Application of machine learning emulators in parameter identification for a distributed hydrological model

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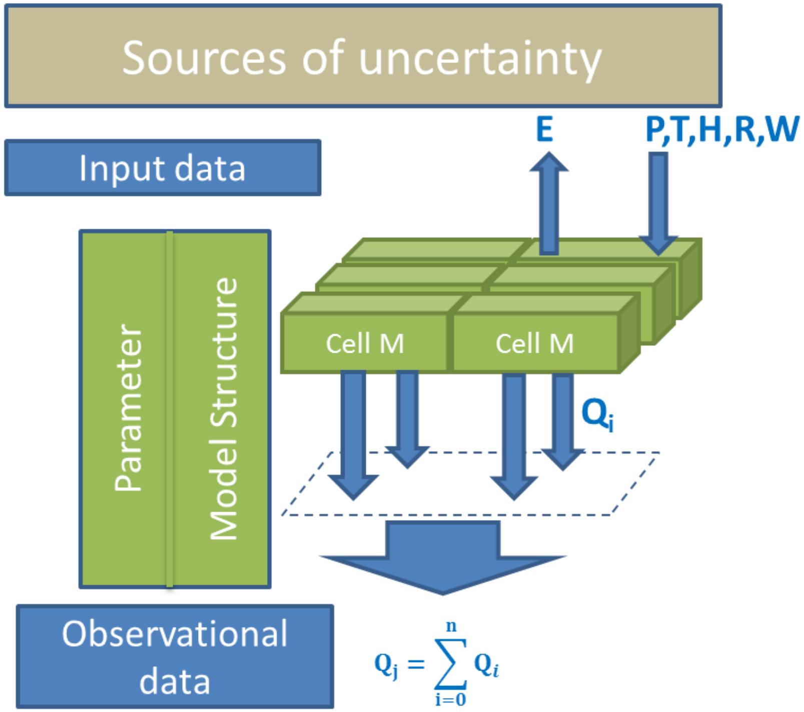
1. Motivation and Objectives

- Environmental and water resources related decisions rely upon wide range of modelling results.

- Model predictions are generally imperfect

- Need for uncertainty analysis and communicating model simulation results in terms of uncertainty bounds rather than with only crisp values.



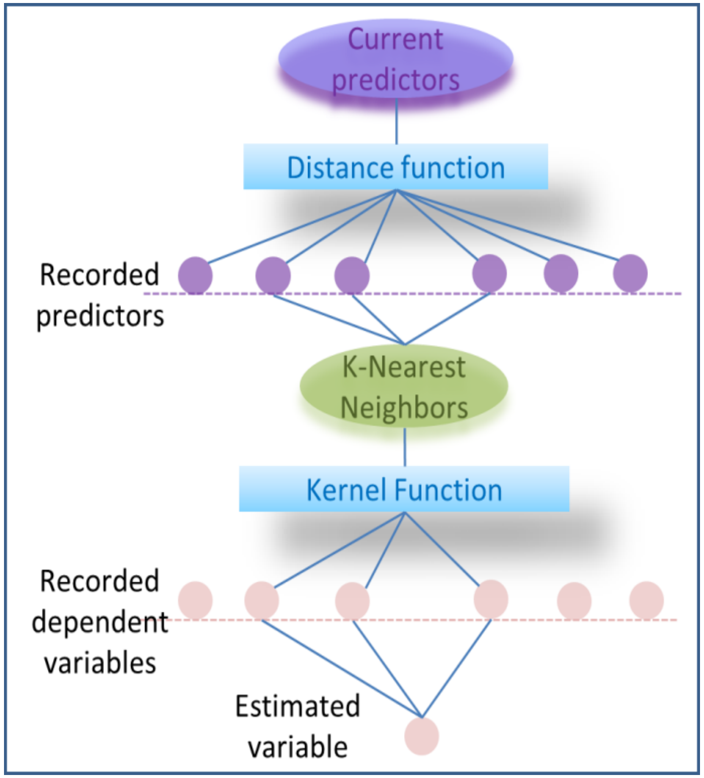
1. Motivation and Objectives

Main goal:

To emulate the time consuming Monte Carlo (MC) simulation for applications in parameter identification

Specific objectives:

