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Seasonal forecasting of river flows: a review of the state-of-the-art

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Abstract This paper reviews the state-of-the-art in seasonal forecasting of river flows. Most previous studies have used statistical methods, which been shown to be more reliable than dynamical approaches. However, empirical techniques have limitations; and successful applications of downscaled GCM data show that this approach may also have potential for seasonal forecasting of hydrology.

Key words dynamical models; downscaling; GCMs; river flow; seasonal forecasting; statistical models; UK

INTRODUCTION

The scientific challenge of seasonal forecasting of river flows has clear societal relevance because forecasts have the potential to inform the operational management of water systems as varied as reservoir control for hydro-electric power generation, flood alleviation or agricultural irrigation schemes (Wedgbrow *et al.*, 2002). Moreover, river flow forecasting helps increase human preparedness in anticipating water-related hazards (e.g. floods or droughts).

Associations between river flow and atmospheric/oceanic indicators have been shown in many parts of the world: Costa Rica (Krasovskaia *et al.*, 1999), USA (Dracup & Kahya, 1994; Ely *et al.*, 1994), Australia (Abawi & Dutta, 1998; Kiem & Franks, 2001), Germany (Stahl & Demuth, 1999), and Spain (Trigo *et al.*, 2004). Nonetheless, most seasonal forecasting studies have focused on climatic variables, particularly precipitation (Washington & Downing, 1999; McGregor & Phillips, 2004). Eshel *et al.* (2000) achieved statistically significant forecasts of meteorological droughts in the Eastern Mediterranean at up to 13 months lead time. Yet, Wilby (2001) has suggested better forecasts may be possible for river flow than for precipitation because of the delays and combination effects between precipitation and groundwater discharges. Seasonal forecasting studies have also largely been confined to tropical regions, possibly because of the predictability of the El Niño Southern Oscillation (ENSO) and the impacts of ENSO events (Mason *et al.*, 1999; Goddard *et al.*, 2001). However, growing evidence suggests that seasonal river flows of more northern extratropical regions may be predictable (Trigo *et al.*, 2004; Wilby *et al.*, 2004; Svensson & Prudhomme, 2005).

This paper aims to review the state-of-the-art in seasonal forecasting of river flows and the skills associated with different techniques by investigating their applications to different regions of the world, including the UK.

STATISTICAL METHODS

Empirical models are developed from historical data to find statistically significant relationships between one or more predictors and the target variable of interest (e.g. river flow or precipitation). Linear regression techniques are most commonly used (Table 1). Svensson & Prudhomme (2005) used multivariate regression for two regions of Great Britain (i.e. the Southeast and Northwest) to predict summer river flow anomalies using eight predictors from winter river flow, airflow indices, sea surface temperatures (SSTs) and temperature differences. The models explained 55% (61%) of the variance in river flow in the Northwest (Southwest). Prediction of extreme flows was more skilful than for intermediate flows. Similarly, Wilby (2001) found that the winter North Atlantic Oscillation (NAO) explained 40% of the variance in August river flow of three UK rivers. For the River Thames (UK), Wilby *et al.* (2004) reported the greatest variance explained in flows for August (46%) and summer months (35%) using winter geopotential height, mean sea level pressure (MSLP), SSTs and sea ice concentrations (SIC).

Table 1 Summary of studies using statistical methods to predict river flow.

Region	Method	Predictand	Most significant predictor(s)	Reference
UK	Stepwise linear regression	Monthly mean river flow	500 hPa Geopotential height, Bering Sea ice concentration and Madeira MSLP	Wilby *et al.* (2004)
UK	Regression	Summer monthly mean river flows	Winter NAOI	Wilby (2001)
UK	Regression	Regional mean summer river flow	SST and temperature differences between different regions of the North Atlantic	Svensson & Prudhomme (2005)
UK	Expert System	Summer river flow	Geopotential heights, SIC, MSLP, SST, Central England Temperature and Arctic Oscillation Index	Wedgbrow *et al.*(2005)
Australia	Categorical composites	December–May river flow	ENSO indices	Kiem & Franks (2001)
Australia	Categorical composites	August–February river flow	Southern Oscillation Index	Abawi & Dutta (1998)

