Response to Reviewer #1

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.

Generally speaking, the paper is well written and it the nicely summarizes the major research works on advanced data assimilation citing numerous papers. Still, I suggest the authors give more details on the most innovative ones (see point 2).

Please see response to point 2) below.

1) In the introduction of Section 2, the authors distinguish 3 types of DA problems: state correction, parameter calibration and error updating problem. The literature described in Section 2.1 deals with both state and parameter correction (p3424 l4, p3425 l1), I then recommend that the title would be modified and the definition of the vector x be extended to state plus parameters. For sequential algorithm, the dynamics of the model parameters is usually prescribed by a random walk process. This should be added as a comment to Eq (1). In addition, the question of non-linearity between the control and the observation space is even more relevant when the model parameters are controlled.

The ability to incorporate unknown or time varying parameters into the state vector was noted briefly on Pg3424 (line 3-4) of the original manuscript. The text will be expanded (as a comment to Eq. (1) on p3425, L3) as follows to incorporate the suggestions made by the reviewer:

… and ε_{k+1} denotes the observation error with mean $\overline{\varepsilon}_{k+1}$ and covariance R_{k+1}. **In this notation, the parameter vector Θ is considered to be time invariant and can be determined from either physical principles or parameter calibration. Unknown or time varying parameters can be incorporated into the state vector to form a joint state-parameter estimation problem (e.g. Moradkhani et al. 2005a). For sequential algorithms, the dynamics of the model parameters is usually prescribed by a random walk process. It is important to note that such joint estimation may increase the non-linearity between the state and observation space and exacerbate the computational challenges highlighted in this section. An alternative approach is to conduct dual estimation, where the unknown parameters and model states are estimated separately in a parallel or interactive fashion (e.g. Moradkhani et al., 2005b; Vrugt et al.,, 2005)**. The predictive distribution of $\boldsymbol{Z}_{k+1}$ …

However the authors feel maintaining Θ in the notation as an invariant set of parameters determined outside of the DA scheme is important since this reflects common practice. Hence Eq. (1) and the title of Section 2.1 are kept as is.

2) The description of innovative methods of EnKF for non-Gaussian pdfs should be more detailed, especially the bimodal example from Zhou et al (p3426 l14). This seems particularly relevant for precipitation errors distributions.

The following text will be added to the new manuscript on P3426, L16 to provide a clarification on this:

… of EnKF drastically for bimodal distributed parameter fields. **Here, the normal score transformation is made for each time step and each grid cell, using the simulated values from the ensemble to construct space-time specific probability density functions (PDFs). The EnKF is applied on these normal-score**

transformed values, which are then back transformed based on the established relationships between physical values and normal-score transformed values. It has yet to be …

3) I agree that the computational cost for EnKF and PF can be too high for operational application (p3426 l5), some ideas on how many members are usually needed for these methods and up to which control size they can be applied should be given. Also, please quantify what is meant by "large" on p3427, l28 when referring to variational methods and their advantages versus filtering and stochastic algorithms.

Thanks for the suggestion. Clarifications on the computational cost of EnKF and PF will be provided in the revised manuscript (P3426- P3427).

For EnKF (P3426, L5):
… The size of the sample used in the EnKF or UKF may prove computationally burdensome in an operational environment. **Typically, hundreds of ensemble members are needed for reliable updating without filter inbreeding (e.g., Hendricks Franssen and Kinzelbach, 2008), although for land surface problems often smaller ensemble sizes (e.g., less than 100) are used. EnKF has also been applied on large scale problems which involve over 105 unknown states and parameters**. Another limitation of the EnKF is that …

For PF (P3427, L15):
… the number of particles required for physically-based distributed hydrologic models may limit operational applications of PF. **Typically, even for small problems with only a few unknown states and parameters, thousands of ensemble members are needed for reliable characterization of the posterior PDF. The particle filter has not been tested for problems with thousands of unknown states and parameter, which is still pending further investigation**. To alleviate this problem …

For the point on variational methods, the following text will be added in the revised manuscript to comment on the term "large":

…The variational techniques can be particularly appealing when the covariance matrix is **large (for example, corresponding to more than 105 unknown states and/or parameters)** such that defining meaningful error covariance matrices is impractical …

4) The Section on error and noise updating should be related to the notion of propagating the covariance matrices. This section should be revised with a proper distinction between describing the model error and how to update them along the assimilation procedure. I suggest merging this section with 3.1.

This comment appears to suggest that the reviewer has interpreted Section 2.2 to be discussing the temporal evolution of the covariance matrices defined in Section 2.1. This is not the purpose of this section, rather it is to highlight that DA has also been used in the context of stochastic error models for correcting the (often) deterministic forecasts of existing hydrological models. To avoid confusion, the title of Section 2.2 will be changed to "Error updating" and additional clarification will be provided at the beginning of Section 2 (P3428, L5).