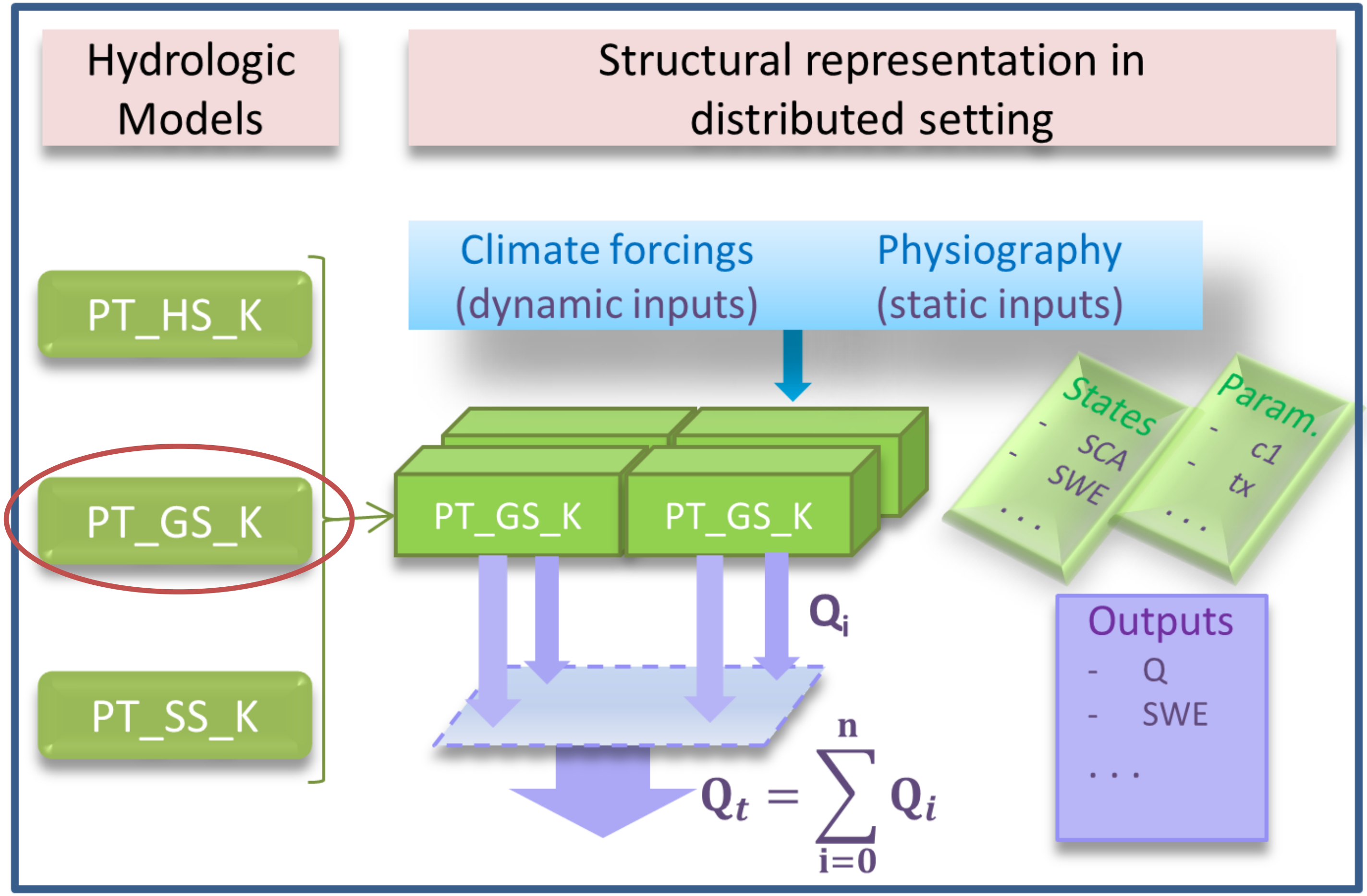
- Assess the possibility of using pLoA as a likelihood measure
- Evaluate the viability of using random forest (RF) and k-nearest neighbors (KNN) as emulators of the MC simulation



after Araghinejad (2014)

2. Methods and materials

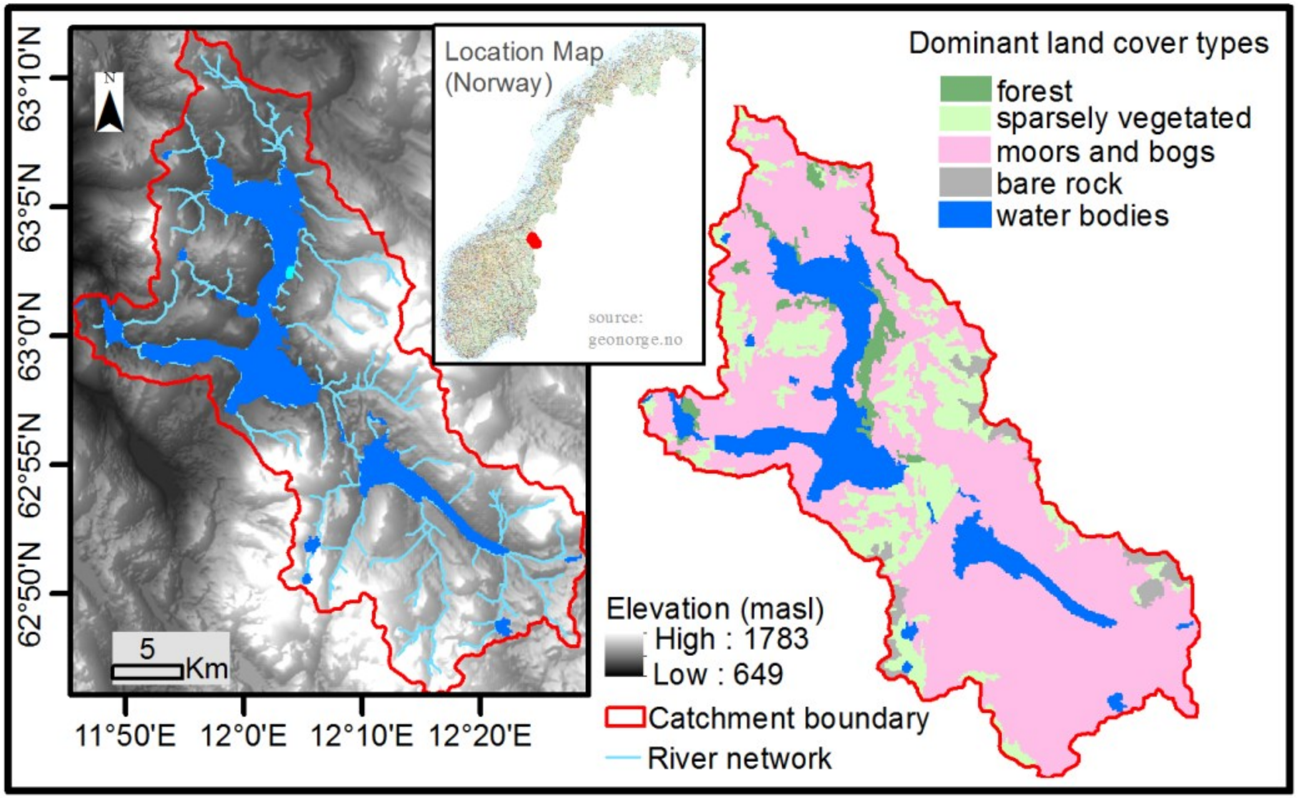
The Statkraft Hydrologic Forcasting Toolbox (Shyft)



2. Methods and materials

The Nea-catchment and available data

- Discretized into 812 grid cells
- Climatic data:
  - Precipitation
  - Temperature
  - Humidity
  - Solar radiation
  - Wind speed
- Physiograpic data:
  - Fractional area of forest cover, lakes, reservoirs, and glaciers
  - Grid cell elevation and area
- Streamflow



Physiography and location map of the Nea-catchment.

