Use of evaporation and streamflow data in hydrological model calibration

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The conventional method of hydrological model calibration is based on observed streamflow data at catchment outlets.

Nowadays, availability of remote sensing based evaporation data provides additional dataset for hydrological model calibration.

This study illustrates the model performance in Single-variable and multi-variable calibration using evaporation (ET) and streamflow (Q) data.
Approach to model calibration

- DEM
- Land cover
- Soil
- Climate

SWAT Model Set up

Obs. Discharge (Q) & Evaporation (GLEAM ET) data

Model calibration

Single variable (Q, ET)

Multi-variable (Both Q & ET)

Ranking Method
Study Area

Chindwin River Basin

- **Location**: Mostly in Myanmar
  - Small part of India
  - Located in North-western part of Myanmar

- **Total area**: 111,000 Km²

- **Main River**: Chindwin
  - Main tributary of Irrawaddy River

- **Avg. Annual Rf**: 770 mm – 3900 mm

- **Avg. Annual Temp**: 21°C

- **Land cover**: Mostly forest
Approach to model calibration with ET & Q

Single variable calibration

- **Model parameters**
- **Simulations (2000) – 1st Run**
  - Q based
    - New para range
    - Simulations - 2000
    - Performance analysis
      - (4 iterations)
      - MNSE as OF
  - ET based
    - New para range
    - Simulations - 2000
    - Performance analysis
      - (4 iterations)
      - MNSE as OF
Calibration with only Q improves the model performance with respect to Q estimates, but with a poor performance with respect to ET estimates and vice versa.
Approach to model calibration with ET & Q

Single variable calibration

- Model parameters
  - Simulations (2000) – 1st Run
    - Q based
      - New para range
      - Simulations - 2000
    - ET based
      - New para range
      - Simulations - 2000
  - Performance analysis (4 iterations)
    - MNSE as OF

Combine the total simulations of each iteration (18,000 simulations)

Multi-variable calibration

- Performance of Q and ET (18,000 simulations)

Ranking Method

\[ P_r = \frac{(N + 1) - R^i}{N} \]

Extracted from (Finger et al., 2011)
Multi-variable calibration

Taking the threshold as 90th percentile of ranking value out of 18000 simulations

Calibration only with ET results in high variability of Q performance.
Multi-variable calibration – Q+ET

Simulations passes the 90th percentile threshold limits
Approach to model calibration with ET & Q

Single variable calibration

- Model parameters
- Simulations (2000) – 1st Run
- Q based New para range
- ET based New para range
- Simulations - 2000
- Performance analysis (4 iterations) MNSE as OF

Multi-variable calibration

- Combine the total simulations of each iteration

Performance analysis (4 iterations) MNSE as OF

Ranking Method

\[ P_t = \frac{(N + 1) - R_t}{N} \]

Extracted from Finger et al., 2011)

Performance of Q and ET (4000x5 simulations)

90th percentile of each Q and ET
### Multi-variable calibration

<table>
<thead>
<tr>
<th>Evaluation Criteria for OF (MNSE)</th>
<th>Q</th>
<th>ET</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>min</td>
<td>max</td>
</tr>
<tr>
<td>NSE</td>
<td></td>
<td></td>
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<tr>
<td>Ranking overall MNSE</td>
<td>0.12</td>
<td>0.93</td>
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<tr>
<td>90\textsuperscript{th} percentile of MNSE for each Q and ET</td>
<td>0.82</td>
<td>0.91</td>
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<tr>
<td>PBIAS (%)</td>
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<td></td>
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<tr>
<td>Ranking overall MNSE</td>
<td>-40.9</td>
<td>-8.6</td>
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<tr>
<td>90\textsuperscript{th} percentile of MNSE for each Q and ET</td>
<td>-18.6</td>
<td>-10.8</td>
</tr>
</tbody>
</table>
Parameter Space

- **Threshold**: 90th percentile of MNSE of each Q and ET as thresholds (14 parameter sets)
- **Ranking (Q + ET)**
- **Ranking (ET)**
- **Ranking (Q)**

**90th percentile of ranking value as threshold**

(1800 parameter sets)
No clear pattern emerges to correlate the ranges of the estimated parameters and with evaluation techniques. Evaluation based on ranking of Q results in minimum parameter space compared to the other three criteria.
Conclusions

- Calibration with only Q improves the model performance with respect to Q estimates, but may be a poor performance respect to ET estimates and vice versa.

- With multi-variable calibration, reasonably good performances can be achieved for both variables (Q and ET).

- Initial thresholds can avoid the presence of low performance of one variable in overall model performance.

- The uncertainty affecting the estimated parameters and their range of variability change when applying different evaluation criteria.
THANK YOU