.

A non-linear NN (Smith 1993) approach is employed to do the MOS as the association between atmospheric variability and streamflow is non-linear (Cannon & Whitfield 2001), thus necessitating a non-linear link between the GCM-simulated fields and observed streamflow anomalies. If the association between the GCM large scale and observed streamflow anomalies is sufficiently non-linear in our studied area, then the NN recalibration approach should prove more beneficial compared to a linear approach.

MOS deterministic forecast

A non-linear MOS procedure is used to do deterministic streamflow forecasts. The ensemble mean of the 12 ensemble members of the forecasted GCM variables is calculated. This procedure averages out the noise and leaves more of the predictability signal. By using a non-linear downscaling model a signal which exceeds the noise is intended to be found.

MOS was applied to relate the GCM variables to streamflow using a non-linear NN model. The cross-validated forecasted results were compared to observed May-June spring flow and are presented in a map showing the skill for each streamflow station and conclusions will be drawn based on the geographic location of the stations.

MOS probabilistic forecast

Seasonal averages of each GCM variable and for each ensemble member are calculated. A non-linear NN was applied to each of the 12 members. The probability of being above-, near- or below normal was calculated by counting the number of times a category is hit by any of the 12 ensemble members.

Cross-validated forecasts for each of the 12 ensemble members are produced leading to a probability forecast for each season of the 36 years. Probabilistic MOS based forecast is performed for the ten most skilful streamflow stations found when doing the deterministic simulations. The GCM predictor variable used was the variable producing highest skill for the deterministic simulations. The spread of the probability forecast has been analyzed in the way that the forecasts of all individual members will be presented in a figure. How much of this spread is caused by the chaotic character of the atmosphere or by the typical spread of the non-linear NN is discussed.

Neural network (NN)

The non-linear model used in this study is the multi-layer feed forward NN. NNs are able to perform non-linear mapping between input and target values. Training is accomplished by presenting a set of input-output pairs of vector values to the NN and subsequently modifying the internal parameters of the network until the output generated is close to observed values (Zhang & Govindaraju 2000). A two layer feed-forward NN can approximate arbitrarily well any continuous non-linear function given a set of inputs and a sufficient number of hidden neurons (Hornik *et al.* 1989).

The two-layer NN used in this work includes one hidden layer containing ten neurons and one output layer with one neuron. The transfer function associated to the neurons in the hidden layer was a hyperbolic tangent sigmoid transfers function (Equation (1)). To the output neuron, it was associated a linear (Equation (2)) transfer function. The mathematical expressions of the functions are as follows:

$$\text{hyperbolic tangent sigmoid}: \qquad o = \frac{2}{(1+e^{(-2\cdot i)})-1} \qquad (1)$$

$$\text{linear}: \qquad o = i \qquad (2)$$

where i is input and o, the output.

All NN were trained using gradient descent back-propagation. To define the optimum moment for stopping the training procedure, early stopping was used. The early stopping technique prevents the NN to over-fit by stopping the training if the network performance on a test vector (a reserved part of the training subset) fails to improve (Demuth & Beale 1994). To avoid instabilities, as suggested by Hsieh & Tang (1998) among others, an ensemble of ten runs was generated, each one starting from different initial conditions. The ensemble average was considered as the final output of the NN. All NN tests were performed using Matlab.

Verification method

The verification of the forecast models was done using one-out cross-validation. This method was chosen due to the relatively small sample size. Input and output values at a given year are excluded from the data series and are used as validation to the trained model. The NN is then trained using 80% of the remaining data for the proper training and 20% as a testing period for the early stopping. This procedure is repeated until all elements of the input set have been excluded from the set and estimated after the NN training.

To verify the skill of the deterministic forecast, the correlation coefficient between observed and forecasted values is checked, as well as its statistical significance.

The skill of the probabilistic forecast was verified by means of ranked probability skill score (RPSS) (Wilks 1995). The RPSS is used to evaluate a model's skill in capturing categorical probabilities relative to climatology. The method is as follows:

The streamflow peak values are divided into three categories. Values below the 33rd percentile fall into the below normal category, above the 66th percentile into the above normal category, and the rest, in the near normal category. The proportion of ensemble members falling into each category gives the categorical probability forecast. The rank probability score (RPS) is given by:

$$RPS = \sum_{m=1}^{n}\left[\left(\sum_{j=1}^{m} y_j\right) - \left(\sum_{j=1}^{m} o_j\right)\right]^2 \qquad (3)$$

where o_j and y_j are the predicted and observed probabilities and n is the number of categories. The observed probabilities equal one if the observation falls in the category and zero otherwise.

