

Advances in improving streamflow predictions, with applications in forecasting

Professor Dmitri Kavetski
Associate Professor Mark Thyer

Intelligent Water Decisions Research Group
(www.waterdecisions.org)

School of Civil, Environmental and Mining Engineering
University of Adelaide



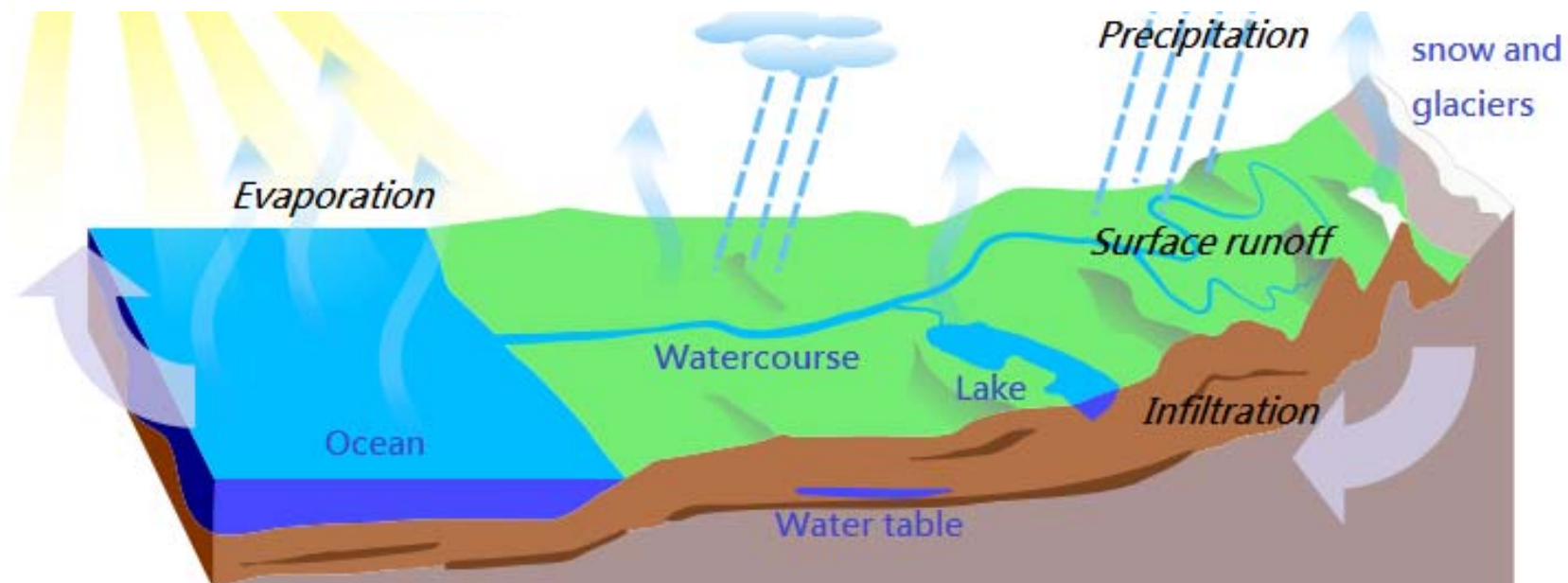
Acknowledgements

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Catchment-scale hydrological modelling

- Scientific and engineering hydrology
 - Understanding flow dynamics, improving model “realism”
 - Flood forecasting, drought prediction, and everything in between
- Major component of broader environmental studies
 - Eg, hydrological models provide inputs into larger-scale models such as General Circulation Models (GCMs)



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Practical impact of hydrological models

- Used across many levels of environmental management and decision-making (and increasingly so!)
 - Eg, Australian Bureau of Meteorology streamflow forecasts used for flood forecasting / mitigation, dam operation, water allocations, agricultural uses, etc
- Economic scale of major operations:
 - South East Queensland floods of 2010/11 caused \$5 billion damage and impacted 200,000 people (QLD Government, 2013)
 - Australia's irrigated crops: \$13.5 billion annual value (ABS, 2013)

=> Credible predictions are expected

=> Must recognize and communicate uncertainties

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Operational Advances ↔ Research Advances

Even moderate advances = huge value!

Outline

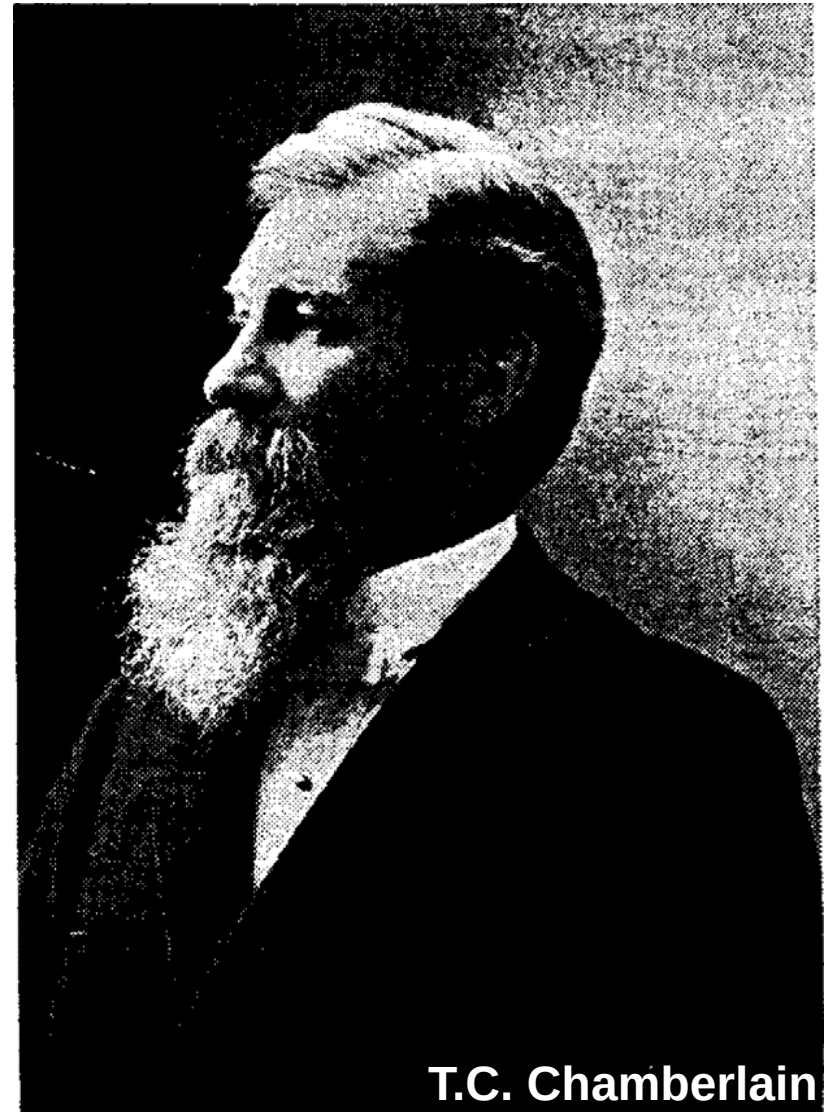
- Improving Hydrological Predictions
 - Overview of advances in flexible modelling, in lumped and spatial outcomes
 - Improving model calibration / optimization
 - Spatial rainfall modelling
- Improving streamflow probabilistic predictions
 - Importance of persistence for reliable probabilistic streamflow across time scales
 - Practical guidance on residual error models to improve reliability and precision of probabilistic predictions
- Impacts on Forecasting

Flexible models in hydrology: Method of multiple working hypotheses

- Scientists often develop “parental affection” for their theories
- Chamberlin’s method of multiple working hypotheses

“...the effort is to bring up into view every rational explanation of new phenomena... the investigator then becomes parent of a family of hypotheses: and, by his parental relation to all, he is forbidden to fasten his affections unduly upon any one”

Chamberlin (1890)



T.C. Chamberlain

Multiple working hypotheses in hydrological modelling

- Multiple alternative rainfall-runoff model structures
 - In simplest case, change numbers of “buckets” in model
 - More generally, include conceptual and physical representations (eg, Fenicia et al 2016; Clark et al 2015)
 - Test using multiple metrics/diagnostics, cross-validation
 - Multiple representations of uncertainty
 - Simplest case, eg, unweighted/weighted least squares
 - More generally, different data transformations, etc (eg, McInerney et al, 2017)
 - Again, multiple metrics/diagnostics, cross-validation
- => More robust findings suitable for operationalization

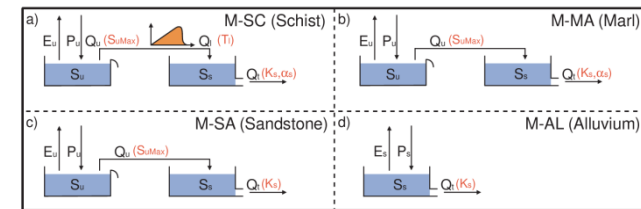
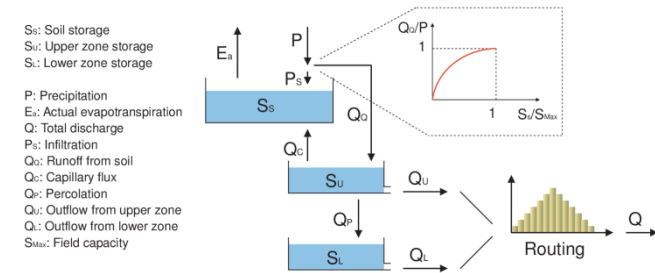
Flexible Hydrological Models

Motivation

- “One-size-fits-all” approaches do not work very well for specific catchment
- Some models, such as GR4J, developed to provide good performance “on average”
- Good starting point, but can we improve performance in catchments of interest?

