Seasonal streamflow forecast: a GCM multi-model downscaling approach

Kean L. Foster and Cintia B. Uvo

ABSTRACT

This work investigates the predictability of seasonal to inter-annual streamflow over several river basins in Norway through the use of multi-model ensembles. As general circulation models (GCMs) do not explicitly simulate streamflow, a statistical link is made between GCM-forecast fields generated in December and average streamflow in the melting season May–June. By using the Climate Predictability Tool (CPT) three models were constructed and from these a multi-model was built. The multi-model forecast is tested against climatology to determine the quality of the forecast. Results from the forecasts show that the multi-model performs better than the individual models and that this method shows improved forecast skills if compared to previous studies conducted in the same basins. The highest forecast skills are found for basins located in the southwest of Norway. The physical interpretation for this is that stations on the windward side of the Scandinavian mountains are exposed to the prevailing winds from the Atlantic Ocean, a principal source of predictive information from the atmosphere on this timescale.

Key words | canonical correlation analysis, climate predictability tool, downscaling, general circulation model

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INTRODUCTION

Hydropower constitutes 99% of Norway's electricity generation (SN 2008) and streamflow is essential information in this field, as operation planning is dependent on this information. The longer the lead-time is of information regarding streamflow, the more effective the planning can be. This means that some sort of forecast is needed. At present, as general circulation models (GCMs) do not explicitly simulate streamflow (Xu 1999), they lack the spatial and temporal resolution that is necessary to use a model to downscale the GCM forecasts to streamflow. Some well-known downscaling approaches are polynormal regression (Hewitson 1994), neural network (NN) (Nilsson *et al.* 2008) and canonical correlation analysis (CCA) (Landman & Goddard 2005).

Norway's winter climate is mainly influenced by westerly winds from the Atlantic (Hellström *et al.* 2001). When these winds encounter the Scandinavian mountain range the air is forced to rise resulting in precipitation on the western side of the mountain range. According to Nilsson *et al.* (2008) the expected skill values for coastal regions are higher as GCMs are run with prescribed observed sea surface temperatures (SST). It is therefore expected that the basins near the coast on the western side of the Scandinavian mountain range will have the highest skill values.

The aim of this study is to investigate the predictability of seasonal to inter-annual streamflow over several river basins in Norway through the use of multi-model ensembles. GCM-forecast fields generated in December are related to average streamflow in the melting season May–June, i.e. having a lead time of four months. The multi-model forecast is tested against climatology to determine the quality of the forecast.

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DATASETS

The data for streamflow used in this study are seasonal means for May–June, calculated from daily measurements at gauging stations in different basins across Norway (Figure 1) from 1968 to 2003. Care was taken to select catchments where there were little human influences on the streamflow. The gauging stations are operated by the Norwegian Water Resources and Energy Directorate (NVE).

Atmospheric forecast variables from two different GCMs, ECHAM4.5 (Roeckner *et al.* 1996) and ECHAM5 (Roeckner *et al.* 2006), were used as predictors. The GCMs are run at the International Research Institute for Climate and Society (IRI), Columbia University. As these are atmospheric models, SST fields that drive the models are provided externally. The ECHAM4.5 GCM uses persisted SST anomalies, i.e. the persisted anomaly is added to the evolving climatological cycle of SST to obtain the full SST forcing (e.g. Goddard & Mason 2001). The ECHAM5 GCM uses constructed analogue SSTs for the development of the forecasts. Constructed analogue SSTs are generated as a linear combination of a number of analogue SST fields selected from historical data (Van den Dool 1994, 2007).

Both models have a grid T42 resolution that corresponds to a Gaussian grid of 2.8125° along the longitude and a variable grid in latitude. The latitudes considered for the development of this work were (71.15775°N) (68.36775°N) (65.57761°N) (62.78734°N) (59.99702°N) (57.20663°N) (54.41619°N) (51.62573°N) (48.83524°N) (46.04472°N) (43.2542°N) (40.46365°N) (37.67308°N) (34.88252°N) (32.09194°N) (29.30136°N). The forecast datasets used are freely available from IRI (http://iridl.ldeo.columbia.edu/SOURCES/.IRI/.FD/).

The variables used included meridional wind velocity at 850 hPa, total precipitation and zonal wind stress. Seasonal and ensemble averages of GCM forecasts made in December for each variable were calculated for two different seasons, January–February–March (JFM) and February–March–April (FMA). The initial domain of the GCM variables is a window that spanned from 72°N to 29°N and 76°W to 76°E.

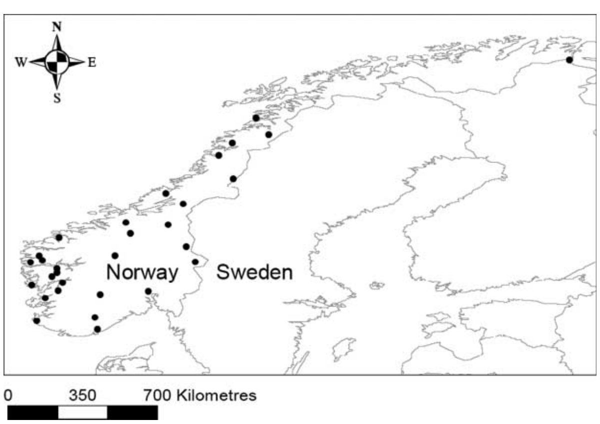

Figure 1 | Map of the Scandinavian Peninsula showing the location of all the gauging stations used in this study.