The climatology forecast is the proportion of historical observations in each category and is calculated using Equation (3). The climatological probability of each category is one third. The RPSS (Equation (4)) is calculated as:

$$RPSS = 1 - \frac{RPS(forecast)}{RPS(\text{climatology})} \qquad (4)$$

The RPSS ranges from $-\infty$ to 1.0; the highest value indicating a perfect forecast. A negative value of RPSS implies that the forecast has less accuracy than climatology.

RESULTS AND DISCUSSION

Canonical correlation analysis

The CCA pattern analysis of JFM GCM ensemble mean variables showed that the two GCM variables producing highest correlations between the canonical vectors were zonal wind (Figure 2(c); correlation coefficient = 0.44) and moisture (correlation coefficient = 0.40). Figure 2 shows the correlation patterns of the first mode between ensemble mean of JFM 850 hPa zonal wind and observed MJ seasonal streamflow for 1968–2004. The g-map (Figure 2 (a)) implies

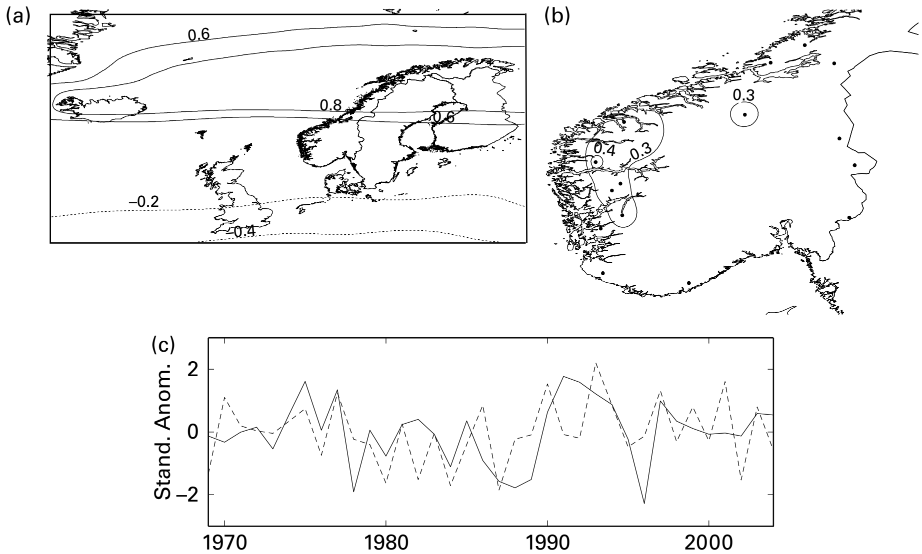

Figure 2 | Correlation patterns of the leading mode of a CCA analysis for 1968–2004. (a) g-map (b) h-map (c) Canonical vectors of the ensemble mean of JFM 850 hPa zonal wind (dashed line) and observed MJ seasonal streamflow (solid line) (Patrik Nilsson).

that strong westerly winds over the North Atlantic are positive correlated with five streamflow stations (h-map in Figure 2(b)) on the Norwegian south west coast. A North Atlantic Oscillation (NAO) like pattern (Figure 2(a)) in the North Atlantic Ocean is associated with the streamflow anomaly dipole in south western Norway. Based on the analysis of the physical mechanisms relating the GCM-variables to the streamflow, the 850 hPa zonal wind and 850 hPa moisture predictors were chosen for the development of deterministic and probabilistic streamflow forecasts.

MOS deterministic forecast

The CCA analysis demonstrated the likely existence of predictive skill, and is followed by a deterministic downscaling of large scale predictions of the GCM variables to provide streamflow forecasts. The predictive skill for the individual stations is expressed in terms of correlation between the downscaled GCM variables and the MJ streamflow and is listed in Table 1 and the geographic location of the forecasting skill is presented in Figure 3.