Aim

- “Flexible” model that can be tailored to catchments / processes of interest
- Parsimonious => Fast to calibrate/simulate
- Robust => Under cross-validation using multiple metrics (Nash, signatures, etc)



Fenicia F, Kavetski D, Savenije HHG (2010) Elements of a flexible framework for hydrological modelling, *WRR*
 Clark et al (2015) A unified approach for process-based hydrologic modeling, *Water Resources Research*
 and references therein / subsequent work

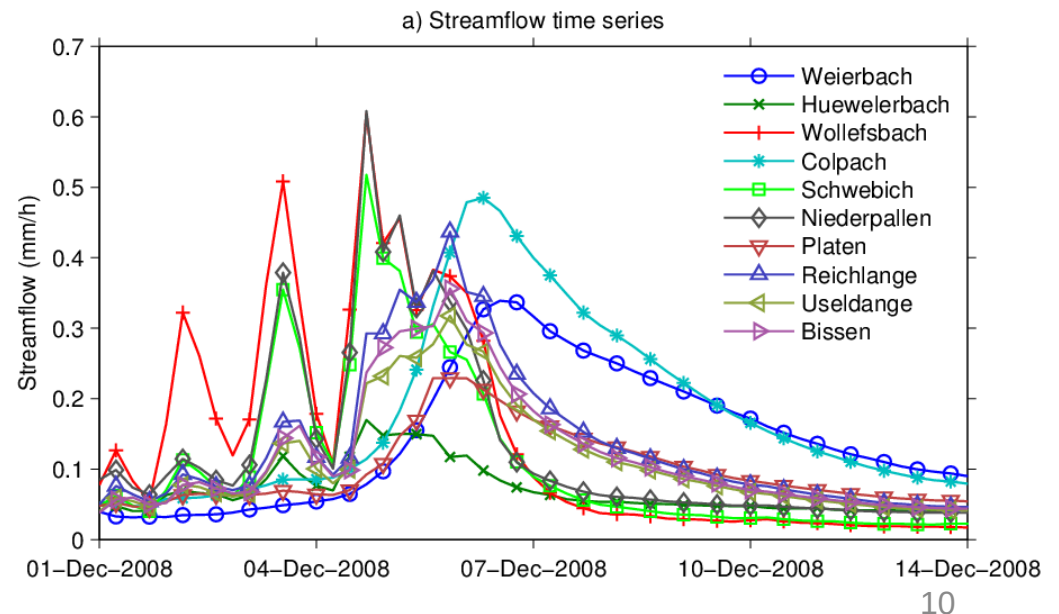
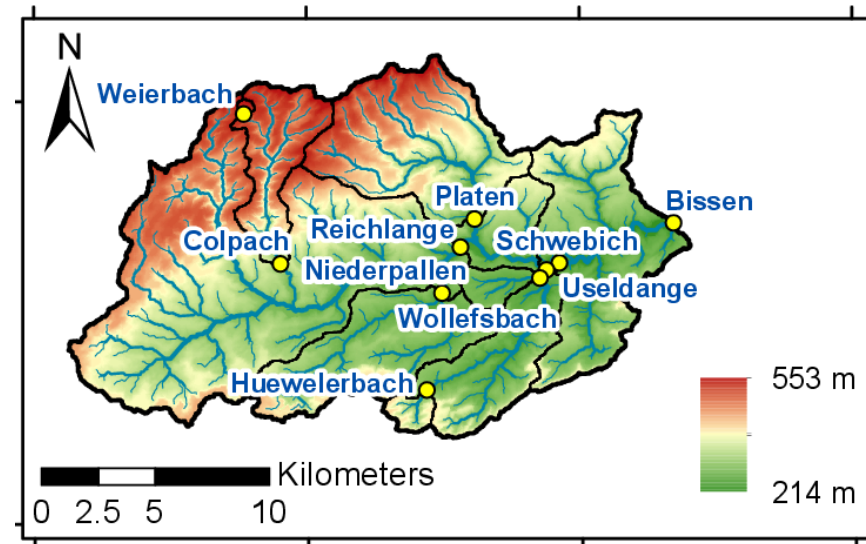
The challenge of spatial variability

Study area

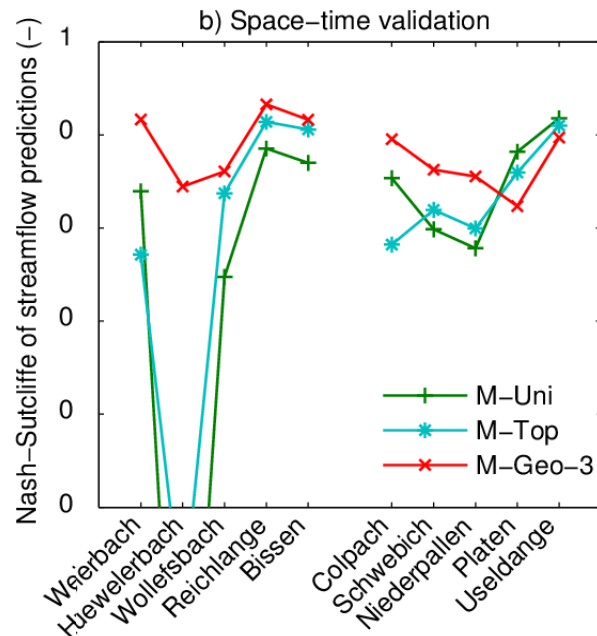
- **Atttert** basin in Luxembourg
- 300 km²
- Densely gauged
- Extensive fieldwork insights

Research questions

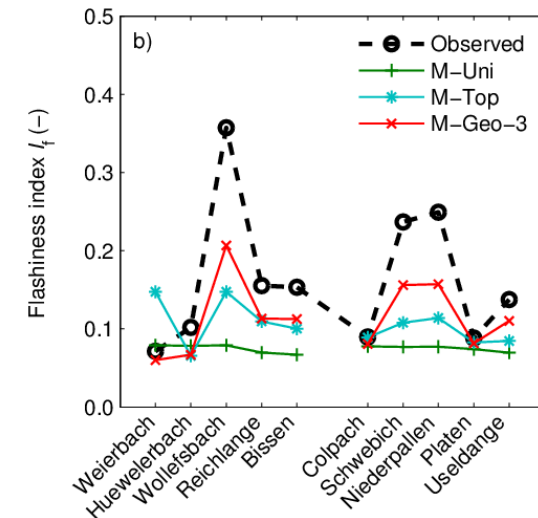
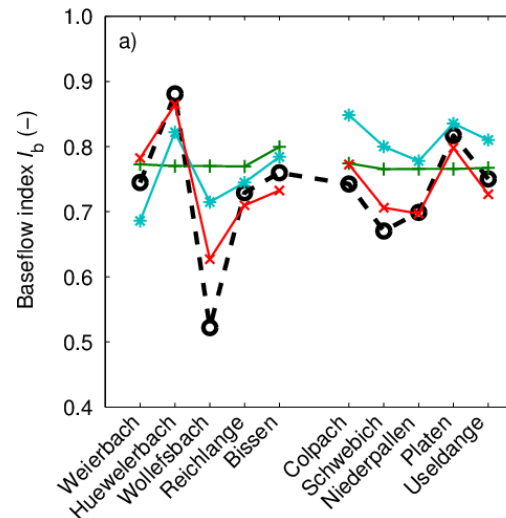
- Why are the **streamflow dynamics** so different (dominant controls?)
- How to build a **distributed model** that reproduces streamflow diversity
- Can such models be exploited for practical / **operational prediction**?



Distributed application of SUPERFLEX



Use different model structures in each HRU type
Space-time validation, streamflow series and signatures



Science: Identify dominant processes, reconcile model vs fieldwork

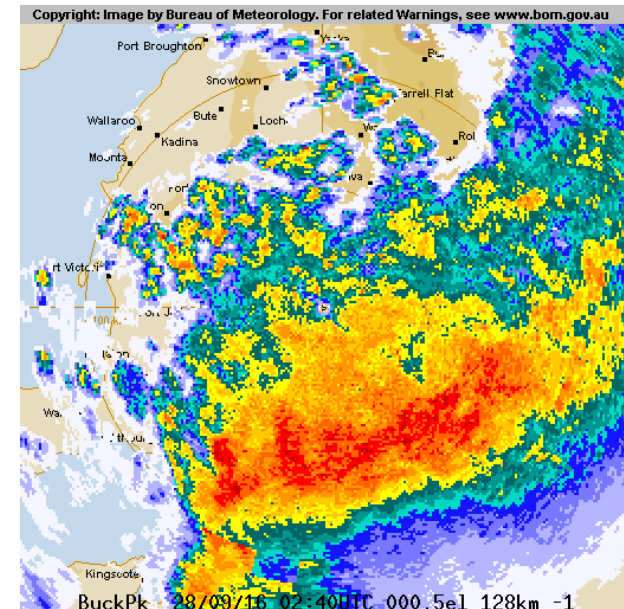
Operational: Capture diverse spatial streamflow patterns across 10 locations using “simple” model with 11 calibrated parameters

=> Pilot collaboration with German Forecasting Services

Fenicia et al (2016) From spatially variable streamflow to distributed hydrological models: Analysis of key modeling decisions, *WRR*, 52, 954-989

Spatial Rainfall Modelling

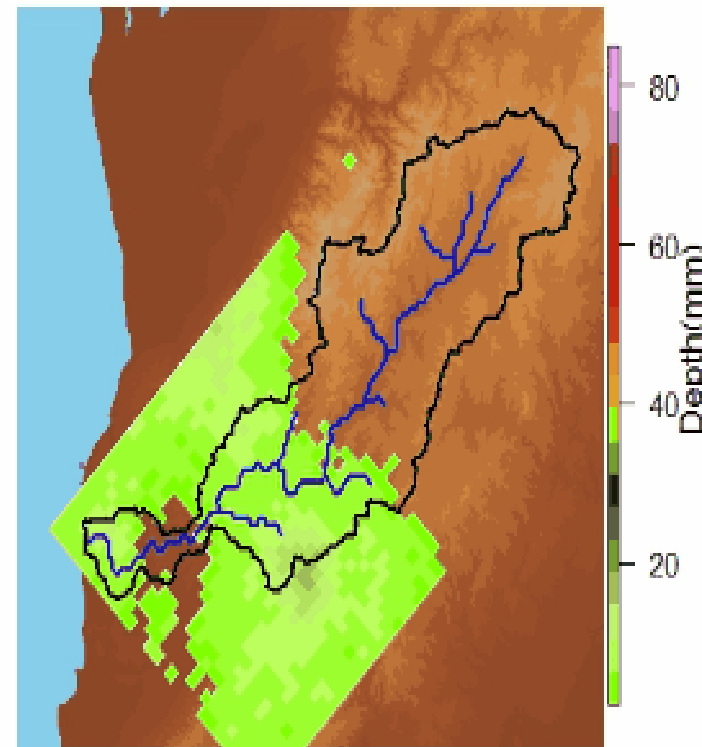
- Motivation
 - Water management needs stochastic rainfall models to provide reliable estimates of floods / drought risks
 - Spatial rainfall variability has big impact on catchment response
 - Most stochastic spatial rainfall models not simple enough to be used in practice
- Aim
 - Develop stochastic model that continuously simulates daily rainfall fields
 - Parsimonious => Fast to calibrate and simulate
 - Flexible approach => Choose your own spatial resolution



Realistic continuous rainfall fields

- Daily simulations for Adelaide's water supply catchment: Onkaparinga catchment
- Tested using a comprehensive and systematic evaluation framework
- Majority of spatio-temporal statistics of simulated rainfall were statistically indistinguishable from statistics of observed rainfall
 - Strengths: Rainfall occurrences/amounts, wet/dry spell distributions, Annual volumes/extremes and spatial patterns
 - Weaknesses: Total annual rainfall in dry years (lower 5%) was overestimated.