2. Methods and materials

Parameter identification using the time-relaxed limits of acceptability approach

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Parameter uncertainty analysis for an operational hydrological model using residual-based and limits of acceptability approaches

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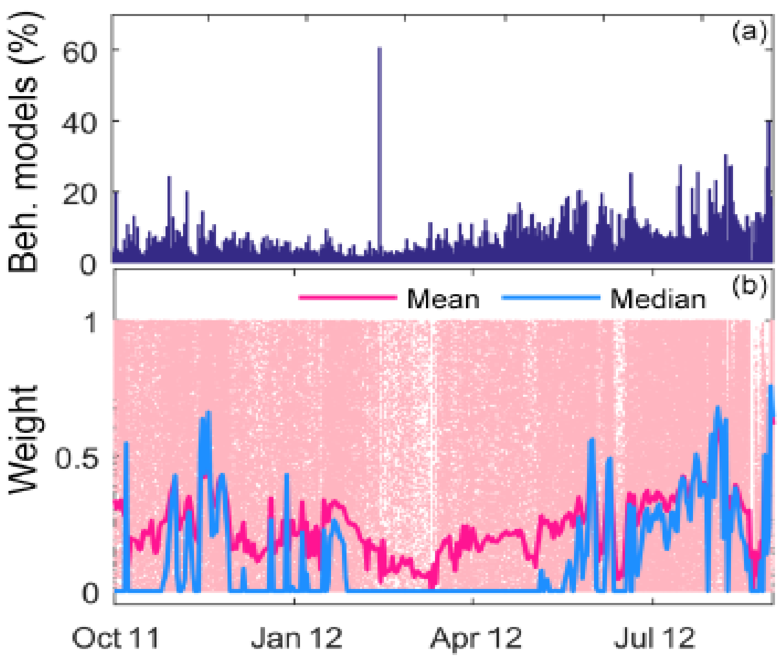
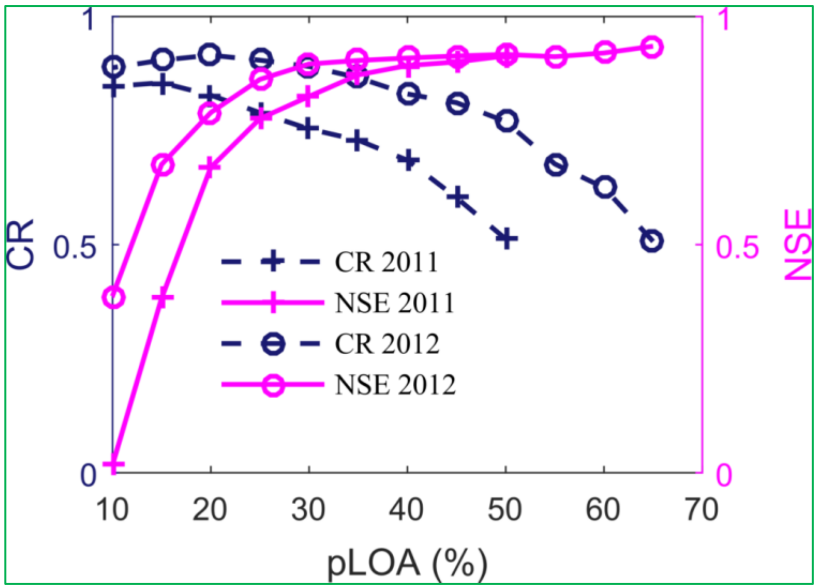


