

An aerial photograph showing a town with a church in the center, surrounded by extensive flooding. The water is a murky brown color, covering large areas of the town and surrounding fields. The buildings are densely packed, and the church is a prominent white structure with a tall spire. The sky is overcast, and the overall scene depicts a significant flood event.

Seasonal to decadal flood forecasts for UK using a hybrid (AI - large climate model ensemble) approach

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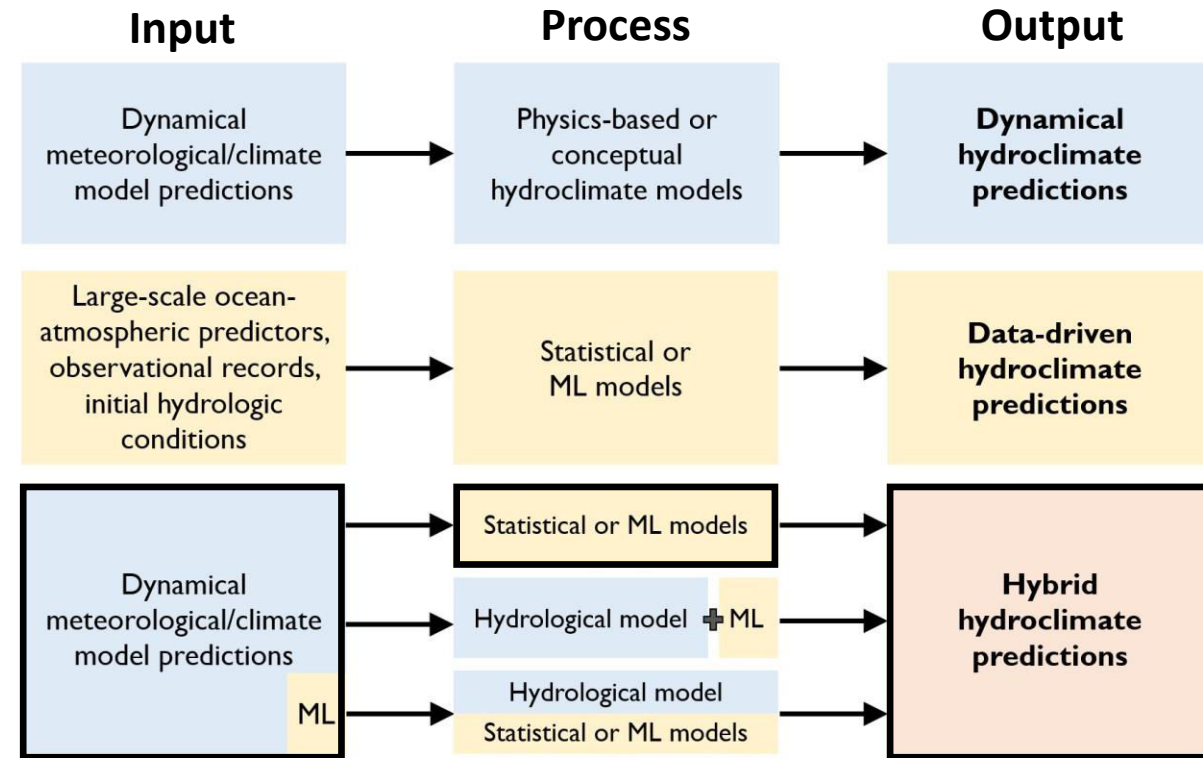
@simmoulds

Hybrid seasonal flood prediction

We use a hybrid approach to predict monthly Q_{\max}

These differ from both dynamical and data-driven predictions

We use a hybrid approach whereby dynamical climate predictions are supplied to a quantile regression forest (QRF) ML algorithm



