Hydrol. Earth Syst. Sci. Discuss., 5, S2639–S2642, 2009
www.hydrol-earth-syst-sci-discuss.net/5/S2639/2009/
© Author(s) 2009. This work is distributed under
the Creative Commons Attribute 3.0 License.

Hydrology and Earth System Sciences Discussions

Interactive comment on "Mapping model behaviour using Self-Organizing Maps" *by* M. Herbst et al.

M. Herbst et al.

Received and published: 7 March 2009

The authors greatly acknowledge the constructive work of the reviewers which allowed us to submit an improved and partly more comprehensible version of the original manuscript. In the following we briefly discuss their main issues of concern:

Referee#4: Suggests adding an extra figure that reveals more details on the relationship between different objective functions (Signature Indices), in particular in order to elucidate potential trade-offs which are supposed to exist between objective functions (Signature Indices) that are sensitive to the high flow and low flow segments of the hydrograph.

Authors: Commonly, dependencies between more than two variables are visualized and detected using scatterplot matrices. For n variables this requires N = $(n^2 - n)$ / 2 single scatterplots (omitting the diagonal and everything below it). Thus, in our case with n = 5 we yield 10 scatterplots, which is still a quite tractable amount of information (unfortunately it was not possible to include the figure in this comment). Irrespective of its analytical qualities, using scatterplots beyond this relatively low number of variables quickly gets impractical.

One of the standard applications of SOM is correlation hunting by means of the component plane visualization (see e.g. Kaski, 1997). Because the SOM provides a clustering of a multi-dimensional data set the component planes visually allow detecting dependencies between its constituent variables which reveal themselves in correspondences or contrariness of colour patterns. Although being less analytic with respect to the type of relationship between two variables (e.g. negative linear, exponential etc.) the visualization of the SOM fully benefits from our facility to discern coloured patterns which are presented on a two-dimensional plane. Most notably, the required number of component planes only grows linearly (i.e. $N = n$) with the number of variables. For example, the corresponding patterns of *%BiasFDC* and *%BiasFHV* in Fig. 1 of the paper make clear that these variables grow proportionally (and probably with a similar 'gradient') whereas *%BiasFMM* behaves exactly the opposite way. Something quite similar can be stated with regard to *%BiasRR* and *%BiasFLV*, although the relationship might be less pronounced in this case. When comparing Fig. 1 of the paper with its corresponding scatterplot matrix we don't think that the latter offers much more information, at least in the context of our study. Thus, we prefer not to include it in the paper.

Referee#4 suggests including more information on the comparison (of the Signature Indices) with conventional objective functions, e.g. RMSE and including an additional plot in Fig. 1, 2 and 6 that would serve this purpose.

Authors: In Herbst and Casper (2008) it has also been our intention to reveal the relationship between the ordering structure of a SOM (which was trained on entire sim-

HESSD

5, S2639–S2642, 2009

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Discussion Paper

ulated discharge time series) and a variety of statistical performance measures. To this end, we used a colour-coding of the SOM nodes according to the mean values of different performance measures that correspond to the simulation results attributed to each node (see Fig. 2 in Herbst and Casper, 2008). The authors agree that a similar visualization would bridge a gap to the first paper. Correspondingly, we calculated the mean values of four statistical performance measures (RMSE, Nash-Sutcliffe coefficient of efficiency – CEFF, Willmott's Index of Aggreement – IAg, and the correlation coefficient R^2) for the model results attributed to each node of the SOM. The resulting plot is now included as Fig. 6c. Not surprisingly, it shows that the ordering structure of the Signature Index SOM is still reflected in the ordered pattern of the four statistical objective functions which, additionally, show (the expected) close correlations. However, according to Fig. 2, 6b and 6c, it is not possible to establish a clear relationship between the Signature Indices and the performance measures. With regard to the position of the optima on both mappings, it can be seen that the BMU in Fig. 6b does not coincide with the optima of the performance measure in Fig. 6c. These findings suggest that a SOM trained on these statistical performance measures would have extracted less independent 'information' from the model data (note that the information extracted by these measures is hardly meaningful in the hydrological context; see Gupta et al., 2008). This leads us to the conclusion that, with very high probability, the results for the BMU of a SOM trained on these measures would have displayed different time series characteristics in comparison to the results given in Fig. 7a.

Referee#4 suggests including the SCE-UA results in Fig. 9

Authors: We agree that it is also interesting to compare the SCE-UA result and the BMU results in terms of Signature Indices. Accordingly, the SCE-UA result was included in Fig. 9.: It displays Signature Index properties that are very similar to both of the aforementioned BMU realizations. Interestingly, the SCE-UA results perform slightly worse with respect to *%BiasFHV* and markedly better with respect to *%BiasFLV*, compared to most of the BMU realizations. In any case, this result still does not

HESSD

5, S2639–S2642, 2009

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Discussion Paper

allow inferring that, relative to a BMU solution, minimizing the RMSE will always lead to a ‘better’ *%BiasFLV* while simultaneously cutting back on *%BiasFHV* performance. According to Fig. 6c and 6b the results for *%BiasFLV* are supposed to deteriorate towards the position of the RMSE optimum which lies roughly three map units above the BMU.

Referee#4 would like the authors to stress that the simulations provided by the BMU of a SOM trained on Signature Indices outperform the simulations obtained from a SOM of time series data in term of the *%BiasFLV* metric.

Authors: We agree that this is a detail that should be mentioned and which is supported quite well by other results: The comparison of Fig. 6a and 6b as well as Fig. 9 suggests that the SOM trained with time series data and the SOM based on Signature Indices most notably differ with respect to the representation of the long-term behaviour of the system.

Referee#4 suggests including the references to the papers by Reusser et al. (2009) as well as Abramowitz et al. (2008).

Authors: We agree that these papers present highly relevant work in this field and will be included in our reference list. At the time when the original manuscript of our present paper was submitted to HESSD these studies were still not available or still not known by the authors.

Referee#4 suggests rewording the first sentence of the abstract.

Authors: In the final version of the paper this sentence will be slightly modified.

HESSD

5, S2639–S2642, 2009

Interactive Comment