Response to Reviewer #2

Note: reviewer comments, author responses, and the revision of the original manuscript are shown in black, blue, and **(bold) purple**, respectively. Page and line numbers for both comments and responses refer to the original manuscript published in HESSD.

1) Because the paper focuses on challenge and opportunity (also progress) for DA application in operational hydrologic forecast, the current way of introduction of DA theory (section 2) looks like somehow redundant. A more concise way of introduction would be appropriate.

Indeed, the focus of this paper is on the progresses, challenges and opportunities for DA applications in operational hydrology. Section 2 is designed to discuss the challenges and opportunities from the theoretical perspective and to also provide a context for discussions in the other sections. If the reviewer is referring to the state-space model shown in Eqs (1) and (2) on page 3424 as the redundant information, we feel that including this general DA framework is necessary since all the discussions in Section 2 on the theoretical aspects in terms of progresses and challenges are based on this framework and the notation used in Eqs. (1) and (2). Consequently, we prefer to keep this part of the introduction in Section 2 to maintain a minimum level of self-containedness.

2) Page 3421, the second paragraph, here the authors want to contrast the DA for hydrology application with that for meteorological and atmospheric application; however, the picture is vague: why DA application for meteorology could achieve more progress (as the authors claimed in the paper) ; is this difference mainly related to the building of community-supported, open-source modelling systems, or other physical or dynamical reasons (regarding the difference between land hydrologic and atmospheric systems) could play an important role?

We agree with the reviewer on this and will add additional text after the second paragraph on Page 3421 to clarify:

It is important to note that in addition to community support and the use of new sources of data (e.g., satellite-based products), other factors may have also contributed to the seemingly greater advances of DA in operational meteorology than in operational hydrology. These include, among other reasons, the differences in the underlying physical system (i.e., atmospheric vs. land/hydrologic systems), types of data and procedures used by the forecasting systems, as well as other historical/societal reasons such as more funding and higher relevance of good forecasts (e.g., for aviation and military) for operational meteorology. For example, in contrast to developments in operational meteorology, developments (in both science and technology) in operational hydrologic forecasting have taken place more on a local, national and regional (i.e., in the case of trans-boundary rivers) rather than multi-national or international scale. Also, hydrologic forecasting systems often employ workflows with numerous models that represent different processes (see Weerts et al., 2010 for a list with hydrologic models or modules used by various hydrologic operational centers), all linked together to provide a forecast for the up- and downstream (often high-risk) locations. This has rendered it less straightforward to apply consistent automated DA procedures across the hydrologic forecasting systems.

3) Section 3.1, here the authors talked less about another group of precipitation uncertainty and its representation in operational DA for hydrology: the uncertainty from GCM or regional climate model that produce the precipitation forecast; because a lot of seasonal (and large-scale) hydrological forecast applications are based on using precipitation from these models, more discussion and references are needed for this category.

A paragraph will be added to the end of Section 3.1 to briefly discuss handling uncertainty in precipitation forecasts from NWPs used in large-scale hydrologic modeling.

In large-scale hydrologic modeling and DA applications, statistically reliable quantitative precipitation estimates (QPEs) may need to be generated based on outputs from numerical weather prediction (NWP) models, often aided with other available sources of precipitation information (e.g., stations, radars, and satellites). Statistical post processing (e.g., downscaling and bias correction) of NWP-based precipitation estimates is commonly practiced to close the scale gap between NWP outputs and hydrologic applications and to reduce the systematic bias in the NWP precipitation estimates, while at the same time reproducing the observed local-scale space-time variability in precipitation and other forcing variables (e.g., Clark et al., 2004a and 2004b; Piani et al., 2010; Rojas et al., 2011). Ehret et al. (2012) however caution the use of bias correction on precipitation and other outputs from global and regional circulation models for hydrologic applications and propose that improving the simulations from these models (e.g., via increased resolutions and ensemble predictions) is the most promising solution for reducing the uncertainty in precipitation estimates from these models.

4) Section 3.3.4, it's not clear that how to quantify the capability of the multi-model ensembles for representing the uncertainty of simulating processes; e.g., the options that the multi-model framework provides may not fully include all the possible processes level representations, or say, incomplete sampling of the structural space.