Slater *et al.* (2023) HESS

Hybrid seasonal flood prediction

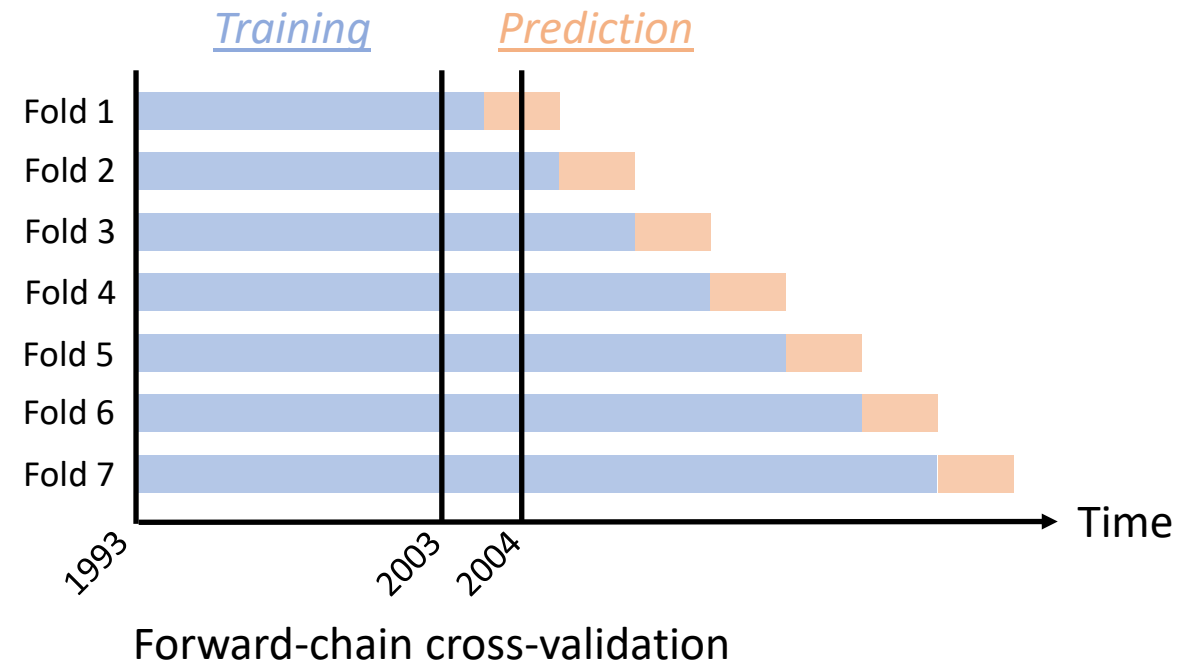
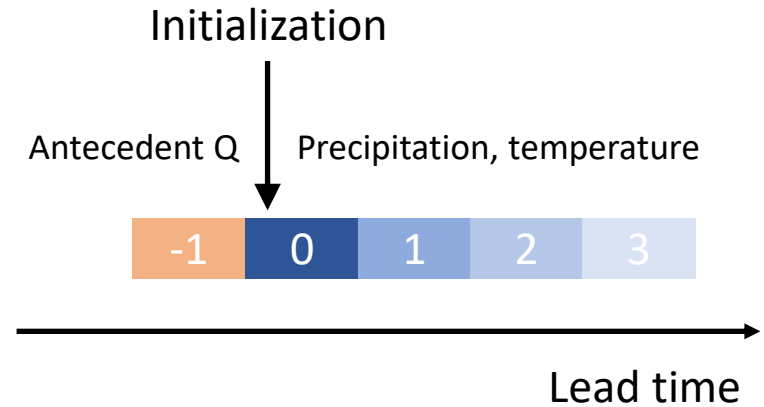
Monthly precipitation and temperature from the C3S multimodel ensemble

Antecedent streamflow and precipitation

Static catchment attributes from CAMELS-GB

How should we build a hybrid seasonal flood forecasting system?

Forecast setup:

