Upskilling – Uncertainty reduction and representation in seasonal forecasting

QJ Wang

LAND AND WATER
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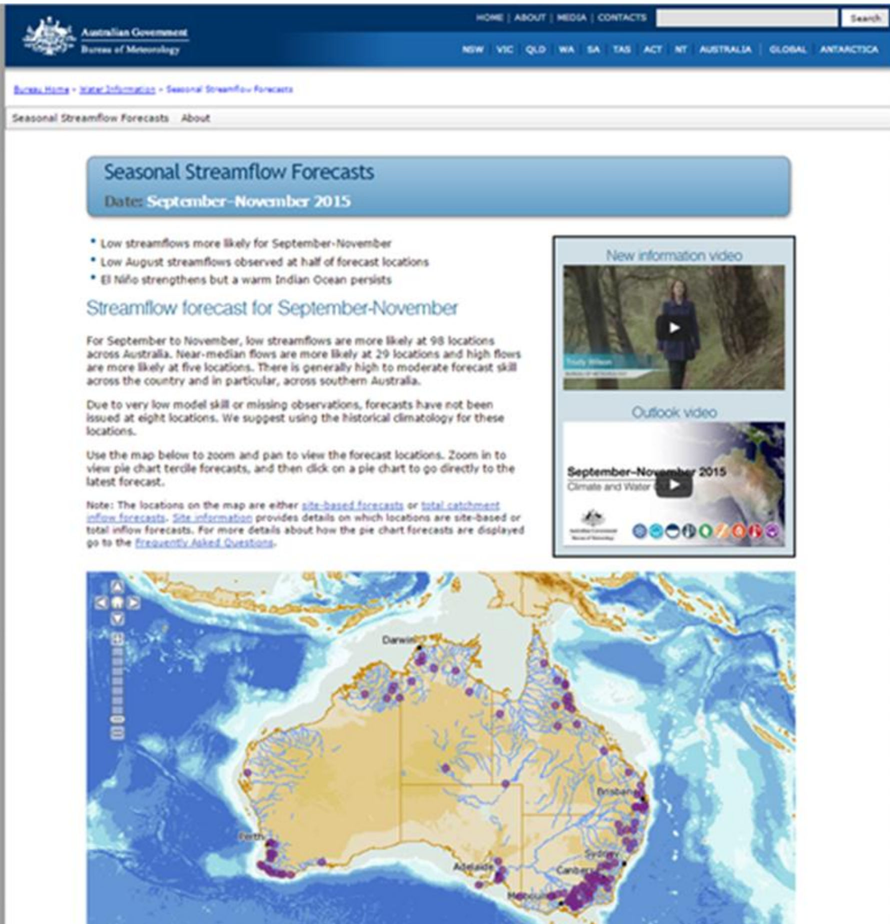
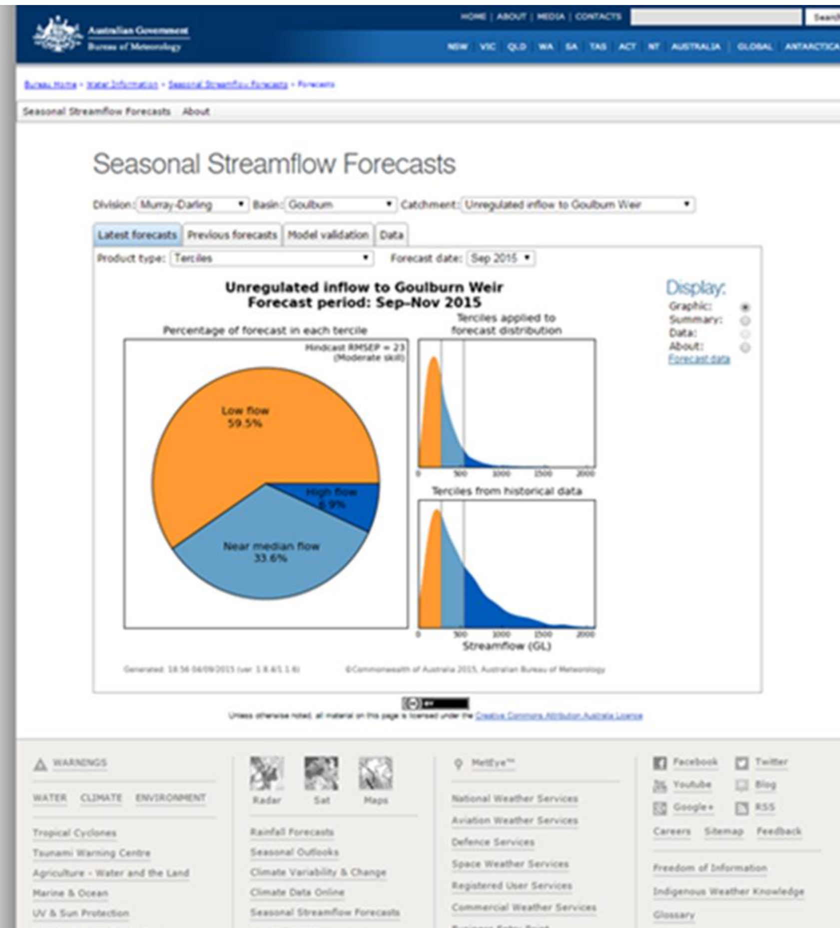
Seasonal streamflow forecasting service in Australia





