Seasonal forecasting of reservoir inflows using remotely sensed precipitation estimates in data sparse regions

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Introduction

Early river flow forecasting systems relied on accurate ground based measurements of precipitation at meteorological stations – a basic input requirement that is still difficult to achieve in data sparse and/or physically remote regions [1]. Remotely sensed, near real-time precipitation estimates have the potential to address these shortcomings and may offer particular advantages for strengthening flow forecasts for large, transboundary river basins [2].

Figure 1: Location of the River Naryn basin and Toktogul reservoir within Kyrgyzstan [3].

Methods

Tropical rainfall Measuring Mission (TRMM) precipitation estimates were among several predictor variables used to forecast inflows to Toktogul reservoir, Kyrgyzstan (Figure 1). Multiple linear regression modelling proceeded in two steps. First, a large number of lagged, time-averaged and spatially-explicit candidate variables was reduced to a smaller set of statistically significant, independent predictors. Second, the forecast skill of chosen predictors (Table A) was determined using cross-validation (k-folds technique) (Figure 2). All model predictions were benchmarked with respect to the Zero Order Forecast (ZOF) and the HydroTest tool [3] was used to derive five metrics of model forecast skill (Table B).

Ongoing research focuses on other potential sources of predictability such as the relationship between precipitation and large scale climate drivers. For example, the NOAA ESRL linear correlation tool [4] can be used to plot correlation between SOI and re-analysis precipitation (Figure 3).

Model	Predictors	R^2_{adj} (%)	SE (m^3s^{-1})
ZOF	Month	81	147
Q0 (*t*+0)	Month, Discharge$_{1,1}$, TRMM optimal cell$_{0,4}$	90	109
Q1 (*t*+1)	Month, Discharge$_{1,1}$, TRMM optimal cell$_{1,3}$, Temperature$_{1,1}$	89	110
Q2 (*t*+2)	Month, Discharge$_{2,1}$, TRMM optimal cell$_{2,1}$	85	132
Q3 (*t*+3)	Month, TRMM optimal cell$_{3,1}$	84	136

Table A: Summary of regression model predictor variables, explained variance (R^2_{adj}) and standard errors (SE) by forecast horizon (*t* + 0-*t* + 3 months). Variables are lagged by *t* months and averaged over *n* previous months (e.g. Discharge$_{t,n}$). Source: [5].

