

# Multi-objective calibration of a hydrologic model using multi-objective screening

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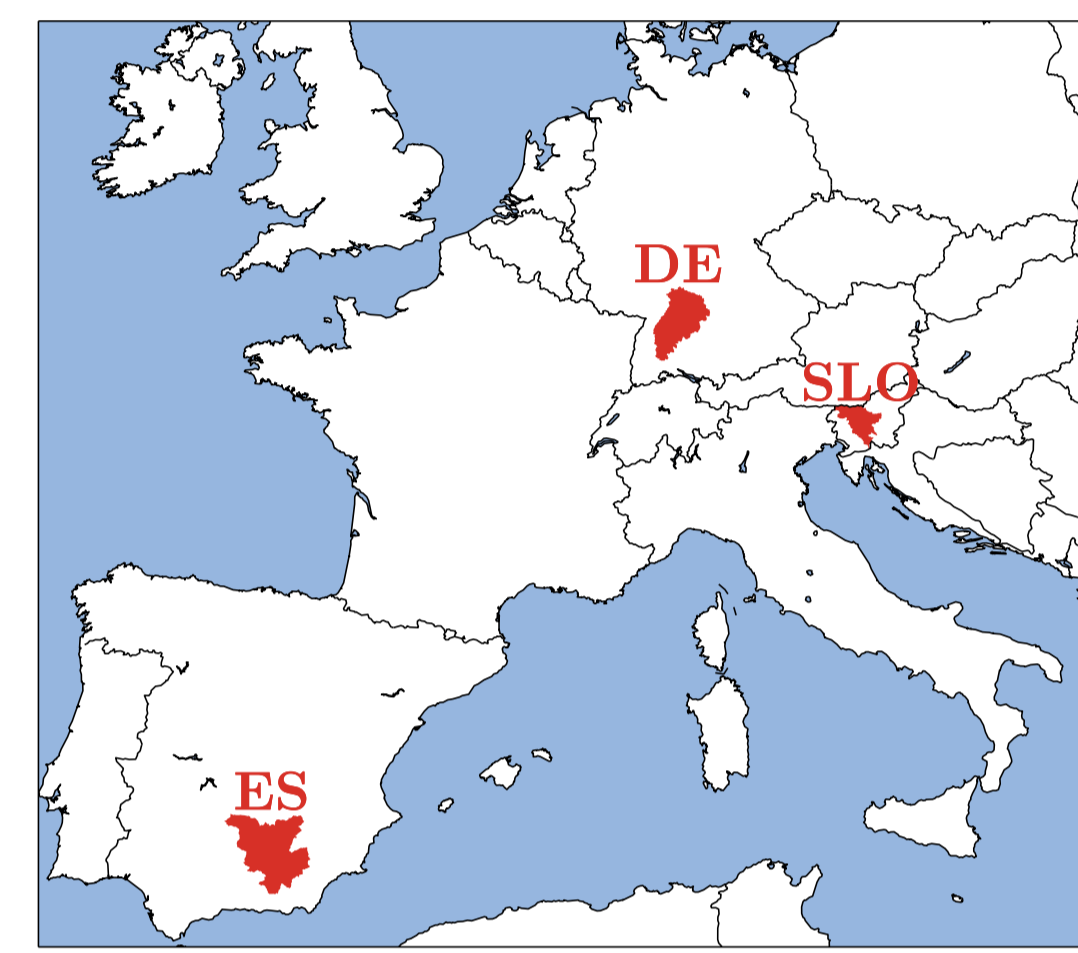
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## 1. Introduction

Hydrologic models are traditionally calibrated against discharge. Recent studies have shown however, that only a few global model parameters are constrained using the integral discharge measurements. It is therefore advisable to focus only on this **informative subset of parameters** during calibration. To constrain a larger subset of parameters, **multiple objectives** might be considered and a multi-objective calibration algorithm should be applied. The questions are (1) which subset of parameters can be constrained using these multiple objectives and (2) do multi-objective calibration algorithms benefit from only using this subset of parameters during calibration.