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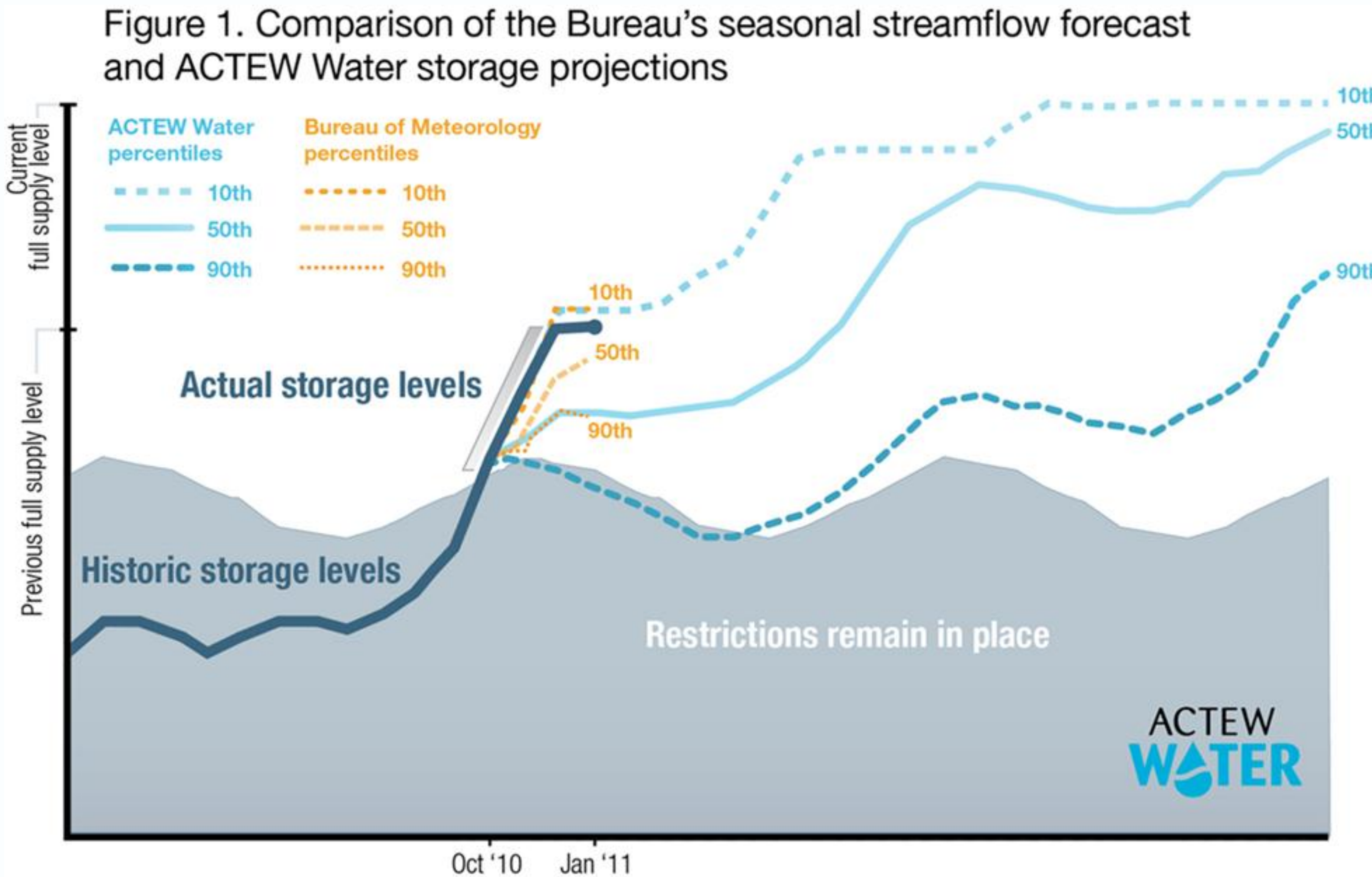
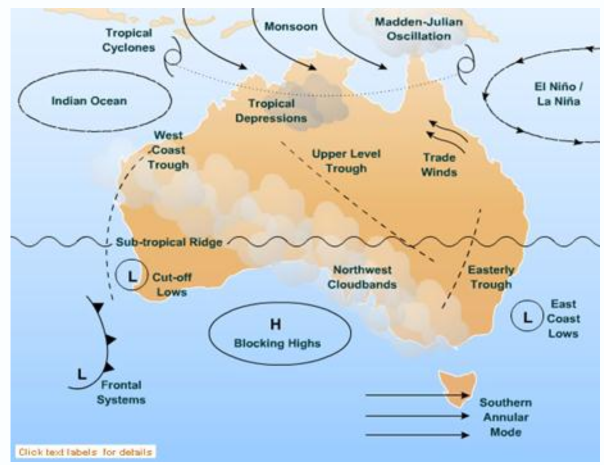
Seasonal streamflow forecasting service in Australia



Two sources of predictability

- **State of the catchment**
  - Glacier, snow, soil moisture, groundwater, in-stream storages, …

- **State of the climate**
  - Atmosphere, ocean, land



Challenges

- **High quality forecasts - Skill and reliability**
- **Meeting user needs**

The Bayesian joint probability (BJP) method

- **Predictors –> Predictands**
- **Issues**
  - Heteroscedasticity
  - Zero value
  - Data
- **The BJP solution**
  - Transformations
  - Censored data
  - A joint probability model, with Bayesian inference

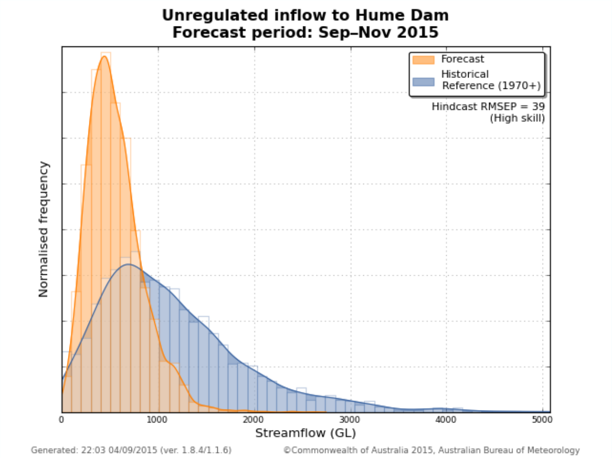
Wang, Robertson and Chiew (2009) ***Water Resources Research***

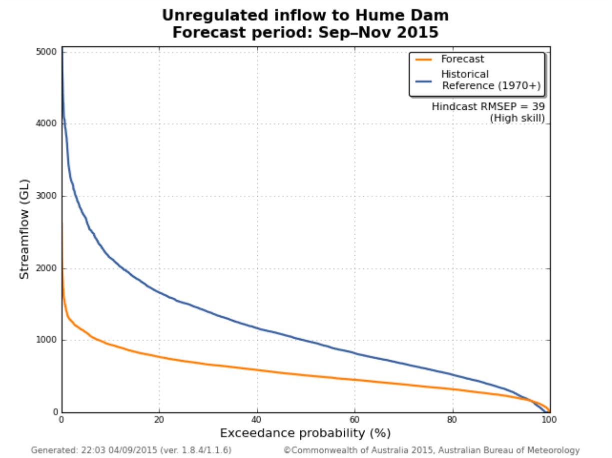
Wang and Robertson (2011) ***Water Resources Research***

