Improving probabilistic predictions of daily streamflow

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Motivation

• Evaluating uncertainty in hydrological predictions is important for decision making and risk assessment

Aims

• Improve probabilistic predictions of daily streamflow
• Comprehensive evaluation of approaches for representing predictive uncertainty
• Provide recommendations for researchers and practitioners

Focus

• Aggregated approaches that use residual error models to represent total predictive uncertainty
• More pragmatic than decompositional approaches (e.g. BATEA) that identify individual sources of errors
Challenging features of residuals in hydrology

- Errors are heteroscedastic (larger errors in large flows)
- Errors have persistence (not independent between time steps)
- Key Challenge: Identifying residual error models that represent both “features” to achieve reliable and precise probabilistic predictions.

Streamflow time series

Residual errors time series

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

- Research Gap: No study had comprehensively compared the range of residual error models for representing heteroscedasticity in residuals

<table>
<thead>
<tr>
<th>Residual Error Model</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>No heteroscedasticity</td>
<td></td>
</tr>
<tr>
<td>SLS</td>
<td>Standard least squares (error sd is constant)</td>
</tr>
<tr>
<td>WLS</td>
<td>Weighted least squares (error sd increases linearly with predictions)</td>
</tr>
<tr>
<td>Log</td>
<td>Log transformation</td>
</tr>
<tr>
<td>Logsinh</td>
<td>Logsinh transformation (error sd increase “tapers off” with predictions)</td>
</tr>
<tr>
<td>BC (inferred λ)</td>
<td>Box-Cox transformation with inferred λ parameter</td>
</tr>
<tr>
<td>BC0.2</td>
<td>Box-Cox transformation with fixed λ= 0.2</td>
</tr>
<tr>
<td>BC0.5</td>
<td>Box-Cox transformation with fixed λ= 0.5</td>
</tr>
<tr>
<td>Reciprocal</td>
<td>Reciprocal transformation</td>
</tr>
</tbody>
</table>
Features of Comprehensive Evaluation

- Improve the robustness of recommendations
- Multiple Catchments
  - 23 climatologically diverse catchments from Australia and USA
- Two Hydrological Models
  - Lumped conceptual models: GR4J and HBV
- Multiple performance metrics
  - Reliability, precision and bias
  - Cross-validation over 10 yr
- Theoretical insights to understand differences in performance
  - Theoretical similarities and differences
  - Synthetic analysis
- McInerney et al (WRR2017)
Key Findings: Empirical Results

- Results are dependent on catchment type (perennial/ephemeral)

“Best” Residual Error Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log</td>
<td>Best reliability in perennial. Good precision and bias in perennial.</td>
</tr>
<tr>
<td>BC0.2</td>
<td>Best precision in perennial. Best reliability in ephemeral. Good precision and bias in ephemeral.</td>
</tr>
<tr>
<td>BC0.5</td>
<td>Best bias in perennial. Best bias and precision in ephemeral.</td>
</tr>
</tbody>
</table>

Not Recommended:
- SLS, WLS, Logsinh, BC(inferred \( \lambda \)), Reciprocal
- Either worse reliability, precision or bias or more complex
Transformational approaches (Log, BC) outperform direct approaches (WLS)

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

- Log transformation better reliability and precision than WLS

- Theoretical Insight: Transformational approaches (Log and BC) better capture skew and kurtosis in observed residuals than WLS
Box-Cox Transformation (fixed lambda) outperforms log transformation in Ephemeral Catchments

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

  - BC0.2 has similar reliability, but much better precision and bias than log
  - Log produces poor precisions (unrealistically large uncertainty) and large bias in ephemeral catchments
  - Theoretical Insight: BC transformation better handles zero flows than log in ephemeral catchments
Choose multiple “best” residual error models due to performance trade-offs across multiple metrics

- Not possible to choose a single model that performs best across all metrics

Pareto Optimal Approaches
- Perennial: Log, BC0.2 and BC0.5
- Ephemeral: BC0.2 and BC0.5
Broad Recommendations

In **perennial** catchments, use
- Log transformation if reliability is important
- Box Cox transformation with fixed $\lambda=0.2$ if precision is important
- Box Cox transformation with fixed $\lambda=0.5$ if low bias is important