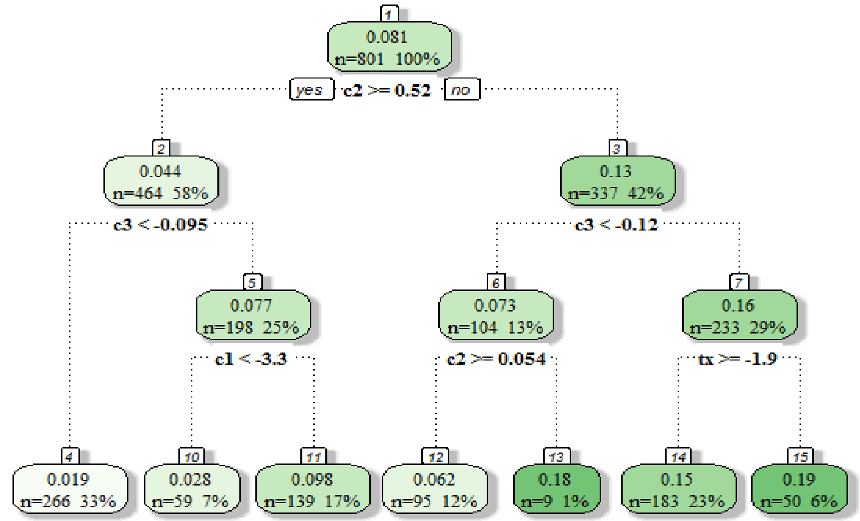


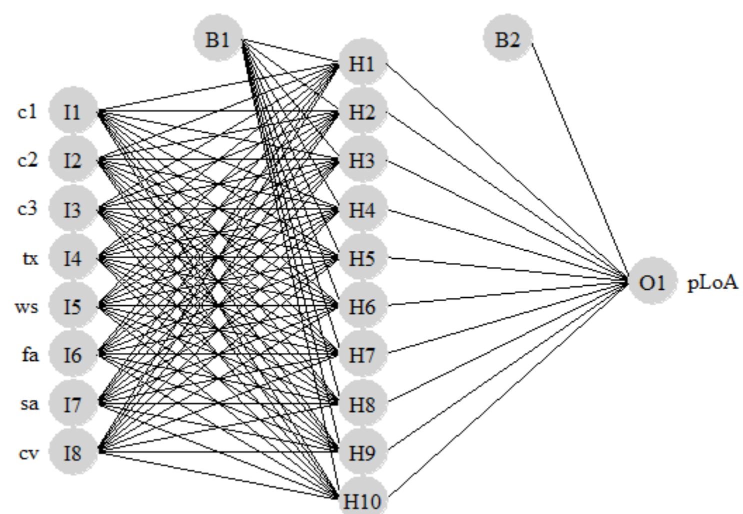
Effect of the percentage of model predictions falling within the observation error bounds (pLoA) on modelling efficiency (NSE) and uncertainty (CR)

2. Methods and materials

Machine learning modelling

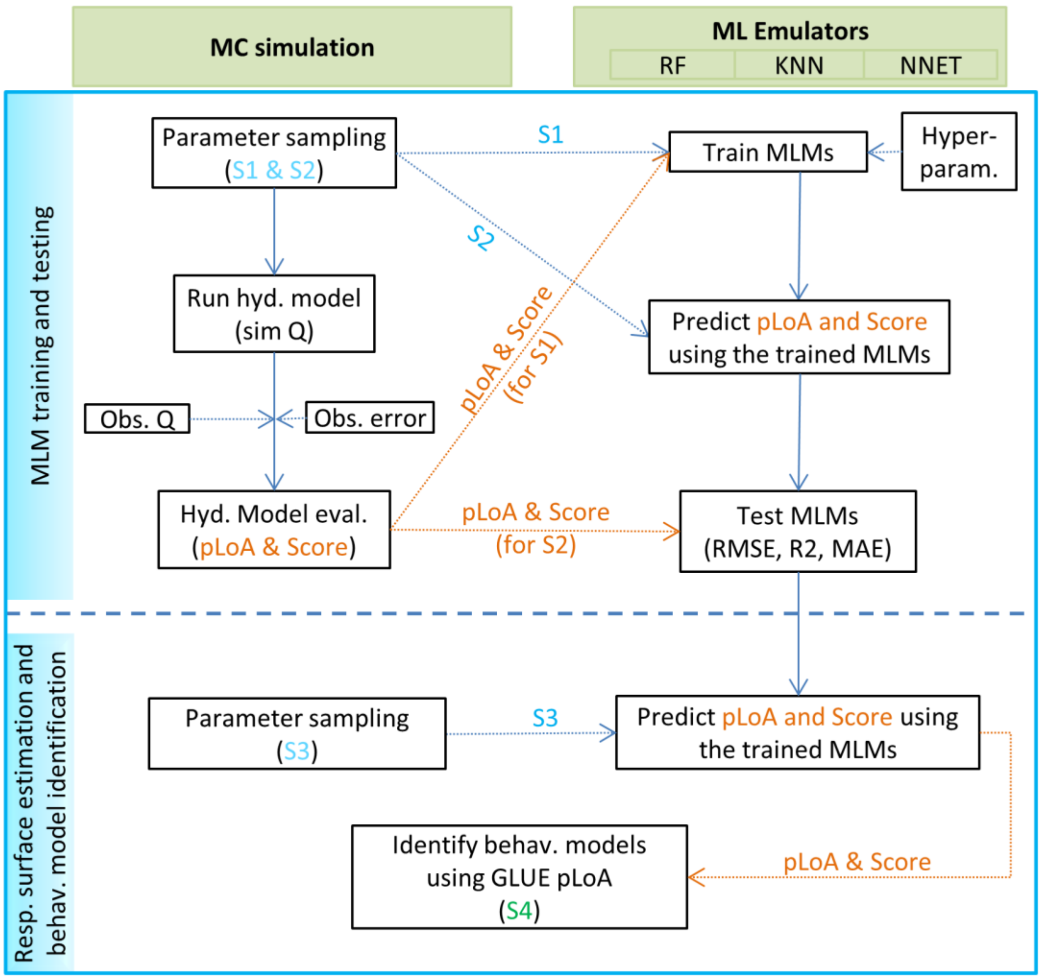
- three machine learning models (MLMs) considered to emulate the Monte-Carlo (MC) simulation
  - Random forest (RF)
  - K-nearest neighbors (KNN)
  - Artificial neural network (NNET)
- two sets of MLMs were trained
  - model parameter values (as covariates), and
  - pLoA and score (as target variables)
- relevant hyper-parameters of the MLMs were optimized





2. Methods and materials

Coupling of the machine learning emulators with the LoA approach



Parameter samples used in building and application of the MLM-based emulators.

Sample	Size	Description
S1	4000	Used for training the MLMs
S2	1000	Used for testing the MLMs
S3	95000	Used to predict the response surface
S4	-	Behavioural samples