A classification approach was used by Kiem & Franks (2001) whereby annual, December to May average river flows in Australia were grouped according to the ENSO index. Using a *t*-test, the mean flow of each group (defined as El Niño, La Niña or Neutral) was shown to be significantly different. Future river flow forecasts could be made based upon the past mean flow of the group corresponding to the ENSO forecast. Similar results were found by Abawi & Dutta (1998) who also studied the impact of ENSO on spring and summer (August to February) streamflow in Australia. Forecasts were possible several months in advance based on phases of the Southern Oscillation Index (SOI).

An Expert System (ES) was used by Wedgbrow *et al.* (2005). The aim of ES is to classify the target variable (i.e. predictand) according to predictor value and then to create a set of rules for prediction in the form of a decision tree comprising of "IF…THEN" statements. This method has been applied to summer river flows in the River Thames (UK) using seven variables including geopotential heights, SIC, MSLP and SST. Initial results showed a success rate of 79% and 89% for August and summer river flow, respectively (Wedgbrow *et al.*, 2005).

Many statistical studies for the UK focus upon the forecast of summer river flows from winter indicators because water resources are under greatest demand and stress at this time (Wedgbrow *et al.*, 2002). For example, Wedgbrow *et al.* (2002) explored the relationship between monthly river flows (June to November) with atmospheric and oceanic indices, and found the most significant correlations occurred in the summer months whilst there were few to no correlations in September, October and November. This reveals that river flow forecasting skill may be weaker in winter than summer.

DYNAMICAL MODELLING

Currently the most reliable tools for seasonal forecasting are statistical; but potential for reliable dynamical forecasts is great (Table 2; Zwiers & Von Storch, 2004). Dynamical based forecasts involve the integration of General Circulation Models (GCMs) that represent atmospheric, oceanic, land surface and hydrological interactions and processes as a set of mathematical equations. GCMs are started with a set of initial conditions, which are run through the equations and solved every few minutes at a large number of grid points covering the Earth. Observational data are incorporated into the GCMs using Data Assimilation Systems (DAS). DAS have allowed the development of large climatic data sets, such as the NCEP/NCAR[1] re-analysis and ECMWF[2] ERA-15 and ERA-40. The latest data set (ERA-40) is based on a re-analysis of meteorological observations from 1957 to 2002, providing 45-year records for a large number of meteorological variables (Uppala *et al.*, 2005). The outputs from re-analyses can be used to explore GCM limitations and potential. For example, ERA-15 precipitation data were tested for their ability to represent observed river runoff in the Aral Sea Basin, Central Asia (Schar *et al.*, 2004). The results showed that December–April precipitation was significantly correlated (r = 0.92) with observed

[1] National Centres for Environmental Prediction/National Centre for Atmospheric Research
[2] European Centre for Medium Range Weather Forecasts

Table 2 Summary of studies using dynamical models to predict river flow.

Region	GCM model	Downscaling	Reference
Northeastern Brazil	Hadley Centre LDA model	Linear regression	Galvao *et al.* (1999)
USA	NCEP/NCAR reanalysis	Stepwise, multiple linear regression and RCM (RegCM2)	Wilby *et al.*(2000)
USA	NCEP Medium Range Forecast	Pacific Northwest National Laboratory RCM	Leung *et al.* (1999)
South Africa	Centre for Ocean-Land-Atmosphere Studies T30	Canonical correlation model	Landman *et al.* (2001)
Asia	ERA-15	None	Schar *et al.* (2004)

May to September river discharge; and it was concluded that a reliable river flow forecasting system may be possible using real-time precipitation data from an operational DAS.

The atmospheric–oceanic system is chaotic. As a result, dynamical model runs made with small, random perturbations in input data may produce a different output than without perturbations (Harrison, 2005). To overcome this, multiple (ensemble) runs are made with slightly different initializing conditions to capture the climatic variability from a range of possible outcomes. However, Palmer *et al.* (2004) argued that because of the uncertainty in the GCM equations, runs with a single GCM are not reliable and ensembles should consist of a number of runs from GCMs developed at different research centres, to provide a more representative sampling of possible equation sets. DEMETER[3] is one such project which aims to synthesize data from a multi-model ensemble (Palmer *et al.*, 2004).

