

Interactive comment on “Combining Ensemble Kalman Filter and Reservoir Computing to predict spatio-temporal chaotic systems from imperfect observations and models” by Futo Tomizawa and Yohei Sawada

Anonymous Referee #1

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Major comments:

Section 2.4 "Combination of RC and LETKF" is the scientific innovation that is at the core of the paper, however the authors only explore the idea in a purely textual form. Some equations comparing the three methods (RC-Obs, RC-Anl, LETKF) or perhaps a diagram would be immensely beneficial to the average reader, as that will be more eye-catching, and would help explain the papers innovation.

Section 3 "Experimental Design" mention the parameters used to construct the RC

C1

network, however motivations for the choices are lacking, and would help potential follow-up works, including those by practitioners to intuit logical choices.

Equation (15) represents Gaussian kernel localization, however this is not explicitly mentioned, which seems very strange, as a reader familiar with data assimilation literature would be more familiar with that framing of the method. Additionally, such applications are typically done on the inverse of the matrix R (which is also explicitly taken to be diagonal), through a Woodbury matrix identity application, though such details are glossed over in the text.

The strangest thing is the choice of $m = 8$ for the experimental design. The standard L96 with $m = 40$ variables is known to be very chaotic and have 13 positive Lyapunov exponents. In that regime, a lot is known about the system. However as far as the reviewer can tell, the case of $m = 8$ has to be weakly chaotic by necessity. It would be of benefit to the casual reader (and the reviewer) to state some facts about this regime of the system.

The reviewer wonders if for such a small system it might have been of benefit to examine the more rigorously studied 3-variable Lorenz system, for which a lot is known, in terms of reservoir computing, data assimilation, and general nature of the system. The same type of sparsity experiments could be performed with such a system.

Section 4 "Results" contains a statement to the effect of "if 'e' is set to zero then the LETKF does not work". This is technically true, but very misleading. Take the Kalman filter formula with perfect and full observations $x^a = x^f - (x^f - y^o) = y^o$. Under the regime of perfect observation ($e = 0$, $H = I$), and Kalman filter would replace the analysis by the observations, and collapse the distribution of the uncertainty about the analysis. This means that in this regime, the LETKF would replace each ensemble member by the observations, even if a particular implementation would fail. It would make sense to—instead of using the LETKF—to simply look at the predictive regime of the RC-Obs. The $e = 0.01$ is entirely unnecessary.

C2

The choice of which indices are observed in such experiments is not given as far as the reviewer can tell.

In section 5 "Discussion" the authors mention the generalization of their methodology to other dynamical systems. The authors focus on the generalization to "higher dimensional systems" as their main worry. The reviewer believes that another more substantial worry is that Lorenz '96 is known to be ergodic, while most systems used for NWP are possibly not, (the authors mention the KS system, but that is also possibly ergodic for well-posed initial conditions). It would be of benefit to mention other possible shortcoming on testing only on the Lorenz '96 system.

Technical comments:

L14: "are recently" to "have been recently"

L61, L65 "Neural Networks" (plural).

L70 "trained a"

L72 "toward real-world problems"

L91 "for operational"

L94 "ring structured" to "cyclic"

Interactive comment on Geosci. Model Dev. Discuss., <https://doi.org/10.5194/gmd-2020-211>, 2020.