2.2 Error updating

The error updating problem can be thought of as assimilating the latest observation and its corresponding prediction to inform the predictive distribution of the errors in future model predictions and the (to-be) observed data. **This is not be confused with the propagation of the error covariance matrices in state updating applications. Rather, error updating discussed here refers to the use of DA to condition the predictions of an error model representing the difference between an, often deterministic, hydrologic forecast and the corresponding observations. In other words, data is not assimilated into the hydrologic model with the aim of producing improved forecasts but is used to inform the prediction of future discordances between the model forecast and future observations**. Operational examples include …

5) Please define "Conditional simulation" on p3432 l10.

The sentence on P3432, L10 will be modified as follows:

Conditional simulation methods, **which condition precipitation estimation on observations of precipitation (e.g., from a station network) and/or other information (e.g., topography) (e.g., Rokovec et al., 2012, this issue)**, have the potential to provide more reliable uncertainty estimates.

6) Why is the sentence 3433 l7-10 in italics?

To reduce confusion, the italics will be removed in the revised manuscript.

7) In 3.2, it is not clear how the 4 different approaches in p3433 l12 relate to the mathematical framework of data assimilation algorithms and covariance matrices, especially the second approach.

A comment will be added to the end of the second paragraph on Page 3433 (L16) for some clarification:

Again, these perturbations are based on order-of-magnitude considerations, and may therefore be statistically unreliable. **This approach addresses the model uncertainty term η in Eq. (1) by adding random perturbations to the model physics, while the other three approaches to be discussed below aim to represent the model uncertainty through quantifying the uncertainties in model parameters and/or the model structure with more sophisticated approaches (in addition to adding random perturbations).**

8) Several studies could be cited here on the use of remote sensing data (p3440 l4):
Biancamaria S., M. Durand, K. M. Andreadis, P. D. Bates, A. Boone, N. M. Mognard, E. Rodriguez, D. E. Alsdorf, D. P. Lettenmaier and E. A. Clark, "Assimilation of virtual wide swath altimetry to improve Arctic river modeling." Remote Sensing of Environment, 115(2): 373-381.
Durand, D., K.M. Andreadis, D.E. Alsdorf, D.P. Lettenmaier, D. Moller, and M. Wilson, "Estimation of bathymetric depth and slope from data assimilation of swath altimetry into a hydrodynamic model." Geophysical Research Letters, v.35, L20401, doi:10.1029/2008GL034150, 2008.

These references will be added (P3440, L4).

The potential of assimilating space-born water level information for improved discharge and water depth estimation has been explored in a few studies (e.g., Andreadis et al., 2007; **Durand et al., 2008;** Neal et al., 2009; Matgen et al., 2010; **Biancamaria et al., 2011**).

Studies from Balsamo et al. on the assimilation of SMOS data for the initialization of soil moisture hydrology should also be cited:
Balsamo, G., J-F. Mahfouf, S. Bélair, G. Deblonde, 2007: A Land Data Assimilation System for Soil Moisture and Temperature: An Information Content Study. J. Hydrometeor, 8, 1225–1242. doi: http://dx.doi.org/10.1175/2007JHM819.1
Reichle, Rolf H., Randal D. Koster, Jiarui Dong, Aaron A. Berg, 2004: Global Soil Moisture from Satellite Observations, Land Surface Models, and Ground Data: Implications for Data Assimilation. J. Hydrometeor, 5, 430–442. doi: http://dx.doi.org/10.1175/1525-7541(2004)005<0430:GSMFSO>2.0.CO;2

These references will be added on P3439. In addition, the second paragraph on P3439 will be rewritten/ reorganized to present a better overview of past/existing/future missions for measuring soil moisture.