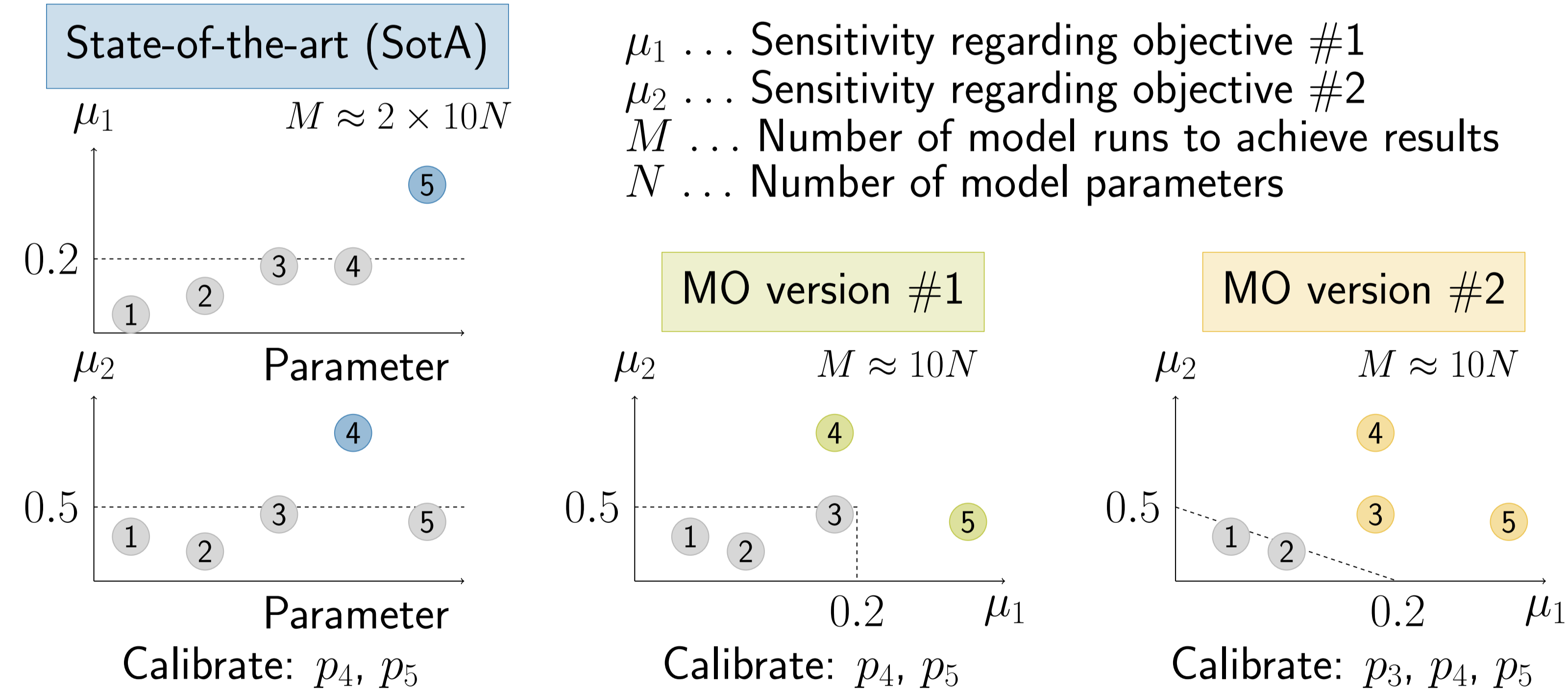
## 2. Model & Study Area

The study is performed using the **distributed hydro-logic model at the mesoscale (mHM)** with 53 parameters. The model uses grid cells as a primary hydrologic unit, and accounts for processes like snow accumulation and melting, soil moisture dynamics, infiltration, surface runoff, evapotransp., subsurface storage and discharge generation. The model is applied in **three distinct catchments** of different hydrological characteristics over Europe.

