

Interactive comment on “A multi-model ensemble method that combines imperfect models through learning” by L. A. van den Berge et al.

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Received and published: 6 December 2010

Response to interactive comment #1 on “A multi-model ensemble method that combines imperfect models through learning” by L.A. van den Berge et al.

(1) The first statement of the reviewer concerns the observation that by linking similar nonlinear model equations major changes in the dynamics might occur.

We agree that the supermodel is not merely a sort of average system, and that, depending on the connections, it can have a very different dynamics. However, we don't see this as a problem but rather as a feature of the approach. The supermodel has the potential to outperform the ensemble averaged simulations of the individual models just because it can display richer dynamical behavior. The learning must ensure that

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the behavior after learning is indeed more realistic.

The idea of the supermodel is that it is a model that has on the one hand sufficient degrees of freedom so that a better model is obtained (compared to averaging) after learning, while on the other hand, since the supermodel is constrained by the individual models, it needs less additional degrees of freedom than e.g. a free-form neural network approach to get close to reality. The degrees of freedom in the latter approach are so immense that successful modeling of high dimensional systems cannot be expected.

(2) The reviewer goes on to caution that beyond the training data, there might be a bifurcation that does not fit the model.

We agree that this might happen. However, in the example of the Lorenz 1963 model we verified that the supermodel accurately described the response of the system to a doubling of one of the parameters. In addition we argue that in the application to climate models we do not expect large qualitative changes in the dynamics. The atmosphere operates in a turbulent regime and so far the state-of-the-art climate models simulate a response to increasing concentrations of greenhouse gases that is characterized by significant changes in the mean, but much harder to detect changes in the variations around the mean. In other words, the probability density functions of most climate variables just shift with the mean without much change to the shape.

(3) The reviewer warns that long term predictions might not be possible.

When talking about predictions, one must be precise about what is being predicted. Long term predictions of the actual state are inherently limited due to chaos, but might improve since the super model is trained to stay close to reality for a short period. What might be predictable on the long term, is the change in certain aspects of the probability density function of climate variables, like the mean, variance, due to a change in an external factor, like increased emissions of greenhouse gasses. We agree that the supermodel is not guaranteed to show improved skill in this aspect, since it was not

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trained specifically to simulate the response to such a change. However, in case of the Lorenz 1963 model, the supermodel did simulate a realistic response to a doubling of one of the parameters.

(4) The reviewer remarks that the minimum strength of the nudging term that is required to achieve synchronization with the truth is probably not so much a measure of the model accuracy, but more a measure of the stability of the model.

We agree and indeed verified this in the paper by calculating the probability density function of the distance between model and truth for a nudging strength of $n=6$ in figure 8 for both super model solutions of the Lorenz 1963 system. The more accurate model 2, that has a lower value of the cost-function, statistics closer to the truth and more accurate auto-correlation values, remains most of the times closer to the truth when coupled to the truth with strength $n=6$, but it has a higher probability of exceeding a distance of 4 than model 1 and therefore needs a higher nudging strength of $n=13$ to remain synchronized according to Definition 1 than model 1.

(5) The reviewer warns that combining models with coupling may actually produce a worse model than the individual models.

Indeed it may, but see our reply to (1), and, in addition, at least in the neighborhood of the data, the short term evolution will be improved compared to the imperfect models.

(6) We thank the reviewer for his reference to the Quin et al 2009 paper in which an alternative learning approach is implemented. A similar cost function is minimized by varying parameters and the initial state of a single model simulation with an additional nudging term to the truth that allows the model to synchronize with the truth during the learning. Our approach is different in that we consider an ensemble of short model simulations from different initial states, do not nudge to the truth and only vary the parameters and not the initial state to minimize the cost function. The parameters in our case are the connection constants of the super model, while Quin et al varied the parameters of a single model. But their approach can also be applied as an alternative

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learning strategy for the connection constants of the supermodel using observed time series.

Interactive comment on Earth Syst. Dynam. Discuss., 1, 247, 2010.

ESDD

1, C129–C132, 2010

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