In general, the MOS model performed well over the Norwegian west coast region and especially over the south-western one. The results are in agreement with Uvo (2003) where the highest skills for precipitation totals were found on the west coast. Three stations, all located on the west coast, showed cross-validation correlations higher than 0.33, which is the threshold for the 95% level of confidence (p-value < 0.05 in Table 1, column 5). The model predictive skill is lower, with some exceptions, for the stations located on the lee side of the Scandinavian mountain range (region including northern Sweden and south/eastern Norway). The physical interpretation of the forecasting skill originates from the fact that the stations close to the Norwegian coast are exposed to prevailing winds from the Atlantic Ocean, which constitute a principal source of predictive information for the atmosphere on the seasonal timescale. The mountains significantly weaken strong frontal systems moving into Scandinavia and form an explanation of the higher skill for the stations on the westward side compared to the leeward side of the mountains.

Results from the CCA analysis show that the most important GCM variables to be used as predictors when forecasting streamflow are zonal wind and moisture. In the third column in Table 1 one can see that the predictors zonal wind and moisture resulted in the highest forecasting skill about the same number of times (13 vs. 10 times) and they are consequently equally important predictors.

Figure 4 shows the scatter diagram for NN based MOS downscaling of MJ streamflow for the station Stordalsvatn using 850 hPa moisture as a predictor. The downscaling

Table 1 | Cross-validated correlations for the NN-based MOS forecasts of MJ streamflow based on GCM ensemble mean predictors. MJ streamflow forecasting skills for the 23 individual Scandinavian streamflow stations are presented. Predictors used are the GCM variables: moisture (m) and zonal wind (zv). The probability value (p-value) corresponds to the level at which the MOS correlations are statistical significant

Streamflow station	GCM variable	Correlation coefficient	p value
Flaksvatn	850 hPa m	−0.29	0.09
Gjedlakleiv	850 hPa zv	0.11	0.53
Stordalsvatn	850 hPa m	0.35	0.04
Sandvenvatn	850 hPa m	0.30	0.09
Bulken	850 hPa m	0.34	0.05
Viksvatn	850 hPa zv	0.27	0.11
Krinsvatn	850 hPa zv	0.13	0.44
Øyungen	850 hPa zv	0.11	0.51
Strandå	850 hPa m	0.35	0.04
Femundsenden	850 hPa m	0.29	0.10
Nybergsund	850 hPa m	0.27	0.12
Magnor	850 hPa zv	0.02	0.89
Suldalsoset	850 hPa m	0.11	0.53
Risefoss	850 hPa m	0.19	0.27
Fetvatn	850 hPa zv	0.13	0.46
Myrkdalsvatn	850 hPa m	0.22	0.20
Grunnfoss	850 hPa m	0.13	0.44
Junosuan	850 hPa zv	0.24	0.16
Kallio	850 hPa m	0.33	0.06
Kukkolan	850 hPa zv	0.16	0.36
Räktfors	850 hPa zv	0.14	0.40
Torneträsk	850 hPa m	−0.05	0.77
Ytterholmen	850 hPa zv	0.10	0.58

shows a statistical significant correlation of 0.35 for the station with the general tendency that the lower streamflow observations are overestimated and the higher observations are underestimated.

The MOS downscaling shows an improvement in forecast skill if compared to the results from Nilsson & Uvo (2003). They used observed SST and zonal wind, which were represented by the u-index (Chen 2000), to forecast MJ river discharge in Bulken, Norway. Their results show that the use of u-index and sea surface temperature anomalies (SST) from February as input to a NN result on a correlation coefficient between observed and estimated MJ flow of 0.71 (>95% confidence). They show that SST solely is not a skilful predictor for MJ flow in Bulken. A statistically significant correlation (0.5) between observed and estimated MJ flow can be reached only if SST in May is used as predictor. If a similar lead-time is considered (predictor from December), observed SST and zonal winds show no skill in predicting MJ streamflow.

MOS probabilistic forecast

The MOS based probabilistic forecast skills, expressed by means of RPSS, are presented in Figure 5. The same predictors as were used for the deterministic downscaling were used for the probabilistic downscaling of streamflow for the ten stations.

