# Practical guidance on representing uncertainty in hydrological predictions

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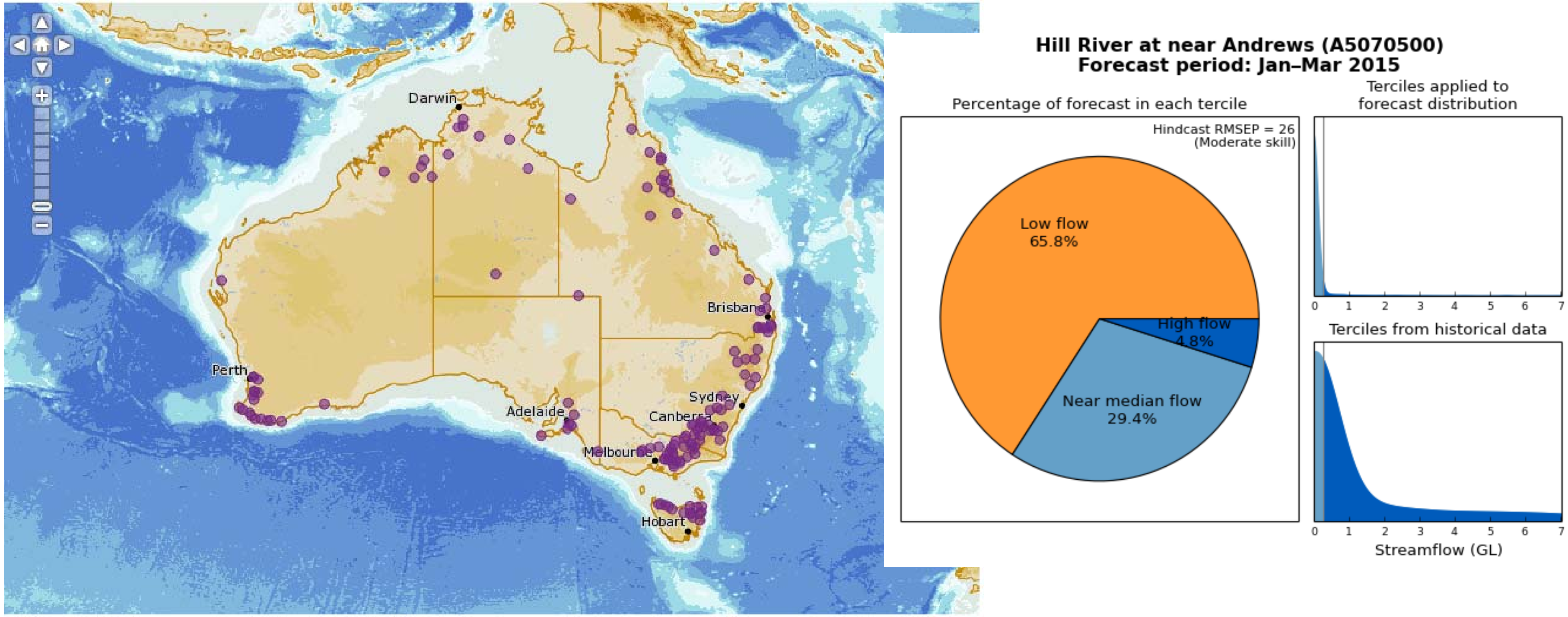
# Motivation

- Hydrological predictions relied upon by wide range of users
- Understanding uncertainty important for decision making