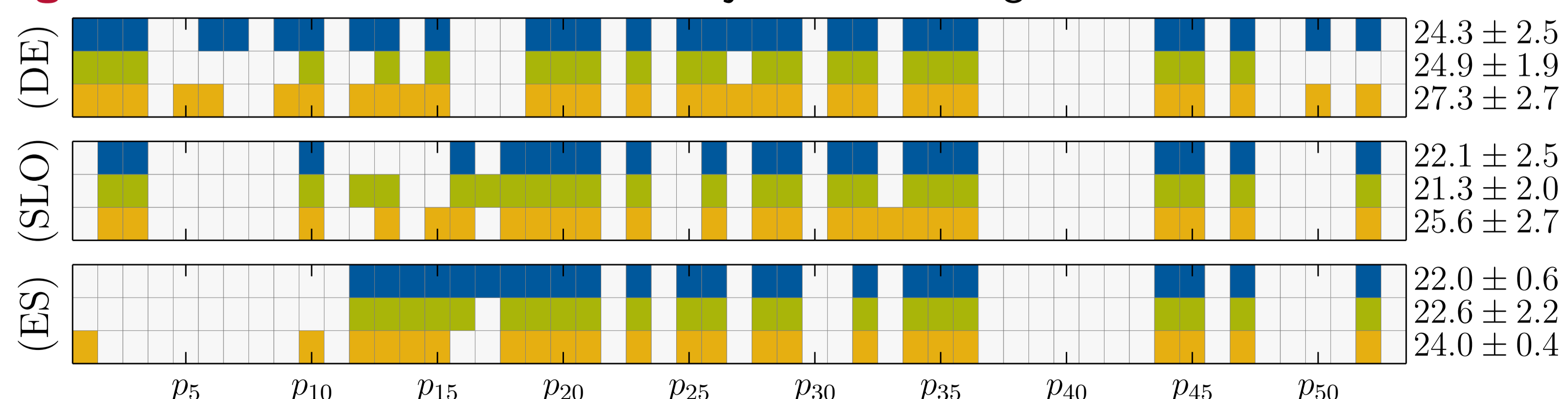


**Fig. 1:** Neckar (DE), Sava (SLO), and Guadalquivir (ES)

## 3. Multi-objective Parameter Screening



**Fig. 2:** Different methods of multi-objective screening



**Fig. 3:** Informative parameters (colored boxes) for all three catchments.  $\mu$  and  $\sigma$  for total number of parameters identified in all 10 screenings can be seen to the right.

## 4. Multi-objective Model Calibration

Pareto-archived dynamically dimensioned search (PA-DDS) algorithm introduced by Asadzadeh and Tolson (2013) using hyper-volume contribution metric and 10 replicates for each of the scenarios  
 Comput. budget: 1000, 2000, 5000, 10 000, 15 000 model evaluations  
 Reference front: 100 000 model evaluations