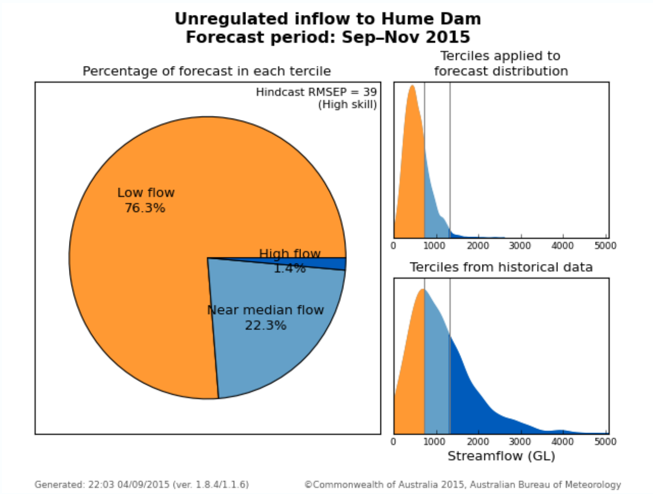
Wang, Shrestha, Robertson and Pokhrel (2012) ***Water Resources Research***

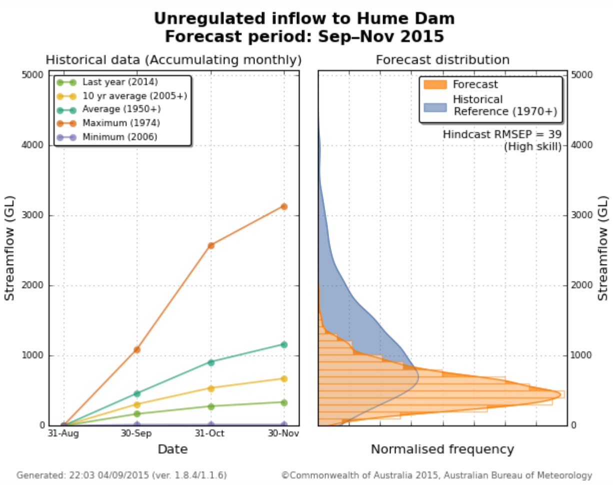
Robertson and Wang (2013) ***Water Resources Management***

Probabilistic forecasts







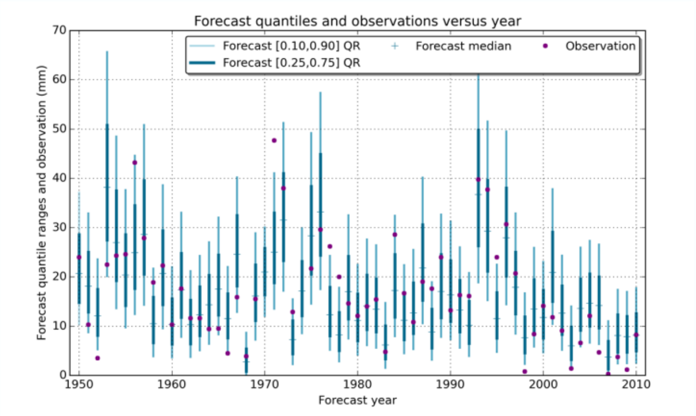


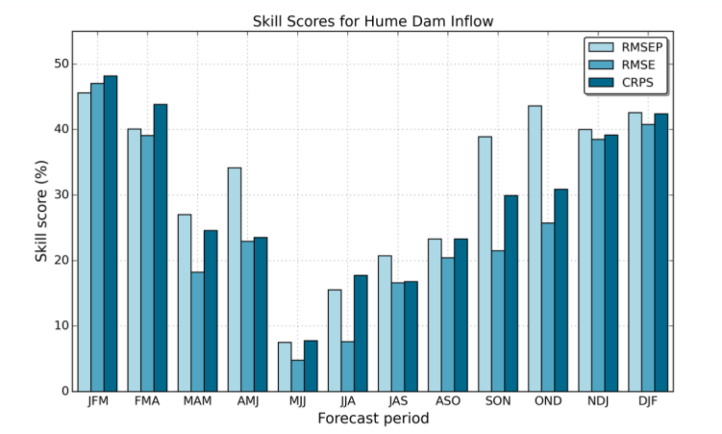
....

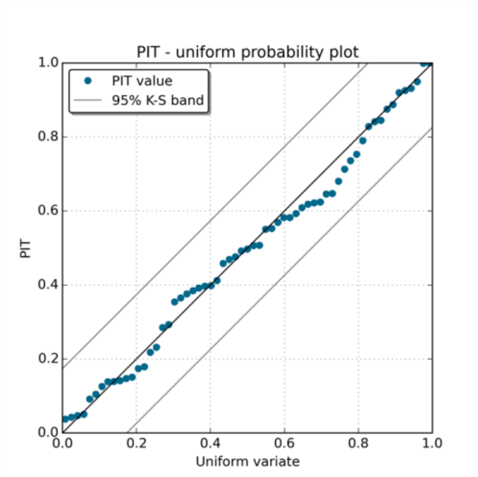
44	72.264	0
45	73.979	0
46	74.132	0
47	74.507	0
48	75.136	0
49	76.356	0.177
50	77.234	2.643
51	77.937	3.011
52	77.952	6.152
53	78.276	6.986
54	78.721	7.312
55	80.045	9.099
56	81.461	12.313
57	81.537	13.697
58	82.374	14.536
59	82.676	16.977
60	82.754	17.938
61	84.262	18.258
62	85.438	19.29
63	86.43	21.252
64	86.505	22.814
65	87.163	24.639
66	89.975	24.976
67	90.277	25.415

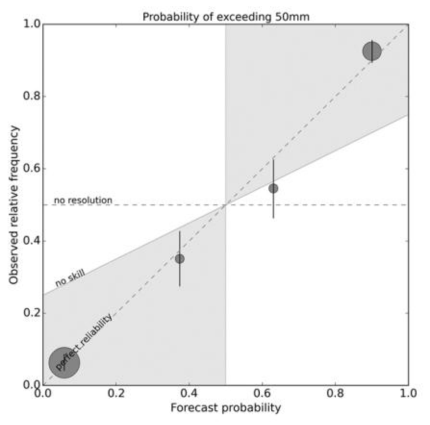
....