Metric	All data	Overall	Cross-validation	Overall
Percent of cases				
Monthly				
Wet day amounts - means	100%	Good	65% 19% 15%	Good
Wet day amounts - std dev	100%	Good	75% 18% 10%	Good
No. wet days - means	100%	Good	64% 25% 11%	Good
No. wet days - std dev	44% 24% 32%	Highly Variable	43% 27% 30%	Highly Variable
Wet spell distribution	43% 46% 11%	Fair - Good	43% 46% 11%	Fair - Good
Dry spell distribution	65% 35%	Good	65% 35%	Good
Total rainfall - means	100%	Good	44% 21% 35%	Highly Variable
Total rainfall - std dev	59% 28% 1%	Good	51% 31% 1%	Good
Total rainfall - lower tail	80% 18%	Good	79% 15%	Good
Total rainfall - upper tail	78% 20%	Good	65% 25% 1%	Good
Annual				
Total rainfall - means	100%	Good	53% 32% 56%	Poor
Total rainfall - std dev	16% 47% 37%	Fair - Poor	37% 16% 47%	Highly Variable
Total rainfall - lower tail	21% 47% 32%	Fair - Poor	26% 26% 47%	Fair - Poor
Total rainfall - upper tail	53% 47%	Good	53% 32% 16%	Good
Wet day amounts - mean	100%	Good	16% 42% 42%	Fair - Poor
Wet day amounts - std dev	100%	Good	84% 16%	Good
No. wet days - means	100%	Good	37% 42% 21%	Fair - Good
No. wet days - std dev	100%	Poor	4% 92% 1%	Poor
Correlations				
Monthly total rainfall	89% 11%	Good	85% 15%	Good
Annual total rainfall	100%	Good	100%	Good
Extremes				
Intensity-Frequency-Duration curve	53% 21% 26%	Good	37% 16% 47%	Highly Variable



Potential Applications

- Evaluate impact of spatial rainfall on flood risks
- Evaluate impact of spatial rainfall uncertainty
- Condition stochastic rainfall model on information from numerical weather models
 - Flexible model structure can be adapted to be used for conditional simulation
 - Potential for use as a Spatial Rainfall Post-Processor for rainfall forecast systems (eg, ACCESS)
 - Main advantage is it fills in space, rainfall forecasts over entire grid
 - Opportunity for spatial streamflow forecasts

Outline

- Improving Hydrological Predictions
 - Overview of advances in flexible modelling, in lumped and spatial outcomes
 - Improving model calibration
 - Spatial Rainfall Modelling
- Improving streamflow probabilistic predictions
 - Practical guidance on which residual error model to improve reliability and precision of probabilistic predictions
- Impacts on Forecasting

Motivation

- Hydrological predictions are relied upon by wide range of users
- Understanding uncertainty is important for decision making and risk assessment

Aims

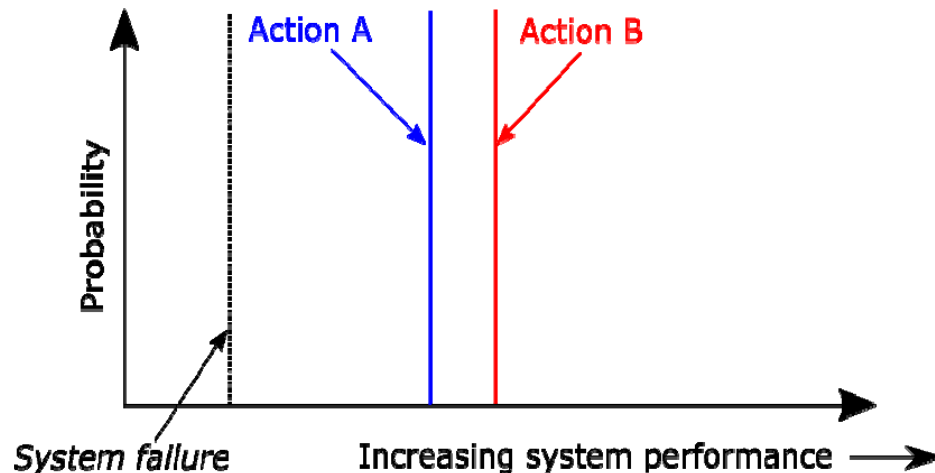
- Overall aim is to improve probabilistic predictions
- Representing uncertainty in hydrological predictions challenging
- We perform comprehensive comparison between approaches for representing uncertainty
- Provide recommendations for practitioners

Quantifying uncertainty improves decision-making providing better risk estimates

- Example: **action A** versus **action B**: Which one would you choose?

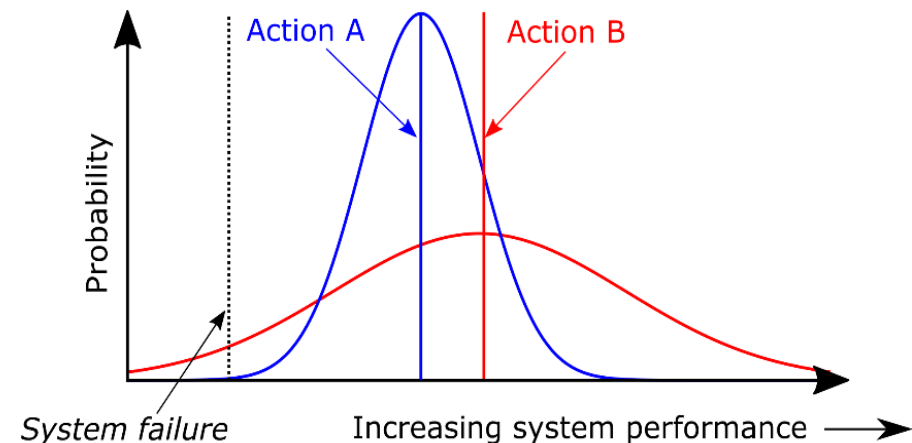
- No uncertainty:

Use “highest performance” outcome → choose action B!



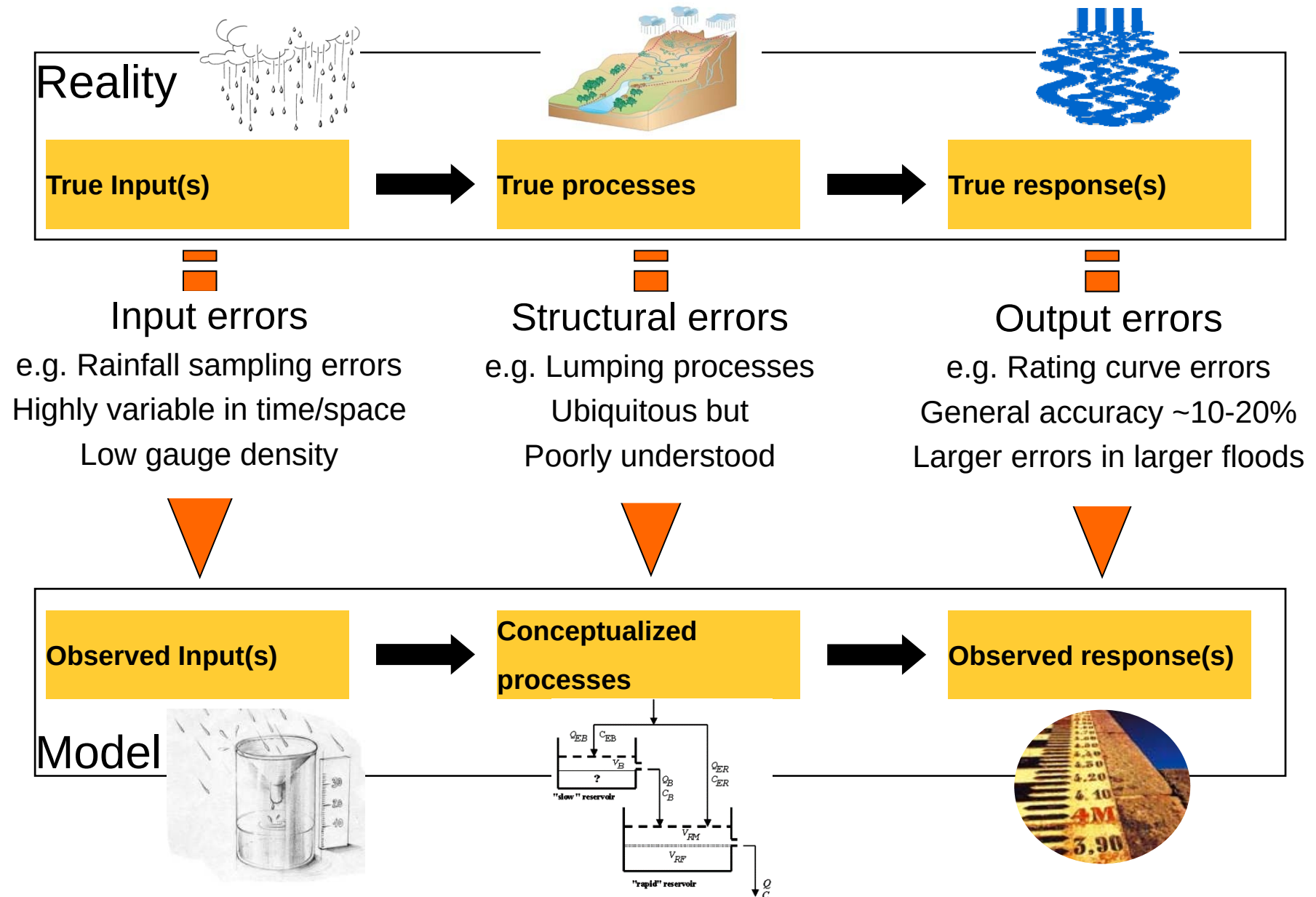
- With uncertainty:

If you want to reduce risk of failure → choose action A!



- Water management is all about balancing risks (risk of floods or droughts)
- If we ignore uncertainty, we under-estimates risks of system failure

