



## **Prediction under change: invariant model parameters in a varying environment**

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Hydrological understanding is commonly synthesised into complex mechanistic models, some of which have become “as inscrutable as nature itself” (Harte, 2002). Parameters for most models are estimated from past observations. This may result in an ill-posed problem with associated “equifinality” (Beven, 1993), in which the information content in calibration data is insufficient for distinguishing a suitable parameter set among all possible sets. Consequently, we are unable to identify the “correct” parameter set that produces the right results for the right reasons. Incorporation of new process knowledge into a model adds new parameters that exacerbate the equifinality problem. Hence improved process understanding has not necessarily translated into improved models nor contributed to better predictions.

Prediction under change confronts us with additional challenges:

1. Varying boundary conditions: Projections into the future can no longer be guided by observations in the past to the same degree as they could when the boundary conditions were considered stationary.
2. Ecohydrological adaptation: Common model parameters related to vegetation properties (e.g. canopy conductance, rooting depths) cannot be assumed invariant, as vegetation dynamically adapts to its environment.
3. No analog conditions for model evaluation: Climate change and in particular rising atmospheric CO<sub>2</sub> concentrations will lead to conditions that cannot be found anywhere on Earth at present. Therefore it is doubtful whether the ability of a hydrological model to reproduce the past is indicative of its trustworthiness for predicting the future.

We propose that optimality theory can help addressing some of the above challenges. Optimality theory submits that natural systems self-optimize to attain certain goal functions (or “objective functions”). Optimality principles allow an independent prediction of system properties that would otherwise require direct observations or calibration. The resulting reduction of the parameter space and hence reduced need for calibration data frees up information that can be used for independent model testing and falsification. Different examples of application of optimality to constrain predictions will be given and the potential to learn from a wrong prediction will be discussed.