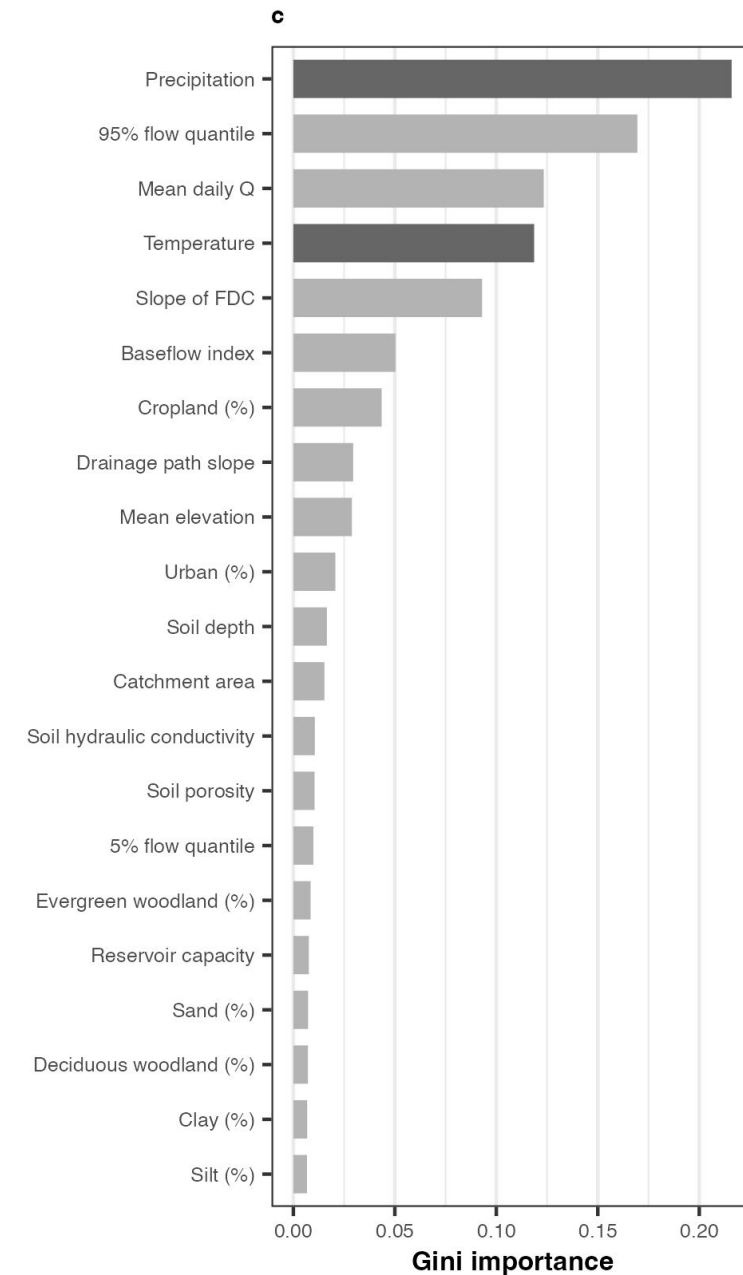
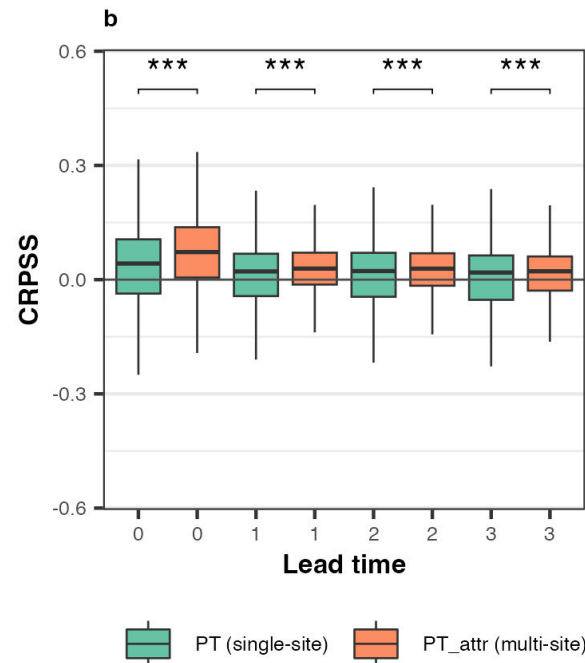
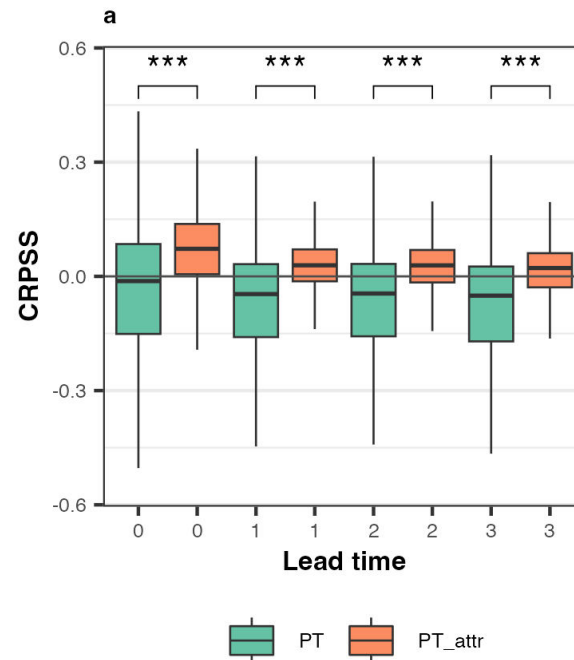


