Evaluation of models using SWAT2005

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SWAT2005, Dübendorf
River Basin System

Problem

SEA

RIVER QUALITY

AGRICULTURE

INDUSTRY

WWTP

SEWERS

HOUSEHOLDS
Problem

VERY COMPLEX

• temporal variability (climate, seasons, weather, human activity)
• spatial variability (land use, river network)

⇒ NEED FOR COMPUTER MODELS

⇒ PROBLEMS TO SOLVE

• many factors of the system are not or poorly known
• all systems are different

• Do models describe reality? comparison to observations
• Are model results confident?

• Must Calibrate models but also evaluate them in prediction mode
Real world values
On a spatial / temporal continuum

Sources of Error

• Recording errors of forcing inputs
• Spatial/temporal discretization

• Spatial discretization of landuse, soil, and topography
• Errors on parameters for landuse, soil, and topography

• Model scale discretization
• Model hypothesis

• Observation and temporal errors for point-source pollution
• Errors on land use practices
• Temporal discretization for diffuse pollution

• Errors on observed values

Observed spatial resolution
Observed temporal resolution
Observed forcing data

Landuse Map
Soil Map
Topographic map

Model spatial structure
Simplified processes
Uncertain parameters

Model diffuse pollution sources
Model point pollution sources

Uncertain model output

Environmental Observations

Residuals:
Observations – Model output
Sources of Uncertainty

→ Parametric Uncertainty - focus of most uncertainty methods
→ Model structural uncertainty
→ Data uncertainties
  • Output uncertainty (errors in streamflow uncertainty)
  • Input uncertainty (errors in rainfall)
→ Inadequate data
→ Last three harder to assess but important
→ For decision makers estimates of combined or predictive uncertainty needed
Uncertainty analysis

ParaSol
Parameter Solutions
ParaSol: calibration

The Model
- Parameter inputs
- State variables
- Model structure
- Boundary conditions

UNCERTAINTY ASSESSMENT

Parameters

Outputs

Parameter value

default

calibrated
Uncertainty analysis

- Initial parameter set
- New parameter set
- Error function
- Computer simulation
- New parameter set
- Error function
- Error function
- Low error function
- "Equally good parameter sets"
Multi-objective calibration based on SCE-UA for minimisation of Global Optimisation Criterion (GOC)

\[
GOC = \sum_{m=1}^{M} \frac{OF_m \ast N_m}{OF_{m,\text{min}}}
\]

Statistics

Threshold for GOC to define “good” parameter sets

Confidence ranges for parameter and/or model outputs
## Errors (Sources of Uncertainty) in Modelling

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<th>Sources of Error</th>
<th>Size of Error</th>
<th>Statistical Analogy</th>
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Typical uncertainty analysis focuses on A-B
But evaluation period, A+C, has information about the level of trust (uncertainty) we should have in our models.

After - Singh 1988 - Hydrologic Systems Rainfall-Runoff Modelling
A Way Forward

Existing uncertainty methods typically
• Involve some subjective decision making on acceptability of simulations (e.g. GLUE)
• Or make overly strict assumptions about model and data correctness and thus have unreasonably small uncertainty bounds (e.g. BARE method and ParaSol discussed in next talk)
• Beven and Young (2003) advocate methods between these two extremes

Singh’s framework provides a way out.
• Use the evaluation period to determine model parameter set acceptability?
• But how? Here we present one option.
Sources of UNcertainty

Sources of UNcertainty
GLocal Assessment using Split–SamplpES
SUNGLASSES: calibration + validation

The Model

- Parameter inputs
- State variables
- Model structure
- Boundary conditions

Outputs

Parameters

CALIBRATION

VALIDATION
ParaSol versus SUNGLASSES Uncertainty

IF PREDICTIONS ARE BIASED: threshold is increased!

OUTPUT UNCERTAINTY INCREASES
SWAT application: Honey creek

- Sandusky watershed, Lake Erie, Ohio
- 338 km²
- SWAT model by University of Florida – Sabine Grunwald and others
- 1 subbasin, 5 HRU’s, 1 river reach, 1 point source
SWAT Sediments Results

Model bias for the sediment loads (%)

ParaSol  SUNGLASSES

Results
Results
The **Sources of UNcertainty GLobal Assessment using Split SamplIES**

- Accounts for global uncertainty without identification of the sources.
- Acceptability based on model criteria to be used for decisions (e.g. total water or nutrient export)
  - Honey Creek model sediment load important
  - Thus use model bias to determine bounds - uncertainty bounds should include the zero bias case.
- **Split-Sampling strategy**
  - Calibrate with first time period (develop population using SCE-UA)
  - Establish acceptability with second period.
Conclusion

• Parameter uncertainty is only small part of global uncertainty when enough data is available

• **SUNGLASSES** is able to catch that uncertainty

• **SUNGLASSES** does not denote cause of uncertainty but instead quantifies the global uncertainty bound
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