3. Results

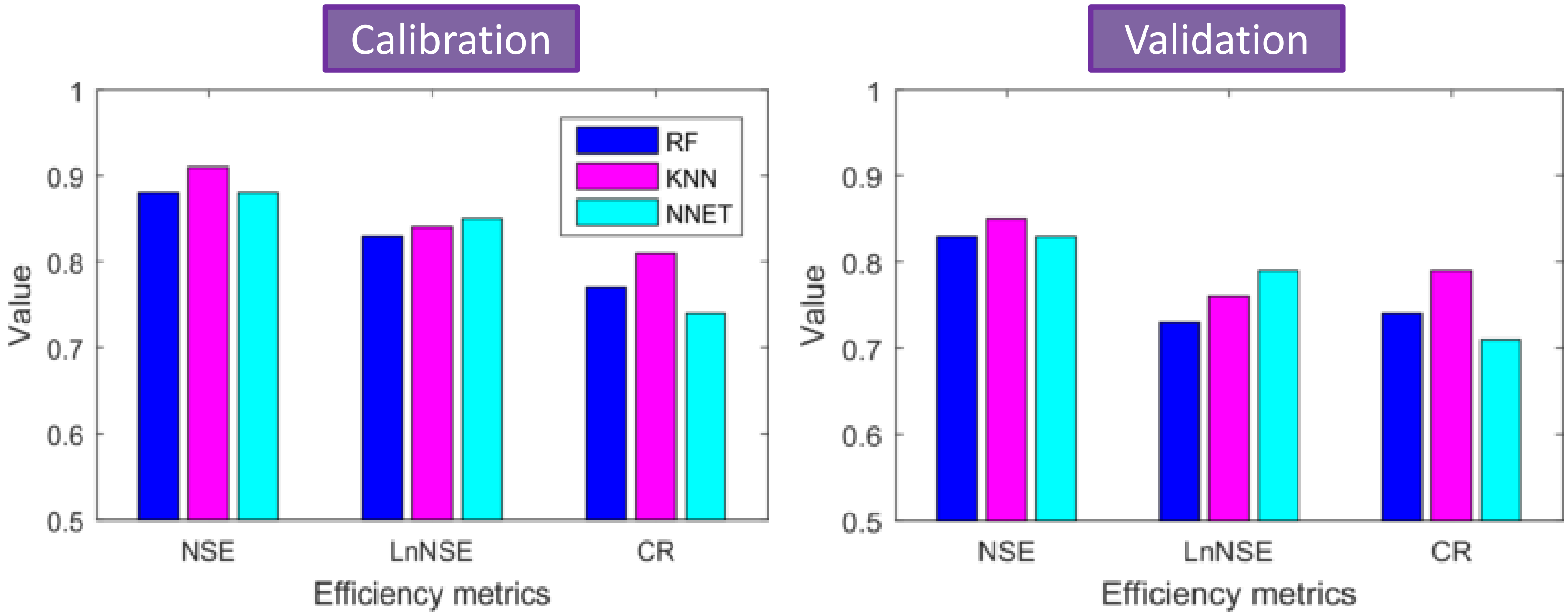
Evaluation of the MLMs capability in reproducing the response surfaces

Evaluation result of the predicted target variables, i.e. pLoA and Score through comparison against values estimated using the MC simulation for the validation samples (the eval. metrics are averaged over four years)

Eval.	pLoA			Score		
Metrics	RF	KNN	NNET	RF	KNN	NNET
RMSE	0.030	0.045	0.029	5.223	7.744	6.187
R^2	0.881	0.735	0.882	0.874	0.724	0.814
MAE	0.017	0.029	0.019	2.942	4.969	3.771

3. Results

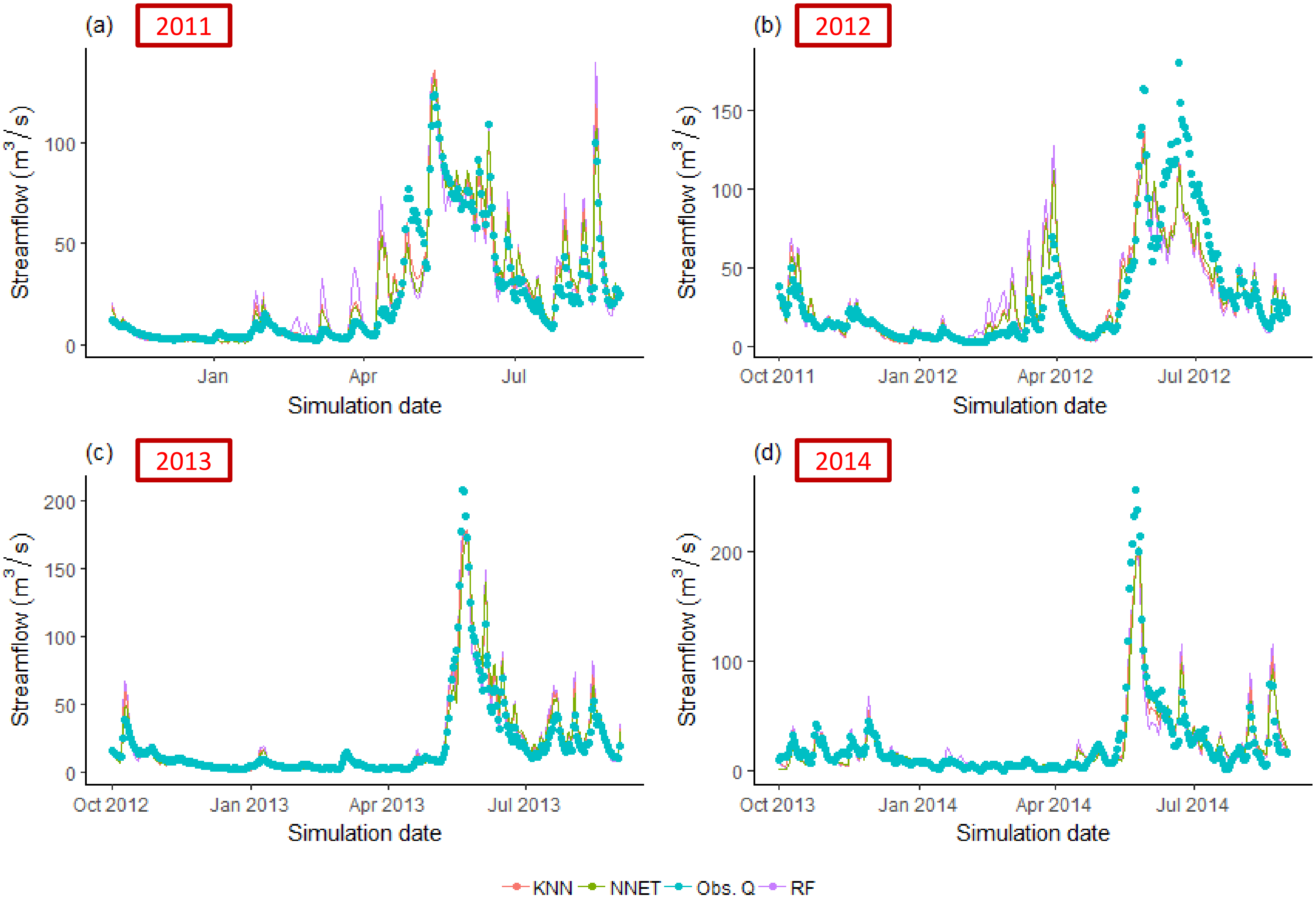
Evaluation of behavioural parameter sets using observed streamflow