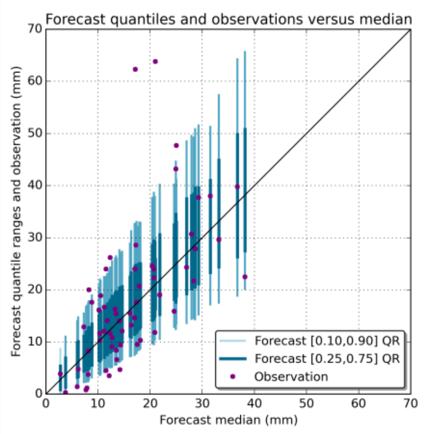
Cross validation

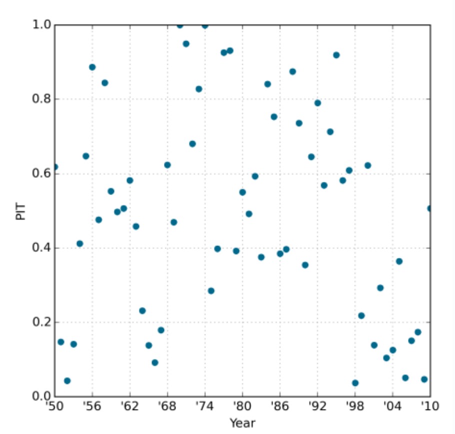












Key learnings

- **Forecasts highly reliable**
- **Skill varying with locations and seasons**

- **Other applications**

Model selection and combination

- **Many candidate predictors**
  - **State of climate**

    SOI, NINO3, NINO3.4, NINO4, ENSO Modoki; IOD, IOE, IOW, II; TSI, SAM
  - **State of catchment**

    Antecedent streamflow; Antecedent rainfall
- **The best model approach**
- **The model combination approach (BMA)**

Robertson and Wang (2012) ***Journal of Hydrometeorology***

Wang, Schepen and Robertson (2012) ***Journal of Climate***

Pokhrel, Wang and Robertson (2013) ***Water Resources Research***

Bennett, Wang, Pokhrel and Robertson (2014) ***Natural Hazards and Earth System Sciences***

Key learnings

- **Two or fewer predictors in each BJP model**
- **Selecting the best model based on predictive ability - a good idea**
- **Model combination - preferred**
  - Taking advantage of strengths of different models
  - Moderating worst forecast errors
- **Other applications**

Incorporating dynamical model outputs

- **Issues**
  - Antecedent streamflow or rainfall –> Not always good indicators
  - Do climate model outputs add value?
- **Incorporating dynamical model outputs to the BJP model**
  - Hydrological model
  - Climate model

Robertson, Pokhrel and Wang (2013) **Hydrology and Earth System Sciences**

Pokhrel, Wang and Robertson (2013) ***Water Resources Research***

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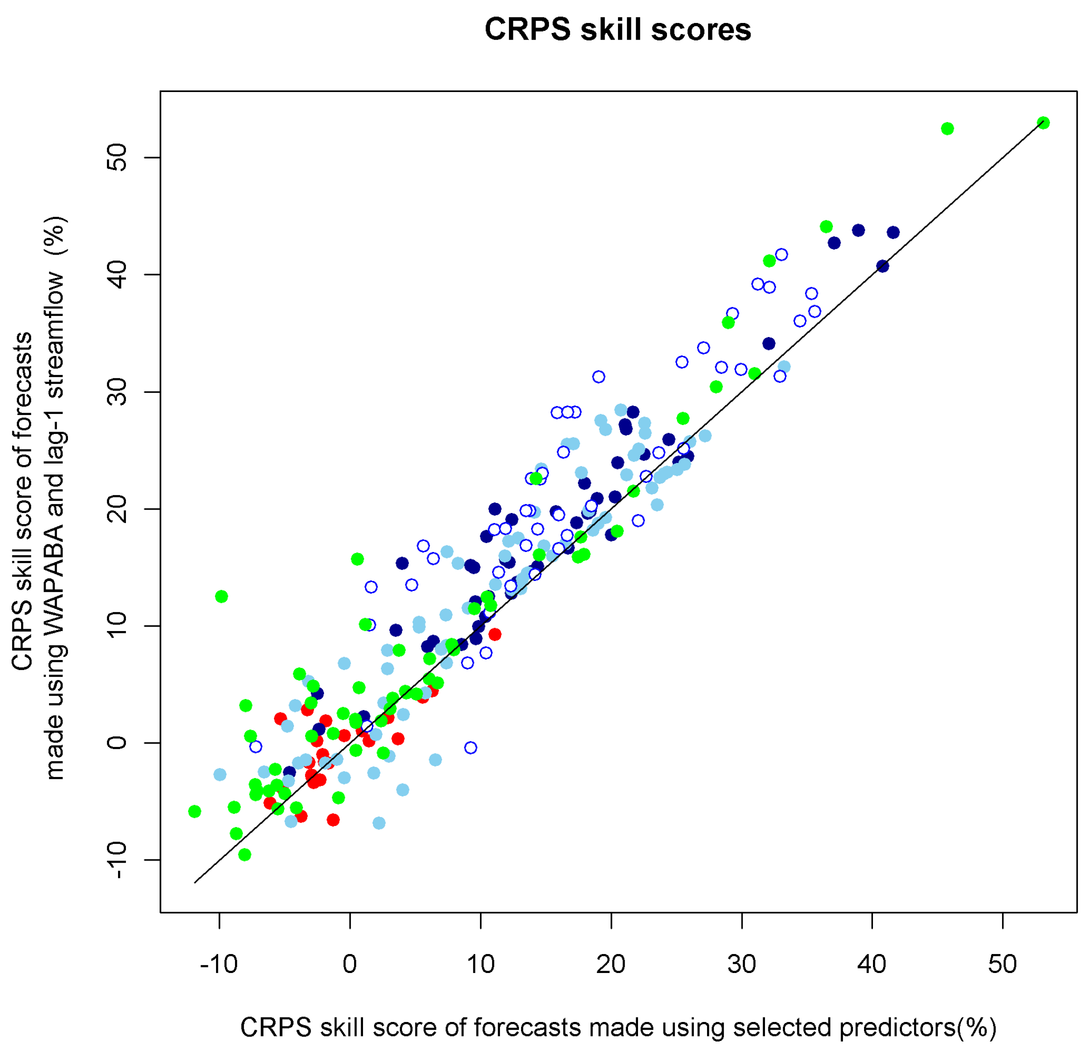
Skill gain



CRPS skill scores
CRPS skill score of forecasts made using WAPABA and lag-1 streamflow (%)
CRPS skill score of forecasts made using selected predictors(%)
-10
0
10
20
30
40
50
-10
0
10
20
30
40
50

Key learnings

- **Incorporating hydrological model outputs**

  Forecast improvement when catchment is

  - wetting up
  - Drying down
  - near saturation

- **Incorporating climate model outputs**

  - Marginal skill increase when using precipitation forecasts
  - No additional benefit when using forecast SST

- **Hydrological model + BJP = Practical option**

What about fully dynamical models?