METHODOLOGY

By using a statistical downscaling method it is possible to reduce or compensate for GCM biases (Lim *et al.* 2007). Due to these biases, which are inherent to each GCM, it is expected that a predictor from one GCM may show a high correlation with the run-off data whereas the same predictor from another GCM may not.

The climate predictability tool

The climate predictability tool (CPT) is a software package developed by IRI which provides a Windows package for constructing seasonal climate forecast models. It is capable of performing model validation, and producing forecasts given updated data. It is used for producing seasonal climate forecasts using model output statistic (MOS) corrections to climate predictions from GCMs, or for producing forecasts using fields of sea-surface temperatures. Although the software is specifically for these applications, it can be used in more general settings to perform canonical correlation analysis (CCA) or principal component regression (PCR) on any data, and for any application.

Steps in the downscaling methodology

The first step in the downscaling technique was to identify the most suitable GCM predictors. The predictors are variables that are forecast by climatic runs of the GCMs in December of each year with up to six months' lead time.

The final choice of predictors is made for each GCM separately as GCMs have inherent biases within their construction (e.g. Ines & Hansen 2006; Charles *et al.* 2007) so that different forecast fields can be better predictors, depending on the GCM. It is important to note that the physical background relating large scale circulation to precipitation over the river basins for which discharge shall be forecast is also considered in this first step.

For this study, four groups of predictors were chosen, namely meridional winds, zonal winds, temperature and precipitation. These were chosen as they were identified as potentially good predictors by previous studies such as Nilsson *et al.* (2008). Final predictors were selected by running a CCA with the different predictors in turn and choosing those predictors that give the best cross-validated Spearman's correlation scores across all the stations, i.e. choosing the predictor that gives the best average forecast. The necessity of such step lies again on the model uncertainty and biases when a climate forecast is performed.

After the predictors were established, the domain for each of the predictors was optimised. This was done by running the CPT with each predictor while making small incremental changes in the domain coordinates.

After the predictors and their domains were determined, a model was constructed for each of the predictors with the help of the CPT. The CPT generates a cross-validated forecast for each of the predictors and calculates the skill of the forecasts. The multi-model forecast is then constructed by calculating the average of the individual forecasts. The final step in the downscaling technique was to calculate the skills of the multi-model forecast and compare them with those of the individual cross-validated forecasts.

Verification method

The verification of the individual forecast models was done using a seven-year-out cross-validation method; this is performed automatically by the CPT when constructing the models. Although the CPT calculates the skills of the forecasts and performs a significance analysis, it is unable to do the same for the multi-model forecast, making it difficult to compare the results.

As a measure of the forecast skill both the coefficient of determination (R^2) and the Nash–Sutcliffe model efficiency coefficient (E) were calculated together with their statistical significance. R^2 is generally accepted as the most reliable estimate of a model's skill (Willmott 1981) and E assesses the predictive power of hydrological models (Nash & Sutcliffe 1970). A bootstrap analysis is performed to determine whether the values of E are statistically significant or not.

The Nash–Sutcliffe model efficiency coefficient is defined as

$$E = 1 - \frac{\sum_i (o_i - p_i)^2}{\sum_i \left(o_i - \overline{o_i'}\right)^2} \tag{1}$$

where o_i and p_i are the observed and predicted streamflow values, respectively, and o_i' is a baseline, in this case the climatology (Nash & Sutcliffe 1970). Nash–Sutcliffe efficiencies can range from $-\infty$ to 1; an efficiency of $E > 0$ means that modelled data is a better predictor than the climatology.

DISCUSSION

Three GCM variables were chosen as the predictors: surface zonal stress from the ECHAM4.5 GCM, meridional velocity at 850 hPa and total precipitation from the ECHAM5 GCM. All three predictors are for the JFM season. This makes sense as the JFM season has the shortest GCM forecast lead time and as the Norwegian climate is heavily influenced by the westerly winds from the Atlantic. These winds have both a zonal and a meridional component, and they transport moisture from the Atlantic over the Scandinavian Peninsula.

Cross-validated R^2 and E values for 10 of the basins are shown in Table 1. As E gives an indication of how the model performs compared to the climatology, it makes sense to use E to compare the individual models to the multi-model.

The multi-model shows a tendency to perform better than the individual models and is a better predictor than the climatology for most of the stations presented in Table 1. ECHAM5 meridional winds at 850 hPa have E values that are higher than the multi-model ones: however, they are statistically significant only for three stations. For these

Table 1 | Cross-validated R^2 and E values for the individual model and multi-model forecasts of May–June streamflow based on GCM ensemble mean predictors.

