hydroMOPSO: A versatile Particle Swarm Optimisation R-package for multi-objective calibration of environmental and hydrological models

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Motivation

- **Many hydrological models** available, some R-based (e.g., TUWmodel, airGR, topmodel) and some need to be run from the system console (e.g. SWAT+, Raven, WEAP, VIC).
- The implementation of multi-objective optimisation algorithms with a **user-defined hydrological model** requires a long programming time and is prone-to-error.
- There is a lack of flexible, efficient and effective multi-objective optimisation tools that can be easily plugged-in with a user-defined hydrological model.

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Our proposal: hydroMOPSO

- Is an R-package for multi-objective optimisation.
- It can be run in GNU/Linux, MacOS and Windows machines.
- It can be **easily** combined with R-based or R-external hydrological models.
- It takes advantage of multi-core machines and network clusters → important reduction of execution time.
- It implements the NMPSO optimisation algorithm (Lin et al., 2018), with an effective configuration (Marinao-Rivas and Zambrano-Bigiarini, 2021).

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Case studies

Benchmark functions

- Three well-known DTLZ problems: DTLZ1, DTLZ2 and DTLZ3 (Deb et al., 2005).
- Each one with three objectives ($M = 3$).

Hydrological models

Two R-based models in a pluvio-nival catchment: **GR4J** (Perrin et al., 2003) and **TUWmodel** (Parajka et al., 2007), with two objectives:

- KGE': For mid- and high flows (Kling et al., 2012).
- $iKGE'_{Garcia}$: for low flows (Garcia et al., 2017).

Objective:

- Identify the Pareto Optimal Front (**POF**)
- Use the hypervolume (HV) (Zitzler and Thiele, 1999) to assess the **accuracy** and **diversity** of the POF.
- Evaluate the number of model runs required to achieve the POF → **efficiency**.

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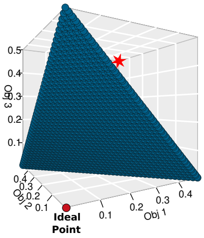
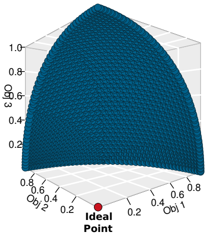
Pareto Optimal Front - Benchmark functions

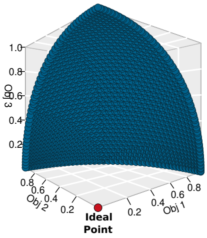
DTLZ1 problem
Minimisation problem. M = 3, D = 7.



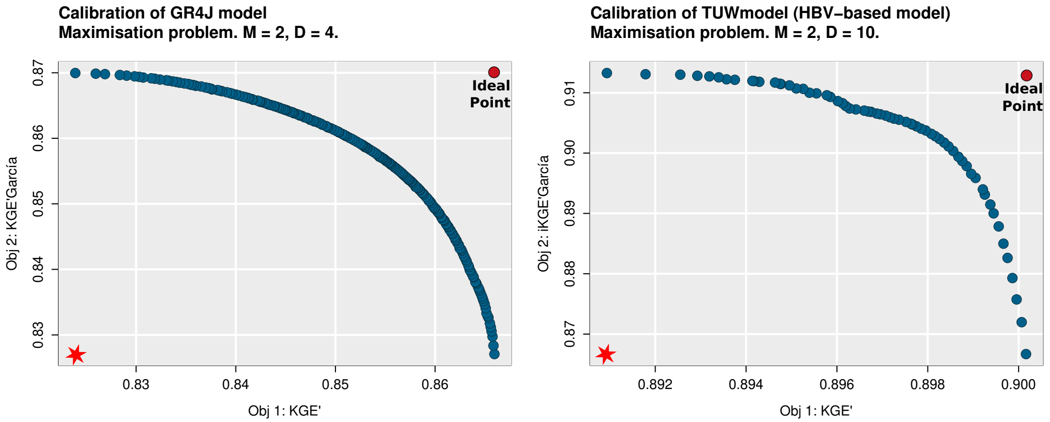
DTLZ2 problem
Minimisation problem. M = 3, D = 12.



DTLZ3 problem
Minimisation problem. M = 3, D = 12.

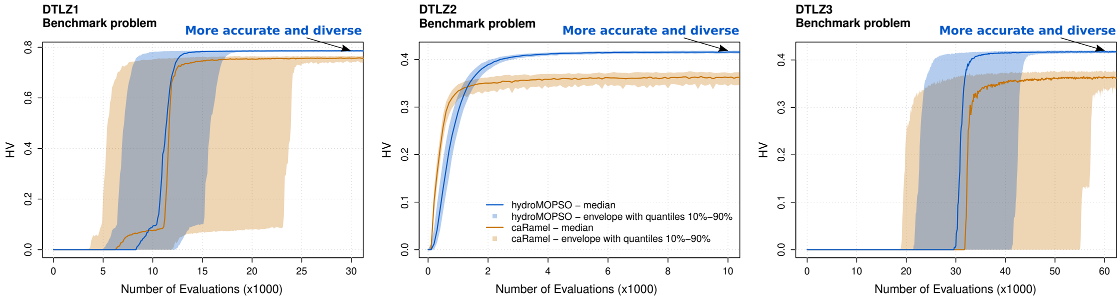


Pareto Optimal Front - Hydrological models



- The true POF is unknown for the optimisation of hydrological models.
- The true POF was **estimated** using `hydroMOPSO` with thousands of iterations. To corroborate, we also use `caRamel`, another R-packge package for MOC.

