This is the response letter to Reviewers' comments on the manuscript **hess-2019-288 "Variational Assimilation of Streamflow Observations in Improving Monthly Streamflow Forecasting"**. The reveiwer's concerns are shown in red boxes and the author's responses are presented in blue colors.

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Hydrology and Earth System Sciences
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Discussions

Interactive comment on "Variational Assimilation of Streamflow Observations in Improving Monthly Streamflow Forecasting" *by* Amirhossein Mazrooei et al.

Anonymous Referee #1

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The paper "Variational Assimilation of Streamflow Observations in Improving Monthly Streamflow Forecasting" aims at proposing a scheme that applies Variational Data Assimilation (VAR DA) in VIC Land Surface Model (LSM) in order to correct the initial state conditions and improve 1-month ahead streamflow forecast by using observed streamflow information. The authors analyzed also the role of VAR DA in Improving Streamflow Simulation and Forecasts. I really enjoyed reading the paper, which I found well written, properly structured and easy to understand despite the complexity of the assimilation approach. Because of this, I recommend a minor revision. However, I still have a few comments which may help the authors to improve their manuscript.

- One of my main concern is the use of an LSM. In particular, besides for the fact that (to the best of authors knowledge) this is the first study that uses LSM and VAR DA together, why did the authors use a semi-distributed model instead of a more simple conceptual lumped model? Because of the complexity of the integration between VAR DA and LSM, the authors introduced some important assumptions (e.g. the use of a constant multiplier) which may affect the final assimilation performances. Therefore, VAR DA (or sequential data assimilation) algorithm could be implemented lumped model in an easier way, and the computational time of the simulation (which is a problem underlined by the authors in the paper) could be reduced.

Response: The motivation of the study here is to validate the gain in the performance of a distributed LSM such as VIC due to application of VAR DA using point-measured streamflow data. In another study we have published recently (Mazrooei and Sankarasubramanian, 2019), we used EnKF sequential DA to correct the state variables of a simpler lumped watershed model, again using observed streamflow data, and evaluate the DA-aided forecasts/simulations. So to our best knowledge, this is the first study using downstream streamflow observations to implement VAR-DA in an LSM. It is certainly true that DA is of interest both in lumped and distributed models, with the latter presenting more of a challenge due to their complexity. Since studies have already considered VAR-DA for lumped models (e.g., Seo et al., 2003; Seo et al., 2009), thus we did not consider VAR-DA application for a lumped model for our analyses. Further, the proposed "k multiplier" approach could work in principle on the lumped watershed models too.

Mazrooei, Amirhossein, and A. Sankarasubramanian. "Improving monthly streamflow forecasts through assimilation of observed streamflow for rainfall-dominated basins across the CONUS." Journal of Hydrology 575 (2019): 704-715.

Seo, Dong-Jun, Victor Koren, and Neftali Cajina. "Real-time variational assimilation of hydrologic and hydrometeorological data into operational hydrologic forecasting." Journal of Hydrometeorology 4.3 (2003): 627-641.

Seo, Dong-Jun, et al. "Automatic state updating for operational streamflow forecasting via variational data assimilation." Journal of Hydrology 367.3-4 (2009): 255-275.

Accordingly, the introduction of the manuscript has undergone a major revision to better address the mentioned points. A comparison between the old version and the new version is presented below where the eliminated text is highlighted in red and the added text is highlighted in green:

1 Introduction

Reliable Monthly-to-Seasonal (M2S) streamflow forecasting provides critical information for water system planning and management (e.g., crop management). Such forecasts also facilitate the allocation of water supplies to different water users (e.g., domestic, agricultural, etc.) and to meet environmental demands (Hamlet and Lettenmaier, 1999; Wood et al., 2002; Devineni et al., 2008). Over the past decades, several strides have been made in M2S streamflow forecasting through utilizing climate forecasts from General Circulation Models (GCMs), following with considerable efforts on uncertainty quantification in the context of real-time hydrologic forecasting (Schaake et al., 2006; Pappenberger and Beven, 2006; Brown, 2010; Mazrooei et al., 2015; Ahmadalipour et al., 2017). Although, several sources of uncertainty in streamflow forecasting have been identified (e.g., uncertainty in model structure and model parameters, inaccurate initial hydrologic conditions, imprecise hydrometeorological forcings), addressing such inherent uncertainties within forecasting approaches have remained a long-standing problem (Ajami et al., 2007; Salamon and Feyen, 2010). Still, effective quantification and further reduction of uncertainties from multiple sources hold great potential for enhancing the accuracy and reliability of hydrologic forecasts (Liu et al., 2012; Pappenberger et al., 2011; Sankarasubramanian et al., 2009; Li et al., 2014). Rainfall is the major contributor to the streamflow and it is the key source of uncertainty in M2S streamflow forecasting for basins under rainfall-runoff regime (Li et al., 2009). Hence, our limited skill in monthly meteorological forecasting is a determining factor for the skill of M2S streamflow forecasting. Furthermore, hydrologic predictability in rainfall-dominated basins is dependent on accurate estimation of soil moisture conditions (Mahanama et al., 2012). Thus, the skill of long-range streamflow forecasting for such basins could be substantially improved by incorporating fine-tuned soil moisture initialization.