# 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

# Bureau of Meteorology
# Seasonal Streamflow Forecasts



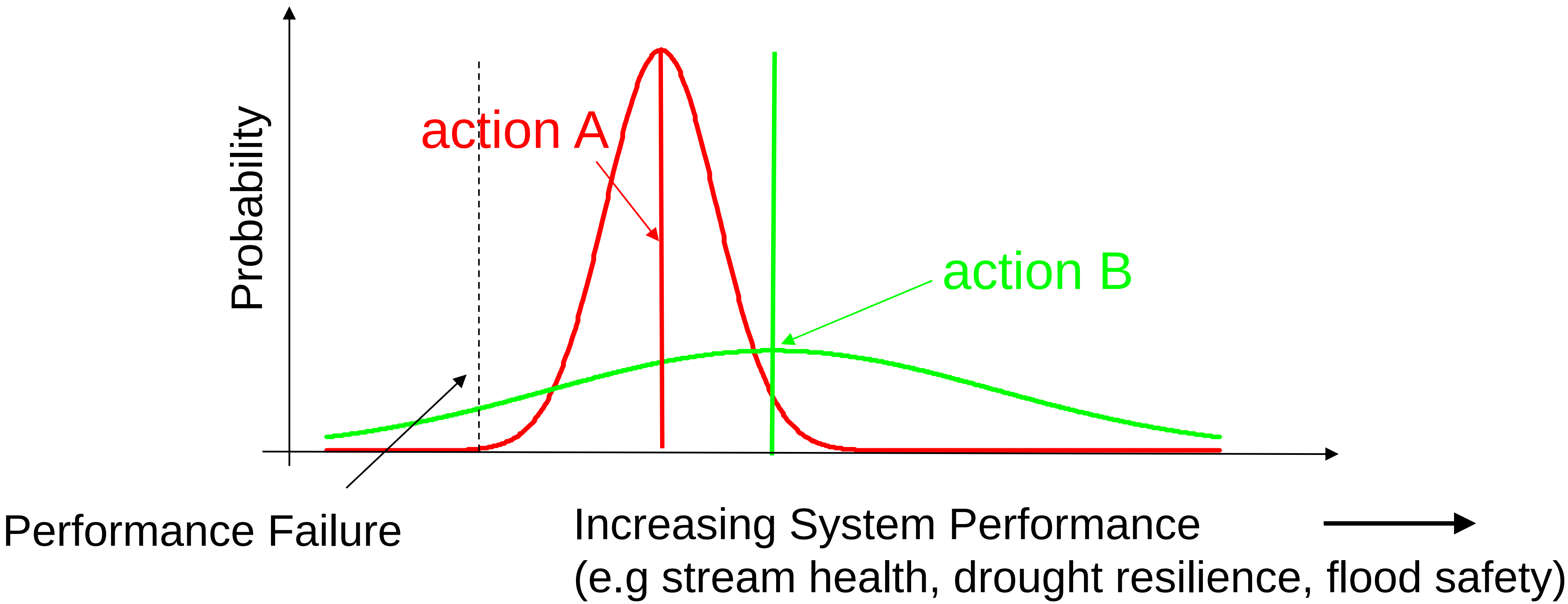

- Seasonal forecasts at ~200 locations
- Relied upon by large number of water managers around Australia
- Hydrological forecasts have wide range of uncertainty
- BOM is using our techniques to characterize uncertainty and ultimately improve probabilistic predictions

