

Interactive comment on “Exploring the impact of forcing error characteristics on physically based snow simulations within a global sensitivity analysis framework” by M. S. Raleigh et al.

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Received and published: 8 January 2015

Raleigh et al. present an interesting attempt to systematically determine how uncertainty in forcing data influences uncertainty in snow simulations. Some of their conclusions seem quite obvious (biases are more significant than random errors, and uncertainty in measured precipitation is the most important factor), but a large effort is often required to demonstrate things that appear obvious with hindsight in hydrological modelling. The increased sensitivity to biases when random errors are introduced is a striking result, however, and there should be more exploration of how this arises.

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I am slightly concerned about how the error distributions have been assigned. It is variances in model outputs that are examined but ranges in model inputs that are specified. The variance of a uniform distribution is larger than a normal distribution over the same range, so these scenarios are not really comparable. It is not clear, in any case, how the ranges given in Table 3 determine the means and variances that would characterize the normal and lognormal distributions. Can this be clarified?

Uncertainty in measurements of snowfall is certainly a major concern, but the upper bound chosen for precipitation biases in the model forcing (+300%) is enormous – much bigger than the stated error of less than 20% of peak SWE for most SNOTEL sites. The reason given for choosing this large uncertainty is to represent areas with drifting snow, but I would argue that the neglect of drifting snow is a missing process in the model, not an uncertainty in its forcing.

Specific comments:

page 13749, line 25 SWE is measured at Col de Porte using a cosmic ray detector, not a snow pillow.

13750, 5 How was reasonable representation of observed SWE judged?

13751, 18 It could be made clear at this stage that normal distributions are used for additive errors and lognormal distribution for multiplicative errors.

13752, 3 In contrast, data assimilation techniques often address random errors that are assumed to be unbiased.

13755, 1 Overview of what?

13756, 12 “due to bias in forcing”

13757, 15 “For all cases, final STi values were generally close ...” sounds a little contradictory; were they all close, or generally close?

13758, 20 Non-physical values would be less common if multiplicative perturbations

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were applied to all forcing variables that cannot be negative, not just precipitation.

13761, 8 Can differences in which variables are of secondary importance be linked to differences in climate at the sites?

13762, 3 It is not so surprising that Q_{li} biases are more important than Q_{si} biases because of the high albedo of snow.

13765, 11 Please consider doi:10.1029/2010EO450004

13766, 2 Note that “constraining P uncertainty in snow-affected catchments” is the aim of WMO-SPICE <http://www.rap.ucar.edu/projects/SPICE/>

13766, 10 Probabilistic forcing is a common and long-standing approach in data assimilation

The forcing error scenarios are described in Figure 1, Table 3 and section 3.2. Is the figure really necessary?

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 11, 13745, 2014.