In agreement with what was found by the deterministic downscaling, the best forecast skills were found for the stations located on the Norwegian south west coast. Five out of six stations located there show a positive RPSS and, thus, outscore the climatology forecast. The stations located on the lee side of the mountain range demonstrate varying results with e.g, one negative (Junosuan) and one positive (Kallio) RPSS for the stations in northern Sweden.

The spread of the probability is analyzed by plotting the 12 ensemble members for the ten streamflow stations for year 1968 (Figure 6). The spread is caused by the chaotic character of the atmosphere in combination with the spread of the NN simulations. The spread caused by the NN is restricted by the fact that ten runs of the NN is generated, each one starting on different initial conditions, and the average of the runs are considered as the output from the NN. The spread was generally slightly smaller for the stations located on the west coast indicating that the chaotic variability is low and the predictive signal in the climate is high, whereas the spread for some of the stations (e.g, Nybergsund; Figure 6) are wider.

SUMMARY AND CONCLUSION

This study focused on seasonal streamflow forecast for 23 basins in Norway and northern Sweden. A downscaling

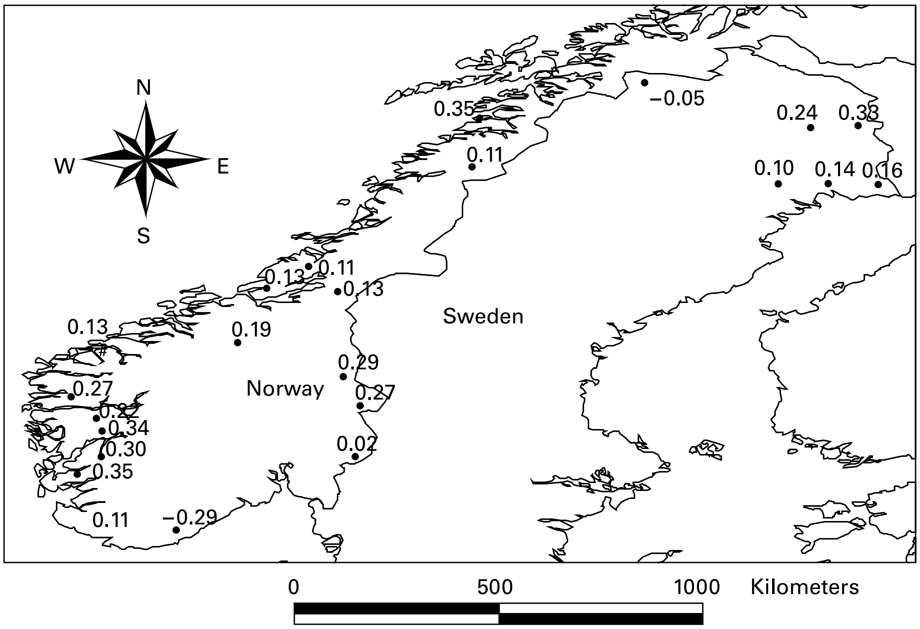

Figure 3 | Geographic location of the forecasting skill for the streamflow stations in Scandinavia expressed as cross-validated correlation coefficients (Patrik Nilsson).

method is used which links large scale circulation and moisture fields, as forecasted from the ECHAM4.5 GCM, to streamflow four months in advance. The average May-June streamflow was chosen as predictand for being representative of the discharge resultant from the spring melting in the investigated basins. A statistical approach (MOS) is applied to relate the predictors to streamflow using a non-linear NN model. The forecasting simulations are done both deterministically, using GCM variables ensemble mean, and probabilistically, using individual GCM ensemble members separately.

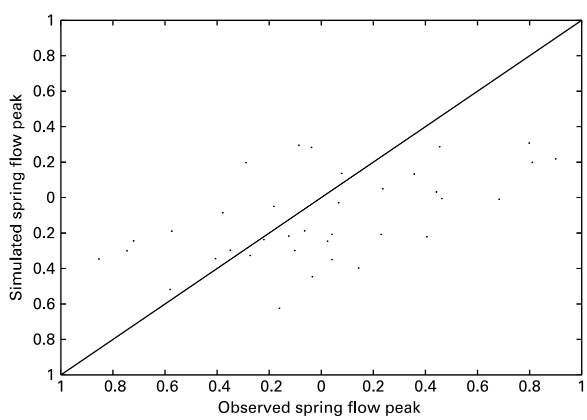

Figure 4 | Scatter diagram for the non-linear MOS–forecast versus the observed spring peak flow for streamflow station Stordalsvatn. The predictor used was standardized anomalies of 850 hPa ensemble mean moisture (Patrik Nilsson).

