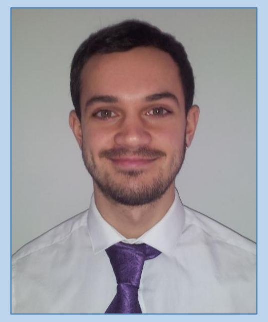
Newcastle University
School of Civil Engineering & Geosciences

Just how difficult is seasonal prediction of river flow?

Seasonal UK Drought Forecasting using Statistical Methods

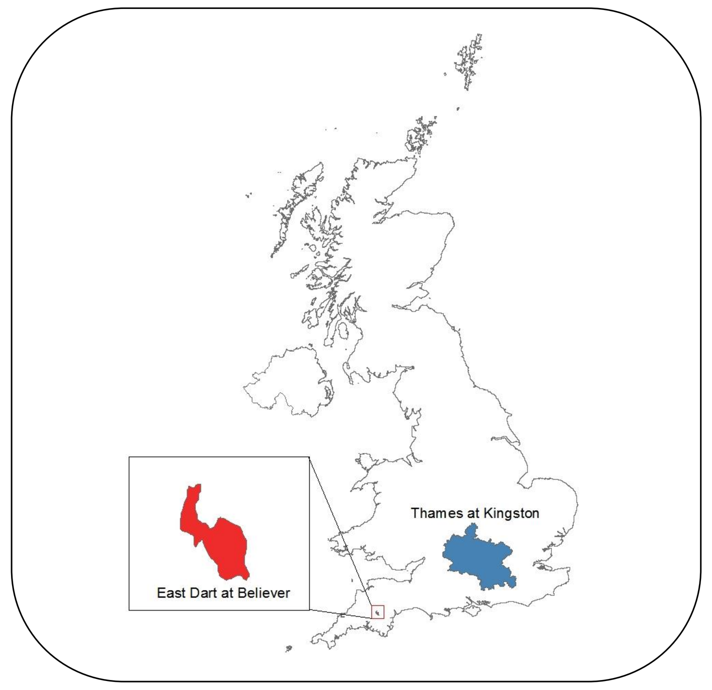


Doug Richardson
Hayley Fowler
Chris Kilsby
Francesco Serinaldi

d.richardson2@ncl.ac.uk

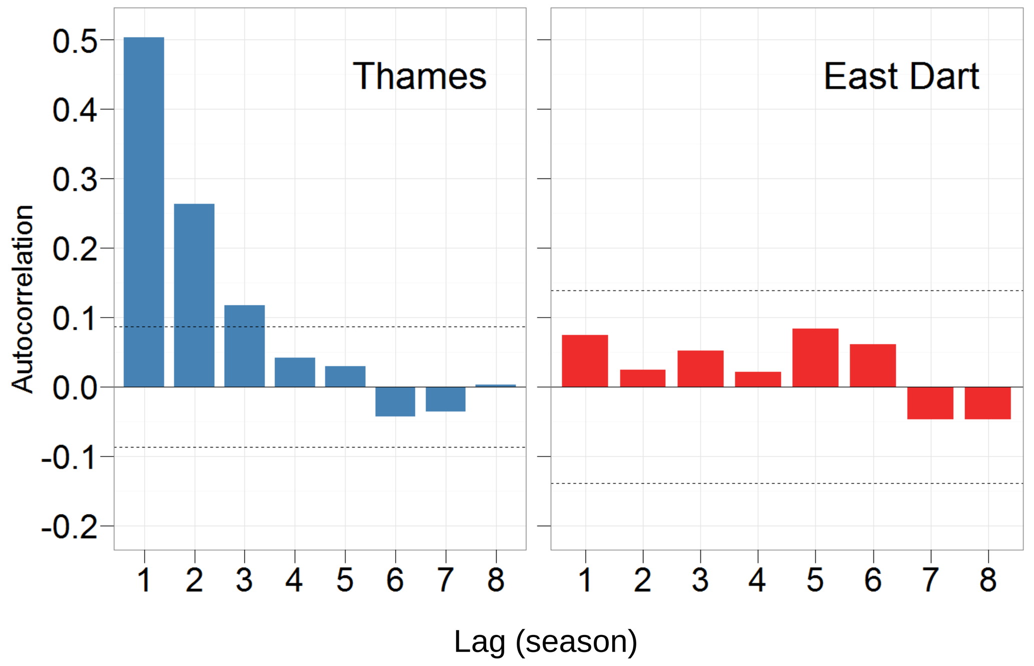
1 The problem

Water resource managers need advance warning to plan for drought. Accurate forecasts of river flow in key regions one or more seasons ahead would be hugely beneficial in managing resources. The inherent memory in streamflow allows hydrological forecasts to predict a future flow level based on the current level. In forecasting this is known as the naïve forecast, which is the benchmark all other forecasts are tested against. The question is, how can we improve upon the naïve forecast for seasonal predictions, particularly if there is little memory? We consider two case studies in the UK, the Thames and East Dart rivers.



2 What is a naïve forecast?

The naïve forecast is the forecast made assuming no model. It is therefore simple, yet is often hard to outperform even with complex forecast models. For the case studies the naïve forecasts might be chosen differently. The autocorrelation function for de-seasonalised flow (Q) shows that in the East Dart there is no significant season-to-season persistence (memory) so a naïve forecast could simply be the seasonal average (climatology). The Thames on the other hand displays significant autocorrelation up to three seasons previous. Here, then, a naïve prediction might be climatology plus the anomaly of the previous season.



Horizontal dotted lines indicate boundaries for statistical significance at the 95% level.