- **Advantages**
  - Conceptually more attractive
  - Ensemble time series forecasts useful for practical applications
- **Disadvantages**
  - Modelling more complex
  - Uncertainty handling much challenging
- **Overall**
  - The way to go

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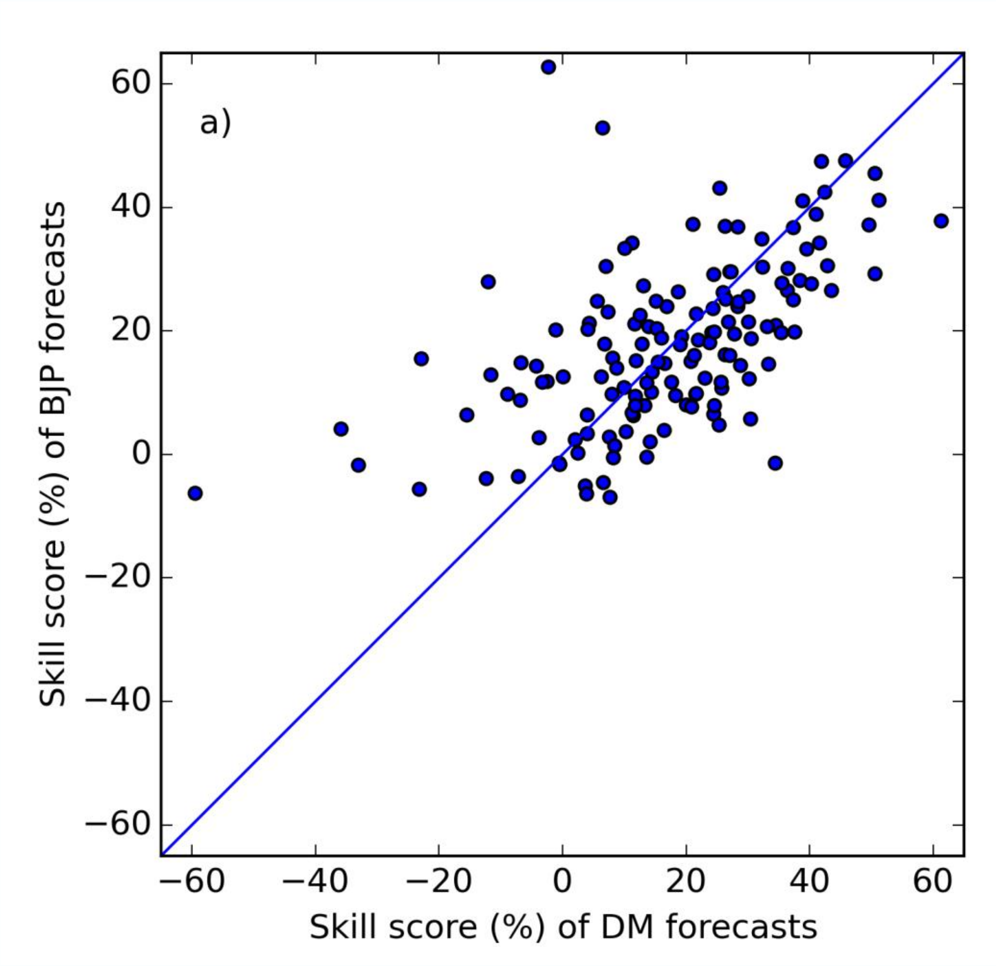
Merging statistical and dynamical forecasts

- **The Bureau of Meteorology service**
  - Currently the BJP is used for operational forecasting
  - The Bureau has also developed a dynamic model (DM)
  - The two models offer complementary skill

Complementary skill



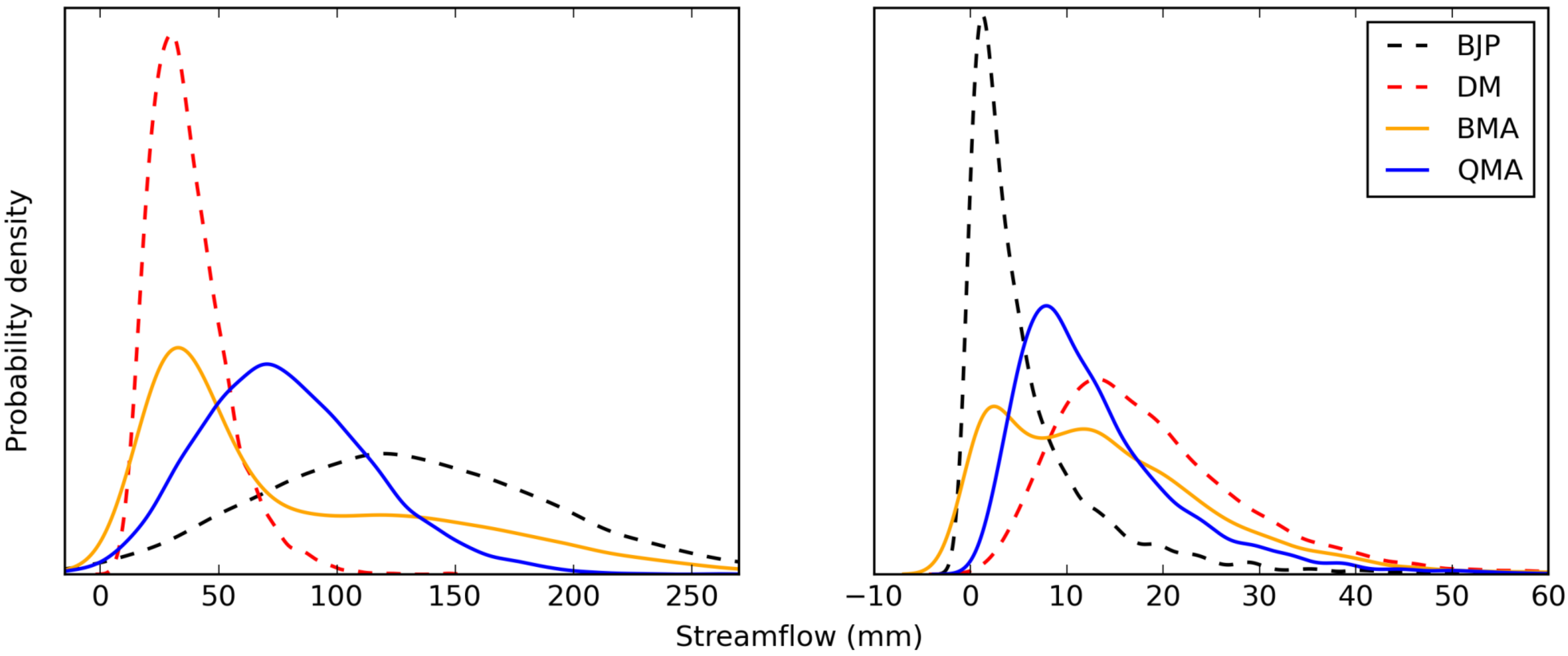
Merging statistical and dynamical forecasts