Data Assimilation (DA) is an effective technique that is able to reduce the errors in model state variables and parameters and consequently improves the model predictability. The basic theory behind DA is to optimally combine the information from model predictions and available observations to correct the model initial conditions. DA have been widely applied in oceanography and atmospheric sciences, especially in operational weather forecasting, and its effectiveness has been well demonstrated. Furthermore, considerable advances in theoretical development of DA techniques in hydrology have been proposed from simple direct insertion methods to complex sequential and smoothing filtering methods (Kumar et al., 2009; DeChant and Moradkhani, 2012; Wang and Cai, 2008), yet its application in hydrologic studies on real-time forecasting is at its infancy (Liu et al., 2012).

Sequential DA such as Extended Kalman Filter (EKF) or Ensemble Kalman Filter (EnKF) is one of the earliest and commonly used methods that has been explored in hydrological studies (Moradkhani et al., 2005; Reichle et al., 2008; Clark et al., 2008). Sequential DA is most suitable when gridded observations are exploited for correcting initial conditions estimated by the model, however its application in distributed hydrologic models demands state-space reformulation of model (in a gridded form) and substantial computing power due to ensemble simulations (Seo et al., 2003).

Alternatively, Variational data assimilation (VAR) is a potentially simpler method as opposed to sequential DA (Jazwinski, 2007). VAR DA is a commonly used technique in global atmospheric assimilation schemes and operational meteorological centers, yet it has not been fully exploited in hydrological studies (Ide et al., 1997; Li and Navon, 2001; Liu et al., 2012). In spite of the substantial research on hydrologic DA, limited number of studies have been focused on VAR DA formulation, application and quantifying the performance gain in M2S hydrologic forecasting. For example, Seo et al. (2003) employed variational assimilation (VAR) to assimilate streamflow and precipitation observations for improving operational hydrological forecasting at short lead times. They revealed that VAR DA significantly improves the accuracy of 40-hour ahead streamflow forecasts over few selected basins in the United States, and concluded that employing VAR DA is more appropriate in real-time forecasting - in comparison to other DA techniques - since it requires less computational demand. Rüdiger et al. (2006) employed VAR DA coupled with the Catchment Land Surface Model (CLSM) in order to assimilate observed streamflow and assessed the direct improvements in initial soil moisture states over three catchments in Australia.

The abundance of hydrologic observations collected over last decades from in-situ measurements and satellite remote sensing has motivated the need to integrate them into DA techniques for improving hydrologic predictions. Accordingly, the potential for DA studies has increased due to availability of remotely sensed data of soil moisture and snow cover area/extent from satellite observations in recent years (Pauwels et al., 2001; Andreadis and Lettenmaier, 2006; Kumar et al., 2016; Clark et al., 2008; Reichle et al., 2008). Remote sensing provides estimations of initial hydrologic conditions over a large extent, thus it could be utilized in regional and continental DA studies. On the other hand, historical in-situ observations such as gauge-measured streamflow records are available for a much longer period of time and contain substantially lower measurement errors compared to satellite observations. Hence, assimilating gauge-measured streamflow also provides a great opportunity to correct model state conditions and consequently improve hydrologic predictions (Seo et al., 2003, 2009; Vrugt et al., 2005; Clark et al., 2008; Moradkhani and Sorooshian, 2008).