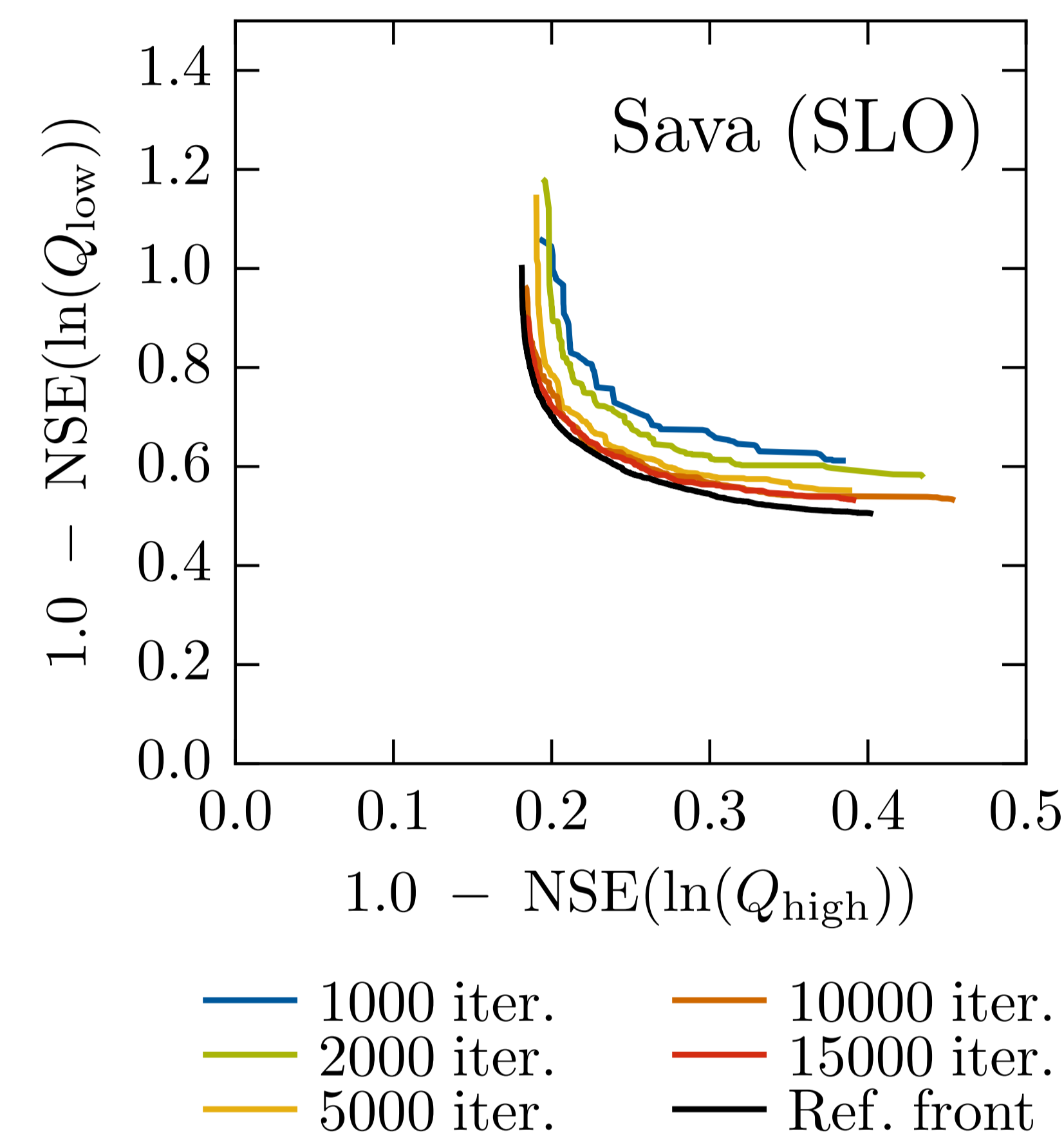
Objective functions used:

