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Interactive Comment

Interactive comment on “HESS Opinions “Ensembles, uncertainty and flood prediction”” *by* S. L. Dance and Q. P. Zou

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Response to Anonymous Referee 1

We thank the referee for his(her) comments on our paper. We address these below.

“. . .its scope is too broad for a commentary the size of a journal article. . ..a listing of problems without a specific focus is not very useful”

The topic of our paper is on the use of **ensemble methods** for flood prediction using coupled meteorological, hydrological and oceanographic models, over a range of time and space scales from local forecasts to climate predictions. This is a cross-cutting interdisciplinary area, with collaborations between some disciplines in their infancy. One of the goals of our paper was to identify common research challenges and questions that transcend the individual disciplines, to seek areas where we may learn from one another and understand better the propagation of uncertainty through chains of coupled models.

To focus on this goal, we have summarized the problems from the different applications while explaining them using examples that scientists from each field can relate to without addressing the work in any individual field in great depth or detail. Indeed, we are glad that the referee agrees that our approach *"[fosters] collaboration and dialogue between researchers"*. We also believe that it is useful to give a scientific overview of the big picture that may be used to influence policy and funding agency agendas, and as such gains credibility by subjection to open discussion and peer review in an interdisciplinary journal such as HESSD.

We will try to make the focus, goals and utility of the paper clearer in the abstract and introduction of the revised paper.

"Its arguments are too uncontroversial for a commentary"
We note that only 5 days after publication online, a lengthy (15 page) response to our article, with 10 international authors, was contributed to the discussion. This is a good demonstration that our article has already provoked a significant response.

"The proposed solutions are either trivial or they rephrase the problem in a different way. In most cases instead of saying what should be done and how, they just indicate who should do the job."
We disagree with the referee. We have tried to write our recommendations succinctly, and hence perhaps some of the detailed implications of these recommendations may have been under-emphasized or not fully explained.

Considering the examples given by the referee:

Q How can we characterize observation errors, taking into account the mismatches in

resolution between models and observations, and different observation types?
A Field campaigns should be carried out to quantify the full error structures associated with key observation types. These will also provide valuable data for evaluating new diagnosis techniques that use data assimilation to estimate such errors (ECMWF, 2009).

As discussed in section 3.1 of the paper, observation errors arise from instrument errors, errors of representativity, errors in the observation operator or forward model, and errors in the observation processing. We wish to understand the detailed structure of the pdf of these errors so that we may optimally use the observations in combination with other data, in data assimilation (or validation/verification). Until now we have often made simplifying assumptions that the errors are unbiased, Gaussian in structure, and components of the error vector are mutally uncorrelated. Thus the only quantities that we need to estimate are the observation error variances (or equivalently the standard deviations). However it is becoming increasingly clear (e.g., Stewart 2010) that understanding the full structure (e.g., spatial and cross-channel correlations) of the observation error covariance matrix is important to maximize the value of the information.

As we noted in section 3.2, there is a significant body of current research on estimating observation errors via diagnostic techniques from operational systems (e.g., ECMWF, 2009). However such techniques need to be validated before we may rely on their estimates. For example, an important contributor to errors of representativity arises from the natural spatiotemporal variability of the observed field (Daley, 1993). Thus in order to estimate observation error structures, a field campaign providing series of high temporal and spatial frequency direct observational data is needed (operational datasets are often too sparse for this purpose). These can then be compared with collocated observations from remote sensing in order to estimate the error correlation structures for the remote sensing observations. For example Bormann et al., 2003 estimated the observation error spatial correlations of atmospheric motion vector (AMV) observations (from geostationary satellite imagery) using collocated radiosonde and AMV

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observations. While Bormann et al., used operationally available data, their methodology provides an approach that would be appropriate for use with appropriate field campaign data.

We will edit section 3.1 and 3.2 to clarify these points.

Q. Are ensemble assimilation schemes theoretically and numerically stable, for nonlinear problems and a finite ensemble size?
A. We should work closely with the mathematical sciences community to understand the analytic and numerical properties of the new algorithms.

For linear models and observations, the classical approach to proving theoretical stability for the standard Kalman filter is to prove that the dynamical system is both"controllable" and"observable" and use these properties to provide bounds on the dynamical system (e.g., Jazwinski, 1970). With the ensemble Kalman filter (without localization), for small ensemble sizes the assumption of positive definiteness of the model covariance matrix does not hold (Livings et al., 2008) and thus classical proofs of stability do not hold. Indeed, it is easy to construct examples where the ensemble filter is unstable. For ensemble filters using covariance localization and inflation, nonlinear models and observations it is less obvious how to proceed to characterize the filter stability, and will require significant knowledge of linear algebra and control theory, and hence collaboration with mathematicians!

We do not propose to modify section 3.1 and 3.2 to explain these issues further, since we believe it would involve a rather technical diversion and negate our aim of keeping the paper succinct and accessible.

Q. How can we achieve observability and identifiability for parameter estimation with current and future models?
A. Designers of model parametrization schemes should take into account issues of identifiability and observability

The concepts of observability and identifiability are defined in section 4 of the paper and we note there that any parameter estimation scheme cannot be expected to work reliably unless both of these properties hold. The popularity of techniques such as GLUE (Beven and Binley, 1992, Ruessink 2005a, 2006) for parameter estimation indicate that many current parameterization schemes exhibit equifinality, and that these issues have not been taken account of in parametrization design.

As a first step, simple sensitivity studies can begin to determine observability and identifiability for a given model of a dynamical system, at the parametrization design phase. For example, by carrying out model runs with perturbed parameters, and determining whether the resulting model outputs have differences that would be distinguished by typical observing instruments (taking into account the fields observed, the accuracy and resolution of the instruments etc.) More sophisticated techniques could also be developed and provide benefit.

We will modify section 4.1 and 4.2 to indicate in our recommendation this possible approach to investigating identifiability and observability at the parametrization design phase.

Q. How can we marry dynamically inspired perturbations with statistical sampling theories?
A. Dynamicists and statisticians should work together to close the gap between sampling based on dynamical ideas and sampling based on statistical ideas.

It may be possible to better establish the properties of the sampling scheme desired by each discipline and hence develop rigorous statistical techniques that respect the properties desired by the dynamicists. For example (as non-statisticians!), we speculate that the ensemble resulting from a technique that chooses dynamically growing modes as ensemble perturbations, could be interpreted by a statistician as a sample of the marginal pdf restricted to the unstable manifold of the model. We will edit section 6 of the paper to amplify this point.

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Additional References

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