Remote sensing products of soil moisture have also become available in recent years. For example, surface soil moisture has been retrieved from a number of passive sensors starting 1978. These include the Scanning Multichannel Microwave Radiometer (SMMR), the Special Sensor Microwave Imager (SSM/I), the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), the AMSR-E, the Windsat radiometer (Windsat), the European Space Agency (ESA) Soil Moisture and Ocean Salinity mission (SMOS, Kerr and Levine, 2008), and the Global Change Observation Mission - Water (GCOM-W). In the meantime, soil moisture products have also been available from active sensors starting 1992, including the Advanced Scatterometer (ASCAT) and the two European Remote Sensing (ERS) satellites (ERS-1 and ERS-2). New sensors, such as the ESA Sentinel-1 mission and the NASA Soil Moisture Active passive mission (SMAP, Entekhabi et al., 2010), will be launched in the next couple of years. Active and passive microwave surface soil moisture retrievals have been generated (e.g., Jeu, 2003; Owe et al., 2008; Li et al., 2010; Liu et al., 2012) and examined in numerous DA studies, although generally in the context of land surface models used in weather forecasting (e.g., Reichle et al., 2004; Balsamo et al., 2007). Examples of more conventional hydrologic applications also exist and demonstrated skill in improving streamflow estimates (e.g., Pauwels et al., 2001; Parajka et al., 2006; Brocca et al., 2010 and 2012). The NASA/German Gravity Recovery and Climate Experiment (GRACE) satellite (launched in 2002) can map Earth's gravity field with enough accuracy to discern month to month changes in the distribution of the total terrestrial water storage on Earth (Tapley et al., 2004). Despite its coarse spatial (>150 000 km at mid-latitudes) and temporal (10 days or more) resolutions, GRACE has been used to effectively measure changes in groundwater, deep soil moisture, and snowpack in some DA studies (e.g., Zaitchik et al., 2008; Su et al., 2010; Forman et al., 2012) .

9) The connection between the MPC method and the DA applications for dual state-parameters estimation and SODA approach (p3445, l25) should be clarified as well as the notion of error covariance matrices.

After careful consideration, we think it is better to remove the last sentence of P3445 in the revised manuscript to avoid confusion.

Studies on DA for operational hydraulics structures and water resources from Jean-Baptiste and Malaterre should also be cited:
Jean-Baptiste Nelly, Malaterre Pierre-Olivier, Dorée Christophe and Sau Jacques, 2011. "Data assimilation for real-time estimation of hydraulic states and unmeasured perturbations in a 1D hydrodynamic model". Journal of Mathematics and Computers in Simulation. June 2011. Vol. 81, Issue 10, pp 2201-2214. DOI=http://dx.doi.org/10.1016/j.matcom.2010.12.021.

This reference will be added (P3446, L20).

... due to the small extension of the modelled river system, simple Auto-regressive (AR) error correction models in combination with MHE were found to outperform **exclusive** state updating techniques. **Nelly et al. (2011) compares the use of sequential Kalman Filter and sequential Particle Filter State Observer in the context of MPC of irrigation canals. Both approaches appear efficient and robust, in which the Kalman Filter is very fast in terms of calculation time and convergence and the Particle Filter has advantages in handling non-linear features of the model.** Breckpot et al. (2010) and Blanco et al. (2010) ...

10) In Section 5.3, a description of the use of DA methods and other control methods for real-time flood forecasting by national and regional centers is missing (cite for example the EFAS project from the EU at the medium range scale and studies from Ricci et al. on operational flood forecasting in France).

Ricci et al.: Correction of upstream flow and hydraulics state with a data assimilation in the context of flood forecasting. Hydrol. Earth Syst. Sci. Discuss., 7, 9067-9121, 2010 www.hydrol-earth-syst-sci-discuss.net/7/9067/2010/ doi:10.5194/hessd-7-9067-2010.

The references to Ricci et al. (the final revised paper in HESS) will be added. Additionally we will add some more references with respect to DA and hydraulic models.

P3419 line 15: ... hydraulic models (e.g., **Shiiba et al., 2000; Madsen et al., 2003; Neal et al., 2007;** Schumann et al., 2009; **Ricci et al., 2011**)

In addition, Thielen et al. (2009) on EFAS will also be cited (P3418, L15):

Effective quantification and reduction of these uncertainties is necessary to enable the generation of forecast products with accurate and actionable guidance on predictive uncertainty to enable risk-based decision making (e.g., **Thielen et al., 2009**; Coccia and Todini, 2010; Weerts et al., 2011).

Additional text (shown below) will be included in the introduction section (on Page 3421, following the text added in response to comment 2) by Reviewer #2) to summarize the difference in using DA for hydrologic forecasting by US and European centers. We think it is more appropriate to add this discussion in the introduction section instead of Section 5.3, which focus on real-time control of hydrologic structures and other water resources systems.

It is also interesting to note that historic developments have led to a difference in the hydrologic forecast paradigms in the US and Europe. In the US, the flood forecasting procedure used by the NWS

River Forecast Centers has traditionally involved manual modifications (MODS; see for instance Seo et al., 2003; Smith et al., 2003) of parameters and states and this is still the case. While in Europe, flood forecasting procedures include more automated adjustments to the hydrologic forecasts, likely due to the fact that in Europe upgrades of flood forecasting systems have taken place since the early 2000s (see for example Werner et al. (2009) that describe some of the developments in flood forecasting systems/procedures in England, Wales, and Scotland). Currently, hydrologic operational centers across Europe apply automated methods like Autoregressive Moving Average (ARMA) or error correction methods, deterministic updating methods (e.g., Moore, 2007), statistical (or post-processing) correction techniques, and to a much lesser degree ensemble data assimilation methods like the EnKF.