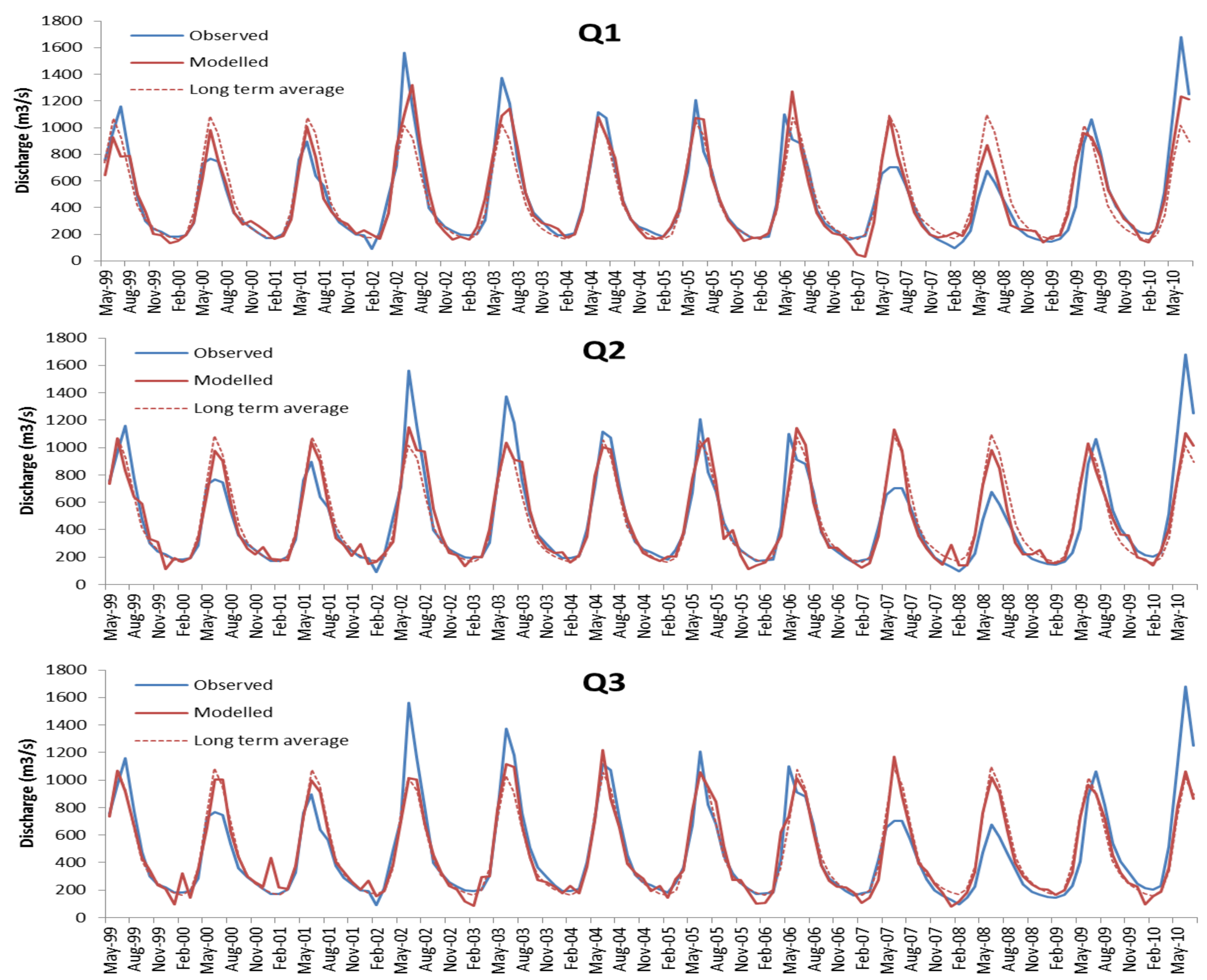

Figure 2: Cross-validated forecasts of inflow to Toktogul reservoir with lead times of one (Q1), two (Q2) and three (Q3) months compared with long term mean monthly discharge (ZOF) for May 1999-July 2010. Source: [5].

Metric	ZOF	Q1	Q2	Q3
Root Mean Squared Error (RMSE) (m^3s^{-1})	151	118	139	144
Akaike Information Criterion (AIC)	702	673	694	697
Nash-Sutcliffe Coefficient (NSC)	0.797	0.878	0.829	0.818
Percentage Error in Peak (PEP) (%)	-34.8	-21.4	-31.6	-27.7
Mean Absolute Relative Error (MARE) (%)	18.6	17.5	19.6	21.6

Table B: Cross-validation results for ZOF, Q1, Q2 and Q3 models. Source: [5].