Objective #1:  $1 - \text{NSE}(\ln(Q_{\text{high}})) \rightarrow \text{Min!}$

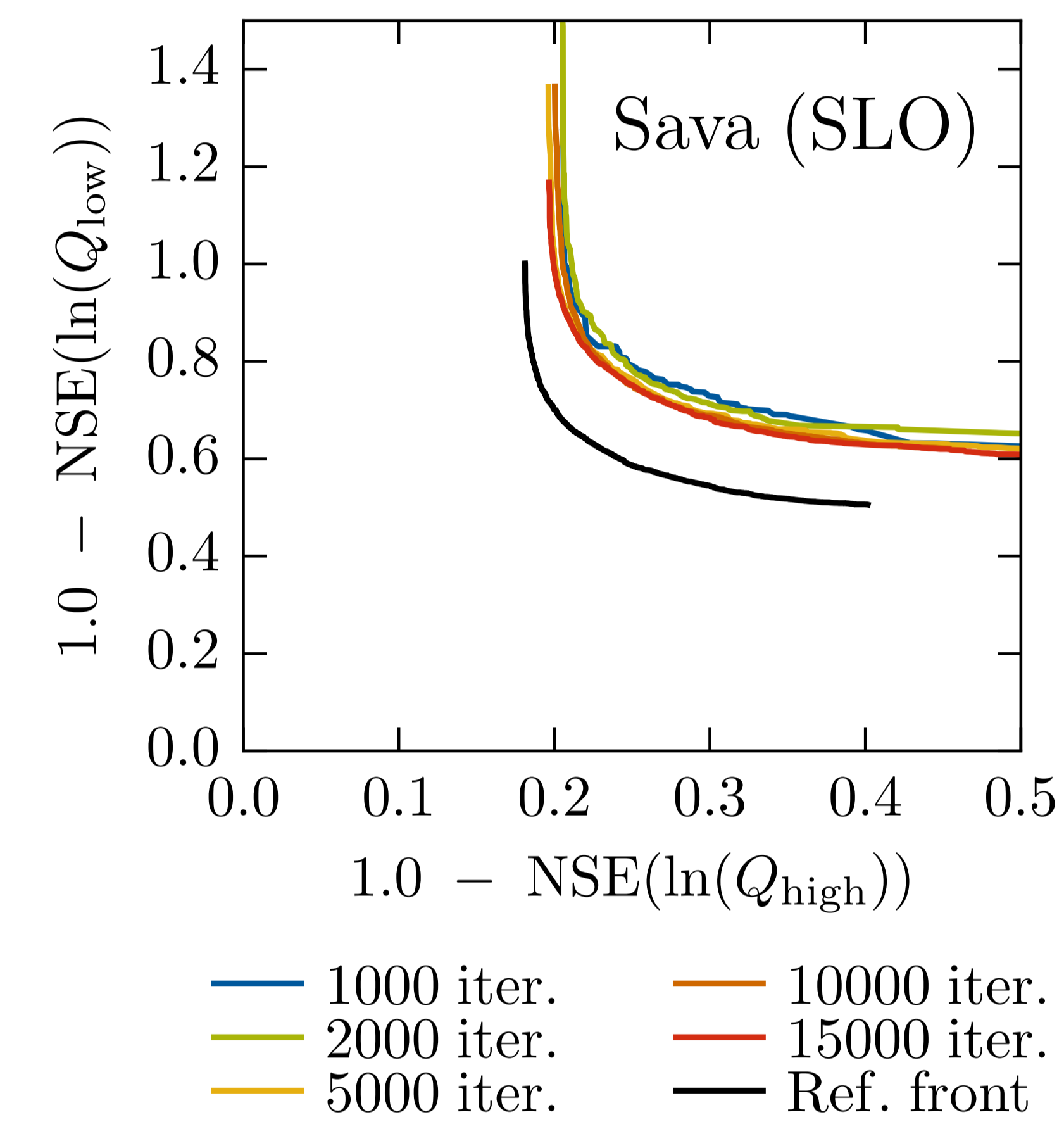
Objective #2:  $1 - \text{NSE}(\ln(Q_{\text{low}})) \rightarrow \text{Min!}$

where  $Q_{\text{high}}$  and  $Q_{\text{low}}$  are the high and low flow discharge values resp. using  $Q_{\text{thres}} = Q_{\text{min}} + (Q_{\text{max}} + Q_{\text{min}}) \cdot 0.05$  to categorize discharge values