- **The Bureau of Meteorology service**
  - Currently the BJP is used for operational forecasting
  - The Bureau has also developed a dynamic model (DM)
  - The two models offer complementary skill
  - **Future service will adopt merged forecasts**
- **Bayesian model averaging (BMA)**
  - Generally works well
  - On rare occasions, merged forecasts too wide and even bi-modal
- **Quantile model averaging (QMA)**

Wang, Schepen and Robertson (2012) ***Journal of Climate***

Schepen and Wang (2015) ***Water Resources Research***

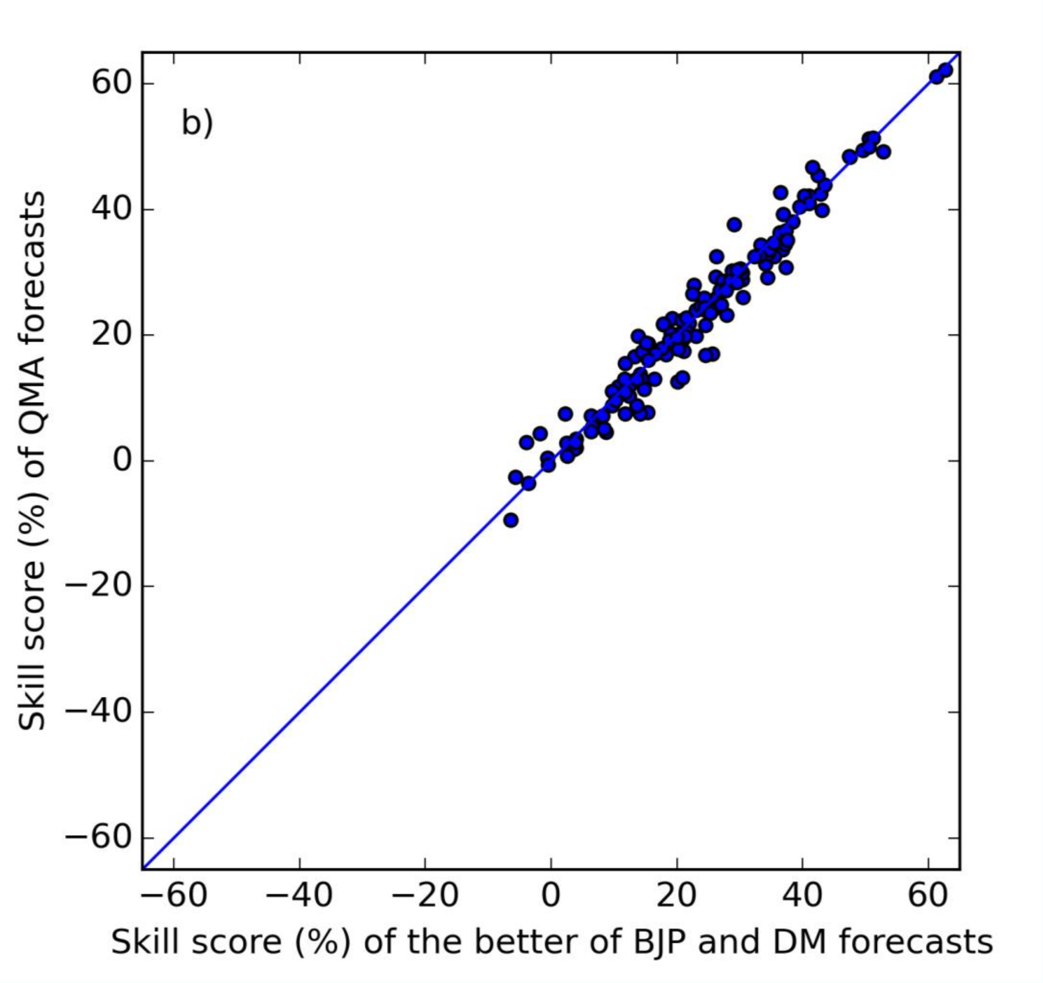
Two examples



Key learnings

- **QMA merged forecasts are preferable**
- **Merging brings out the best skill**

Merging brings out the best skill



Improving climate forecasts

- **Available forecasts are generally of low skill and unreliable**
- **BJP + BMA: A versatile duo!**
- **CBaM (calibration, bridging and merging)**

Schepen, Wang and Robertson (2011) ***Journal of Climate***

Wang, Schepen and Robertson (2012) ***Journal of Climate***

Schepen, Wang and Robertson (2012*)* ***Journal of Geophysical Research***

Schepen and Wang (2013) ***Monthly Weather Review***

Hawthorn, Wang, Schepen and Robertson (2013) ***Water Resources Research***

Schepen and Wang (2014) ***Journal of Hydrology***

Schepen, Wang and Robertson (2014) ***Monthly Weather Review***

Peng, Wang, Schepen, Pappenberger et al. (2014) ***Journal of Geophysical Research***

Peng, Wang, Bennett, Pokhrel and Wang (2014) ***Journal of Hydrology***

Meeting user needs – Key learnings

- **Engage early**
- **Engage continuingly**
- **Respond to feedback**
- **Case studies**

The FoGSS model

- For generating **Fo**recast **G**uided **S**tochastic **S**cenarios

- Ensemble forecasts of monthly volumes of streamflow out to 12 months

- The forecasts become more like natural stochastic scenarios as skill decreases with lead time

Generating a forecast

- **CBaM –> Climate forecasts**
- **WAPABA –> Streamflow forecasts**
- **ERRIS –> Revised streamflow forecasts**
  - Conditional bias correction
  - Updating, injecting and propagating hydrological uncertainty to next lead time

Wang, Pagano, Zhou, Hapuarachchi, Zhang and Robertson (2011) ***Journal of Hydrology***