New References:

Baldocchi, D., and Coauthors, 2001: FLUXNET: A New Tool to Study the Temporal and Spatial Variability of Ecosystem–Scale Carbon Dioxide, Water Vapor, and Energy Flux Densities. Bull. Amer. Meteor. Soc., 82, 2415–2434.

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Biancamaria S., Durand, M., Andreadis, K. M., Bates, P. D., Boone, A., Mognard, N. M., Rodriguez, E., Alsdorf, D. E., Lettenmaier, D. P., and Clark, E. A.: Assimilation of virtual wide swath altimetry to improve Arctic river modeling. Remote Sensing of Environment, 115(2), 373-381, 2011.

Brocca, L., Melone, F., Moramarco, T., Wagner, W., Naeimi, V., Bartalis, Z., & Hasenauer, S.: Improving runoff prediction through the assimilation of the ASCAT soil moisture product. Hydrology and Earth System Sciences, 14, 1881-1893, 2010.

Brocca, L., Moramarco, T., Melone, F., Wagner, W., Hasenauer, S., Hahn, S.: Assimilation of Surface- and Root-Zone ASCAT Soil Moisture Products Into Rainfall-Runoff Modeling, IEEE Transactions on Geoscience and Remote Sensing, in press, 2012.

Durand, D., Andreadis, K.M., Alsdorf, D.E., Lettenmaier, D.P., Moller, D., and Wilson, M.: Estimation of bathymetric depth and slope from data assimilation of swath altimetry into a hydrodynamic model. Geophysical Research Letters, 35, L20401, doi:10.1029/2008GL034150, 2008.

Madsen, H., Rosbjerg, D., Damgard, J., and Hansen, F.S., 2003, Data assimilation into MIKE 11 flood forecasting system using Kalman filtering, Water Resources Systems - Hydrological Risk, Management and Development, IAHS Publ no 281, 75-81.

Moore, R.M.: The PDM rainfall-runoff model, Hydrol. Earth Syst. Sci., 11, 483-499, doi:10.5194/hess-11-483-2007, 2007.

Neal, J.C., Atkinson, P.M., Hutton, C.W., 2007, Flood inundation model updating using an ensemble Kalman filter and spatially distributed measurements, Journal of Hydrology, 336, 401-415.

Nelly, J.-B., Pierre-Olivier, M., Christophe, D., and Jacques, S.: Data assimilation for real-time estimation of hydraulic states and unmeasured perturbations in a 1D hydrodynamic model, Journal of Mathematics and Computers in Simulation. 81(10), 2201-2214, doi:http://dx.doi.org/10.1016/j.matcom.2010.12.021, 2011.

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Reichle, R.H., Koster, R.D., Dong, J., Berg, A.A.: Global Soil Moisture from Satellite Observations, Land Surface Models, and Ground Data: Implications for Data Assimilation. J. Hydrometeor, 5, 430–442, 2004.

Ricci, S., Piacentini, A., Thual, O., Le Pape, E., and Jonville, G.: Correction of upstream flow and hydraulic state with data assimilation in the context of flood forecasting Hydrol. Earth Syst. Sci., 15, 3555–3575, doi:10.5194/hess-15-3555-2011, 2011.

Shiiba, M., Laurenson, X., Tachikawa, Y.: Real-time stage and discharge estimation by a stochastic-dynamic flood routing model, Hydrological processes, 14, 481-495, 2000.

Smith, M. B., Laurine, D. P., Koren, V. I., Reed, S. M., and Zhang, Z.: Hydrologic Model Calibration in the National Weather Service, in: Calibration of Watershed Models, Water Science and Application 6, edited by: Duan, Q., Gupta, H., Sorooshian, S., Rousseau, A., and Turcotte, R., AGU Press, Washington, D.C., 133–152, 2003.

Thielen, J., Bartholmes, J., Ramos, M.-H., and de Roo, A.: The European Flood Alert System – part 1: concept and development, Hydrol. Earth Syst. Sci., 13, 125-140, 2009.

Werner, M., Cranston, M., Harrison, T., Whitfield, D., and Schellekens, J.: Meteorol. Appl., 16, 13–22, 2009.

Parajka, J., Naeimi, V., Blöschl, G., Wagner, W., Merz, R., and Scipal, K.: Assimilating scatterometer soil moisture data into conceptual hydrologic models at the regional scale. Hydrology and Earth System Sciences, 10, 353-368, doi:10.5194/hess-10-353-2006, 2006.

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