3 Climate as a predictor

The forecasting potential of various oceanic and atmospheric indices thought to influence European climate was assessed by hindcasting summer streamflow using climate variables from the preceding winter and spring.

The large potential predictor set was reduced by calculating correlations between summer flow and lagged predictor indices. Most correlations are relatively weak but this is not surprising given the local nature of river catchments, especially true for the small East Dart catchment.

Thames

Predictor	ρ
Spring Q	0.67
Winter Q	0.35
Winter West Pacific (WP)	0.21
Spring East Atlantic-West Russian	0.21
Spring East Pacific-North Pacific (EPNP)	-0.20
Winter Arctic Oscillation	-0.20
Winter EPNP	-0.19
Spring Nino 1.2	-0.18
Spring WP	0.17
Spring East Atlantic	0.16

East Dart

Predictor	ρ
Spring East Atlantic-West Russian (EAWR)	0.35
Spring Pacific Decadal Oscillation (PDO)	-0.21
Winter PDO	-0.20
Spring Southern Oscillation	-0.16
Winter North Atlantic Oscillation	-0.15
Spring Arctic Oscillation	0.13
Winter Pacific-North American	-0.13
Winter West Pacific	0.13
Winter EAWR	0.12
Spring Nino 1.2	0.11

Strongest Spearman correlations with summer flow. ■ indicates significant at the 95% level.

4 Modelling procedure

Generalised Additive Models for Location, Scale and Shape[1] (GAMLSS) is a statistical modelling framework that extends upon Generalised Linear/Additive Models. It offers advantages over these classical methods by:

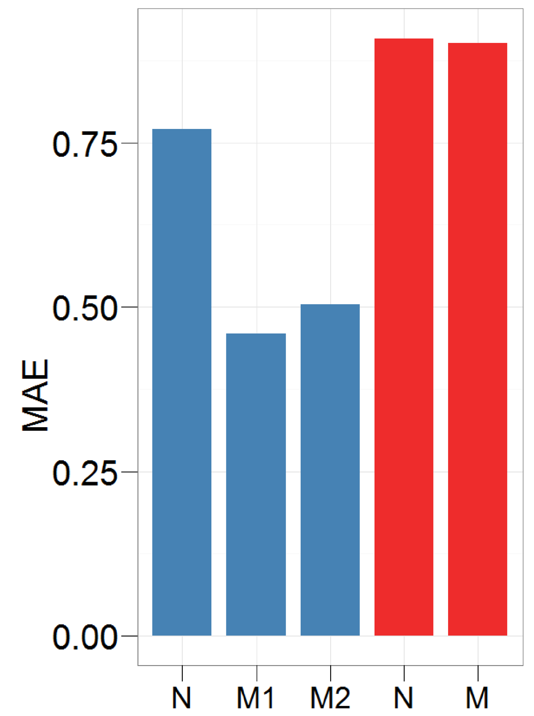
- relaxing the restriction that the response variable must follow a distribution belonging to the exponential family,
- allowing the modelling of the scale and shape parameters (related to the dispersion, skewness and kurtosis) as well as the location parameter (related to the mean).