The motivation of this study is to improve monthly streamflow forecasts using month-ahead climate forecasts which specify the uncertainty in the forcings. For this purpose, VAR DA based on observed streamflow data is incorporated in

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1 Introduction

Reliable Monthly-to-Seasonal (M2S) streamflow forecasting provides critical information for water system planning and management (e.g., crop management). Such forecasts also facilitate the allocation of water supplies to different water users (e.g., domestic, agricultural, etc.) and to meet environmental demands (Hamlet and Lettenmaier, 1999; Wood et al., 2002; Devineni et al., 2008). Over the past decades, several strides have been made in M2S streamflow forecasting through utilizing climate forecasts from General Circulation Models (GCMs) with several efforts on uncertainty quantification in the context of real-time hydrologic forecasting (Schaake et al., 2006; Pappenberger and Beven, 2006; Brown, 2010; Mazrooei et al., 2015; Ahmadalipour et al., 2017). Although, several sources of uncertainty in streamflow forecasting have been identified (e.g., uncertainty in model structure and model parameters, inaccurate initial hydrologic conditions, imprecise hydrometeorological forcings), addressing such inherent uncertainties combined within forecasting approaches have remained a long-standing problem (Ajami et al., 2007; Salamon and Feyen, 2010). Still, effective quantification and further reduction of uncertainties from multiple sources hold great potential for enhancing the accuracy and reliability of hydrologic forecasts (Liu et al., 2012; Pappenberger et al., 2011; Sankarasubramanian et al., 2009; Li et al., 2014). Further, rainfall is the major contributor to streamflow variability and remains as the key source of uncertainty in M2S streamflow forecasting for basins under rainfall-runoff regime (Li et al., 2009). Under these regimes, our limited skill in precipitation forecasting is a determining factor for the skill of M2S streamflow forecasting. Nevertheless, an accurate estimation of model's soil moisture conditions could overcome the limited skill of precipitation forecast and further improve streamflow forecast in rainfall-runoff regimes (Mahanama et al., 2012). Thus, data assimilation techniques for correcting model's soil moisture conditions provide lots of promise in improving M2S streamflow forecasting in rainfall-runoff regimes (Moradkhani et al., 2005; Reichle et al., 2008; Clark et al., 2008).

Data Assimilation (DA) is an effective methodology that is able to reduce the errors in model state variables and parameters and consequently improves the model predictability. The basic idea behind DA is to optimally combine the information from model predictions and available observations to correct the model initial conditions. DA have been widely applied in oceanography and atmospheric sciences, especially in operational weather forecasting, and its effectiveness has been well demonstrated. Furthermore, considerable advances in the theoretical development of DA techniques in hydrology have been proposed from simple direct insertion methods to complex sequential and smoothing filtering methods (Kumar et al., 2009; DeChant and Moradkhani, 2012; Wang and Cai, 2008; Aubert et al., 2003; Kumar et al., 2014), yet its application in hydrologic studies on real-time forecasting is at its infancy (Liu et al., 2012). Of these methods, sequential DA such as Extended Kalman Filter (EKF) or Ensemble Kalman Filter (EnKF) is one of the earliest and commonly used methods that has been explored in hydrological studies (Moradkhani et al., 2005; Reichle et al., 2008; Clark et al., 2008). Sequential DA is most suitable when gridded observations are considered for correcting initial conditions estimated by the model, however its main limitation on the application in distributed hydrologic models stems from the requirement of state-space reformulation of model (in a gridded form) along with the substantial demand of the computational power arising from ensemble simulations (Seo et al., 2003).

Alternatively, variational data assimilation (VAR DA) is a potentially simpler method as opposed to sequential DA (Jazwinski, 2007). VAR DA is a commonly used technique in global atmospheric assimilation schemes and operational meteorological centers, yet it has not been fully exploited in hydrological studies (Ide et al., 1997; Li and Navon, 2001; Liu et al., 2012). In spite of the substantial research on hydrologic DA, limited number of studies have been focused on VAR DA formulation, application and quantifying the performance gain in M2S hydrologic forecasting. For example, Seo et al. (2003) employed VAR DA to assimilate streamflow and precipitation observations for improving operational hydrological forecasting at short lead times. They employed VAR DA in a lumped watershed model, Sacramento Model, and found that it significantly improves the accuracy of 40-hour ahead streamflow forecasts over few selected basins in the United States. Since Sacramento Model is commonly used in operational streamflow forecasts, they also suggested VAR DA is more suitable for real-time forecasting - in comparison to other DA techniques - since it requires less computational demand. Rüdiger et al. (2006) employed VAR DA coupled with the Catchment Land Surface Model (CLSM) in order to assimilate observed streamflow and assessed the direct improvements in initial soil moisture states over three catchments in Australia. However, the entire study is a synthetic study where observed forcings were used in improving streamflow and latent-heat flux predictions.