Multi-site model outperforms single-site models

Our QRF model is trained across all catchments and months at once

To benefit from this approach we need to include static catchment attributes

The resulting model *PT_attr* outperforms single-site models fitted separately for each catchment



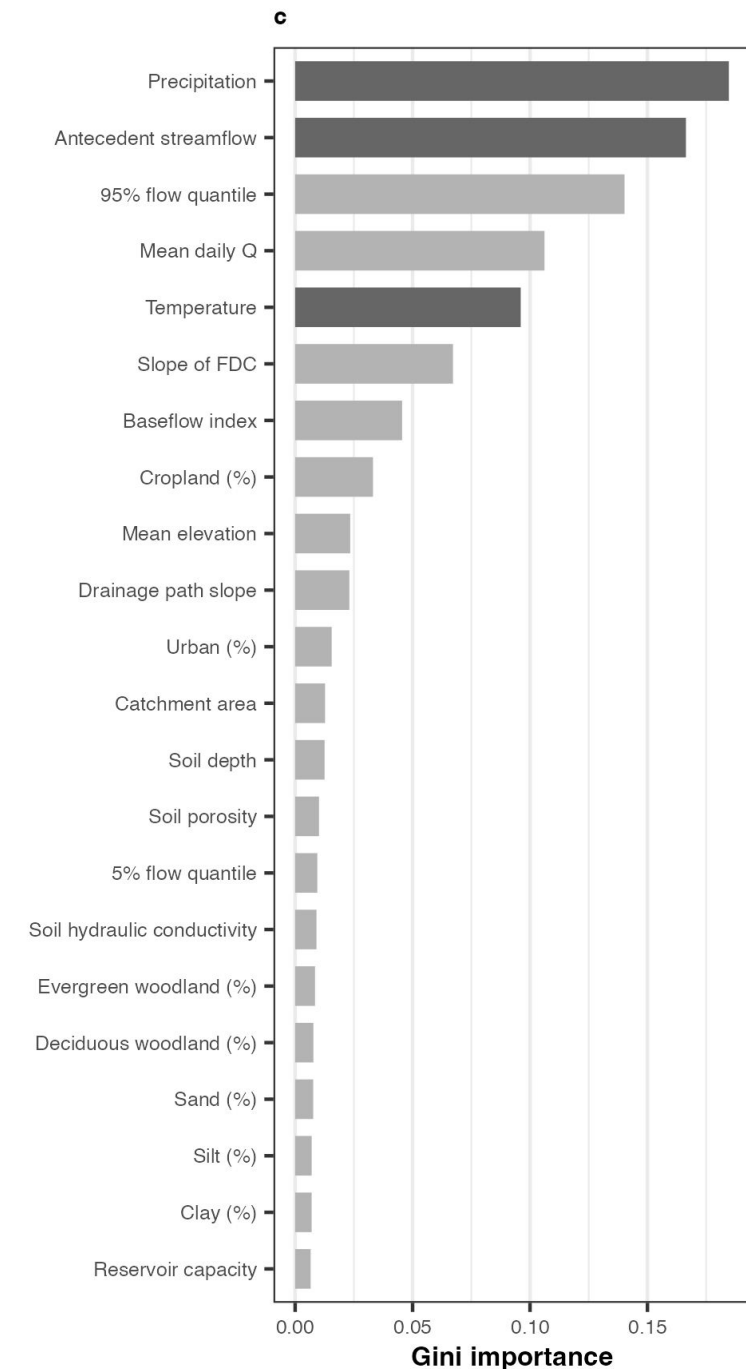
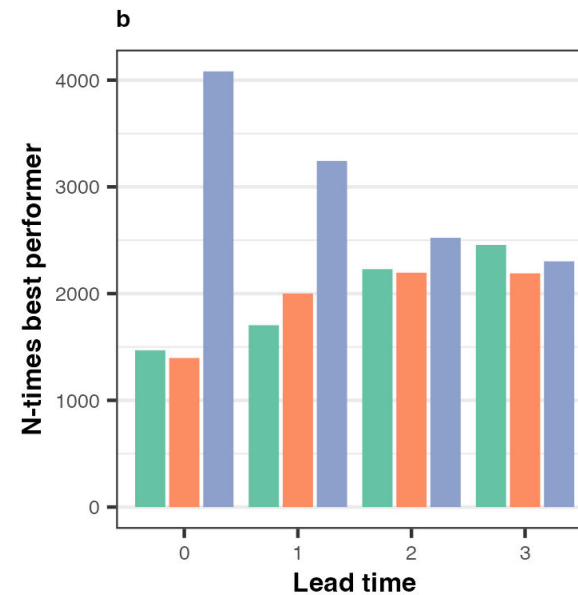
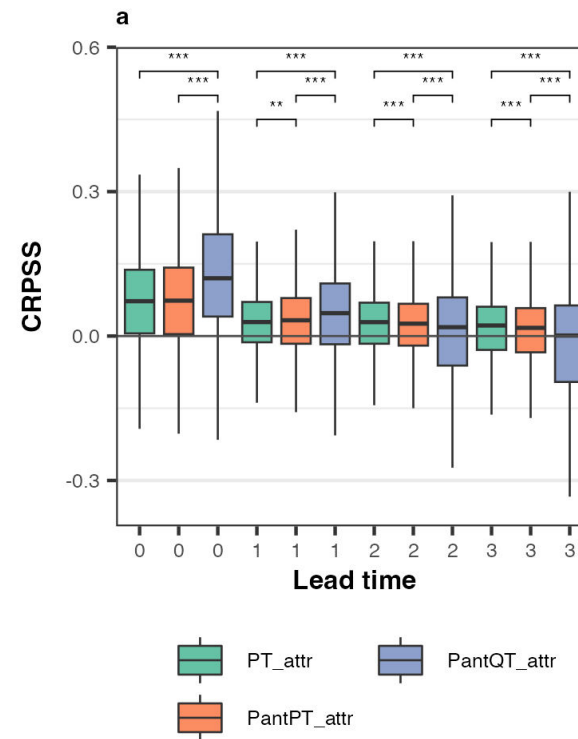
Including antecedent conditions adds skill

