## Authors’ Response to Editors/Reviewers of

# SMASH v1.0: A Differentiable and Regionalizable High-Resolution Hydrological Modeling and Data Assimilation Framework

*GMD,*

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**RC:** ***Reviewers’ Comment***, AR: Authors’ Response, ☐ Manuscript Text

Dear Editors and Reviewers,

We greatly appreciate your time and effort in handling our manuscript. We extend special thanks to the reviewers for their thorough and constructive comments, which have significantly improved our work. Below, we provide a point-by-point response addressing the reviewers’ concerns.

We hope these revisions have strengthened our manuscript and made it more suitable for publication in GMD.

François Colleoni and Pierre-André Garambois, on behalf of the authors.

## 1. Reviewer 1

### 1.1. General comments

**RC:** ***I appreciate the authors’ efforts in addressing my previous comments. I found most of my comments were well addressed. I recommend a minor revision with following additional comments for the authors to consider.***

AR: Thanks

### 1.2. Comment

**RC:** ***Why 350 integrations is used for calibration?***

AR: The number of 350 iterations was somewhat arbitrary, chosen during the regionalization process using a neural network. The optimization algorithm employed does not rely on other stopping criteria besides the maximum number of iterations. In our case and based on our experiments and the behavior of the loss descent (Huynh et al., 2024b), this value was set to 350, which is sufficiently high to allow the optimizer to reach a reasonable level of convergence (Figure 1).

**RC:** ***I cannot agree with the authors. Routing scheme can be fully parallelized over the entire spatial domain. A well paralleled river routing model does not need to be solved in a sequential manner from upstream to downstream.***

AR: The sentence suggesting that full spatial parallelization is not possible will be revised to clarify that this limitation applies specifically to the routing model implemented in our case. We would be grateful if you could suggest us a more efficient routing approach.

> Although the time-stepping loop cannot be parallelized, and the routing scheme in `smash` must be solved sequentially from upstream to downstream, allowing only partial parallelization over the entire spatial domain, the approach still offers a substantial reduction in computation time.

**RC:** ***I cannot agree with this response. It is critical to compare the calibrated model with the default model with***

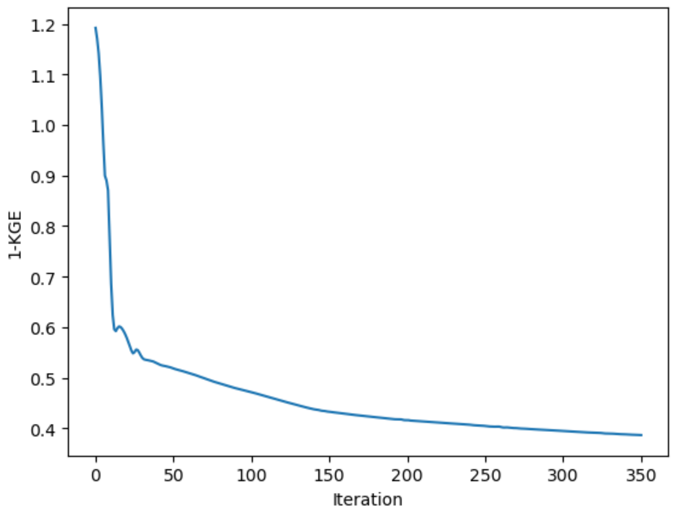


Figure 1: The descent of the cost function for the CONUS case.

***default (not uniform calibration) parameter values. If there is no improvement from default parameters to calibrated parameters, then why spending efforts on make the model differentiable? I highly suggest the authors to report the performance of default model.***

AR: A conceptual model is only meaningful when properly calibrated. `smash` does not include physically valid default parameters, but instead uses numerical defaults only to ensure proper initialization. Model performance is systematically improved when calibrated parameters replace these initial values. To our knowledge, there are no hydrological modeling studies based on fully conceptual models that compare the performance of calibrated parameters versus "default" parameters. We do not believe that including such a comparison would add value to the article. However, a boxplot showing the performance with "default" parameters is provided in Figure 2. Moreover, although not explicitly mentioned in the paper, the spatially uniform calibration does not require the use of the adjoint model. Optimization is performed using a gradient-free optimizer (few details can be found here here). For this reason, we define the spatially uniform calibration as our performance baseline.

- Uniform: spatially uniform parameters (gradient-free optimization)
- Distributed: spatially distributed parameters (gradient-based optimization)
- Multi-Linear: a multiple linear regression is used as transfer function from descriptors to spatialized parameters (gradient-based optimization)
- ANN: a multi-layer perceptron composed of 3 hidden layers is used as a transfer function from descriptors to spatialized parameters (gradient-based optimization)

**RC:** ***In this case, it is not non-inertial shallow water model. It is confusing.***

AR: You are right — there was a mistake in our previous response and in the manuscript. We plan to implement a dynamic wave model that neglects the convective acceleration term, but retains local acceleration and pressure gradient terms (Bates et al., 2010). We will clarify this point in the revised version to avoid confusion.