# Uncertainty estimation important for making informed decisions

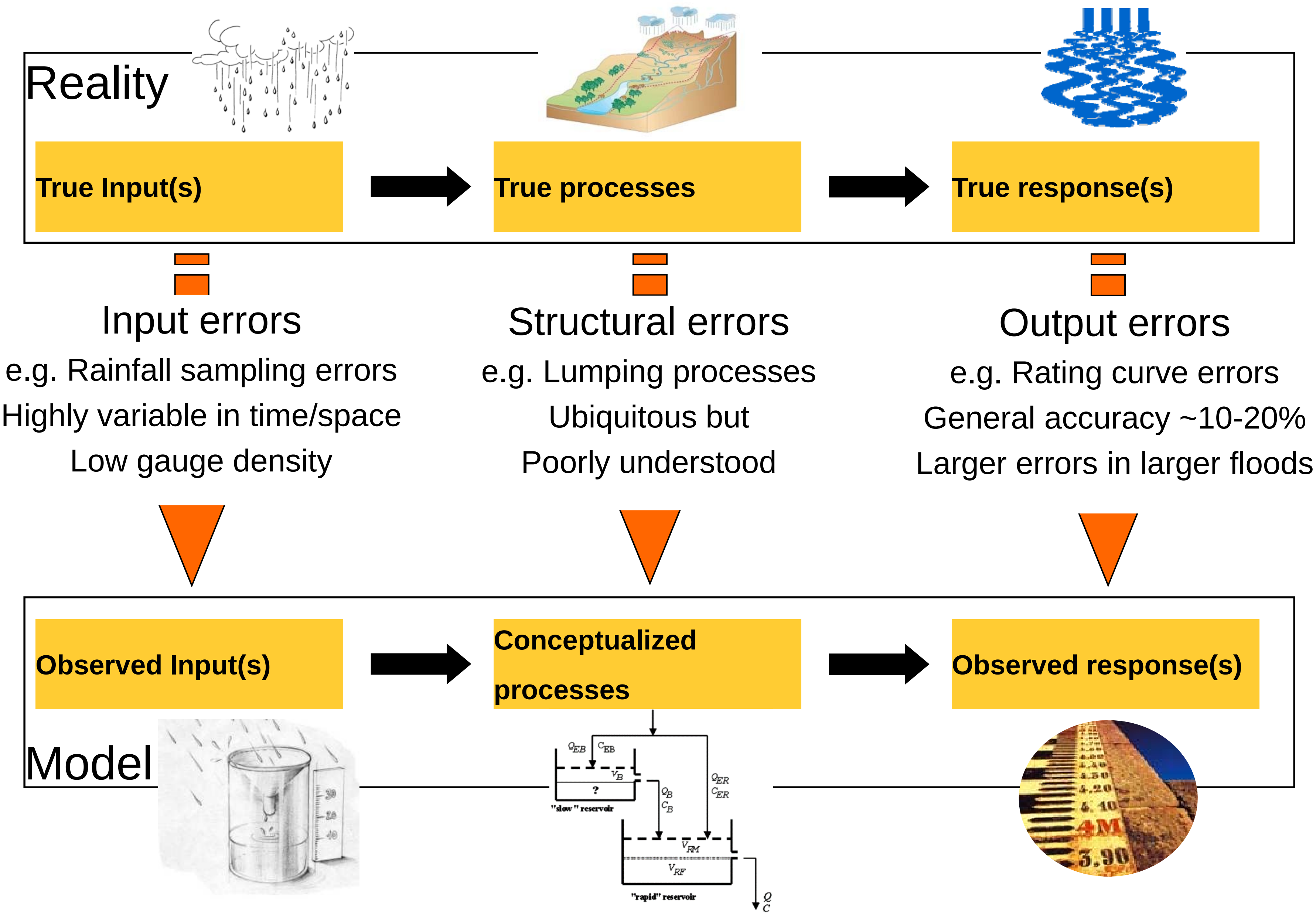
- Example: action A versus action B: Which one would you choose?
- No uncertainty:

  Use "highest performance" outcome → choose action B!
- With uncertainty:

  If risk-averse choose action with lowest probability of failure→ choose action A!



