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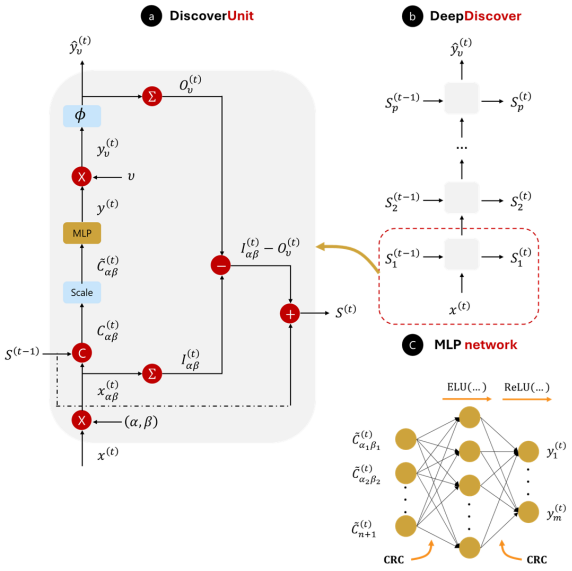
Towards Autonomous Physics Discovery of Reservoir-Type Earth System Models

ADOUBI VINCENT DE PAUL ADOMBI
University of Quebec at Chicoutimi

Modeling complex Earth systems often relies on mechanistic formulations that encode prior physical knowledge into predefined model structures. These approaches provide interpretability and physical consistency but may introduce structural biases when imposed formulations do not fully reflect system-specific dynamics. In parallel, data-driven models offer flexibility and predictive power, yet often lack interpretability and physical grounding. Hybrid physics-AI frameworks within Scientific Machine Learning (SciML) have sought to combine these strengths, but most remain built upon fixed conceptual structures defined a priori [1]. This work addresses a key limitation in current SciML approaches: the absence of methods that enable the autonomous discovery of model structure under explicit physical constraints. We introduce DeepDiscover, a framework designed to learn reservoir-type dynamical systems directly from data while enforcing conservation laws, causal consistency, steady-state balance, and process decorrelation [2]. Unlike hybrid models that embed prescribed governing equations, DeepDiscover allows internal process representations and reservoir interactions to emerge from data within a constrained and differentiable architecture. As a proof of concept, the framework is evaluated on 569 catchments from the CAMELS-US dataset in a regional daily streamflow modeling experiment. The inferred internal states and processes exhibit strong functional consistency with established conceptual models despite the absence of imposed equations. Controlled perturbation experiments further demonstrate physically coherent responses to variations in climatic forcing, indicating that the learned dynamics respect conservation principles rather than acting as purely statistical mappings. While DeepDiscover does not yet extract closed-form symbolic equations, it demonstrates that structural inference of physically consistent reservoir-type systems is feasible within a physics-constrained learning paradigm. These results position the framework within the physics discovery branch of SciML and suggest a pathway toward more autonomous, interpretable modeling of complex Earth and environmental systems governed by interacting reservoirs.



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[1] Adombi, A.V.D.P., 2025. Scientific machine learning in hydrology: a unified perspective. Earth Science Informatics, 18(4): 522. DOI: https://doi.org/10.1007/s12145-025-02021-6

[2] Adombi, A.V.D.P., 2026. DeepDiscover: towards autonomous discovery of bucket-type conceptual models – a proof of concept applied to hydrology. Journal of Hydrology, accepted.