GAMLSS models were selected with various combinations of the strongest correlated variables as covariates. These were ranked according to several different forecast accuracy measures, which were also calculated for the naïve forecasts. The Diebold-Mariano test[2] was also used to assess the statistical significance of difference in models' forecasts.

1. Rigby, R.A. and D.M. Stasinopoulos, *Generalized additive models for location, scale and shape.* Journal of the Royal Statistical Society Series C-Applied Statistics, 2005. **54**: p. 507-544.
2. Diebold, F.X. and R.S. Mariano, *Comparing Predictive Accuracy.* Journal of Business & Economic Statistics, 1995. **13**(3): p. 253-263.

5 Do these climate indices improve predictions?

The Mean Absolute Error quantifies predictive performance, with a score of zero indicating a perfect forecast. For the Thames, several GAMLSS models were more accurate than the naïve. However, amongst the GAMLSS models there is no significant distinction between those with just previous streamflow as covariates and those with climate indices as well. For the East Dart, none of the GAMLSS models yielded more accurate forecasts than the naïve method, highlighting the usefulness of persistence in streamflow forecasting.

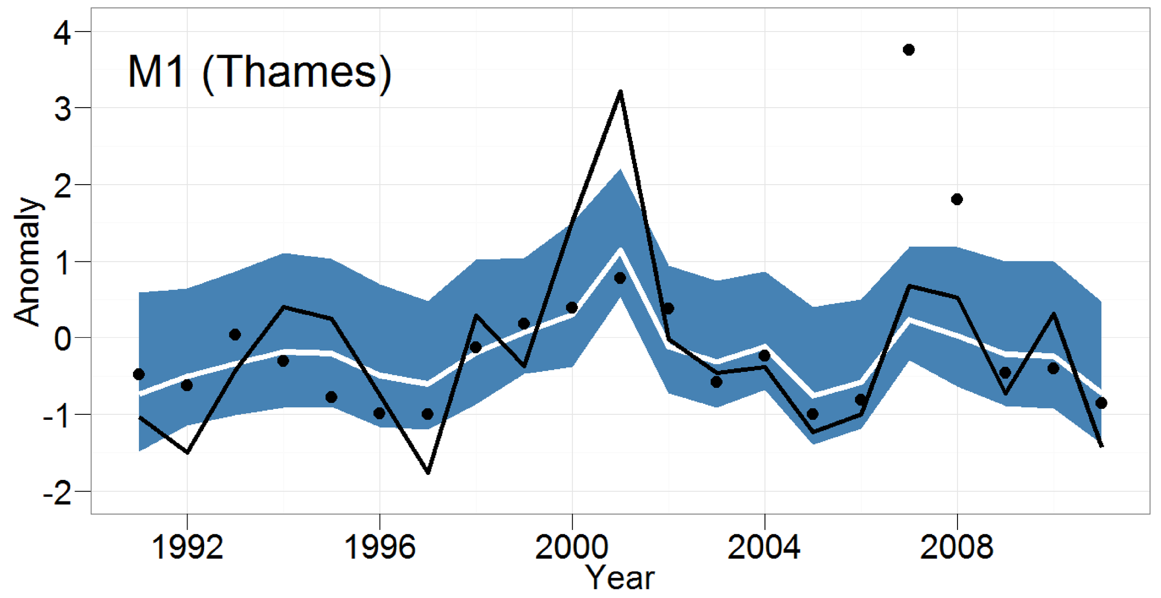


GAMLSS Model	Covariates
M1 (Thames)	Spring Q Winter Q Spring EAWR
M2 (Thames)	Spring Q
M (East Dart)	Spring EAWR Spring PDO

Blue M1, M2 and N indicate two GAMLSS models and the naive for the Thames. Red M and N indicate a GAMLSS and naïve model for the East Dart.

6 Conclusions

Seasonal forecasting of river flow is difficult even with strong persistence between seasons. Without this persistence, forecasts are even harder; models would benefit from identification of climatic processes with a significant influence on the flow regime. These relationships are difficult to identify even if present, and are likely to vary from catchment to catchment.



Black points are summer river flow observations, the white line is the median forecast, the blue ribbon is the 95% prediction interval and the black line is the naïve forecast.