Comparison of the potential skill of raw and downscaled GCM output for river flow forecasting: a UK case study

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Hydrologic extremes (floods and droughts) are expected to become more commonplace under changing climatic conditions (Kundzewicz et al. 2007). These extremes can be very costly economically and to society as a whole. Skilful hydrological forecasts at a seasonal time-scale, defined here as 1 to 6 months, could potentially mitigate these harmful effects through advanced warning. This could aid water management decision making and increase human preparedness for extreme conditions. The need of research on the seasonal forecasting of river flows is becoming more apparent in the UK after the drought experienced in 2004-06, and the summer 2007 floods.

The aim of the work described here is to define a benchmark (or upper limit) in the potential skill of forecasting river flow using Global Climate Seasonal forecasts. The research is twofold: (1) Global Circulation Model (GCM) outputs are used directly in the form of re-analysis data, and (2) downscaled GCM precipitation is used to drive a hydrological model. The research focuses on the River Dyfi at Dyfi Bridge in West Wales, UK, a temperate basin of relatively small area (471.3 km^2) (Figure 1). The basin was chosen as it is near natural which implies that the climate-flow signal should be stronger than one with human influences. The Probability Distributed Model (PDM) was used to model the Dyfi river flows. PDM converts rainfall and potential evaporation (PE) to river flow at the basin outlet (Moore, 2007). Daily basin-averaged rainfall and PE and daily river flow data were used to calibrate (01/05/1980 to 30/04/1990) and evaluate (01/05/1991 to 30/04/2001) the PDM.

The input GCM data used are taken from ERA-40, which is a 45 year re-analysis of meteorological observations produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Uppala et al. 2005). The ERA-40 data was available at 2.5 ° x 2.5 ° and at a reduced 1.5 ° x 1.5 ° grid resolution. The re-analysis data at the closest land-based grid point to the Dyfi basin were extracted (52.5 °N 357 °E and 52.5 °N 357.5 °E for 1.5 ° and 2.5 ° resolution respectively). The stratiform and convective precipitation and snowfall were summed daily for

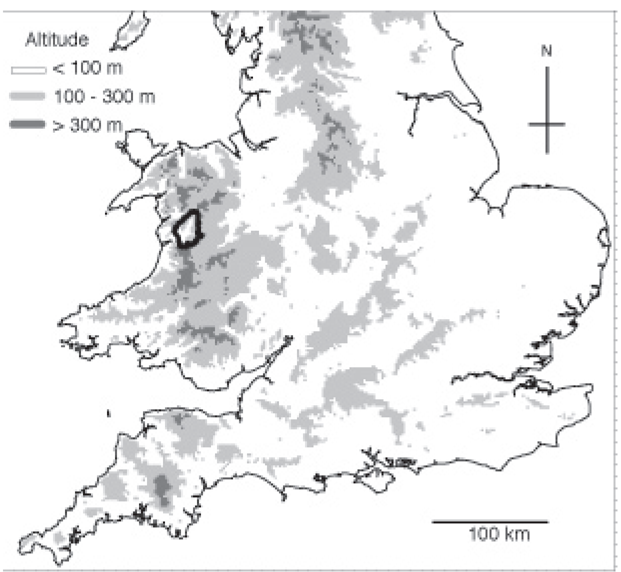

Figure 1: A map showing the south of England and Wales and the case study basin, the Dyfi at Dyfi Bridge (heavy line).

the grid points, and run through the PDM, whilst the PE data was left unchanged from the model calibration data set.

Owing to the coarser resolution of the ERA-40 data in comparison with the spatial scale of the river basin, the Statistical Downscaling Model (SDSM, Wilby et al. 2002) Version 4.1 was utilised to produce rainfall at the basin scale. Multiple linear regression models (one per month) were used to link large-scale atmospheric (ERA-40) predictors with basin scale rainfall (observed), and then a stochastic weather generator produced 10 downscaled daily rainfall series. The predictors were normalised prior to SDSM calibration over 01/05/1980 to 31/01/2002. Three predictor variables explained best the basin-scale rainfall at the two ERA-40 grid resolutions: geopotential (Z) at 500 hPa, zonal velocity (u) at 850 hPa and meridional velocity (v) at 850 hPa for 1.5 ° resolution, and Z at 500 hPa, u at 500 hPa and v at 850 hPa for 2.5 ° resolution.