In **ephemeral** catchments, use
- Box Cox transformation with fixed $\lambda=0.2$ if reliability is important
- Box Cox transformation with fixed $\lambda=0.5$ if precision/bias important

Based on ‘median’ results across 23 catchments, individual catchment results can differ.
Impact: Significant improvement in probabilistic performance

- Larger impact in ephemeral catchment
- Improved reliability
- Improved precision 105% to 40% of obs streamflow
  - Reduce predictive uncertainty by factor of 2!!!
- Reduced bias from 25% to 4%

**Log transformed flows**

**BC0.2 transformed flows**
Impacts: Bureau of Meteorology Seasonal Streamflow Forecasts

- Recommendations used to enhance monthly streamflow post-processor

**Log/Logsinh**

- High skill: >10 months with reliable forecasts more precise than climatology
- Log/Logsinh: 25-30% sites with high skill

**BC0.2**

- High skill: >80% of sites with high skill
- Preliminary results, subject to peer review (Woldemsekel et al. in prep)
Summary

• Comprehensive evaluation of approaches for predictive uncertainty
  • Eight Residual Error Approaches: Simple=>Complex
  • Multiple catchments/hydro models/performance metrics
  • Theoretical Insights: Understanding reasons for differences in performance

• Broad recommendations
  • “Best” Pareto optimal residual error models in different catchment types
  • Significant reductions in predictive uncertainty, while maintaining reliability

• Practical implications: Simplest is often best!
  • Smart use of simple approaches => best predictive performance
  • Simple to implement for researchers practitioners

• Future research opportunities
  • “Best” residual error model selected from existing approaches
  • Opportunity to improve predictions across flow range, esp near-zero/zero flows

Water Resources Research
## Key Findings: Theoretical Insights

<table>
<thead>
<tr>
<th>Residual Error Model</th>
<th>Outcome and Insight</th>
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| **Log**              | **Best Reliability in Perennial and Ephemeral**  
  - Captures heteroscedasticity in residuals better than SLS  
  - Captures skew and kurtosis in residuals better than WLS  
  - Logsinh performance similar to log due to estimated logsinh parameter values |
| **BC0.2**            | **Best Precision in Perennial**  
  - BC (inferred λ) has poor precision due to overfitting of low flows  
 **Better Precision and Bias than log in Ephemeral**  
  - captures zero flows better than log |
| **BC0.5**            | **Best Bias in Perennial**  
 **Best Bias and Precisions in Ephemeral**  
 **Poor Reliability** |
Impacts on Forecasting: Bureau of Meteorology Seasonal Streamflow Forecasts

- Seasonal forecasts at ~300 locations
- Used by water managers around Australia
- Based on Statistical and Dynamic Seasonal Streamflow Forecasting System

**Dynamic Seasonal Streamflow Forecasting System**

1. Rainfall forecasts (daily)
2. Rainfall post-processing
3. Rainfall $\rightarrow$ Runoff Model + Calibration Approach
4. Streamflow post-processing

Applied Recommendations to enhanced streamflow post-processor at monthly time scale
Choose multiple “best” residual error models due to performance trade-off’s: Pareto optimal approaches

- Not possible to choose a single model that performs best across all metrics
- Pareto Optimal Approaches
  - Perennial: Log, BC0.2 and BC0.2
  - Ephemeral: BC0.2 and BC0.5
Multiple Performance Metrics: 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

![Graphs showing different types of prediction performance](image)
Approaches to modelling uncertainty: Find the right tool for the job

- **Decompositional:** Estimate individual sources of uncertainty (e.g. BATEA)
  - Diagnose dominant sources of uncertainty
  - Computationally challenging, requires more data and expertise
  - Not really “off-the-shelf” method

- **Aggregated:** Estimate total uncertainty in predictions
  - Lump all uncertainty into single residual term
  - Common, easy to apply => “off-the-shelf”
  - Unable to estimate the dominant sources

For decision-making, total predictive uncertainty is of key interest

Focus: Evaluate residual error models for representing total uncertainty in predictions
### Key Findings: Empirical Results: “Best” Residual Error Models

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