# Sources of Errors in Hydrological Modelling

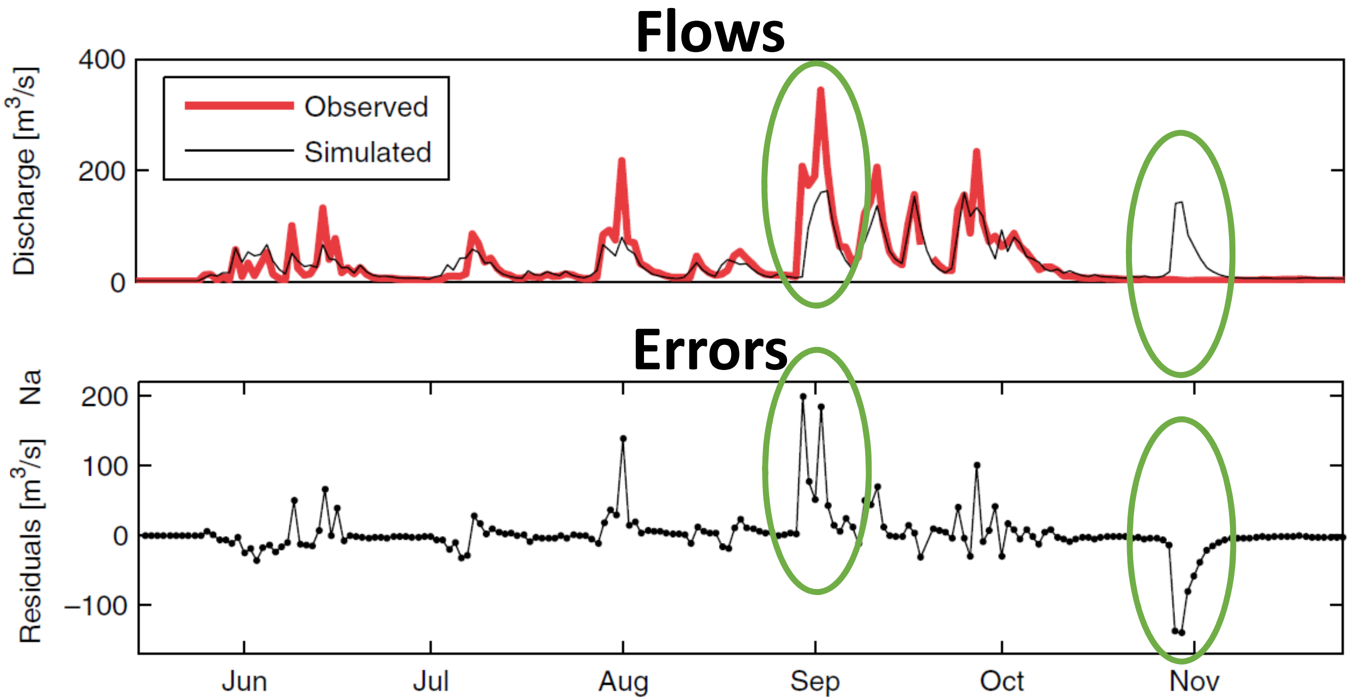


# Approaches to modelling uncertainty: Selecting the right tool for the job

- Explicitly model individual sources of uncertainty
  - Advantage of diagnosing dominant sources of error
  - There are tools to do this: Bayesian total error analysis (BATEA)
  - But these are currently research tools, i.e. need significant expertise, and not as yet easy to use for practitioners

- Model total uncertainty in predictions
  - Lump all errors together (errors=observed-predictions)
  - Simpler to implement than BATEA
  - Practical approaches are available which can produce reliable probabilistic predictions of total uncertainty
  - Unable to determine the dominant source of error

# Challenges in modelling errors

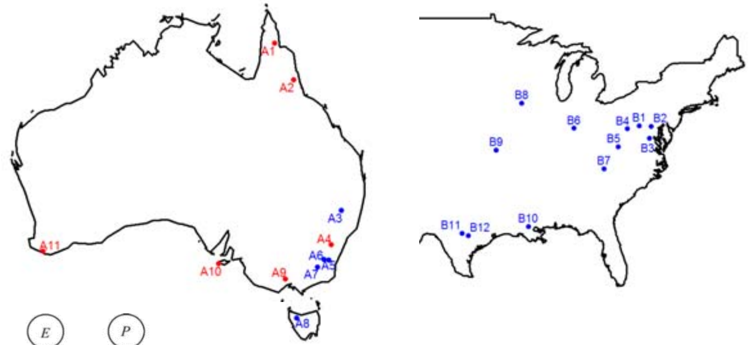


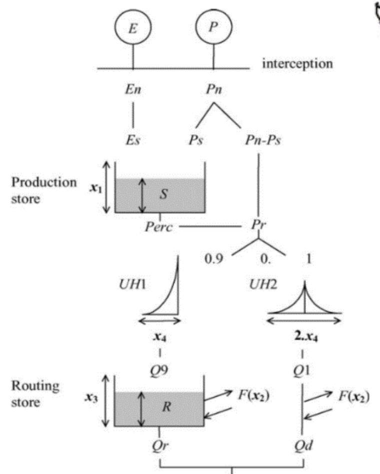

[Beven and Westerberg, 2011]