Sources of Errors in Hydrological Modelling

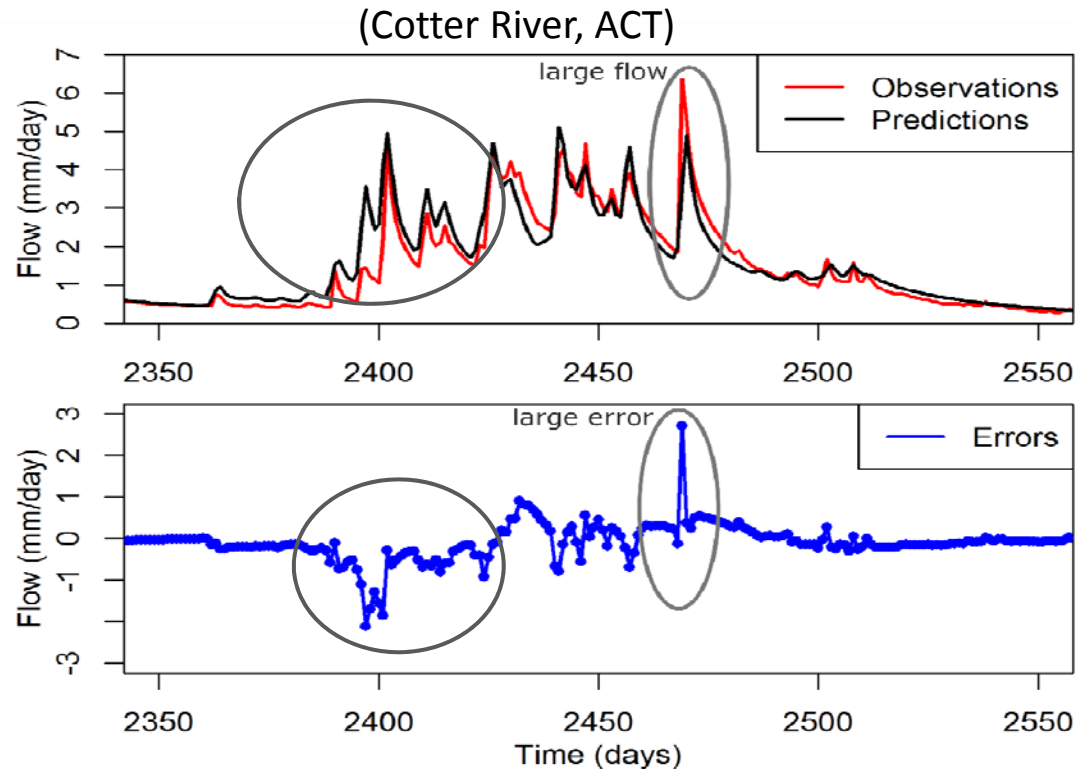


Approaches to modelling uncertainty: Find the right tool for the job

- Decompositional: Estimate individual sources of uncertainty
 - Advantage of diagnosing dominant sources of error
 - Eg, Bayesian Total Error Analysis (BATEA), Kavetski et al (2006+)
 - Requires more advanced Bayesian and MCMC technology
 - Requires more extensive data support, more expertise in applying, => not really an “off-the-shelf” method available to practitioners
- Aggregated: Estimate total uncertainty in predictions
 - Lump all uncertainty into single term
 - Residual error models: $\text{residual} = \text{obs} - \text{pred}$, estimate $p(\text{residual})$
 - Easy to articulate, especially in its simpler forms
 - Very common in engineering practice and literature => “off-the-shelf”
 - But: unable to estimate the dominant source of error

In operational settings the predictions are key, so this presentation will focus on the development of aggregated approaches that estimate the total uncertainty in predictions.

Challenging features of residuals in hydrology



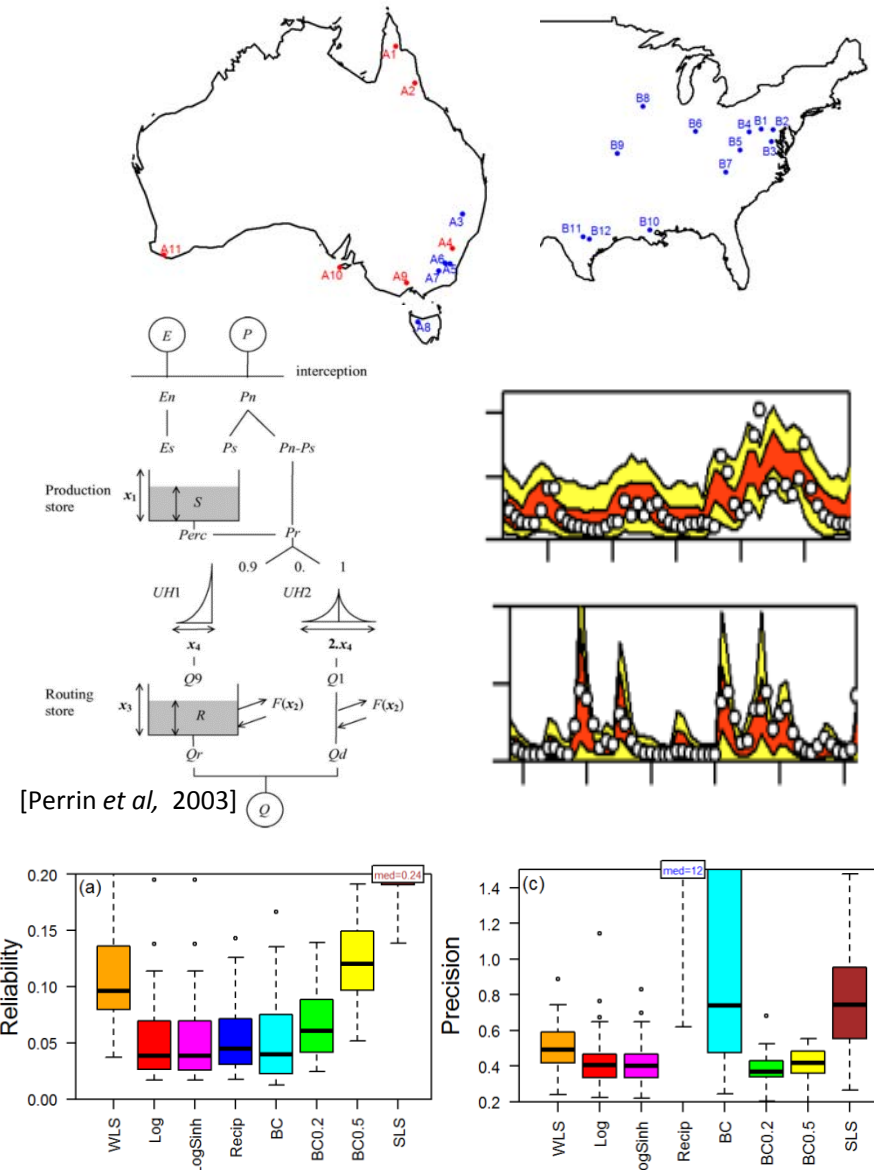
**Streamflow
time series**

**Residual
errors time
series**

- **Errors are heteroscedastic** (larger errors in large flows)
- **Errors are persistence** (not independent between time steps)
- Appropriate representation of both “features” is required to achieve reliable probabilistic predictions

What is the “best” residual error model for making daily streamflow probabilistic predictions?

- Research Gap: No study had compared the wide range of residual error models
- 8 different residual error models
 - SLS, WLS, log, logsinh, Box-Cox transforms
- Comprehensive comparisons
 - 23 catchments from Australia and USA
 - 2 hydrological models (GR4J, HBV)
- Cross-validation over 10 yr period
 - 3500+ model calibrations
 - 4000+ CPU hours (150 days) on HPC
- Multiple performance metrics
 - Reliability, precision and bias
- McInerney et al (WRR2017)

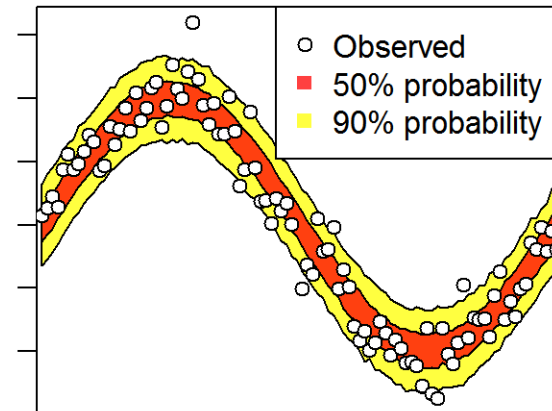


What makes good probabilistic predictions?

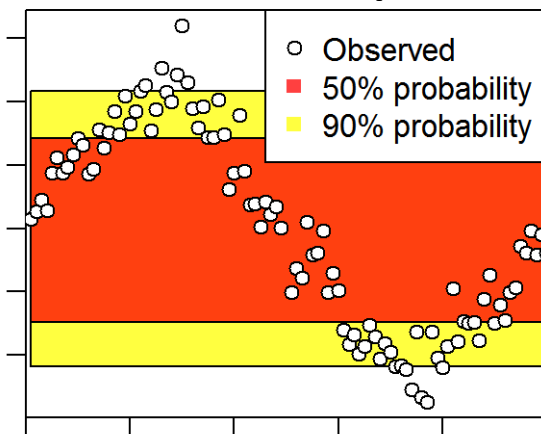
We want predictions that are

- **Reliable:** Predictions statistically consistent with observed data
- **Precise:** Small uncertainty in predictions
- With **low volumetric bias:** total volume from predicted flow matches observations

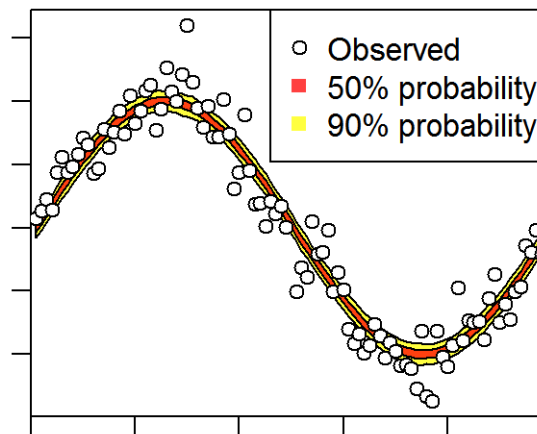
Reliable, precise, unbiased



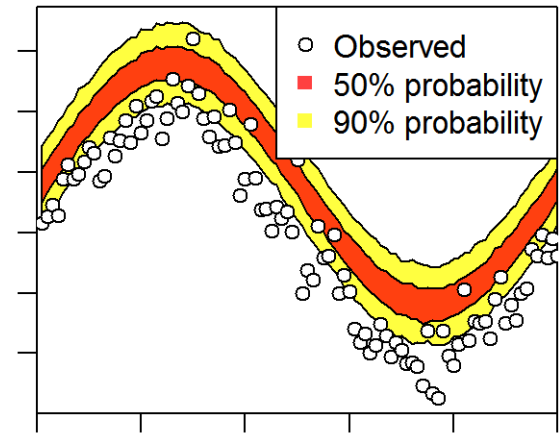
Reliable but imprecise



Precise but unreliable



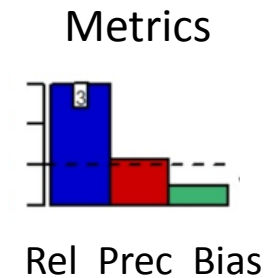
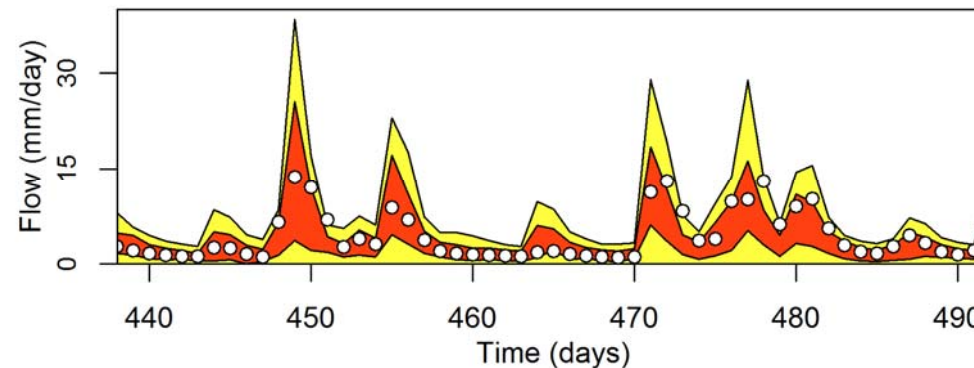
Biased