Implicitly accounted for by physics-based models

We compare antecedent streamflow (*antQ*) and antecedent precipitation (*antP*)

At short lead times models with *antQ* outperform those without

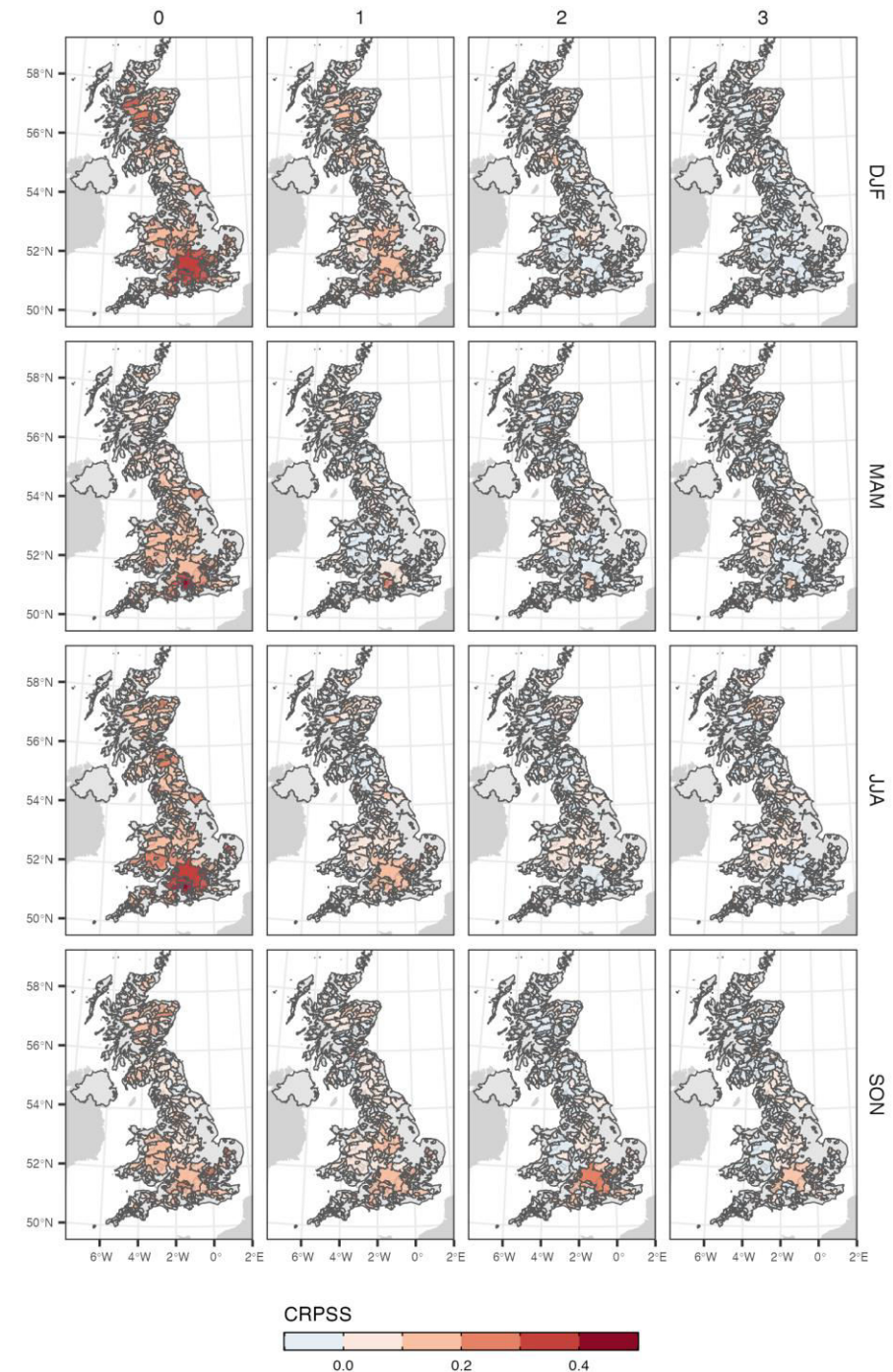
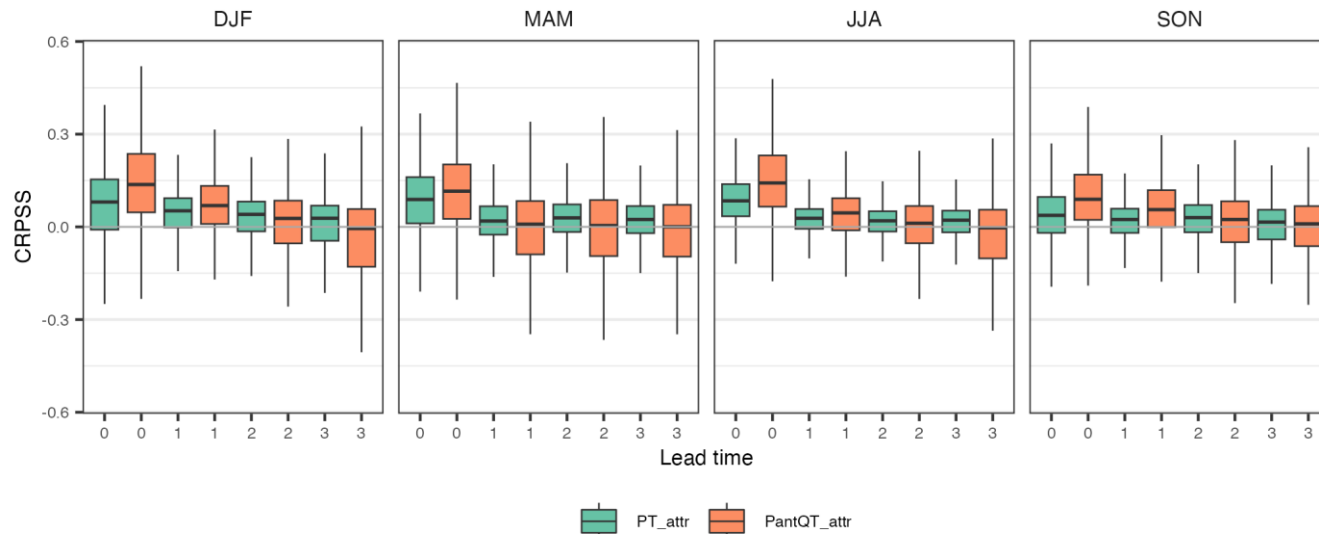
As lead time *increases* the number of stations including *antQ* *decreases*



Skill varies seasonally

Skillful predictions across all seasons for lead time 0

In DJF >75% catchments are skillful in lead time 1 (i.e. 4-8 weeks from initialization)