We fully agree with the reviewer that a multi-model ensemble may not fully address the uncertainty associated the model structure and it is a challenge to quantify the uncertainty representation by a multi-model ensemble. This point will be made more explicitly in the revised paper by adding the following comment to the beginning of the second paragraph in Section 3.3.4:

It is important to note that, although the multi-model ensemble approach is widely known to increase predictability, a model ensemble (e.g., developed with the options provided by the multi-model or multi-parameterization frameworks discussed above) may not represent a complete sampling of the model space. One typical challenge involved in such an approach is then concerned with understanding the dependence or independence among the models, as well as the relationship between the model spread and the total predictive uncertainty. Based on the notion of conditional bias, Abramowitz and Gupta (2008) introduced an innovative "model space" metric that allows measuring the distance between models in a theoretical model space, thus helping to quantify how much independent information each model is contributing to representing the predictive uncertainty. Another typical challenge in a multi-model ensemble approach is concerned with developing an effective strategy to optimally combine the individual models …

5) Page 3441,second paragraph (Line13-29),here the authors talked about mapping coarse resolution remote sensing data with model estimates; there is an important issue that can affect the efficiency

of DA methods to use remote sensing data: the intrinsic correlation among model estimates that are within a same grid of remote sensing data; say, if the model estimates show large heterogeneity, the benefit of knowing their spatial aggregation might be relatively small compared with the homogeneity counter-parts. Since this issue might provide both challenge and opportunity for DA application, the authors may want to give comment and discussion about it.

If we understand the reviewer correctly, this refers to the fundamental fact that the observations carry no information on spatial patterns within the footprint, which can affect the efficiency of DA. We agree with this and made the point more explicitly in the text. The sentence on P3441, L21-23 will be modified as follows in the revised manuscript:

While approaches can and have been developed to deal with such issues (e.g., Zaitchik et al., 2008), they tend to be observation specific and hence not generically available**; also, they do not overcome the fundamental lack of information on spatial patterns at scales finer than the observation footprint. This can affect the efficiency of DA when assimilating coarse remote sensing data into relatively high resolution models, presenting both challenges and opportunities for realizing the full potential of DA in such applications.** Conceptual "mapping" can also be a problem…

New references:

Abramowitz, G., and H. Gupta (2008), Toward a model space and model independence metric, Geophys. Res. Lett., 35, L05705, doi:10.1029/2007GL032834.

Clark, M.P., Gangopadhyay, S., Hay, L.E., Rajagopalan, B., and Wilby, R. L.: The Schaake Shuffle: A method to reconstruct the space-time variability of forecasated precipitation and temperature fields. Journal of Hydrometeorology, 5, 243-262, 2004a.

Clark, M.P., Gangopadhyay, S., Brandon, D., Werner, K., Hay, L. E., Rajagopalan, B., and Yates, D.: A resampling procedure for generating conditioned daily weather sequences. Water Resour. Res., 40 (4), doi:W04304 10.1029/2003WR002747, 2004b.

Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., and Liebert, J.: HESS Opinions " should we apply bias correction to global and regional climate model data?", Hydrol. Earth Syst. Sci. Discuss., 9, 5355–5387, doi:10.5194/hessd-9-5355-2012, 2012.

Piani, C., Weedon, G. P., Best, M., Gomes, S. M., Viterbo, P., Hagemann, S., and Haerter, J. O.: Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models, J. Hydrol., 395, 199–215, doi:10.1016/j.jhydrol.2010.10.024, 2010.

Rojas, R., Feyen, L., Dosio, A., and Bavera, D.: Improving pan-European hydrological simulation of extreme events through statistical bias correction of RCM-driven climate simulations, Hydrol. Earth Syst. Sci., 15, 2599–2620, doi:10.5194/hess-15-2599-2011, 2011.

Weerts, A. H., Schellekens, J., and Sperna Weiland, F.: Real-time data handling and forecasting: examples from Delft-FEWS forecasting platform/system, IEEE JSTARS, doi:10.1109/JSTARS.2010.2046882, 2010.