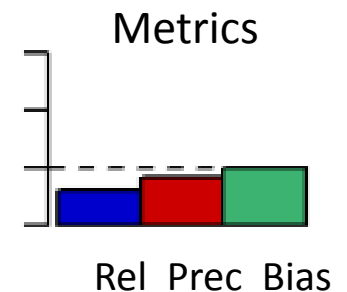
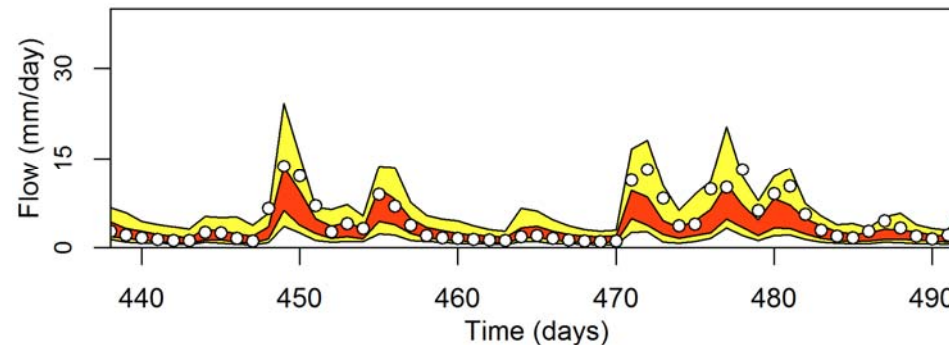
Error model has large impact on probabilistic predictions: Perennial Catchments

- Perennial catchment (Spring River, USA), GR4J hydro model

Weighted Least Squares (WLS)



Log transformation

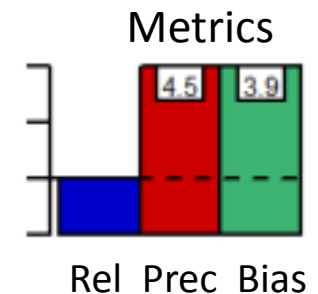
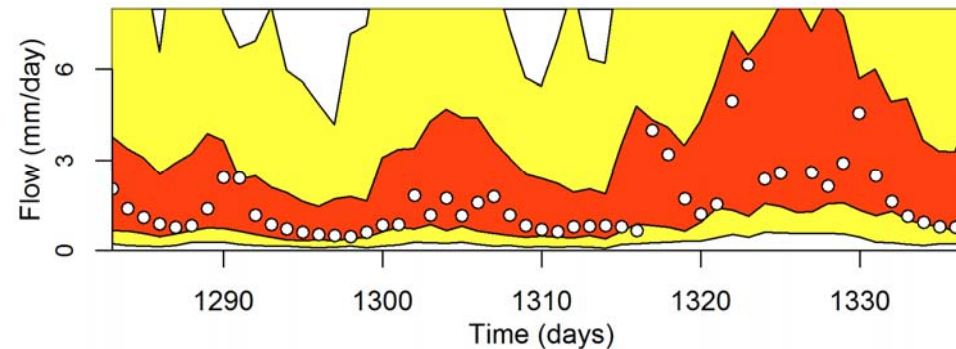


- Weight least squares has poor reliability and worse precision
- Log transformation better reliability and precision
- Transformational approaches (Log and BC) better handle skew in observed residuals

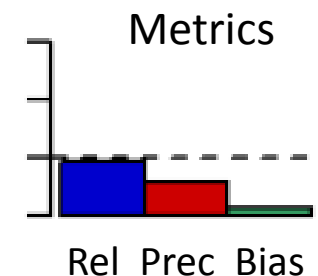
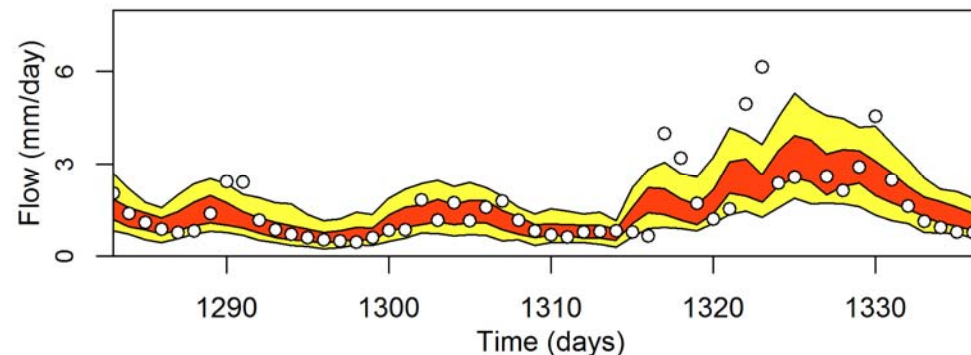
Error model has large impact on probabilistic predictions: Ephemeral Catchments

- Ephemeral catchment (Rocky River, SA), HBV hydro model

Log transformed flows

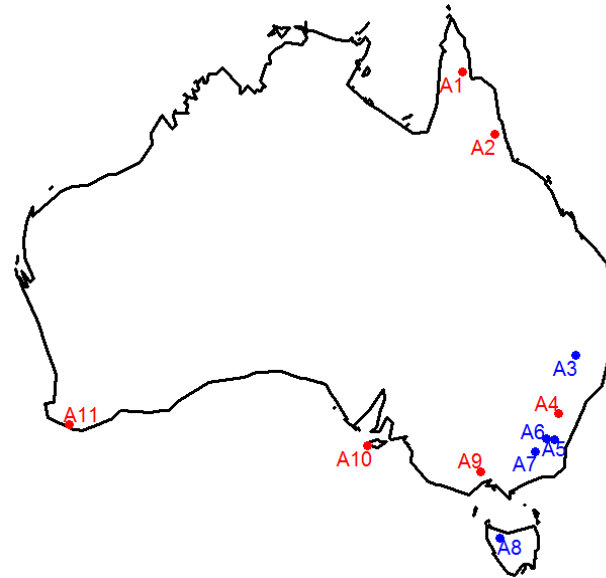
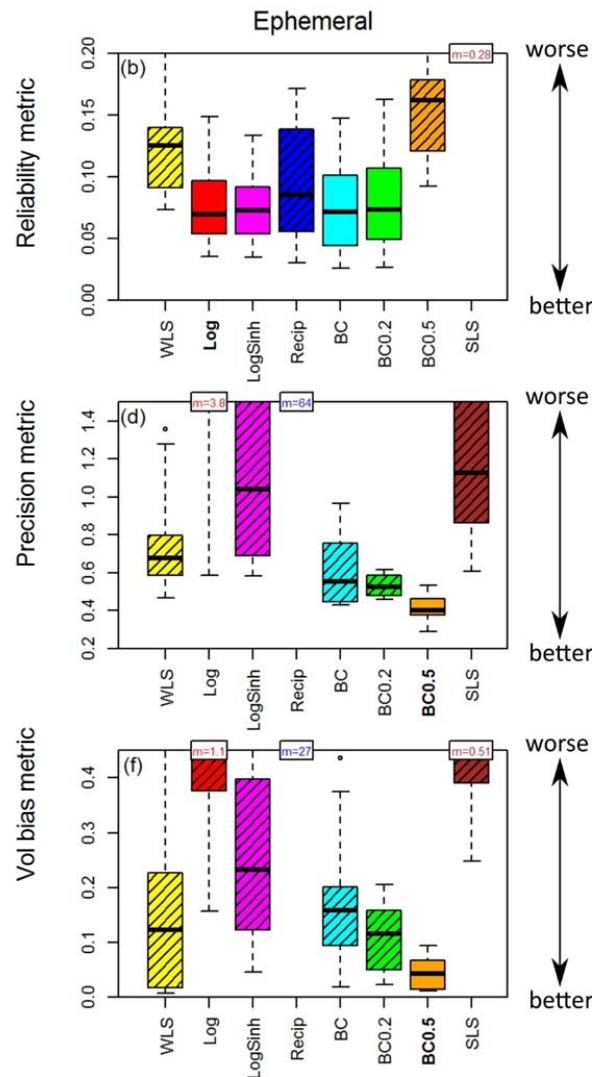


Box Cox transformed flows



- Log produces poor precisions (unrealistically large uncertainty) and large bias in ephemeral catchments
- Box Cox transformation ($\lambda=0.2$) performs much better
- BC transformation better handles zero flows in ephemeral catchments

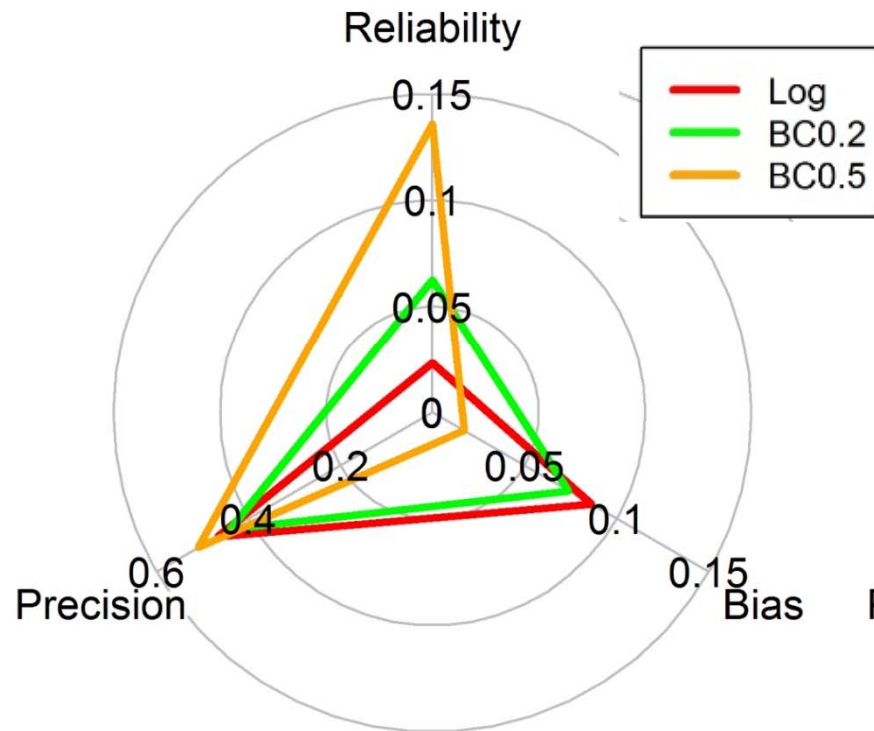
Improvements in probabilistic performance largest in ephemeral catchments



