Hydrol. Earth Syst. Sci. Discuss., 10, C895–C898, 2013
www.hydrol-earth-syst-sci-discuss.net/10/C895/2013/

Hydrology and Earth System Sciences Discussions

Interactive comment on "Legitimising neural network river forecasting models: a new data-driven mechanistic modelling framework" *by* N. J. Mount et al.

N. J. Mount et al.

nick.mount@nottingham.ac.uk

Received and published: 17 April 2013

We are grateful to Professor Solomatine for his positive remarks and his recognition of the important step forward that our paper makes. He is correct in his understanding that our paper develops a new data-driven, mechanistic modelling framework and uses a novel relative sensitivity analysis as the basis for sensitivity explorations we undertake within it. However, we are concerned that there may be some confusion / misunderstanding about the purpose of the framework, our application of sensitivity analysis, and how it relates to the two distinct (but linked) issues of 'mechanistic legitimacy' and 'physical legitimacy'. Indeed, we note that his only significant criticism is that our use

of the sensitivity analysis does not go far enough, and that we should be attempting to 'reveal the physics' of the model rather than just legitimise its mechanics. As a result, Professor Solomatine suggests that the use of a more complex rainfall-runoff model would be of benefit to the paper.

It is clear from these comments, and to some extent those of Reviewer 1, that our arguments about what legitimising a model involves needs further clarification. This has been achieved in our revised paper. A general overview can be developed from the literature surrounding hydrological model verification (which we now include in our revised manuscript), in which two distinct but linked notions of model legitimacy exist: mechanistic legitimacy and physical legitimacy (Figure 1). The two are subtly different: i.e. the general sensibility of the model's internal structure and behaviour patterns does not necessarily equate to the extent to which they can be shown to map to the physical processes that are anticipated within a given catchment.

Mechanistic legitimacy is concerned with the structure and mechanistic behaviour of a model, and can be usefully evaluated in purely mechanistic terms. A great deal of work has been focussed on structural elements of ANN (see Reviewer 1, comments 3-4 to which our revised paper has responded). However, very little has focussed on elucidating and interpreting mechanistic behaviours (i.e. via examination of the magnitude, stability, continuity and coherency of the response function). These mechanistic behaviours are particularly important as they can reveal useful information about a model irrespective of any efforts to interpret them physically. This makes them potentially powerful as a means of discriminating between models in catchments for which physical process knowledge is scant. It means that they are a valuable means of supporting model selection above and beyond goodness-of-fit metrics. For example, an ANN response function that displays low continuity is likely to be indicative of over-fitting. This is an important mechanistic characteristic of a model that will not be detected via goodness-of-fit, and that reduces the legitimacy of the model. It is, however, a characteristic that does not necessarily have any direct physical interpretation. Thus, we have purposely avoided conflating mechanistic and physical legitimacy in our paper and argue that understanding a model's mechanistic legitimacy is an important objective in its own right whilst also forming an essential pre-cursor to determining its physical legitimacy.

Given this stance, and the fact that the ideas surrounding the mechanistic legitimacy of models will be unfamiliar to many data-driven modellers, we have purposefully chosen to exemplify our framework in the simplest possible manner using the most appropriate models. We thus use ANN models whose structure and internal mechanistic behaviours can be very easily presented and understood by the reader, and that do not lend themselves to a detailed, physical interpretation (i.e autoregressive forecasting offers limited scope for examination of physics). This ensured that we could clearly establish the role of mechanistic legitimacy in data-driven modelling, and explore the interpretation of the characteristic relative sensitivity patterns that are associated with it, in their own right.

We agree with the Editor that by focussing solely on mechanistic legitimacy in this way, the paper has not demonstrated the potential of the DDMM framework and the sensitivity analysis approach that underpins it with respect to physical legitimisation of models. We also agree that a more complex rainfall-runoff model would be a good way in which to do this. However, this paper is already substantive and presents numerous subtle but important ideas about model legitimacy that are missing from existing literature and that have been commended by Reviewer 1. To try to add in alternative models and additional interpretations of physical legitimacy would risk making the value of these arguments less clear, not more. We therefore argue that the use of our framework to assess a model's physical legitimacy – perhaps using the example of a rainfall-runoff model – would be better undertaken in a separate, follow-on paper, which we would be delighted to generate.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 10, 145, 2013.

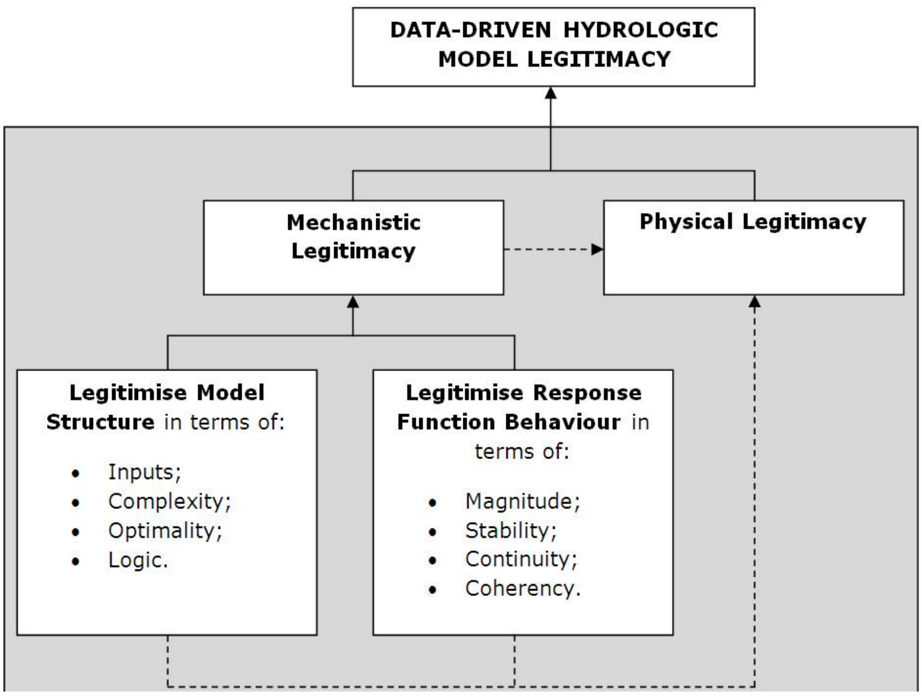

Fig. 1. Figure 1. Elements of hydrological model legitimacy.