- **Errors scale with flow** (heteroscedastic)
- **Errors have persistence** (not independent between time steps)
- Appropriate representation of both required for reliable probabilistic predictions

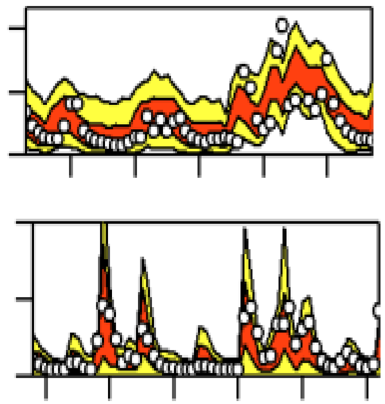
# Comprehensive comparison of approaches for treating predictive errors

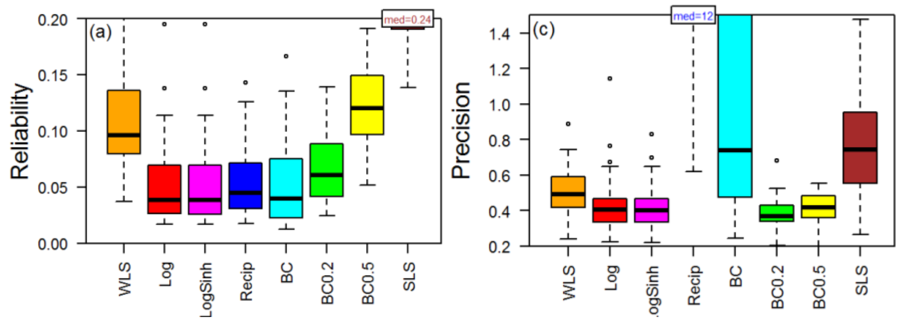
- First empirical and theoretical comparison between wide range of approaches (simple=>complex)
- 8 different approaches
- 23 catchments from Australia and USA
- 2 hydrological models (GR4J, HBV)
- Cross validation with 10 yrs data
- ~3500 model calibrations
- ~4000 CPU hours (150 days) on Tizard
- Multiple performance metrics
- Surprising results!
- Submitted to WRR soon






[Perrin *et al*, 2003]