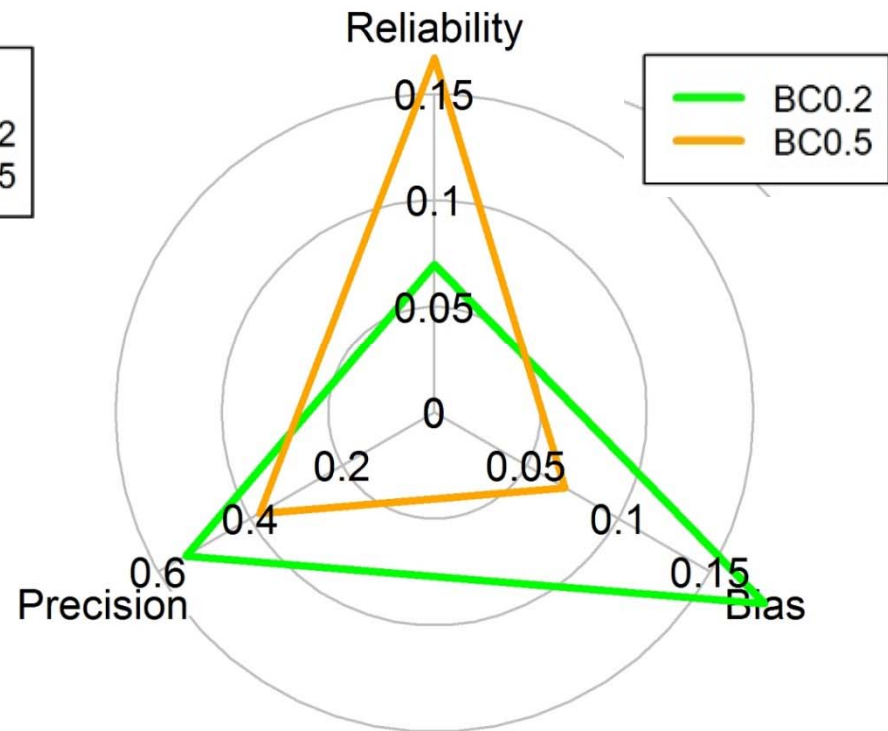
- Improved reliability
- Improved precision 105% to 40% of obs streamflow
- Reduced bias from 25% to 4%

Can't always get everything that we want

(c) Representative case study (B1/GR4J)



(d) Representative case study (A7/GR4J)



- In most catchments, tradeoffs between reliability, precision and bias seen even amongst the “best” error models
- Further investigation underway to reduce tradeoffs

Key Insights

- Error models based on Box-Cox transform produce more reliable predictions
- Choosing the best error models depends on the type of flow regime in the catchment.
- More complex error models do not necessarily produce the best predictions
- No single error model performs best in all aspects of predictive performance

Broad Recommendations

In **perennial** catchments, use

- Log error model if reliability is important
- Box Cox transformation with $\lambda=0.2$ if precision is important
- Box Cox transformation with $\lambda=0.5$ if low bias is important

In **ephemeral** catchments, use

- Box Cox transformation with $\lambda=0.2$ if reliability is important
- Box Cox transformation with $\lambda=0.5$ if precision/bias important

Does not include an in-depth analysis of performance trade-offs

Summary

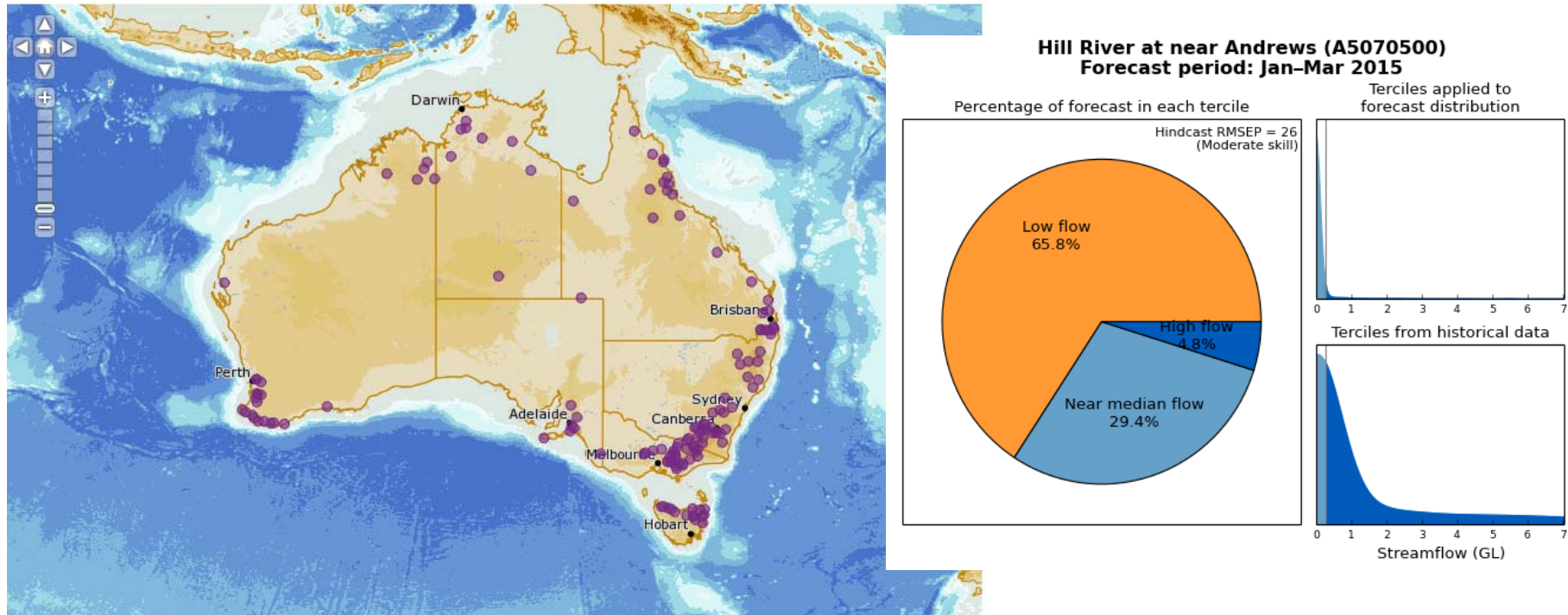
- Comprehensive evaluation a range of approaches for modelling total predictive uncertainty
 - Eight Approaches: Simple=>Complex
 - Empirical results: 23 catchments and 2 hydro models
 - Theory: Understanding when and why approaches provide good or bad predictive performance, e.g. ephemeral versus perennial catchments
- Broad recommendations
 - Selection of error models to use in different catchment types
 - Achieve reliable and precise probabilistic predictions
- Practical implications: Simplest is often best!
 - Prudent use of simple approaches => best predictive performance
 - Simple to implement for practitioners
 - Further work ongoing to reduce performance tradeoffs

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Bureau of Meteorology

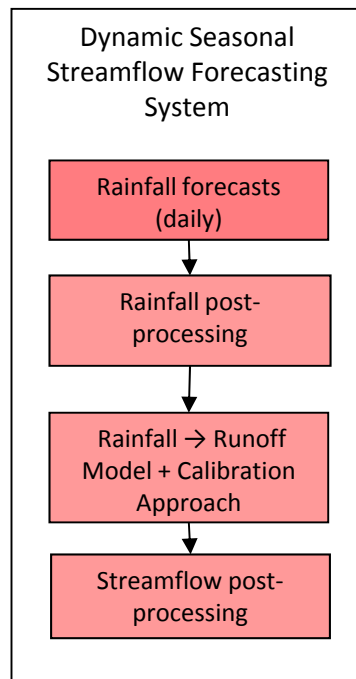
Seasonal Streamflow Forecasts



- Seasonal forecasts at ~300 locations (for registered users) ~ 100 locations for public
- Used upon by large number of water managers around Australia
- Hydrological forecasts have wide range of uncertainty
- BOM is using our techniques to characterize uncertainty and ultimately improve probabilistic predictions

Impacts on Forecasting: Streamflow post processing at monthly time step

- Strategic Objectives of Bureau's Seasonal Streamflow Forecasting (SSF) System
 - Aims: Provide forecasts across a wide range of Australian sites



Enhanced streamflow post-processor at monthly time scale

Outcomes:

- Majority of sites with reliable forecasts
- Majority of sites with forecast “sharpness” better than climatology
- Operationalised within Bureau's system

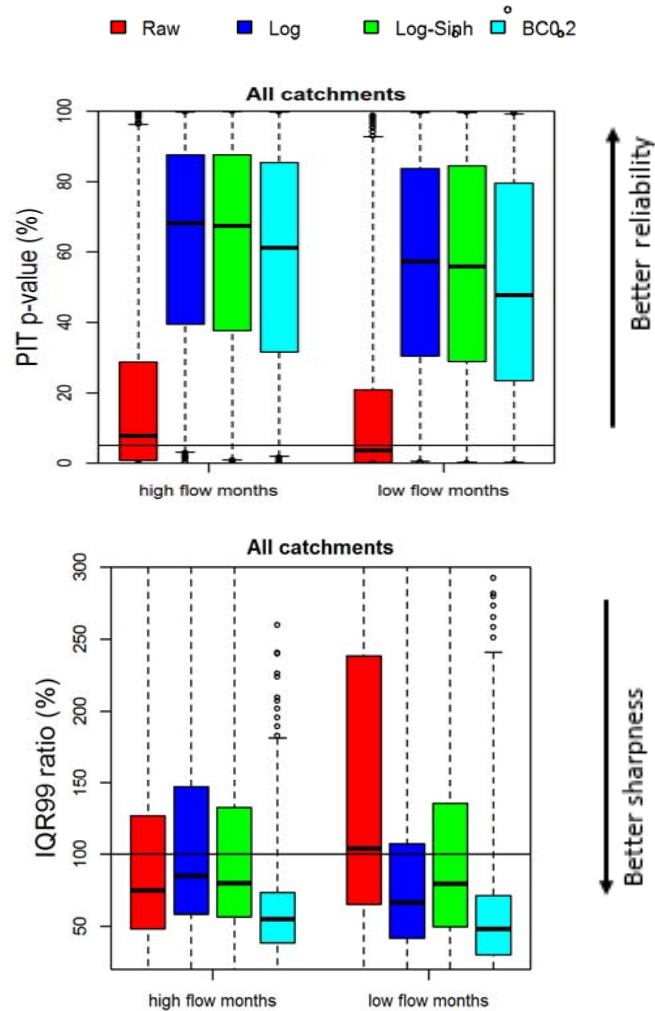
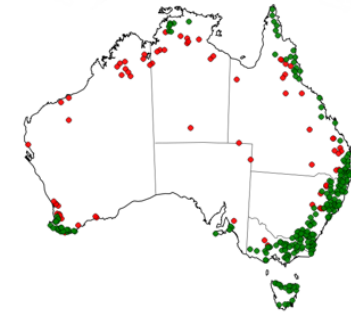
Note: results presented in the remainder of this presentation are preliminary and still need to undergo peer review and therefore may change

Enhance Streamflow Postprocessor at Monthly and Seasonal Time scale

- Evaluated different residual models for post-process streamflow forecasts at monthly time scale
 - Raw: No Post-Processing
 - Log, logsinh and BC0.2
- Evaluation on wide range of 300+ catchment across Australia
 - Classified into dry and wet using Aridity Index < 0
- Multiple metrics
 - Reliability (PIT plot p-value)
 - Sharpness (Inter quantile range for 99th percentile)
 - Expressed as % of climatology IQR
 - $> 100\%$ sharpness is worse than climatology
 - $< 100\%$ sharpness is better than climatology
 - CRPS SS