The ability of GCM and downscaled GCM rainfall time series to reproduce river flow was assessed partially through the percent exceedance flow (QN). For example the Q5 value is the river flow which is equalled or exceeded 5 % of the time (high flow index), and the Q95 value is the river flow which is equalled or exceeded 95 % of the time (low flow index). The flow duration curves illustrating this information are shown in Figure 2 (page 22) (a) and (b). The simulated river flows driven by ERA-40 precipitation underestimate the simulated (from observed) flows. Input data at 1.5 ° resolution has slightly more accurate river flow estimates compared with 2.5 ° resolution, and this is also shown in the R2 values between observed and modelled flows (-0.143 and -0.238 for 1.5 ° and 2.5 ° resolutions) and the bias (-76.9 % and -82.0 % for Q95, and -72.6 % and -76.9 % for Q5 for resolutions 1.5 ° and 2.5 ° respectively). The negative bias stresses the underestimation of river flow using ERA-40 precipitation as direct input to the hydrological model, to be linked with the underestimated daily precipitation intensity by the GCMs. A possible explanation for the better representation by the 1.5 ° grid point is its closeness to the Dyfi basin compared with the 2.5 ° point.

The downscaling process on average increases the R2 value to 0.407 and 0.366 for resolutions 1.5 ° and 2.5 ° respectively. The flow duration curves show that the modelled river flow using downscaled rainfall series is closer to the evaluated flow (modelled flow from observations during the evaluation period, Figure 2 (a) and (b)). Average biases are -54.1 % and -49.8 % for Q95, and -25.9 % and -19.0 % for Q5 for 1.5 ° and 2.5 ° resolution respectively, which is a marked improvement compared with the earlier direct input of ERA-40 precipitation to the PDM.

The work aimed to define benchmark values for the potential skill of GCM seasonal forecasts for hydrological applications through the direct and downscaled use of GCM re-analysis data. The results at two spatial resolutions highlight that by using ERA-40 precipitation data as direct input to the PDM rainfall-runoff model, the simulated river flow substantially underestimates the observed river flow in the Dyfi basin. This is likely to be due to the inability of the ERA-40 assimilating model to resolve basin-scale (or GCM sub-grid scale) atmospheric processes such as orographic enhancement of rainfall over the Welsh Mountains, and precludes a direct operational use. With the help of a statistical downscaling technique (here SDSM), skills in river flow estimation are significantly improved for both the high and low flows. This pioneering work in Europe of river flow estimation from GCM outputs must be continued in comparing these benchmark results with seasonal GCM forecasts, such as those of the DEMETER multi-model ensemble climate data set as input to the PDM, and by the investigation of the use of different downscaling techniques.

References:

Kundzewicz, Z.W., L.J. Mata, N.W. Arnell, P. Döll, P. Kabat, B. Jiménez, K.A. Miller, T. Oki, Z. Sen and I.A. Shiklomanov, 2007: Freshwater resources and their management. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge, UK, 173-210.

Moore, R. J., 2007: The PDM rainfall-runoff model. *Hydrol. Earth Syst. Sci,*. **11**(1), 483-499.

Uppala, S.M., et al. 2005: The ERA-40 re-analysis. *Q. J. R.. Meteor. Soc.*, **131**, 2961-3012.

Wilby, R.L., C. W. Dawson, E. M. Barrow, 2002: SDSM – a decision support tool for the assessment of regional climate change impacts. *Environmental Modelling & Software*, **17**, 147-159.