Wang, Shrestha, Robertson and Pokhrel (2012) ***Water Resources Research***

Li, Wang and Bennett (2013) ***Water Resources Research***

Pokhrel, Robertson and Wang (2013) ***Hydrology and Earth System Sciences***

Li, Wang, Bennett and Robertson (2015) ***Hydrology and Earth System Sciences***

Li, Wang, Bennett and Robertson (submitted) ***Water Resources Research***

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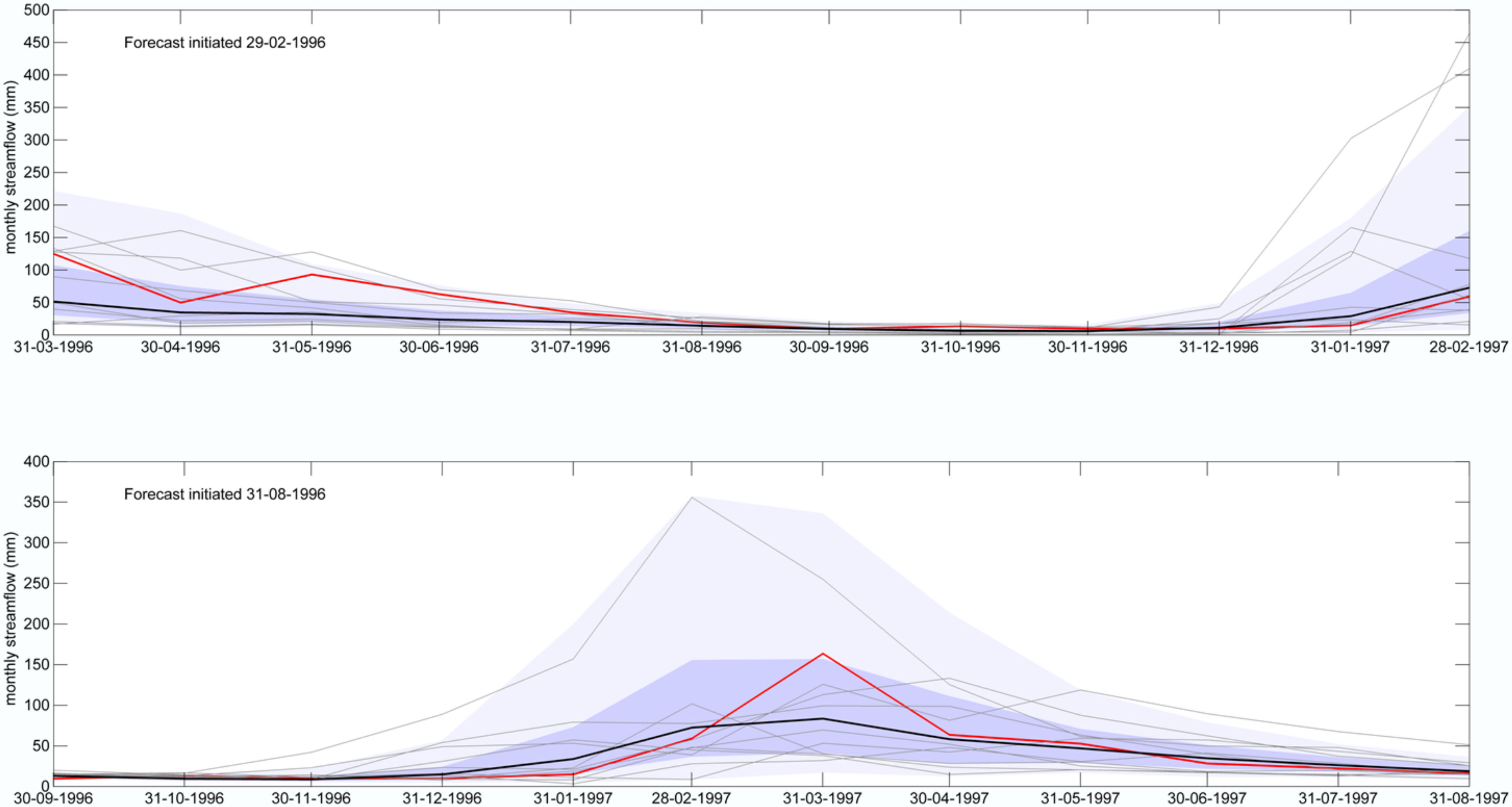
Example forecasts