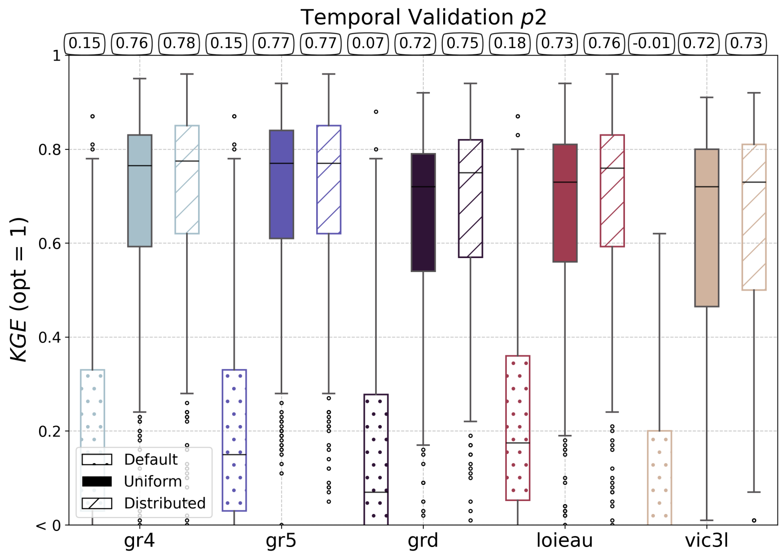


Figure 2: Comparison of the Kling-Gupta Efficiency ($KGE$) performance of different smash hydrological models with spatially uniform "default" parameters, spatially uniform and distributed calibrated parameters.

> Further work focuses on enriching `smash` with hydraulic models, starting with 1D and 2D dynamic wave model that neglects the convective acceleration term, but retains local acceleration and pressure gradient terms (Bates et al., 2010) for numerical implementation simplicity.

**RC:** ***My concern is that it is challenging to rewrite a complex hydrological model in a differential form. I am not aware of any example of differentiable model for complex hydrological models. Then the issue is why we need differentiable model for simplified hydrological model, which is computational cheap and can be easily run tens of thousands of times for calibration. It will be helpful for the authors to add some discussion on this limitation.***

AR: We agree that, for simple hydrological models with only a few parameters, making the model differentiable may not be essential. In such cases, parsimonious models with uniform spatial parameters, calibration in low-dimensional settings can be performed efficiently using optimization algorithms that do not require gradient information or through sampling-based approaches. However, when moving towards spatially distributed calibration or regionalization using neural networks (requiring gradients of spatially distributed model parameters (Huynh et al., 2024b), the situation changes significantly. These approaches typically involve high-dimensional optimization problems, with potentially several thousands of parameters (e.g., in the case studies presented in this article, the number of parameters reaches 8,774 and 4,613 for the CONUS and Aude cases, respectively). In such contexts, exhaustive sampling of the parameter space becomes computationally challenging, whereas adjoint-based methods are well suited for computing accurate cost function gradients with respect to large parameter vectors, enabling efficient gradient-based optimization. This approach is particularly effective for complex models with high-dimensional parameter spaces. We will include a discussion in the manuscript to clarify this point.

The differentiability of the forward numerical model is a key enabler for gradient-based optimization of high-dimensional parameter vectors. For example, in variational data assimilation for 1D or 2D hydraulic models (Monnier et al., 2016; Brisset et al., 2018), or in spatialized hydrology (Castaings et al., 2009; Jay-Allemand et al., 2020). While differentiability may appear unnecessary for simple lumped hydrological models with only a few parameters, where sampling-based calibration or gradient-free methods remain efficient, the situation changes drastically for spatially distributed models involving thousands of parameters. In such high-dimensional settings, exhaustive sampling becomes computationally infeasible. Numerical differentiability enables the computation of accurate gradients of the cost function or model outputs with respect to high-dimensional parameters, thereby facilitating the use of efficient gradient-based optimization methods. This is particularly important when coupling physical models with neural networks requiring accurate gradients, as demonstrated in recent work on learnable regionalization (Huynh et al., 2024b) and internal flux correction (Huynh et al., 2024a) within a spatially distributed model, with large-scale evaluations in (Huynh et al., 2025). These approaches rely on numerically differentiable solvers and accurate gradients enabling to train thousands of parameters effectively. This perspective aligns with Shen et al. (2023), who emphasizes the importance and potential of differentiable modeling in geosciences, highlighting how it can enhance learning, inference, and integration of physical knowledge within hybrid modeling frameworks.

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