Title: A low-dimensional dynamical systems approach for ensemble design and interpretation in climate science
Author(s): Francisco de Melo Viríssimo and David A. Stainforth
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Reviewer Comments:

The authors present an argument that low dimensional conceptual models have not played a substantial role in the design and understanding of "*how different experimental designs affect the information that can be extracted from systems possessing a number of key characteristics shared with climate models*". To this end they propose a conceptual framework to guide ensemble design and interpretation in suitable low dimensional chaotic systems providing a brief illustration and review of their work using the five ODE Lorenz84-Stommel61 as a simple example to illustrate the basic properties of initialization and parameter uncertainty.

The article is inadequate on several levels.

- The title does not represent the article as neither theoretical nor computational methods are presented rather a descriptive program is offered.
- The basic premise that somehow the climate community is unaware of the key characteristics required to design appropriate ensemble is unsustainable. The four key characteristics cited are basic concepts one should expect any climate modeller to be fully aware of. The general thesis that somehow ensemble methodology has been neglected belies the deep connections between the dynamical systems, geophysical fluids and weather, seasonal and decadal prediction communities and the many examples illustrated using low order models.
- The manuscript fails to adequately review the literature of ensemble prediction. Specifically, low dimensional models have been extensively employed to understand the general mathematical properties of error growth, projection onto various choices of dynamical vectors e.g., LVs, BVs, CLVs, FTNMs, SVs etc. Further, the emergence of local attractor states and characterization of local dimension underpins the understanding on which operational ensemble prediction systems across weather to decadal timescales are based. However, the article makes no mention of that body of work and the authors own cited work spans a highly limited set of chaotic low order models.
- There are now a growing number of machine learning approaches to developing stable climate emulators that can effectively learn pde's of the slow manifold enabling cost effective generation of huge ensembles. Examples include neural operator [1] and transformer [2] architectures, or alternate approaches capable of simulating the climate response for any given bespoke emission pathway [3]. None are mentioned. No mention is made of the many applications of data driven and optimization methods for dimension reduction in high dimensional non-autonomous flows to specifically separate physical modes on the slow manifold from the fast decaying modes e.g., [4,5].
- As distinct from initial condition uncertainty, climate is primarily a boundary value problem. Once errors from uncertainties in the initial conditions saturate and phase information is lost, it is uncertainties in boundary conditions and a shift in focus to the systems responses to forcing specifications that becomes the focus i.e., prediction – to – projection. This is barely discussed with no representative example given.

- Mostly the article is a review of the authors own work – much of which is restricted to the L84-S61 system of 5 ODEs - but there is a general paucity of new insights or methodological advances.

References:

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