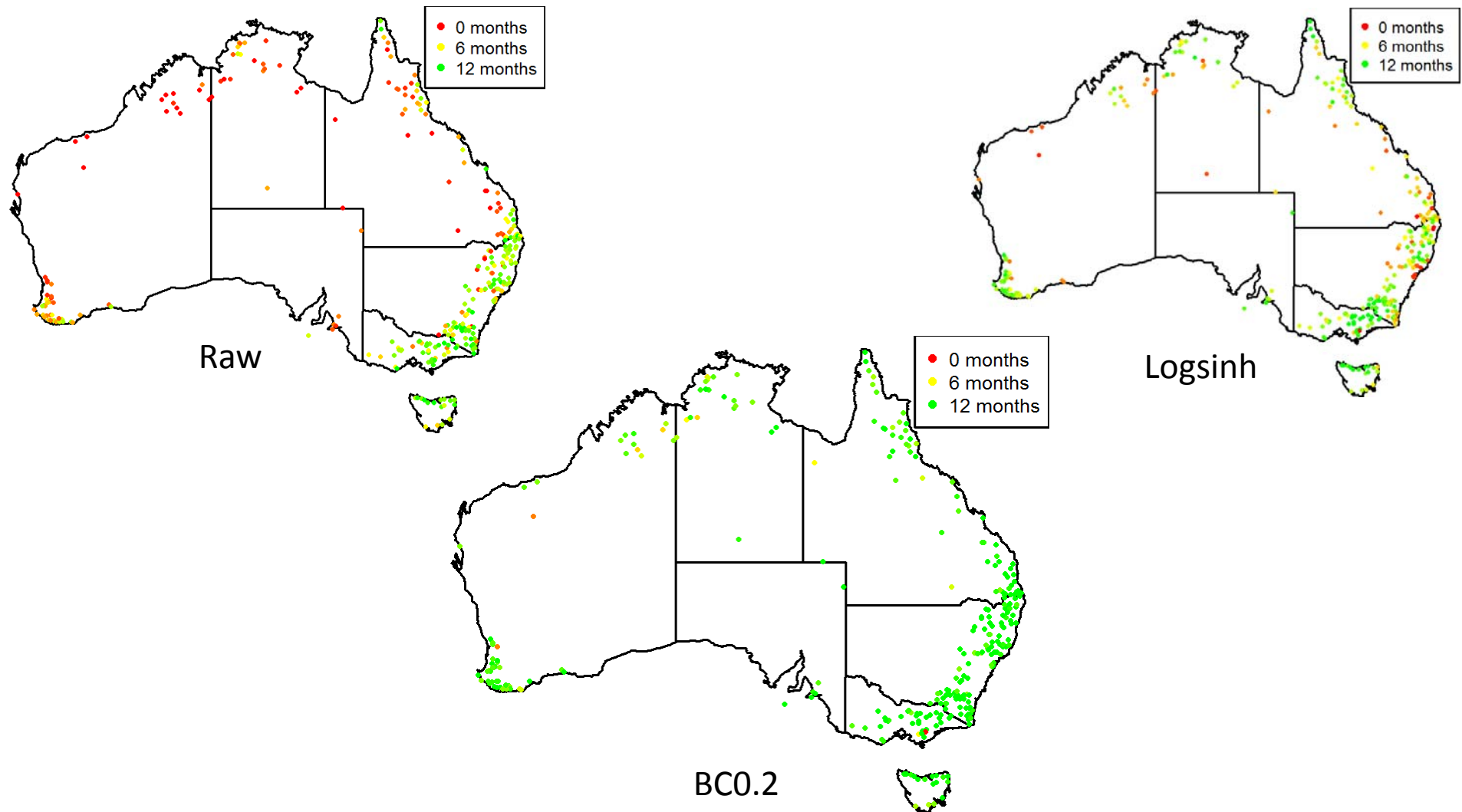


Outcomes for Monthly Forecasts: Better reliability and sharpness



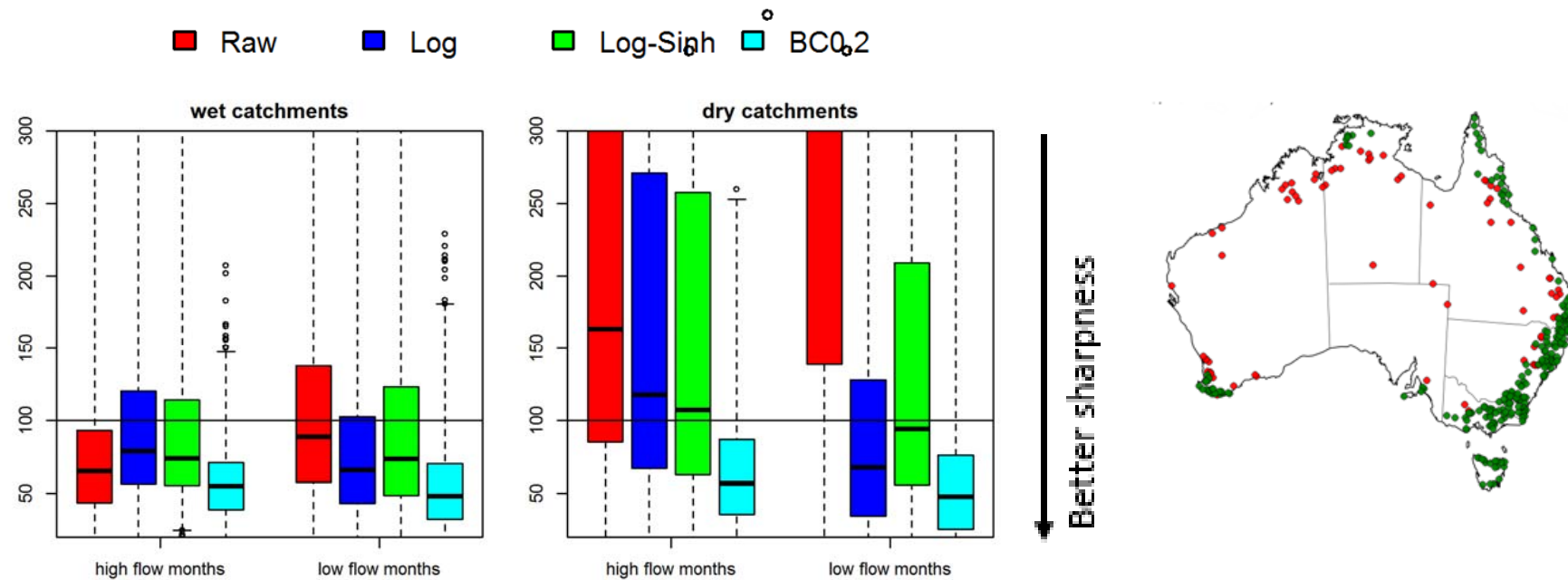
- Post-processing provides more sites with reliable forecasts: Increase from ~50% to >90% sites
- Similar results for CRPS
- BC0.2 provides more sites with sharpness better than climatology: Increase from 60% of sites to ~90% sites

Outcomes for Monthly Forecasts: Better reliability and sharpness



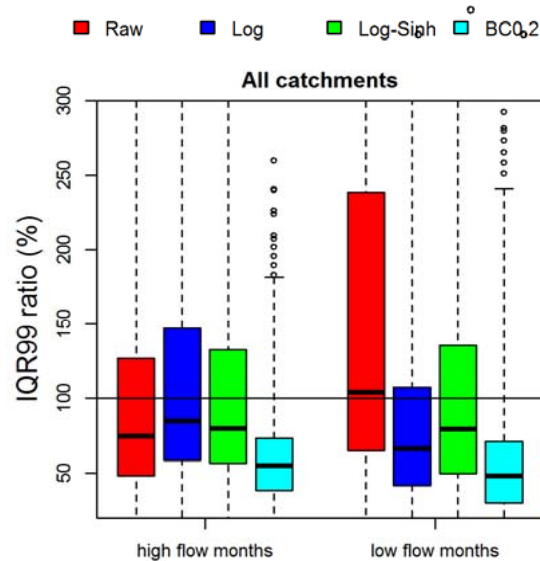
- No. of months at each site with forecasts that are reliable and with “sharpness” better than climatology.

Major increase in sharpness in dry catchments

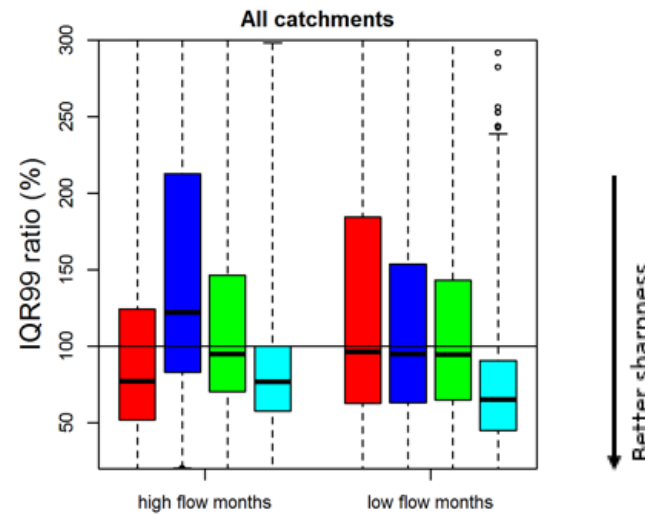


- In dry catchments, high flow months
 - log and logsinh models have >50% of sites worse than climatology
 - BC0.2 only model that provides more (80%) sites with sharpness better than climatology
 - Little change in reliability or CRPS

Improvements in sharpness are bigger for seasonal forecast than monthly forecasts



Monthly forecasts



Seasonal forecasts

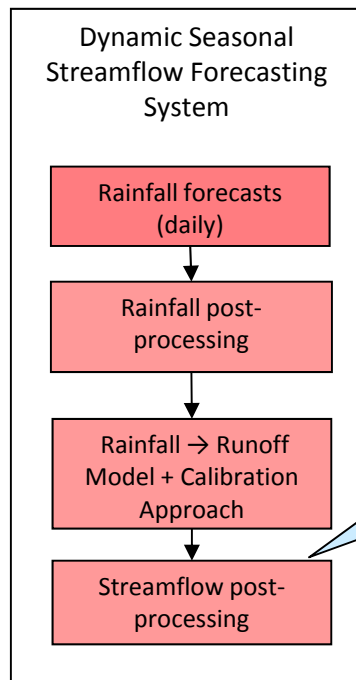
- Seasonal forecast,
 - Log and logsinh: 50% or less sites better climatology
 - BC0.2: >80% sites better climatology
- No difference between models for CRPS and Reliability



Woldemsekel F., Lerat, J., Tuteja, N., Shin, D.H., Thyer, M., McInerney, D., Kavetski, D., Kuczera, G. (2017) Evaluating residual error approaches to post-processing monthly and seasonal streamflow forecasts, *Hydrology and Earth System Sciences* (in preparation).

