Considering Measurement Uncertainty in H/WQ Model Evaluation

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Measurement Uncertainty in H/WQ Modeling

“Should it not be required that every… (field and modeling study) …attempt to evaluate the uncertainty in the results?”

“The use of uncertainty estimation… (should be)…routine in hydrological and hydraulic science.”

- Haan (1995) suggested that uncertainty analysis in H/WQ modeling represents intellectual integrity

- Reckhow (1994) emphasized the importance of communicating uncertainty to stakeholders and decision-makers to improve policy and management decisions
Measurement Uncertainty in H/WQ Modeling

- An important source of uncertainty in H/WQ modeling is measurement uncertainty.
- However, when “measurement uncertainty” is included in uncertainty analysis
  - focuses almost exclusively on model inputs or parameter estimation (e.g. hydraulic conductivity, CN, fertilizer application)
  - does not address uncertainty in measured data, against which model outputs are compared (e.g. flow, water quality)
- This research focuses on uncertainty in measured data used to calibrate, validate, or evaluate H/WQ models.
Measurement Uncertainty in H/WQ Modeling

- Why is the uncertainty in measured H/WQ data typically not considered in model calibration, validation, and application???
  - Until recently…
  - Scientists had not established an adequate understanding of uncertainty in measured H/WQ data
  - No complete uncertainty (error propagation) analysis had been conducted on measured H/WQ data
  - No goodness-of-fit methods had been developed to explicitly consider measurement uncertainty
Objectives

- Objective #1 – Briefly describe a method for estimating the “quality” of calibration, validation, and evaluation data
  - Fundamental scientific estimates
  - Methodology for project-specific uncertainty analysis
  - Focused on uncertainty in measured streamflow and water quality data (TSS, N, P) for small watersheds

- Objective #2 – Describe modified versions of several “goodness-of-fit” indicators that consider measurement uncertainty in H/WQ model evaluation
  - $E_{NS}$, $d$, RMSE, MAE
Objective 1 – Quality of Measured Data

- Root mean square error propagation method (Topping, 1972)
  - includes all steps required to measure flow and water quality data
  - widely-accepted error propagation method
    - previously used for discharge, pesticides
  - combines all potential errors to produce realistic estimates of overall error (cumulative probable uncertainty)
  - assumes potential errors are bi-directional and non-additive

\[
E_P = \sqrt{\sum_{i=1}^{n} (E_1^2 + E_2^2 + E_3^2 + \ldots + E_n^2)}
\]
Objective 1 – Quality of Measured Data

• Created several arbitrary “data quality” scenarios
  • best case, worst case, typical – based on QA/QC, available resources, and monitoring conditions
• Categorized uncertainty sources into procedural categories
  • Q measurement, sample collection, sample preservation and storage, laboratory analysis
• Calculated cumulative uncertainty in resulting data
Objective 1 – Quality of Measured Data

The graph shows the uncertainty (%) for various parameters:
- Q
- TSS
- NO3-N
- Total N
- NH4-N
- Diss. P
- Total P

The uncertainty values range from approximately 0% to 125%.
**Objective 1 – Quality of Measured Data**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Q (%)</th>
<th>TSS (%)</th>
<th>NO$_3$-N (%)</th>
<th>Total P (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Worst case scenario</strong></td>
<td>42</td>
<td>117</td>
<td>421</td>
<td>249</td>
</tr>
<tr>
<td>Typical scenario max.</td>
<td>19</td>
<td>53</td>
<td>69</td>
<td>110</td>
</tr>
<tr>
<td>Typical scenario avg.</td>
<td>10</td>
<td>18</td>
<td>17</td>
<td>30</td>
</tr>
<tr>
<td>Typical scenario min.</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td><strong>Best case scenario</strong></td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>3</td>
</tr>
</tbody>
</table>

**Previous Data**

**Worst Case**
Objective 2 – Modified Goodness-of-Fit Indicators

- Measurement uncertainty should be considered when evaluating H/WQ models.
- Specifically, H/WQ models should:
  - not be expected to simulate/reproduce uncertain data values.
  - produce output within the uncertainty range of measured data.
- The error term \( (e_i = O_i - P_i) \) appears in several popular model goodness-of-fit indicators:
  - e.g. \( E_{NS}, d, RMSE, MAE \)
- This error term should be modified to reflect measurement uncertainty.
Objective 2 – Modified Goodness-of-Fit Indicators

- Developed two error term modifications, based on available measurement uncertainty information.
  - **Modification 1** is most appropriate if:
    - only uncertainty boundary is known (± %)
    - probability distribution cannot be reasonably assumed
  - **Modification 2** is most appropriate if:
    - distribution of uncertainty is known or reasonably assumed
Objective 2 – Modified Goodness-of-Fit Indicators

Modification 1 - if only uncertainty boundary is known

\[ e_i = 0 \]

\[ e_i = \text{boundary} - P_i \]
Objective 2 – Modified Goodness-of-Fit Indicators

- Modification 1 - provides conservative goodness-of-fit estimate
  - Goodness-of-fit improves substantially because minimize $e_i$
  - Facilitates visual assessment

![Graph showing dissolved P loss (kg/ha) over months. The graph includes lower/upper uncertainty boundaries, measured values, and predicted values.](image-url)
Objective 2 – Modified Goodness-of-Fit Indicators

Modification 2 - if distribution of uncertainty is known

\[
e_i = \frac{CF_i}{0.5} \times (O_i - P_i)
\]

In Modification 2, the probability distributions represent possible measured values for each point \(O_i\) not for the entire population of measured data.
Objective 2 – Modified Goodness-of-Fit Indicators

Modification 2 - if distribution of uncertainty is known

\[ e_i = \frac{CF_i}{0.5} \times (O_i - P_i) \]
Objective 2 – Modified Goodness-of-Fit Indicators

- Modification 2 – provides more realistic estimate of $e_i$ when distributional information of measurement uncertainty known or reasonably assumed
  - Goodness-of-fit increased only slightly for measured data with little uncertainty.
  - Modest improvement when data with substantial uncertainty were compared with both poor and good model predictions.
  - **Important result** - poor performance shouldn’t appear satisfactory because of measurement uncertainty, especially for large model structure errors
Recent Model-Related Uncertainty Pubs.


Conclusion and Acknowledgments

• Conclusions related to H/WQ modeling…
  • no longer acceptable to not consider uncertainty in H/WQ modeling
  • advantageous for modelers to quantify the “quality” calibration, validation, and evaluation data

• Insight and groundbreaking work by many contributed to the foundation for this research.
  • Richard Cooper, Ken Reckhow, Keith Beven, Florian Pappenberger, Dmitri Kavetski, Ann van Griensven (and her colleagues), Bruce Beck, Tom Haan, Dan Storm, Raymond Slade.
Upcoming Research on H/WQ Data Uncertainty

• Refine the uncertainty estimation method to facilitate estimation in measured H/WQ data
  • Procedure, field/data form, simple spreadsheet
• Push for increased emphasis on sample collection in QA
• Emphasize benefits of uncertainty estimates accompanying measured H/WQ data sets
• Apply modified goodness-of-fit indicators in H/WQ modeling and other fields
• Incorporate uncertainty estimates and modified goodness-of-fit indicators in SWAT, EPIC/APEX interface
Any Questions??

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