Enhanced model parameter transferability to ungauged catchments through regionally constrained calibration

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Abstract: Accurate hydrological prediction in ungauged catchments remains an enduring challenge, primarily due to the difficulty of transferring parameters across diverse basins. Conventional calibration practices often result in parameter sets that can reproduce observed flows but are of limited transferability to ungauged catchments. This work develops a framework that emphasizes regional consistency during calibration and constructs parameter transfer models, with the goal of strengthening parameter transferability and improving predictive ability in data-scarce areas.

The framework involves three main steps. First, a regional calibration (RC) is performed to establish physically plausible, region-specific parameter sets by jointly calibrating groups of catchments that share similar hydroclimatic characteristics (i.e., in the same precipitation zone), thereby promoting regional consistency across basins. Second, a regionally constrained individual calibration (RIC) is conducted for each catchment, with the goal of retaining local characteristics while mitigating equifinality; this is achieved by incorporating an RC-informed objective function that constrains the parameter search space. Third, to enable parameter prediction in ungauged catchments, machine learning-based transfer models are developed to map physiographic and climatic descriptors to the RIC-calibrated parameters. Moreover, to improve interpretability and ensure the mappings remain physically grounded, SHAP (Shapley Additive Explanations) is used to quantify the relative importance of each descriptor, highlighting the dominant physical controls on parameter variability.

The framework is tested with the Dynamic Water Balance Model (DWBM) across 399 Australian catchments representing a wide spectrum of climate regimes. Input data include multi-decadal daily observations of precipitation, temperature, and discharge, along with descriptors of topography, soils, vegetation, and indices of rainfall seasonality. Evaluation considers parameter consistency and identifiability, the cross-validated accuracy of attribute–parameter regressions, and predictive skill and uncertainty in ungauged simulations.

Results indicate that the RIC yields more consistent parameter distributions while preserving inter-catchment variability, with interquartile ranges of parameter distribution reduced by nearly 50%. Parameter transfer models trained on RIC parameters exhibit robust and physically meaningful relationships with catchment attributes, as reflected in elevated cross-validated R^2 values. When applied to ungauged catchments, RIC-based parameter transfer models outperform unconstrained baselines, achieving higher median efficiency (KGE = 0.70 compared with 0.66), reduced absolute bias (17% compared with 20%), and tighter uncertainty bounds, with uncertainty interval widths shortened by about 25% while maintaining acceptable coverage. SHAP identifies rainfall seasonality (amplitude and timing) as the primary control on model parameters in the study area, enhancing the understanding of hydrological response and reinforcing the physical plausibility of the learned mappings.

This study shows that regionally constrained model calibration improves both the realism and transferability of hydrological parameters. The framework enables physically consistent and interpretable parameter transfer, offering a reliable method for streamflow prediction in ungauged catchments.

Keywords: *Ungauged catchments, streamflow prediction, parameter transfer, regional consistency, explainable machine learning*