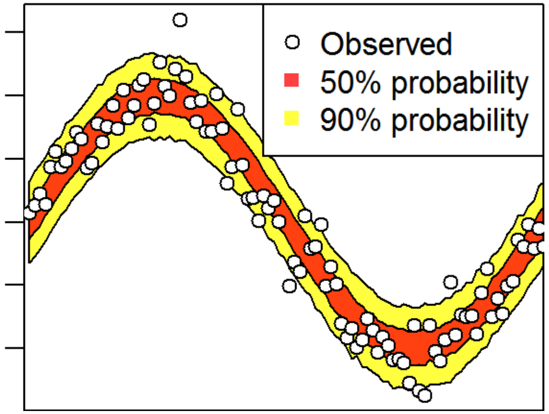


# What makes good predictions?

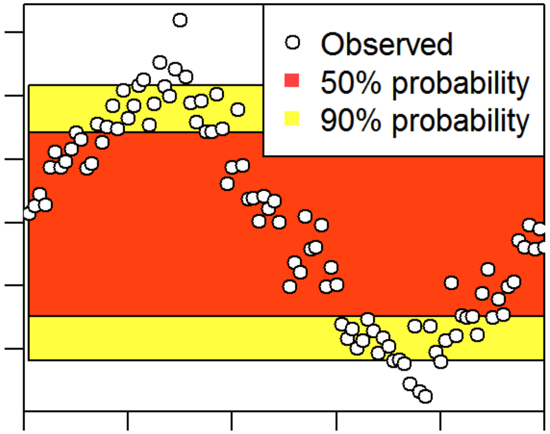
We want predictions that are

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

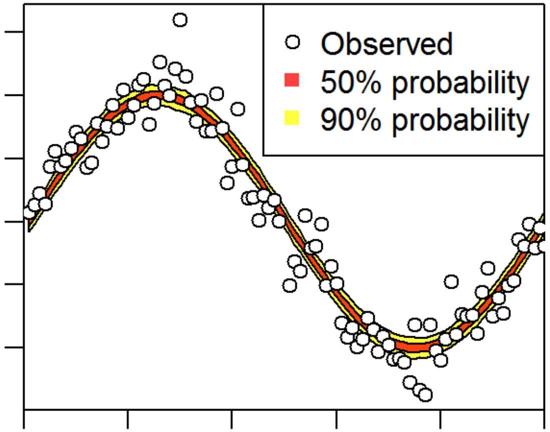
**Reliable, precise, unbiased**



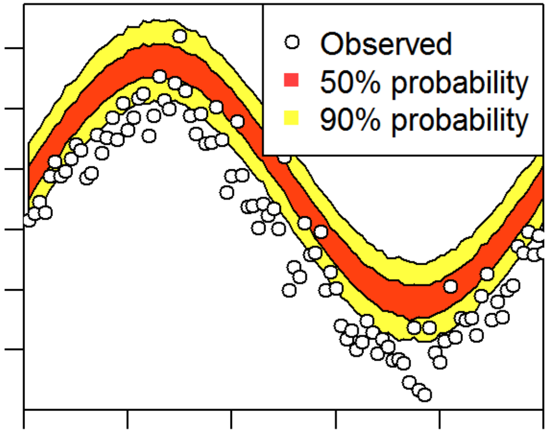