		ECHAM4.5		ECHAM5				Multi-model	
		Zonal stress		Meridional velocity 850 hPa		Total precipitation			
Gauging station	Catch. area (km²)	R^2	E	R^2	E	R^2	E	R^2	E
Bulken (Bul)	1,100	0.00	−0.08	0.25	0.21	0.23	0.23	0.28	0.25*
Eggafoss (Egg)	653	0.14	−0.15	0.19	0.18	0.20	0.20	0.17	0.15
Fetvatn (Fet)	89.2	0.01	−0.08	0.40	0.40*	0.23	0.23	0.36	0.29*
Grunnfoss (Gru)	898	0.08	−0.12	0.38	0.35*	0.29	0.28	0.34	0.25*
Holen (Hol)	229	0.00	−0.12	0.38	0.38*	0.26	0.26	0.36	0.30*
Hovefoss (Hov)	232	0.04	−0.01	0.24	0.24	0.17	0.17	0.32	0.24*
Landbru (Lan)	59.8	0.18	−0.28	0.33	0.33	0.50	0.48*	0.33	0.28*
Myrkdalsvatn (Myr)	157	0.03	−0.04	0.26	0.24	0.16	0.15	0.33	0.27*
Sandvenvatn (San)	464	0.02	−0.02	0.26	0.25	0.11	0.10	0.27	0.24*
Viksvatn (Vik)	505	0.00	−0.09	0.27	0.25	0.24	0.24	0.31	0.27*

Values significant at the 0.05 level of confidence are marked with an asterisk.

three stations the possibility of using a simple model downscaling can be considered after checking for other possible predictors. This multi-model downscaling approach also shows an improvement in forecast skill when compared to the results from Nilsson *et al.* (2008). They used moisture and zonal wind to forecast May–June streamflow in Bulken, Fetvatn, Grunnfoss, Myrkdalsvatn, Risefoss, Sandvenvatn and Viksvaten.

From Figure 2 it can be seen that the highest skills are those near the Norwegian coast and/or on the western side of the mountain range, which was expected. These stations are exposed to the prevailing winds from the Atlantic, which is the principal source of predictive information from the atmosphere. This is in line with the findings of previous studies (e.g. Nilsson *et al.* 2008). Results for some of the stations, such as Eggafoss and Risefoss in Table 1, are lower

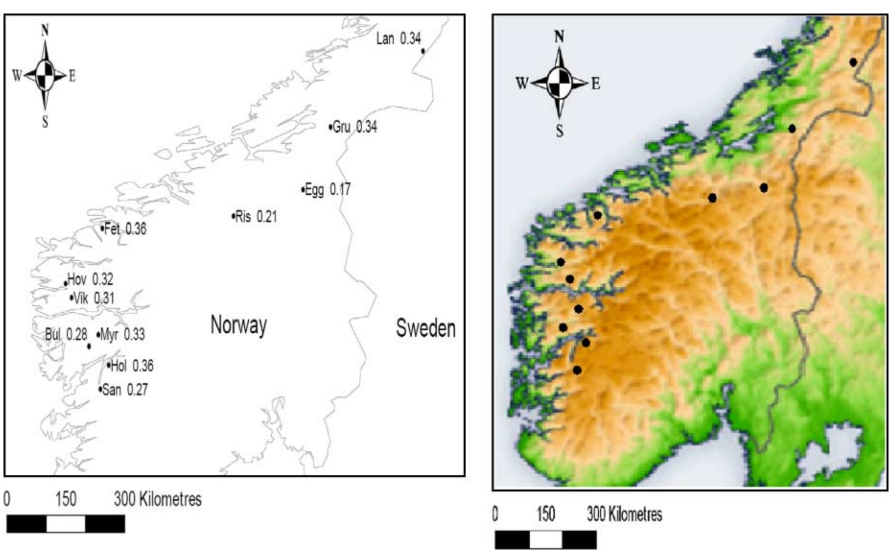

Figure 2 | (Left) Map showing the location of the gauging stations and the multi-model forecast cross-validated R^2 values. (Right) Topographic map showing a part of the Scandinavian mountain range and the location of the gauging stations.

and the physical interpretation of this is that these stations are on the leeward side of the mountains with respect to the meridional and zonal winds.

CONCLUSIONS

The multi-model downscaling approach described in this study shows skill at forecasting the melting season streamflow from large-scale circulation and moisture fields forecast by GCMs four to five months in advance. This method also shows improvements in forecast skill compared to "single" models as well as previous studies done for the same basins. Forecasts made in December for the May–June melt season have been shown to be better than the climatology.

Further studies should be carried out to see whether it is possible to achieve better forecasts. For example, would other GCMs yield more effective predictors, or could any significant anthropogenic signals that may exist be accounted for in the model and in turn lead to more accurate forecasts?

This method has an advantage over previous methods in that it is relatively easy to change the stations and number of stations for which the forecasts are being made. The plug-and-play nature of the method means that models can be changed or upgraded quickly and relatively cheaply. The long lead time of the forecast is useful to the hydropower industry, providing streamflow information for planning at an early stage.

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