Average value of the evaluation metrics for the calibration and validation periods

3. Results

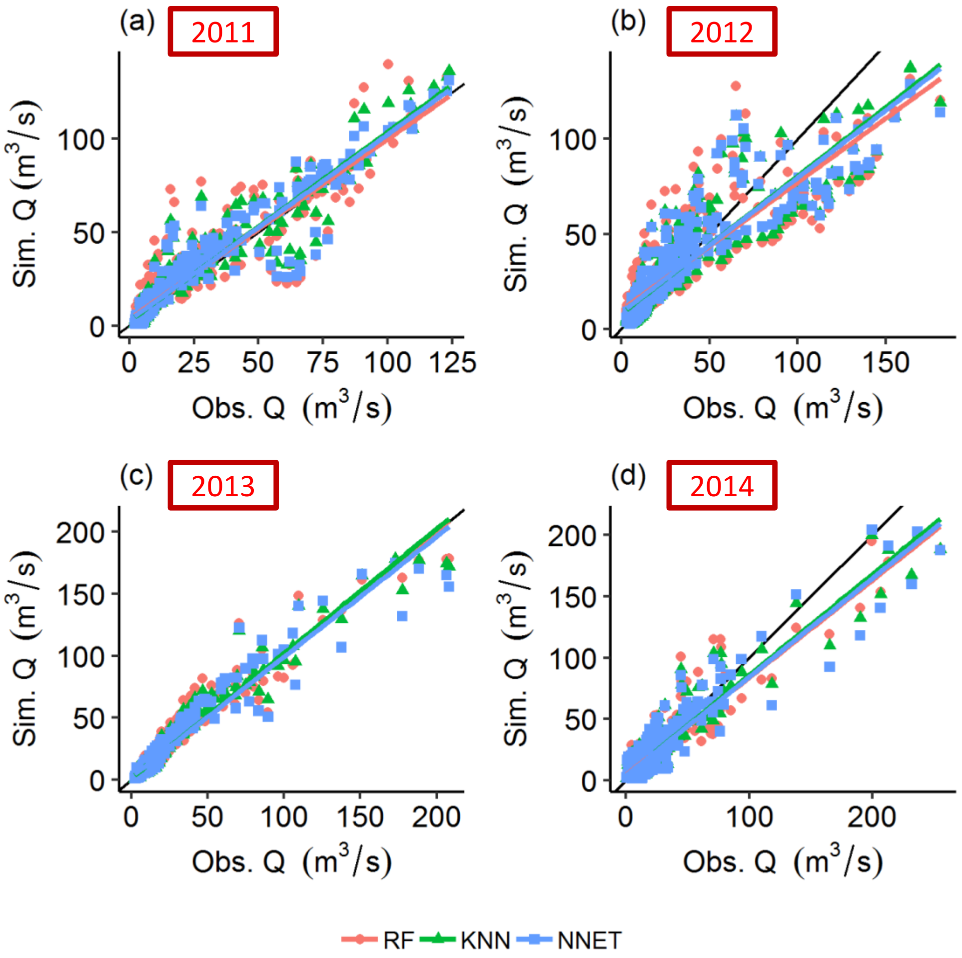
Evaluation of behavioural parameter sets using observed streamflow



Simulated and observed streamflow values for the calibration period, i.e. year 2011 (a) and validation periods, i.e. years 2012 (b), 2013 (c), and 2014 (d).