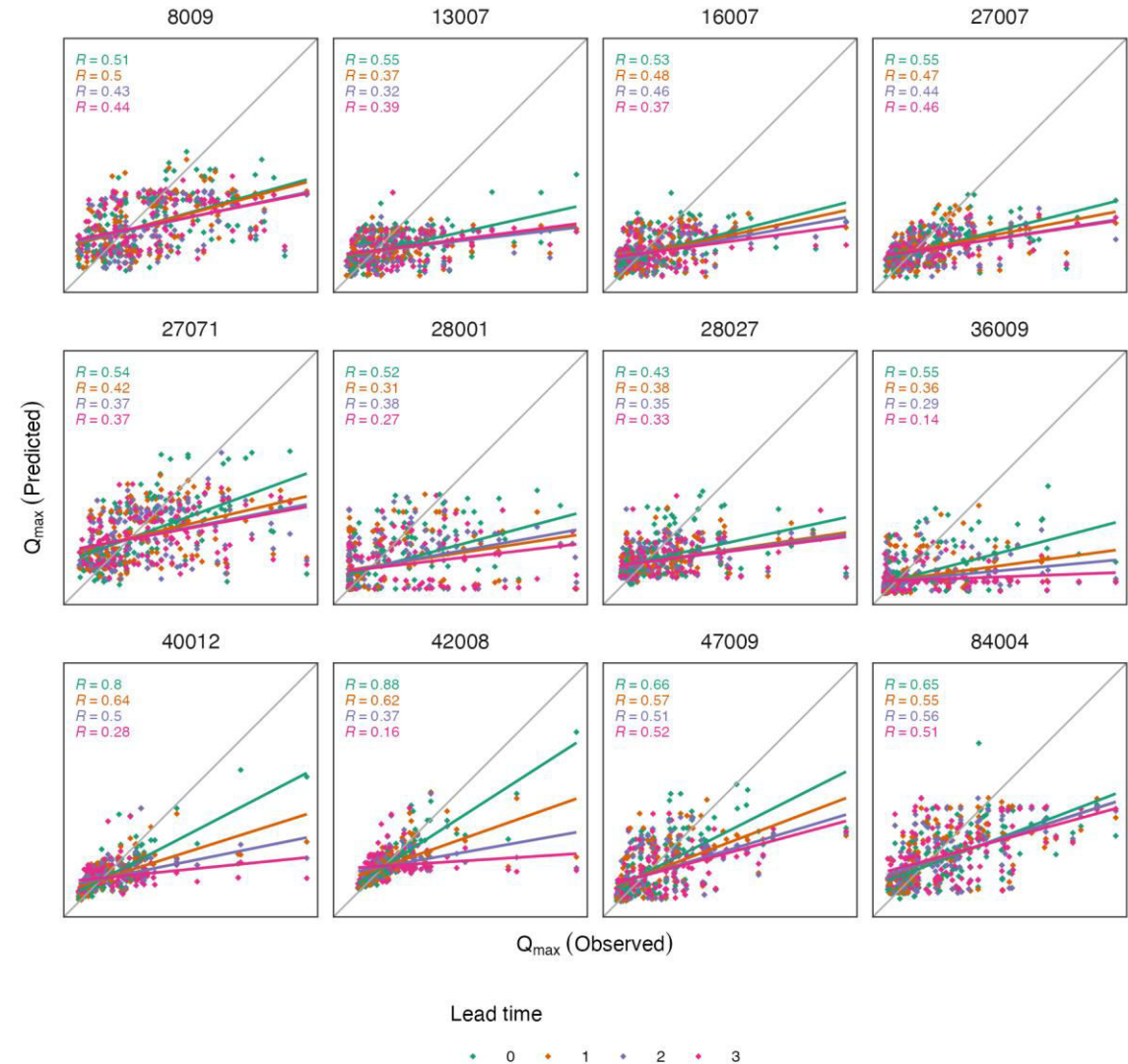


Model tends to underestimate extreme values of Q_{\max}

Higher correlation at shorter lead times

More extreme values of observed Q_{\max} tend to be underestimated

This is more pronounced at longer lead times



Next steps

Comparison with EFAS/GloFAS

Use sub-monthly climate inputs (e.g. weekly)

Explore why certain models perform better in certain catchments

Include remote drivers in models

Ensemble selection to discard less skillful members

Develop a global model