Data outputs from GCMs can be used to forecast river flow by driving rainfall–runoff models. Leung *et al*. (1999) simulated streamflow in the Columbia River, USA, using data from the NCEP Medium-Range Forecast (MRF) GCM as input to a rainfall–runoff model. Modelled peak flow in January and February overestimated observations, which was attributed to an overestimation of atmospheric warming driving snowmelt. This weak forecast skill could be due to limitations in physical representation and the coarse spatial resolutions used by GCMs.

DOWNSCALING

GCMs operate at a resolution in the order of 2.5 to 5° latitude and longitude (Barry & Chorley, 1998). To be useful in hydrological forecasting, data need to be of a finer resolution (~0.2° latitude by longitude) to represent regional climate and river flow variations between drainage basins (Wilby *et al.*, 2000). Two techniques were developed to address this issue: Regional Climate Models (RCMs) and Statistical Downscaling (SD).

Regional climate models simulate atmospheric processes similar to GCMs but at a resolution of 20–50 km; thus, they are more accurate than GCMs at representing climate features induced by land surface variations, such as orographic precipitation (Wilby *et al.*, 2000). When Leung *et al.* (1999) used the Pacific Northwest National Laboratory (PNNL) RCM outputs to simulate stream flow in the Columbia River basin (USA), they found the results were consistently better than using the MRF GCM.

Statistical downscaling methods aim to specify the local, river basin-scale predictand (e.g. precipitation) from a synoptic-scale predictor (e.g. MSLP or geopotential height). These methods include: regression analyses, weather-type classifications and artificial neural networks (Wilby & Wigley, 1997; Feddersen & Andersen, 2005).

Wilby *et al.* (2000) compared the use of SD (step-wise multiple linear regression) and an RCM[4] to downscale NCEP/NCAR re-analysis data to simulate discharge in the Animas River Basin, Colorado (USA). The results showed that both SD and RCM outperformed re-analysis data. SD was the best overall technique explaining 78% of the variance in discharge, compared with 69% for RCM. However, SD showed a bias of –22% whilst RCM showed a bias of only –11%. From these results, Wilby *et al.* (2000) concluded that modelled processes are sensitive to the choice of downscaling technique.

[3] Development of a European Multi-model Ensemble system for seasonal to inTERannual prediction
[4] RegCM2 from the Project to Intercompare Climate Simulations in the USA

DISCUSSION

Theoretically, dynamical approaches should be able to outperform statistical approaches to seasonal forecasting of river flows because of their ability to model climate processes and interactions (Van Oldenborgh *et al.*, 2005). However, in practice, errors and uncertainties in models mean that this is not yet the case. Dynamical models are also more complex and computationally intensive than statistical methods (Goddard *et al.*, 2001). In comparison, statistical methods are based on unrealistic assumptions of stationarity (Wedgbrow *et al.*, 2005). Although this problem can be overcome by continually updating data sets in order to monitor and, if necessary, refine model performance (Washington & Downing, 1999, Zwiers & Von Storch, 2004), there are still limitations caused by the co-linearity or dependence of the predictors in multiple regression analyses. For example in their study, Svensson & Prudhomme (2005) noted co-linearity between temperature differences used as predictors of river flow, and they were able to adjust their methods accordingly to avoid instability in the regression equation.

An alternative method would be to combine both statistical and dynamical techniques to improve river flow forecasts. Downscaling techniques applied to GCM outputs could be used to provide information that could in turn be used in a conceptual hydrological model. This is a promising route as experimented by the University of Washington Hydrology Group[5], Galvao *et al.* (1999), Leung *et al.* (1999) and Wilby *et al.* (2000). However, further research into the potential of combined forecasting approaches is required.

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[5] See http://www.hydro.washington.edu/ (Accessed 25 January 2006)

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