**Reliable but imprecise**




**Precise but unreliable**

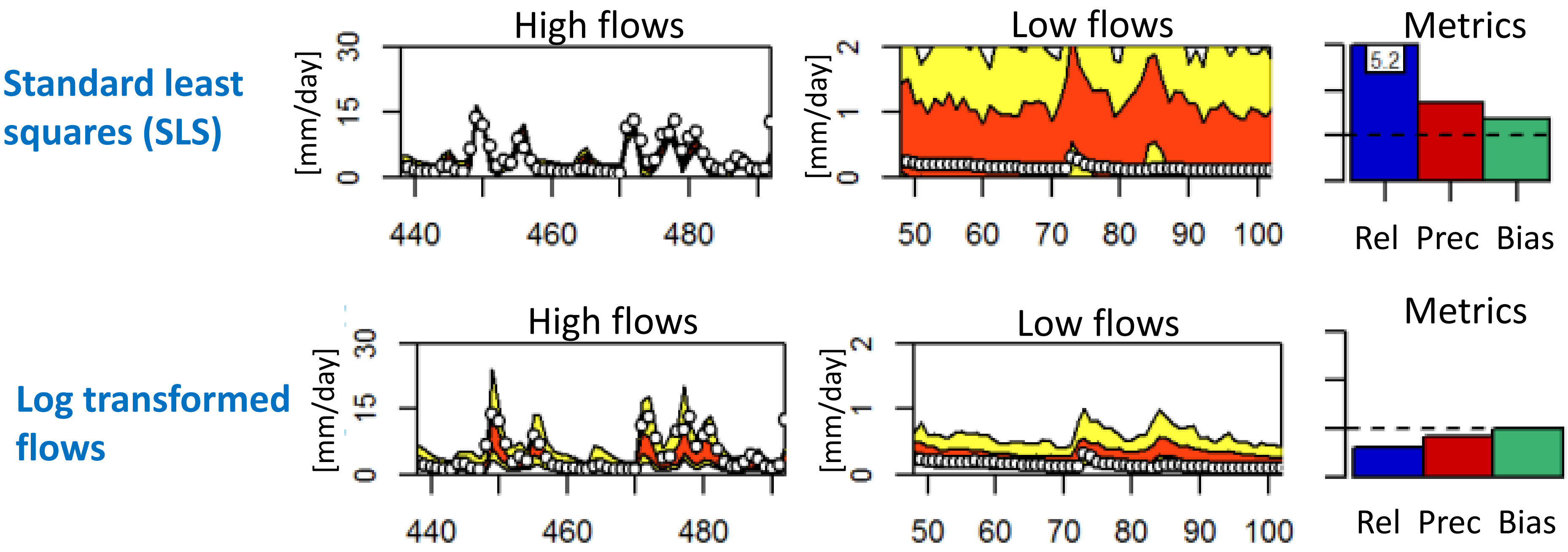



**Biased**



# Choice of error model has large influence on predictive performance

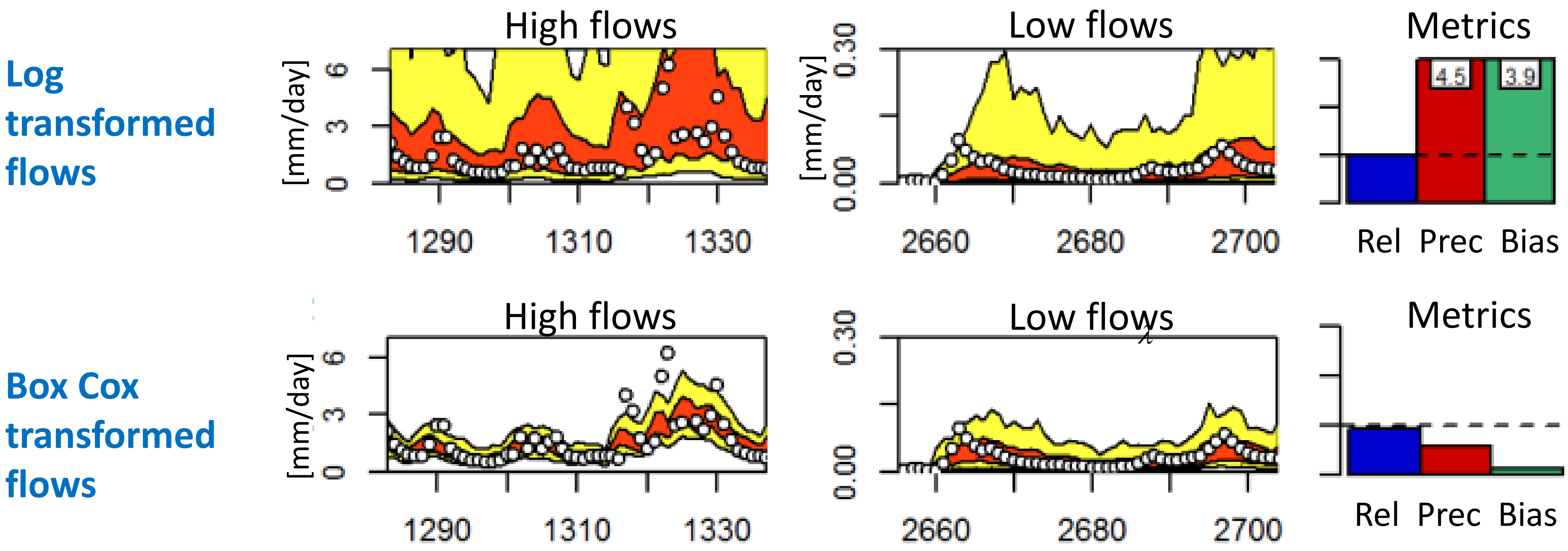
- Perennial catchment (Spring River, USA), GR4J hydro model