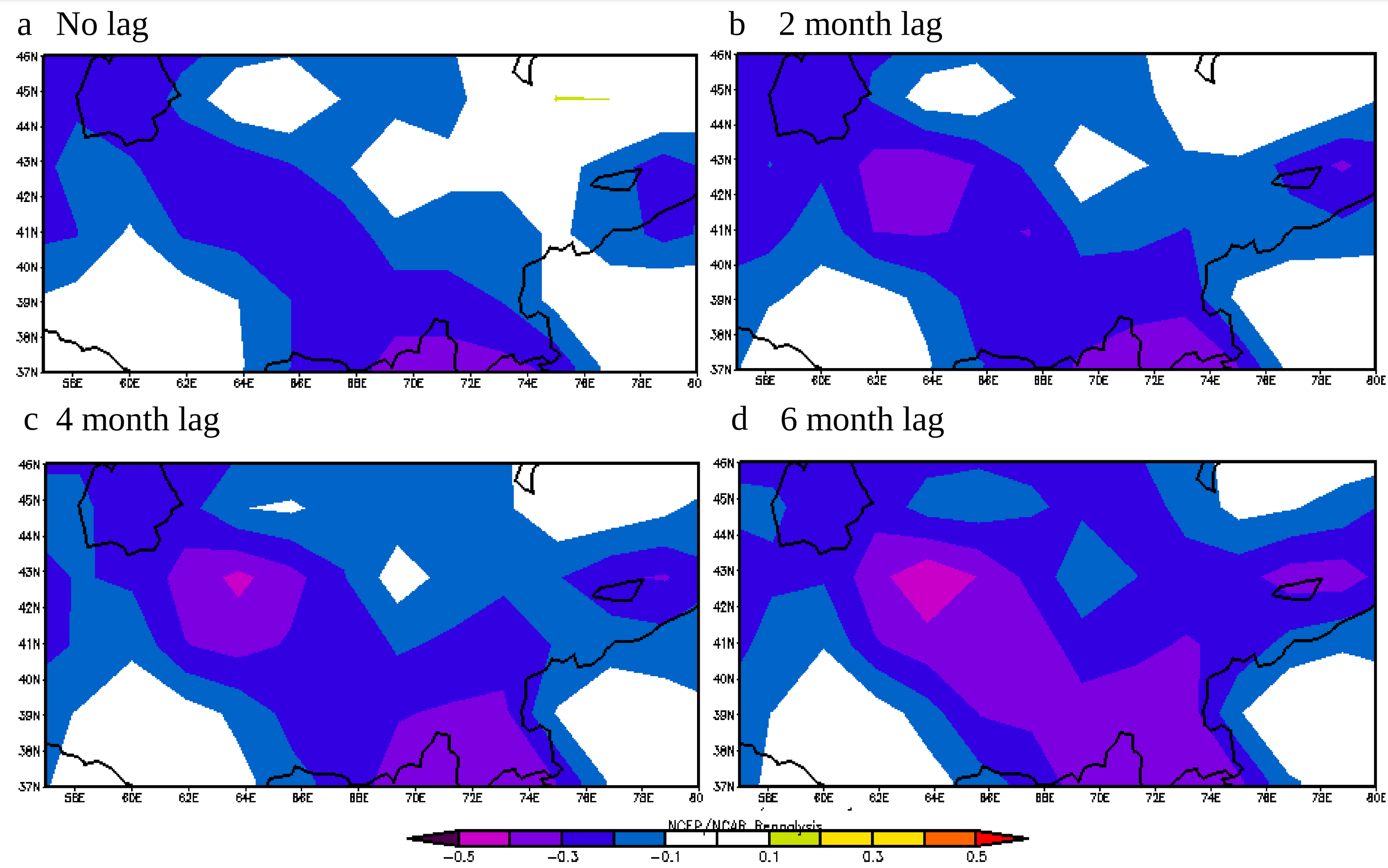

Figure 3: Correlation between Oct-Mar NCEP/NCAR reanalysis surface precipitation and Oct-Mar Southern Oscillation Index (SOI) (plate a) across Central Asia (note Aral Sea located in the northwest) for years 1950-2014. In plates b, c and d SOI leads precipitation by 2, 4 and 6 months respectively. Critical r-value of 0.24 at 0.95 significance level. Source: NOAA ESRL [4].

Conclusions

According to the chosen performance metrics, Q1, Q2 and Q3 models are superior to ZOF for all diagnostics, except MARE for Q2 and Q3. Despite the simplicity of the models and limited data requirements over 80% of the variance in monthly inflows is explained with three month lead, and up to 65% for summer half-year flows based on TRMM estimates of winter precipitation for the Naryn basin.

Statistically significant negative correlations are found across southern Tajikistan between winter SOI and winter NCEP/NCAR reanalysis precipitation. Introducing a lag interval of up to six months increases correlations across Tajikistan, as well as introducing statistically significant correlations across eastern Kyrgyzstan.

These findings suggest that there is potential for improved seasonal forecasting of reservoir inflows across Central Asia. Further research will investigate the possibility for seasonal predictability of precipitation and reservoir inflows from ENSO as well as other large scale climate drivers, such as the Asian Monsoon, both separately and in combination.

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