3. Results

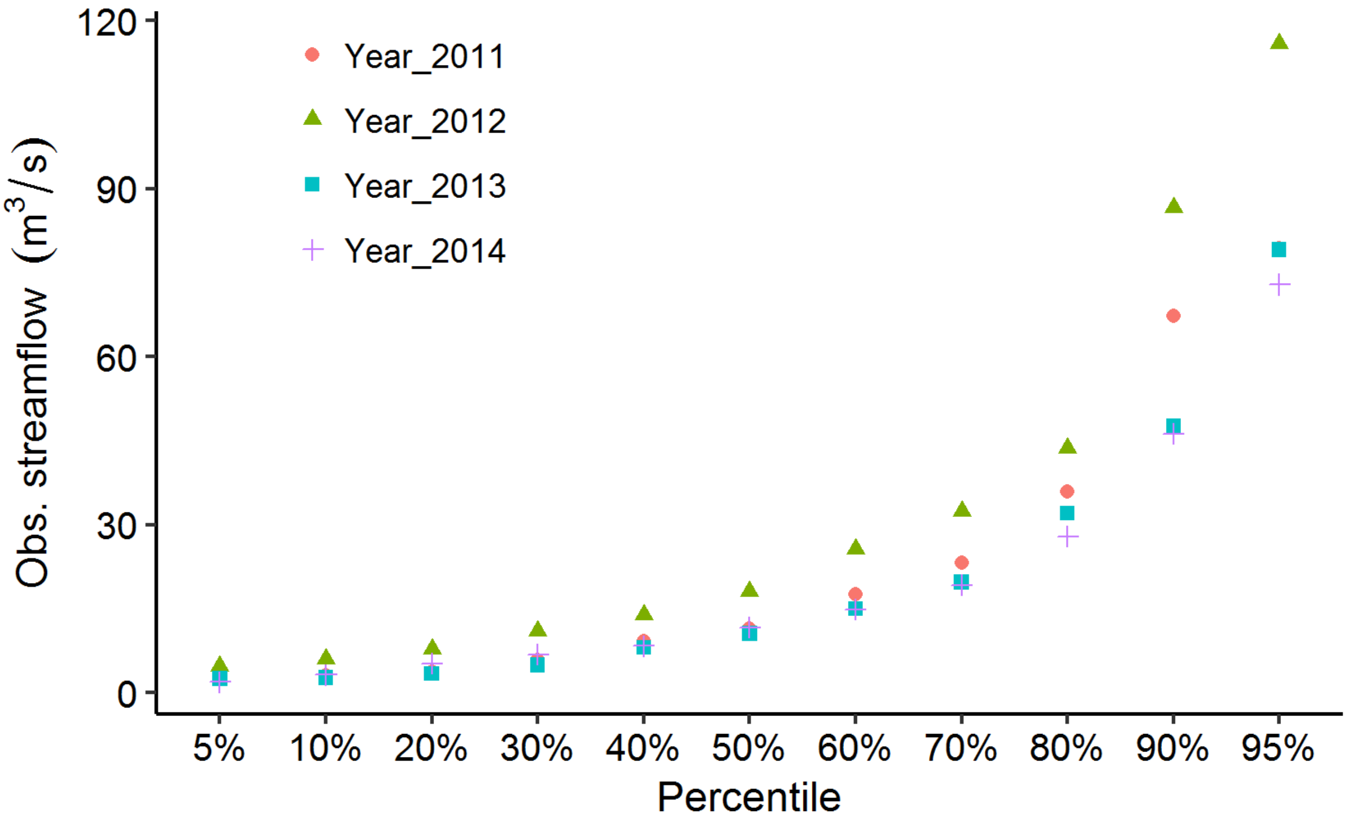
Evaluation of behavioural parameter sets using observed streamflow



Simulated against observed streamflow values for the calibration period, i.e. year 2011 (a) and validation periods, i.e. years 2012 (b), 2013 (c), and 2014 (d).

3. Results

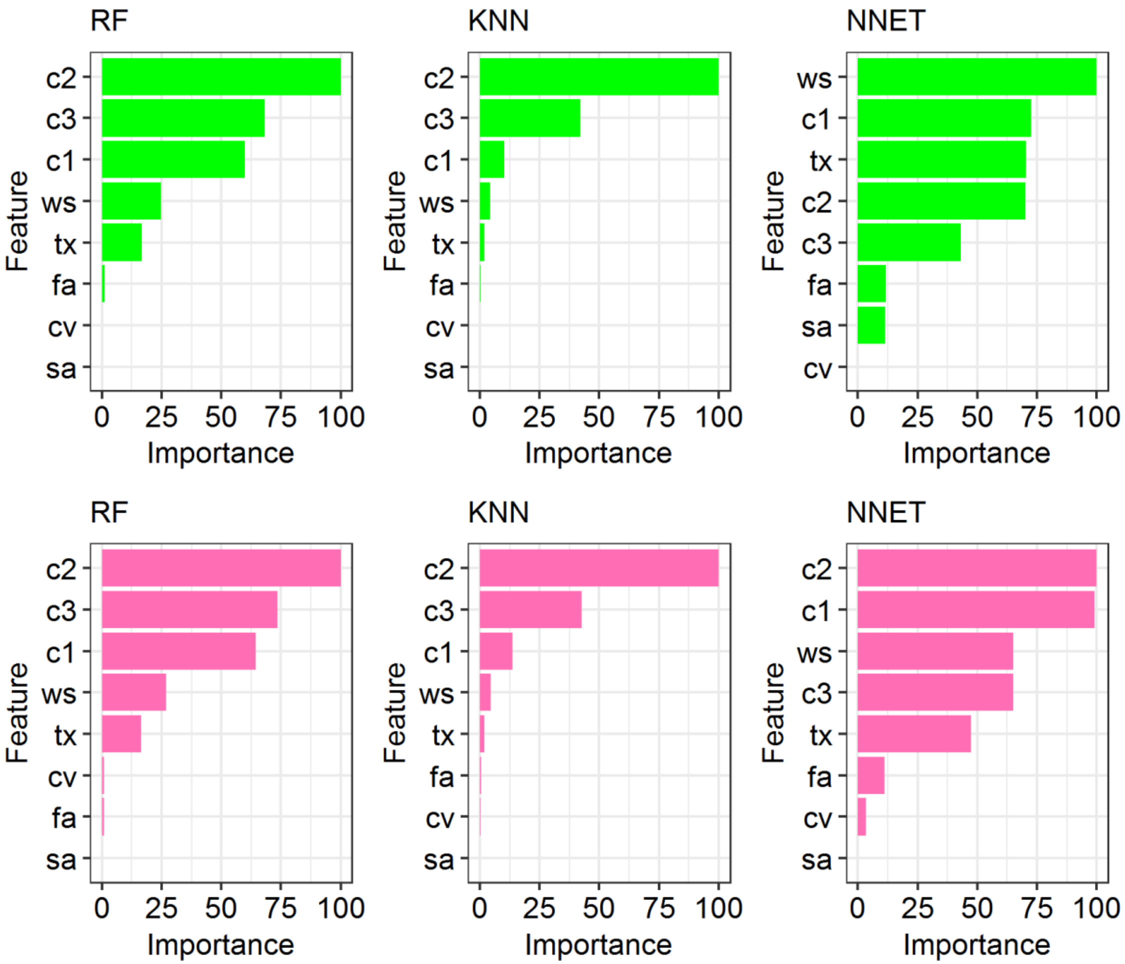
Evaluation of behavioural parameter sets using observed streamflow



Comparison of the percentile observed streamflow values for the calibration period (Year_2011) and validation periods (Year_2012, Year_2013, and Year_2014)