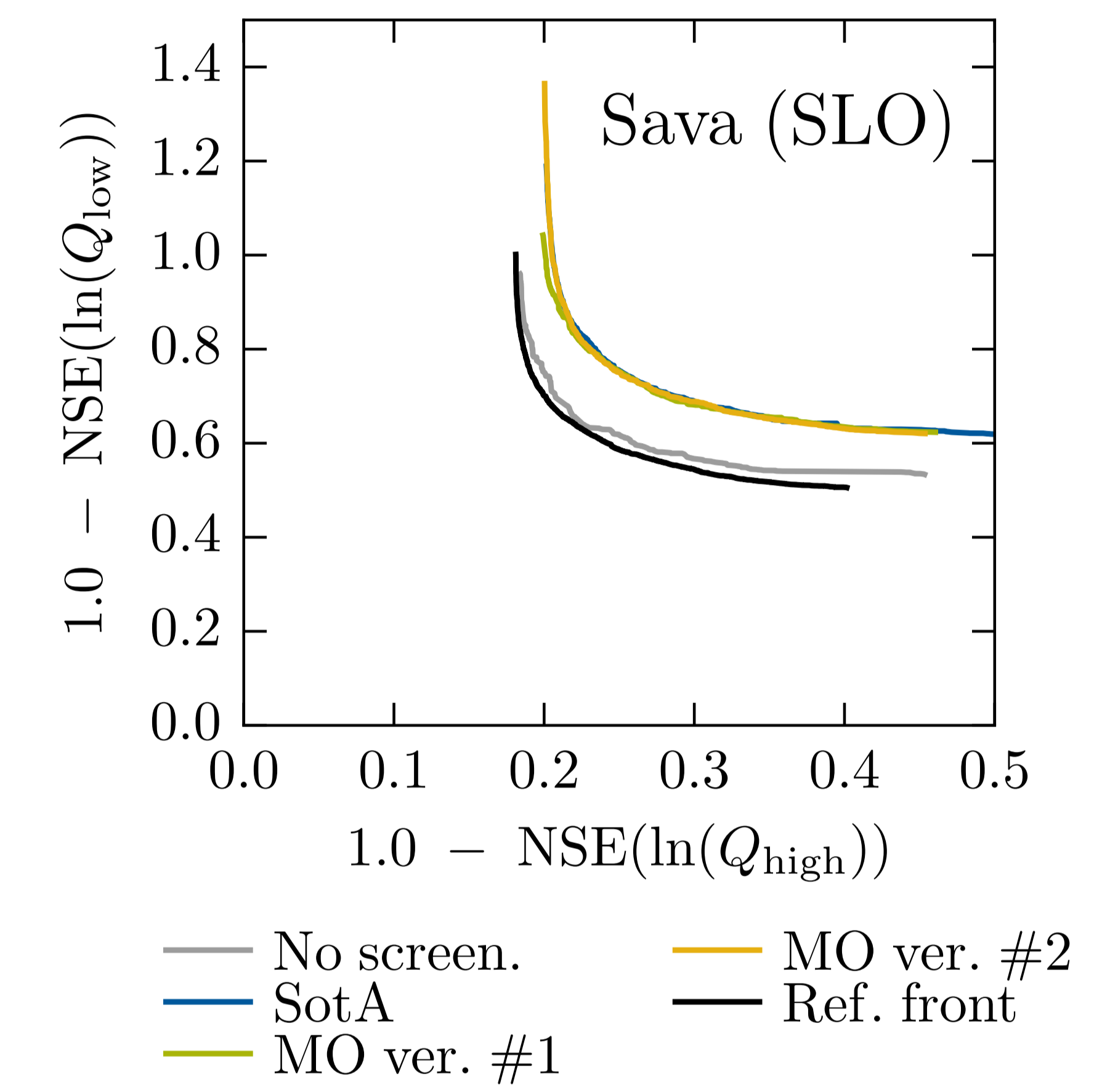
## 5. Results



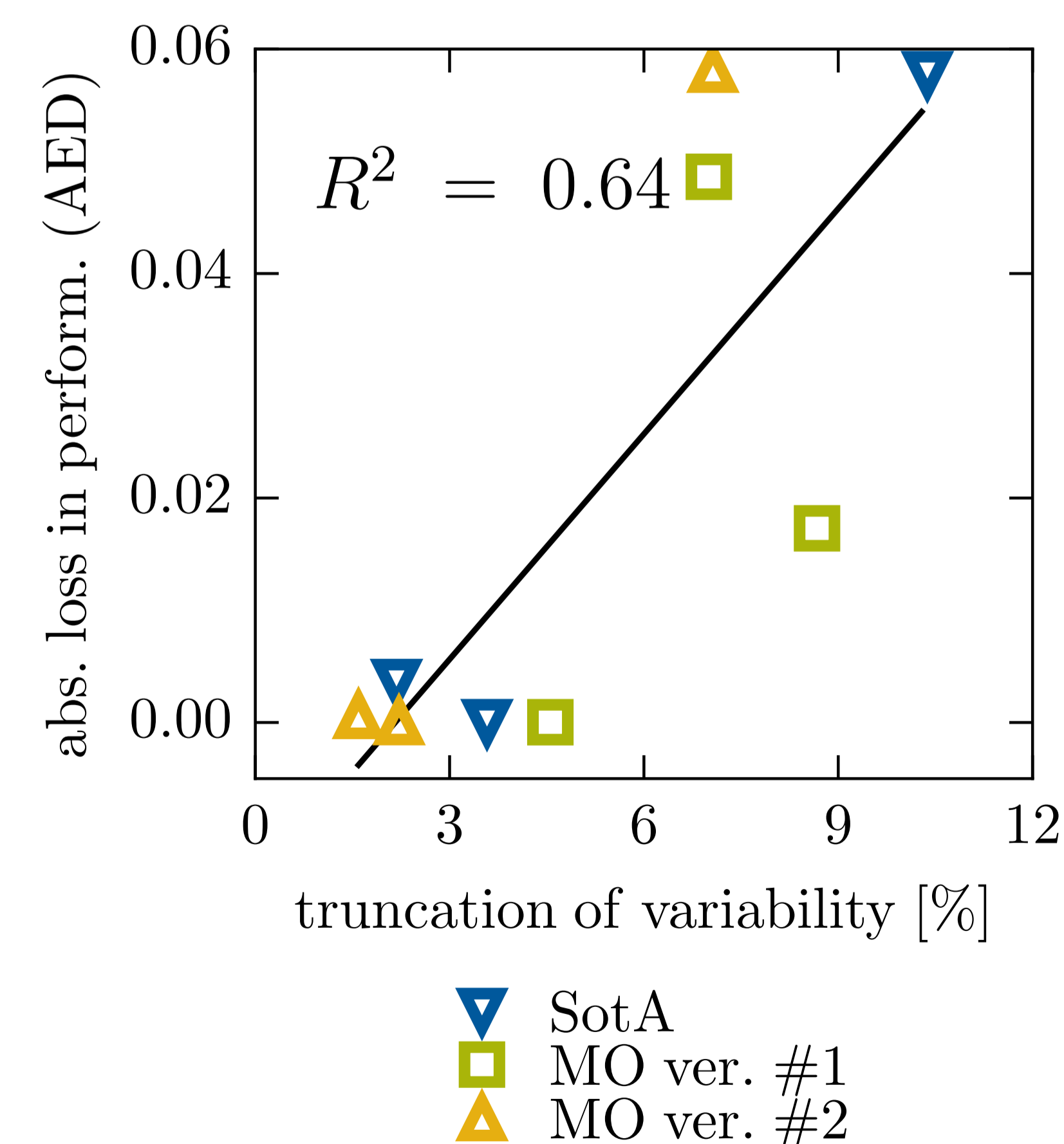
**Fig. 4:** MO calibration results without screening (all 53 parameters are calibrated) using different budgets for PA-DDS



**Fig. 5:** MO calibration results using MO screening #2 (only screened param. are calibrated) using different budgets for PA-DDS



**Fig. 6:** MO calibration results using different versions of screening (only screened parameters are calibrated) using budget of 10 000 model evaluations for PA-DDS



**Fig. 7:** Loss in performance vs. truncation error induced by neglecting screened parameters during PA-DDS calibration

## 6. Conclusions

- The parameter screening **degrades multi-objective calibration quality** relative to non-screening approach (compare Fig. 4 & 5).
- It is not clear yet whether this **performance reduction is specific** to the chosen calibration algorithm or holds also for other MO algorithms.
- The **loss in performance correlates** well with truncation of model variability during parameter screening (Fig. 7).
- The different parameter screening methods tested show **no real difference** from each other in terms of calibration results (Fig. 6).
- The number of **model evaluations** required for screening are **reduced** by a factor of 2 using a multi-objective screening approach instead of the state-of-the-art single objective approach (Fig. 2).

## References

- [1] Cuntz, M & Mai, J. et al. (2015). WRR, 51(8), 6417-6441.
- [2] Behrang, A et al. (2008). WRR, 44(12), W12603.
- [3] Asadzadeh, M, & Tolson, B (2013). Engin Optim, 45(12), 1489-1509.