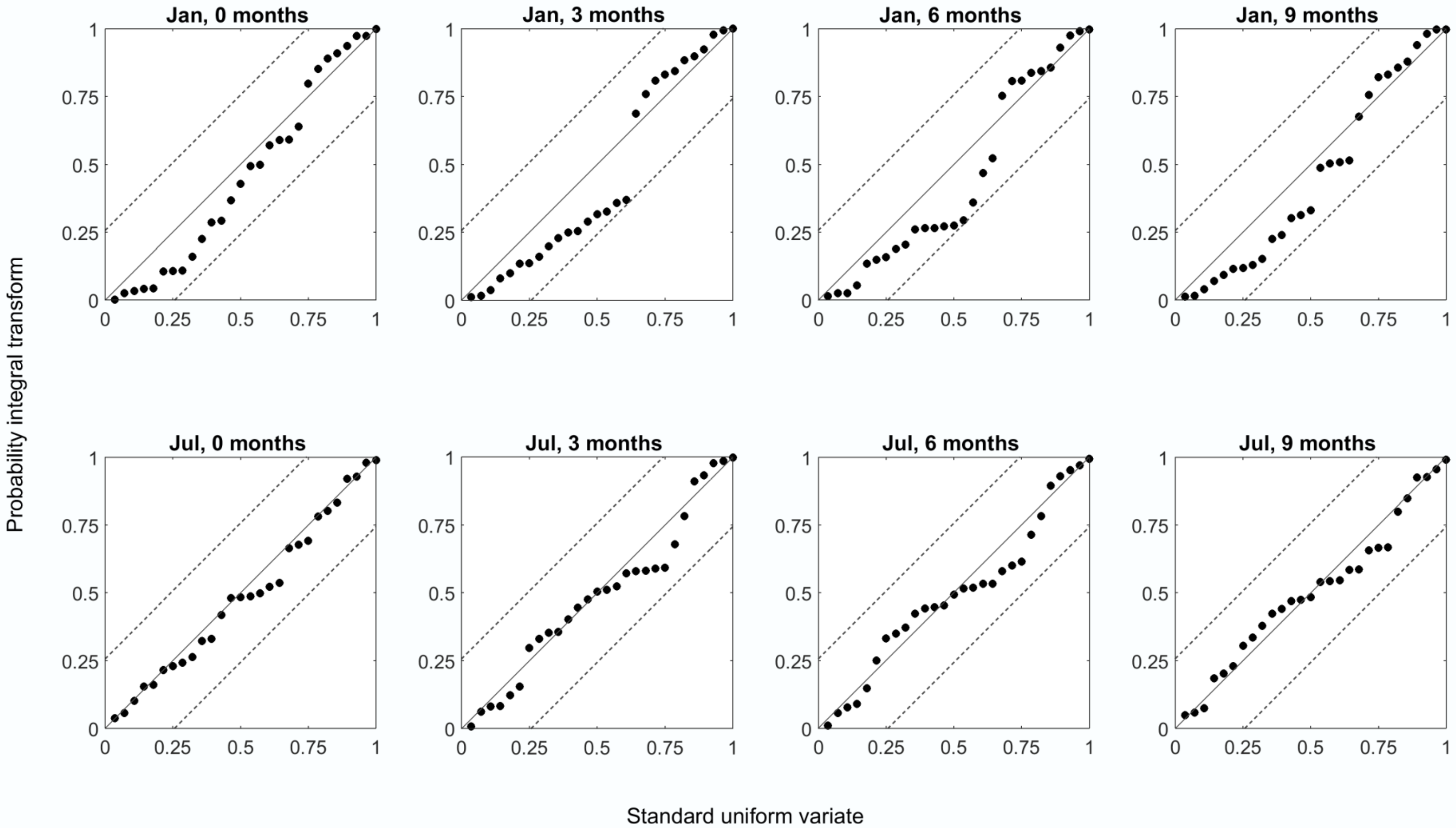
Key learnings

- **Maximizing skill**
  - Extracting the most out of climate model outputs
  - Hydrological modelling: Hydrological model, conditional bias correction, updating

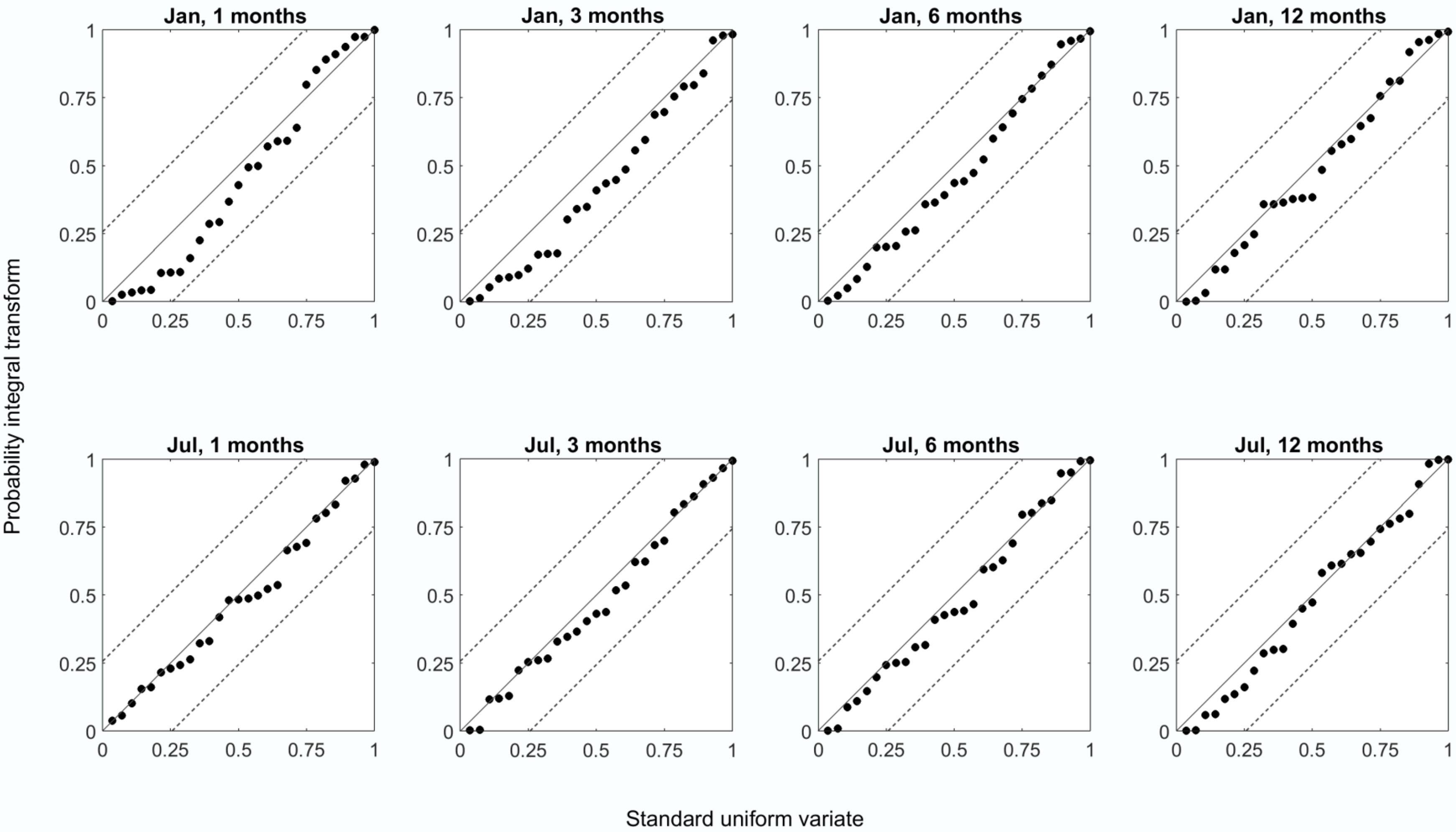
Key learnings

- **Maximizing skill**
  - Extracting the most out of climate model outputs
  - Hydrological modelling: Hydrological model, conditional bias correction, updating
- **Achieving reliability**

Reliability - monthly



Reliability - cumulative



Key learnings

- **Maximizing skill**
  - Extracting the most out of climate model outputs
  - Hydrological modelling: Hydrological model, conditional bias correction, updating
- **Achieving reliability**
  - Reliable climate forecasts
  - Hydrological uncertainty handling

Key learnings

- **Maximizing skill**
  - Extracting the most out of climate model outputs
  - Hydrological modelling: Hydrological model, conditional bias correction, updating
- **Achieving reliability**
  - Reliable climate forecasts
  - Hydrological uncertainty handling
- **FoGSS for water management**
  - Forecast guided stochastic scenarios of monthly streamflow out to 12 months
  - Monthly volume skilful only at short lead times
  - Cumulative volume skilful to longer lead times

Current and future work

- **New BJP**
- **New CBaM**
- **FoGSS adoption**
- **Flood and short-term forecasts**
- **Seamless forecasts**
- **Ensemble climate surfaces (ESDIIM)**

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