- SLS under-estimates uncertainty for low flows, over-estimates uncertainty for high flows
- Log transformation performs much better, as shown by all metrics

# Zero flows have large influence on performance of error model

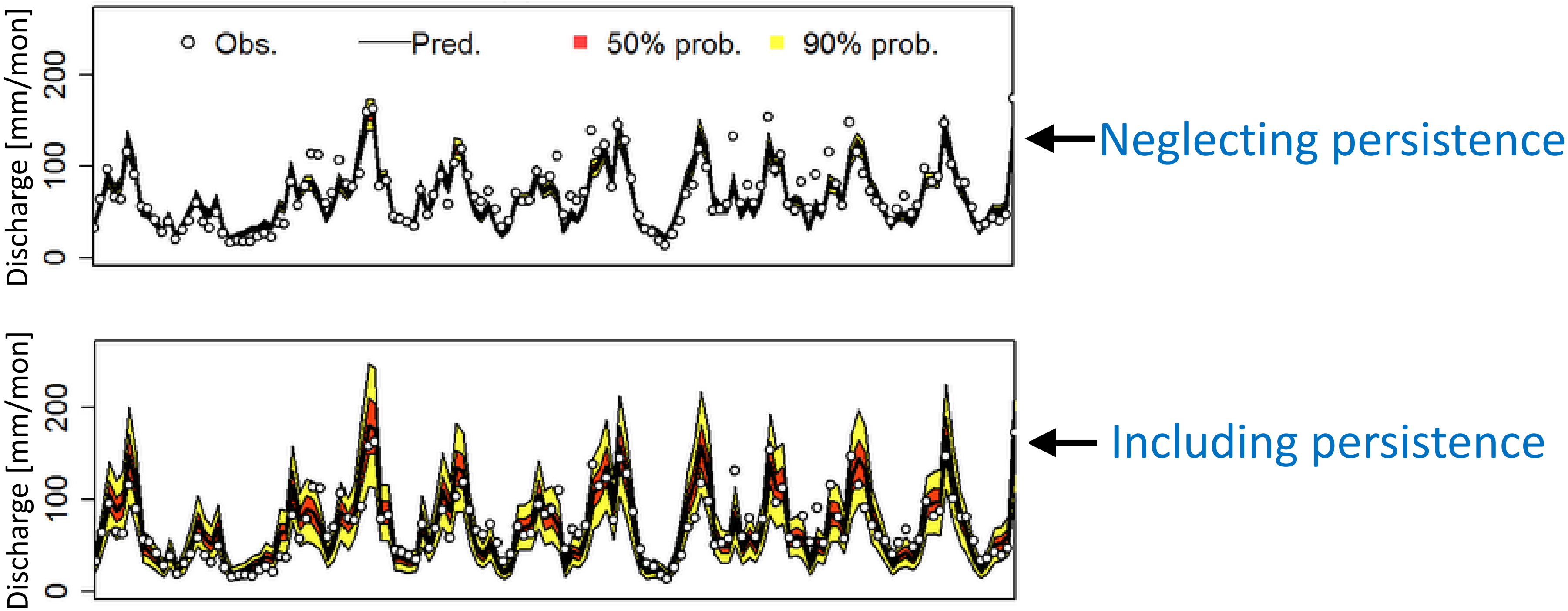
- Ephemeral catchment (Rocky River, SA), HBV hydro model




- Log produces unrealistically large uncertainty limits
- Box Cox transformation (lambda=0.2) performs much better
- Theory used to explain findings

# Importance of modelling persistence

- 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

# Summary and Recommendations

- 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
- Practical Impacts: Simplest approach is often the best!
  - Prudent selection of simple approaches provides best predictive performance
  - Simple to implement for practitioners
  - Study provides practical recommendations to obtain reliable and precise probabilistic predictions
- Looking into developing easy to use software for interested partners