DEMETER–driven prediction of epidemic malaria in Africa: initial results from a continental–scale study

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Background

Epidemics of malaria occur when the disease attacks vulnerable populations with low immunity and are responsible for 155,000 to 310,000 deaths per year in Africa (Worrall et al., 2004). Epidemics may be triggered in areas of normally low transmission by a range of factors including abnormal meteorological conditions, changes in anti-malarial programs, population movement, and environmental changes (Nájera et al., 1998). As part of their global strategic plan for 2005-2015, Roll Back Malaria Partnership (RBM) includes the establishment and maintenance of early warning systems for malaria epidemics, in order to meet the target of 60% detected within two weeks and 60% responded to within two weeks of detection (RBM, 2005). As part of such a system, seasonal climate forecasts, when coupled with models of the disease, have the potential to enable malaria early warning with lead times of several months. Seasonal ensemble prediction system (EPS) forecasts of climate are skilful in some epidemic-prone African regions and the DEMETER seasonal EPS (Palmer et al., 2004) has previously been used successfully to drive a statistical rainfall-driven model for malaria prediction in Botswana (Thomson et al., 2006). As part of the AMMA (http://www.amma-international.org) and ENSEMBLES (http://www.ensembles-eu.org) projects, a process-based model of malaria, Liverpool Malaria Model (LMM, Hoshen and Morse, 2004), which simulates the complex relationship of the disease with climate, has now been coupled with the DEMETER multi-model seasonal ensemble forecasts. By employing a tier-2 approach (Morse et al., 2005) in which DEMETER-driven malaria model predictions are validated against ERA-40-driven model simulations, the requirement for observed malaria data is removed, enabling broad assessment of the potential of the seasonal forecasts for epidemic malaria prediction across Africa.

Coupling a process-based malaria model with a seasonal EPS

The practicalities of coupling a malaria model with a multi-model EPS on a continental scale are not straightforward. Health models are not generally designed for use over many locations or with multiple inputs and handling of many large EPS output files outside the proprietary visualisation and analysis software used by modelling centres can be cumbersome. A number of software tools have been created for data conversion and processing, running of the malaria model, and analysis of results, incorporating the facility of the University of Liverpool's state-of-the-art "MAP2" Beowulf cluster with the potential to make use of up to 900 nodes simultaneously (http://www.liv.ac.uk/physics/hep/Infrastructure/Computing.html). The software tools developed here are not restricted to malaria modelling and may be useful more generally for the coupling of EPS forecasts with application models.

The DEMETER multi-model reforecasts (Palmer et al., 2004) consist of output from a multi-model ensemble of seven different coupled AOGCMs each run with nine different sets of initial conditions. The full multi-model forecasts are available for four forecast start dates per year from 1980-2001 and extend to six months lead time. The ERA-40 reanalysis (Uppala et al., 2005) consists of 44 years of in-situ and remotely sensed data assimilated into a numerical weather prediction model to form a set of global analyses. In order to drive the malaria model with these datasets, temperature and precipitation fields from DEMETER and ERA-40 have been extracted from the ECMWF MARS data archive on a 2.5 degree grid consisting of 30 by 30 grid points from 37.5°N to 35.0°S and 20.0°W to 52.5°E, for the 22 years for which the full seven models are available from DEMETER (1980-2001).

DEMETER-driven ensemble malaria predictions are created by running the malaria model with each of the 63 DEMETER ensemble members as input. ERA-40 data are used to intialise the malaria model. Probabilistic malaria forecasts have been created in this initial assessment by equal weighting of the ensemble members. For each grid point, the ERA-40-driven and DEMETER-driven malaria simulations can be used to define low and high malaria events for the 22–year period (lower tercile, above the median and upper tercile) for three month windows (months 2-4 and 4-6) within each forecast integration period.

In order to assess the performance of DEMETER for malaria prediction, skill scores have been calculated for the DEMETER-driven malaria model forecasts using the ERA-40-driven forecasts as reference. Because the modelled process of malaria transmission exhibits a lag of between one and three months between rainfall and disease peaks, it is important to take into account any skill apparent in the DEMETER-driven forecasts which is in fact due to driving rainfall occurring during the initialisation period (i.e. the ERA-40 observations used as input before the start of the DEMETER forecast). This is an issue of concern for locations where the rainy season starts before the DEMETER forecast origin. Since the timing of the rains varies across the continent a general approach is required. This has been achieved by creating ERA-40-only malaria model forecasts, using the correct ERA-40 driver for the initialisation