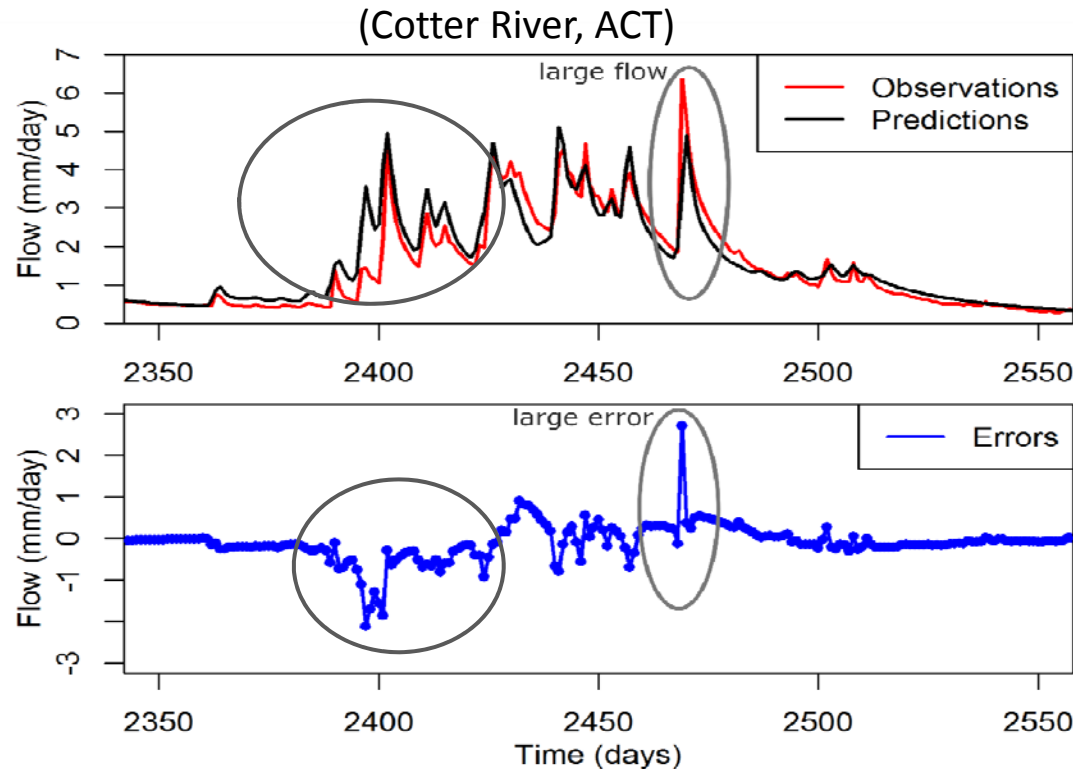
Impact on Forecasts: Towards Seamless Forecasts

- Strategic Objectives of Bureaus Seasonal Streamflow Forecasting (SSF) System
 - Current aims: Provide “seamless” forecasts (seamless = single product able to be aggregated in time from daily to monthly scale)
- Progress towards this objective



Enhanced daily streamflow post-processing (obs. rain)
Outcomes: Incorporating persistence improves reliability when aggregating from daily to monthly time scale

Challenging features of residuals in hydrology



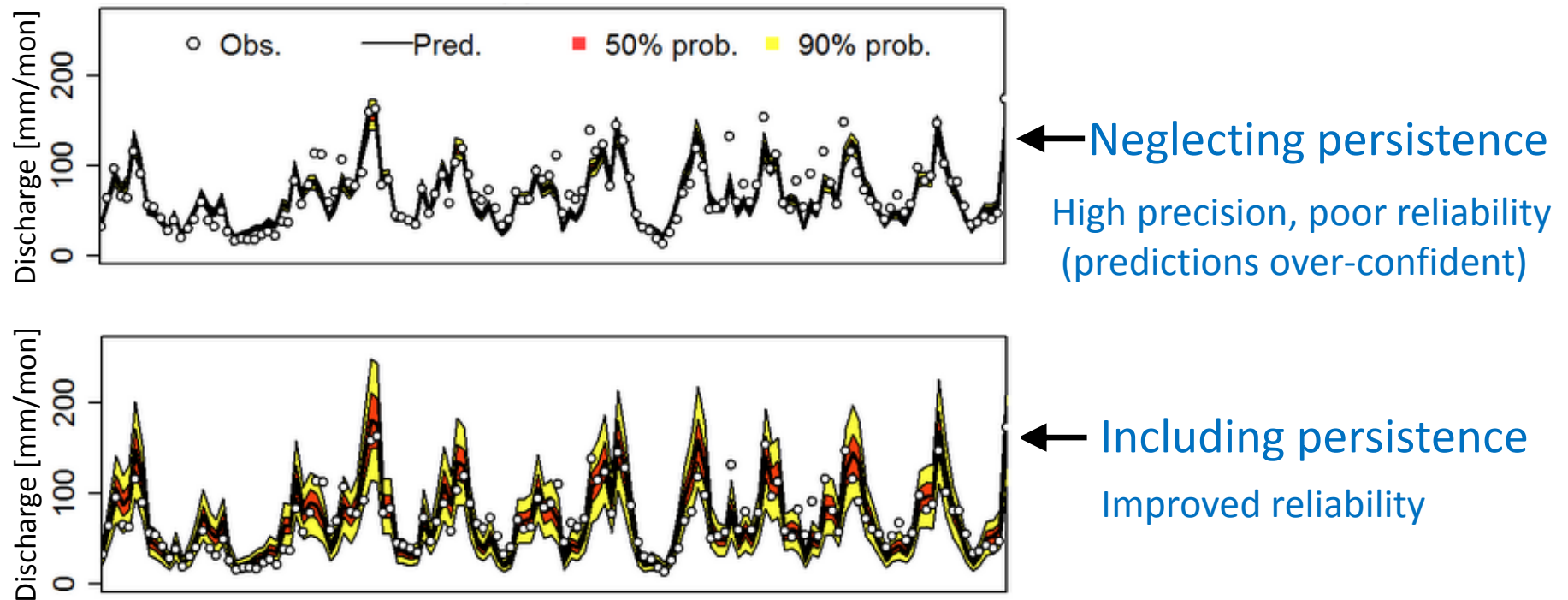
**Streamflow
time series**

**Residual
errors time
series**

- **Errors are heteroscedastic** (larger errors in large flows)
- **Errors are persistence** (not independent between time steps)
- Appropriate representation of both “features” is required to achieve reliable probabilistic predictions

Importance of modelling persistence in errors

- Persistence important when aggregating data
 - E.g. daily predictions aggregated to monthly values

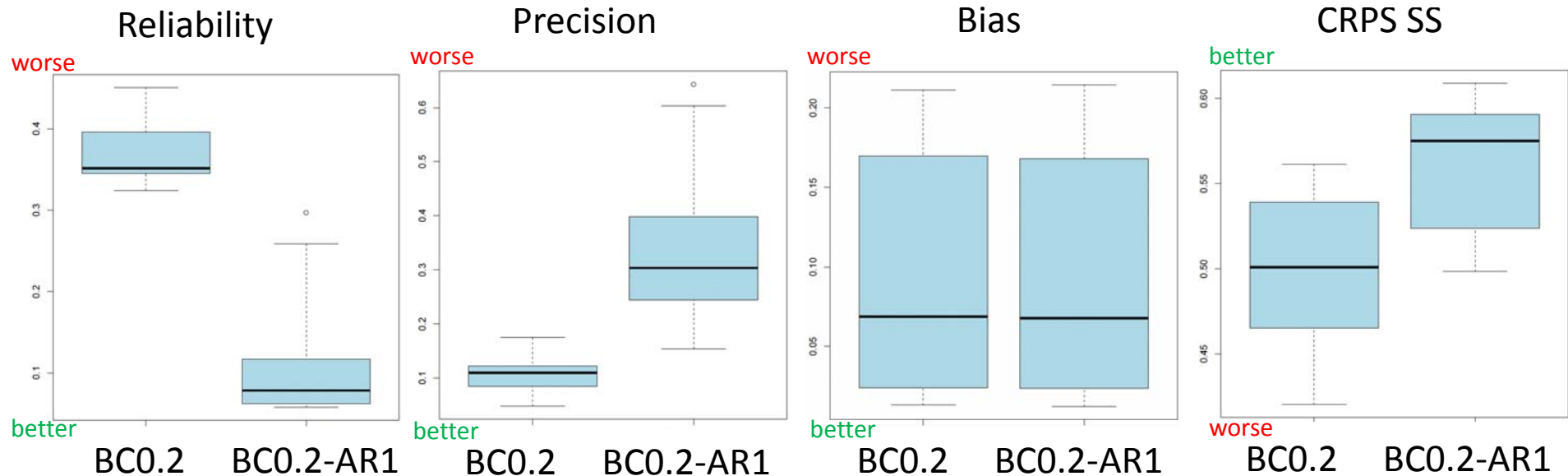
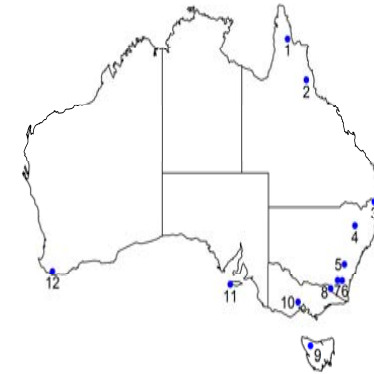


[Evin et al, 2014]

- Ignoring persistence produces under-estimation of predictive uncertainty when aggregating data => under-estimates risks of extreme events

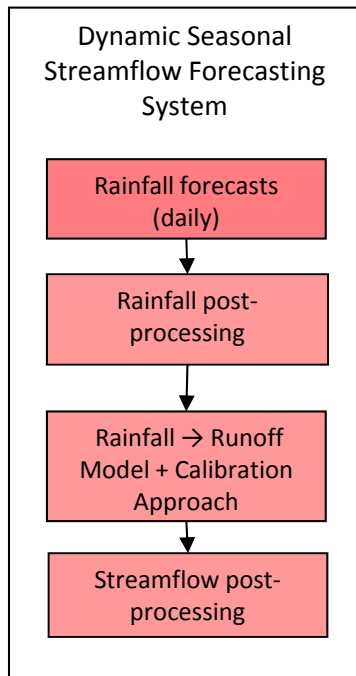
Modelling persistence critical when aggregating daily data

Monthly metrics



- Without Persistence (BC0.2), grossly over-confident: good precision but very unreliable => low CRPS SS
- With Persistence (BC0.2+AR1), credible predictions: lower precision but better reliability => high CRPS SS

Summary: Impacts on Forecasting



1. Enhanced streamflow post-processor at monthly time scale

• **Outcomes:**

- Majority of sites with reliable forecasts
 - Majority of sites with forecast “sharpness” better than climatology
 - Operationalised within Bureau’s system
- Contribution towards Bureaus objective of reliable forecasts at wide range of sites across Australia

2. Enhanced daily streamflow post-processing (obs. rain)

• **Outcomes:**

- Incorporating persistence improves reliability when aggregating from daily to monthly time scale
 - Currently being operationalised
- Contribution towards Bureaus objective of seamless forecasts across a range of time scales (daily to monthly)

Questions?

Further Information

Email: mark.thyer@adelaide.edu.au or connect with me on LinkedIn

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