



Measuring complexity of a spatially explicit hydrologic model for use in parsimonious model building

S. Pande (1), L. Bastidas (2), and M. McKee (2)

(1) Center for World Food Studies, (SOW-VU), VU University Amsterdam, Netherlands (s.pande@sow.vu.nl), (2) Utah Water Research Laboratory, Utah State University, Logan, Utah, USA

We measure complexity of a spatially-explicit conceptual hydrologic model for use in adaptation of model complexity to available data based on Vapnik-Chervonenkis (VC) generalization theory. It fills a gap in quantification of nonlinear hydrologic model complexity as the concept of using its number of parameters for complexity applies generally to linear models. Recently, many studies have used Support Vector Machines (SVMs) in hydrologic modeling, which in turn are based on VC generalization theory. The attraction of using such methods is that it chooses the simplest of “equally better” performing models on a given sample of data, thus formalizing the concept of “parsimonious model building”. However, none of these studies have used either physically based or conceptual hydrologic models – the bottleneck being calculation of complexity of distributed hydrologic models within the framework of VC theory. We here provide analytical bounds on a complexity measure called “covering number” for hydrologic models and show its use in a parsimonious model building approach. We begin with a bucket model with a single reservoir, calculate its complexity, then represent a spatially explicit (or distributed) conceptual model by a network of interconnected reservoirs, and calculate its complexity. We observe that complexity of spatially explicit hydrologic models not only depend on how much spatially distributed it is, but also on the structure of its connectivity, and magnitude of its parameters. For example, we find that a slower reservoir is more complex than a faster one in a single reservoir case. These observations are of relevance in parsimonious model building efforts such as parameter regionalization. We finally show how this measure of model complexity can be adapted to a given sample of data based on bounds on uniform convergence of empirical error (error in prediction calculated on given sample data) to expected error (expectation of empirical error).