Highest predictive skills were found for the stations on the Norwegian west coast and especially over the south-western part. Deterministic forecast resulted in three stations, all located on the west coast, showing cross-validation correlations higher than 0.33, which is the threshold for the 95% level of confidence. The highest probabilistic forecast skills were also achieved on the

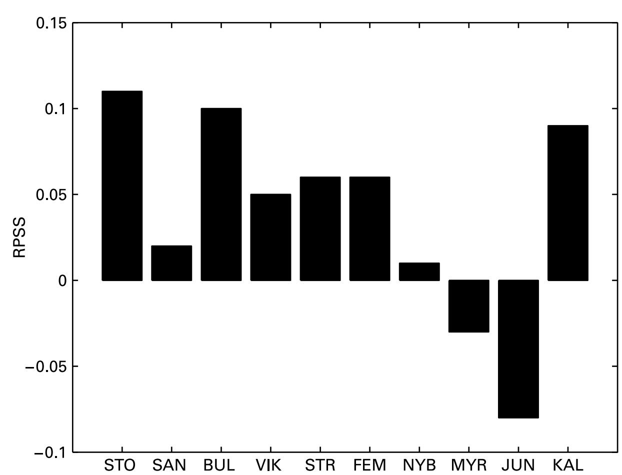

Figure 5 | RPSS over the 36-year cross-validated forecast period for the ten streamflow stations: STO = Stordalsvatn, SAN = Sandvenvatn, BUL = Bulken, VIK = Viksvatn, STR = Strandå, FEM = Femundsenden, NYB = Nybergsund, MYR = Myrkdalsvatn, JUN = Junosuan, KAL = Kallio (Patrik Nilsson).

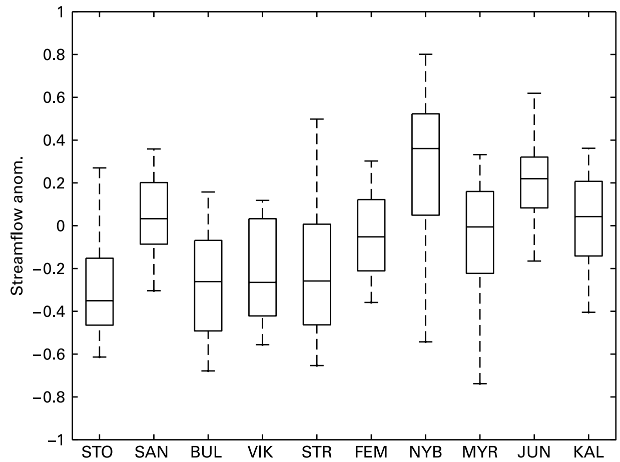

Figure 6 | The spread among the 12 ensemble members for the ten streamflow stations (see station abbreviation in Figure 5) for year 1968. The spread is given in boxplots, in which the median, lower and upper quartiles and minimum and maximum values are given (Patrik Nilsson).

Norwegian south-west coast. Five out of six stations located in that area show a positive RPSS and thus outscore the climatology forecast. The model predictive skill is lower, with some exceptions, for the stations located on the lee side of the Scandinavian mountain range (region including northern Sweden and south/eastern Norway). The physical interpretation of the forecasting skill is that stations close to the Norwegian coast are directly exposed to prevailing winds from the Atlantic Ocean, which constitutes the principal source of predictive information from the atmosphere on the seasonal timescale.

The streamflow forecasts in this study are performed with a total lead-time of four months as the GCM is forced by persisting December SST anomalies through the JFM forecast season (imposing a 1-month lead-time) and the MOS related JFM forecasted from the GCM to May-June streamflow. The climate variability is strongest and most predicable during the winter months when the atmosphere is most dynamically active and justifies the use of JFM GCM variables as predictors. This long lead-time is useful when planning hydropower production as the key information for the hydropower managers is the amount of water in the spring flow.

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