3. Results

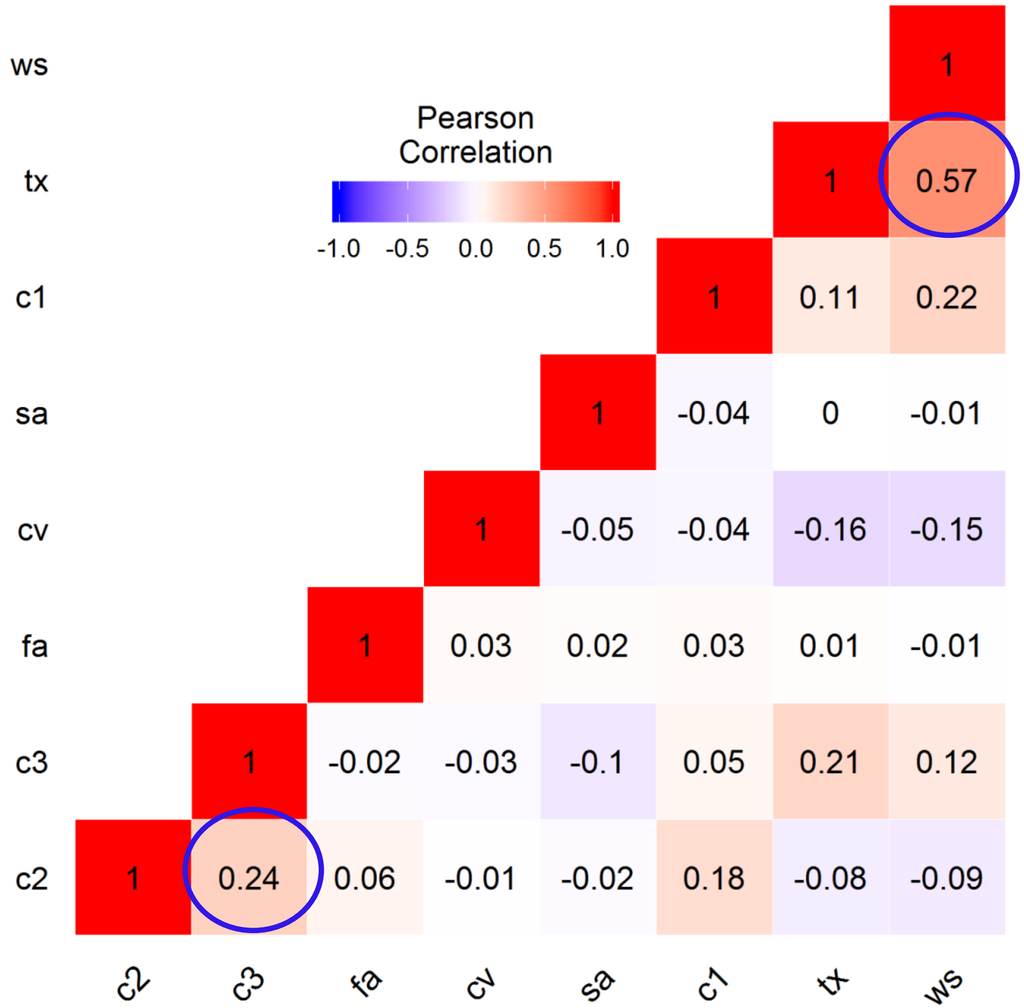
Variable importance and interaction



Relative importance of the hydrological model parameters based on the three machine learning models, i.e. RF, KNN and NNET trained for pLoA (upper row) and score (lower row)

3. Results

Variable importance and interaction



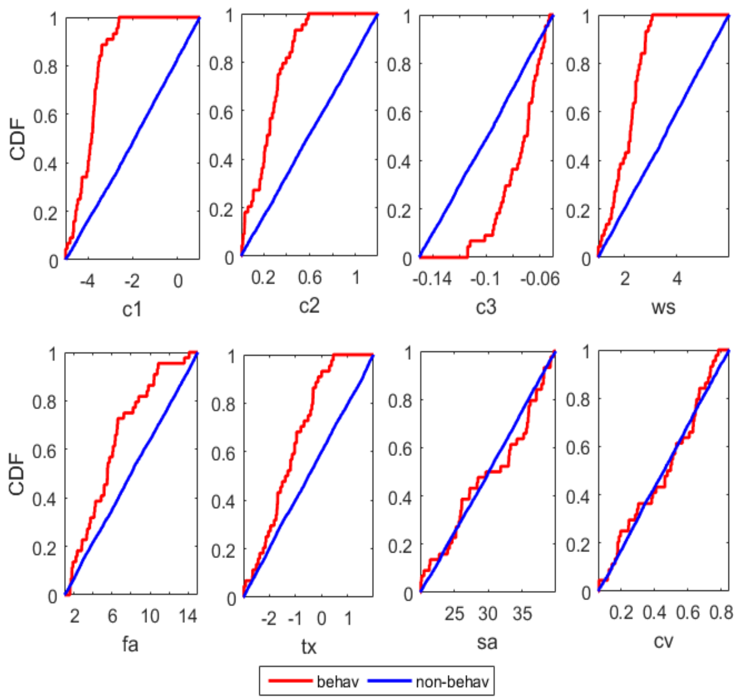
Pearson correlation matrix of the behavioural model parameters identified using the coupled RF and the limits of acceptability approach

4. Concluding remarks

- The MLMs were able to adequately reproduce the response surfaces for the test and validation samples.

- The coupled MLMs and time-relaxed limits of acceptability approach were able to effectively identify behavioural parameter sets.

- Challenges in transferablity of the identified behavioural models in time under different hydrologic condition



- The sensitivity analysis result was consistent with those obtained from previous studies conducted using the residual-based GLUE methodology and the regional sensitivity analysis.

Acknowledgments

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THANK YOU