Hypervolume (HV) - Benchmark functions



All problems were solved with two hundred different initialisations, with each method.

`hydroMOPSO` **vs** `caRamel`:

- `hydroMOPSO` achieves a higher HV than `caRamel` → **POF more accurate and diverse**.
- `hydroMOPSO` requires **less model runs** than `caRamel` to achieve the best HV .

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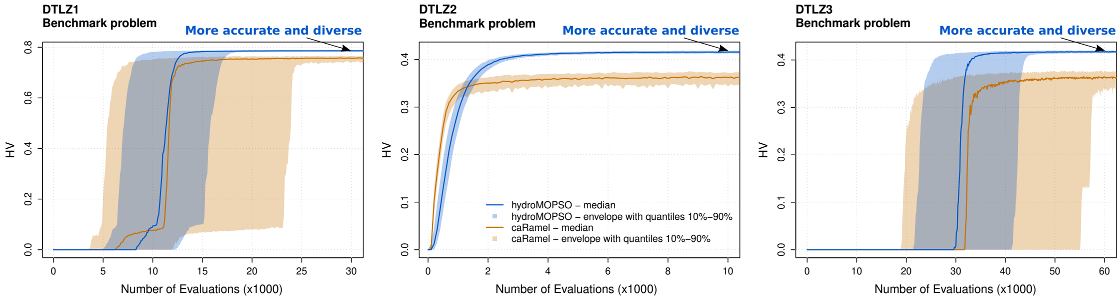

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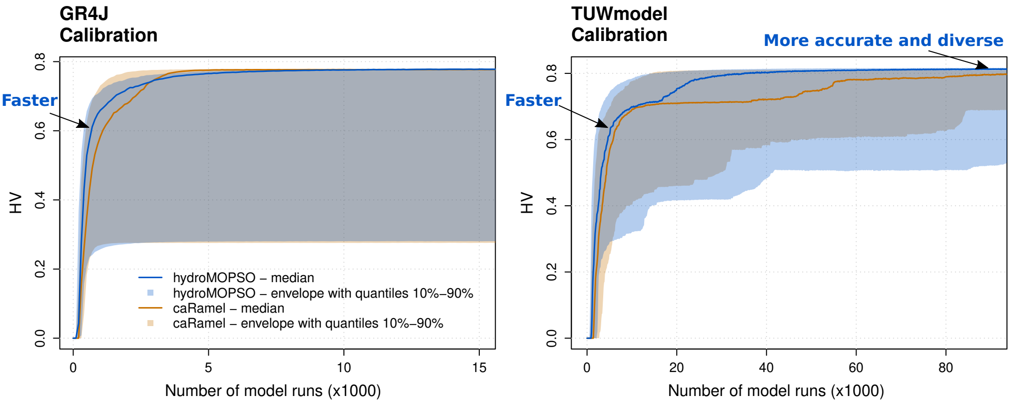

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- For **GR4J**, both algorithms achieve a similar and high HV value, but `hydroMOPSO` **converges faster**.
- For **TUWmodel** `hydroMOPSO` achieves a **higher HV** than `caRamel`, with a **higher accuracy and diversity**.

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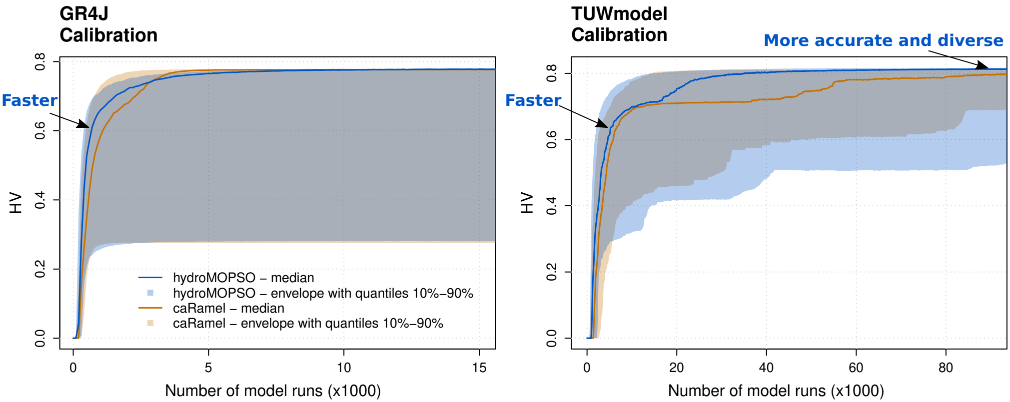

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Conclusions and ongoing work

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- hydroMOPSO was able to **effectively solve** three well-known DTLZ benchmark optimisation problems.
- hydroMOPSO was more efficient and more effective than caRamel in optimising two hydrological models (GR4J, TUWmodel).

Ongoing work

- hydroMOPSO will be soon available on GitLab and CRAN.
- Manuscript is ongoing.
- Upcoming vignettes (tutorials): **TUWmodel**, **GR4J**, **SWAT+**, **Raven** platform, **WEAP**, ...

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Thank you very much for your attention!

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