The abundance of hydrologic observations collected over last decades from in-situ measurements and satellite remote sensing has motivated the need to integrate them into DA techniques for improving hydrologic predictions. Accordingly, the potential for DA studies has increased due to availability of remotely sensed data of soil moisture and snow cover area/extent from satellite observations in recent years (Pauwels et al., 2001; Andreadis and Lettenmaier, 2006; Kumar et al., 2016; Clark et al., 2008; Reichle et al., 2008). Remote sensing provides estimation of initial hydrologic conditions over a large extent, thus it could be utilized in regional and continental DA studies. On the other hand, historical in-situ observations such as gauge-measured streamflow records are available for a much longer period of time and contain substantially lower measurement errors compared to

a Land Surface Model (LSM) to correct the initial conditions. Past DA studies have considered either a conceptual hydrologic model or a distributed model along with observed forcings for evaluating the utility of DA in improving hydrologic predictions, mainly for short-range forecasting lead times (i.e., hourly to weekly), rather than long-range forecasting. Recently, Mazrooei and Sankarasubramanian (2019) analyzed the improved skill of monthly streamflow forecasts over rainfall-dominated basins across the United States, by applying EnKF to correct the initial conditions of a conceptual hydrologic model. This study considers Variable Infiltration Capacity (VIC) LSM in which more complex modeling components - such as interactions between land surface and atmosphere, vegetation dynamics, soil temperature and streamflow response - are explicitly incorporated with a finer modeling time steps (Cox et al., 2000; Feddema et al., 2005; Bonan and Levis, 2006; Zeng, 2010). The challenge in coupling VAR DA and VIC LSM is in incorporating the error in point measurements (i.e., observed streamflow at gauge) to correct the initial conditions of the gridded VIC states. To the best of our knowledge, there are limited efforts on assessing the application of VAR DA using in-situ streamflow observations in correcting VIC LSM initial conditions, and quantifying the resultant improvements in real-time long-range streamflow forecasts. Our hypothesis here is that addressing the two sources of uncertainty - correcting initial conditions and utilizing month-ahead climate forecasts from GCM - will provide us with improved monthly streamflow forecasts, particularly for months with limited skill in climate forecasts (e.g.,summer season). For months with significant skill in climate forecasts arose from ENSO conditions (e.g., winter months), we expect the analyses to provide the added value of VAR DA in improving the monthly streamflow forecast over the climatological forcings of precipitation and temperature.

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satellite observations (Loew et al., 2017; Ford and Quiring, 2019; Swenson et al., 2006). Rüdiger et al. (2006) showed that assimilating streamflow reduces the error in correcting the initial conditions as opposed to the soil moisture conditions using a synthetic setup, since streamflow is an integrator of spatial variability in soil moisture and climate forcings. Hence, assimilating gauge-measured streamflow also provides a great opportunity to correct model state conditions and consequently improve hydrologic predictions (Seo et al., 2003, 2009; Vrugt et al., 2005; Clark et al., 2008; Moradkhani and Sorooshian, 2008).

Given that utilizing observed streamflow in DA applications better reduces the errors in the initial conditions (as opposed to soil moisture observations) (Rüdiger et al., 2006) and VAR DA is more suitable for assimilating point observations over gridded initial conditions for real-time streamflow forecasting (as opposed to sequential DA methods) (Seo et al., 2003), in this study we consider VAR DA for assimilating observed streamflow information into the Variable Infiltration Capacity (VIC) Land Surface Model (LSM).

The motivation of this study is to assess the utility of VAR DA in improving VIC LSM monthly streamflow forecasts through two forecasting approaches: 1) using month-ahead climate forecasts from a GCM and 2) probabilistic streamflow forecasting, known as Ensemble Streamflow Prediction (ESP). Past DA studies have considered either a conceptual hydrologic model or a distributed model along with observed forcings for evaluating the utility of DA in improving hydrologic simulations (aka *"predictions"*), or for short-range forecasting lead times (i.e., hourly to maximum weekly), rather than M2S forecasting. Recently, Mazrooei and Sankarasubramanian (2019) analyzed the improved skill of 1-month ahead streamflow forecasts over rainfall-dominated basins across the United States, by correcting the initial conditions of a conceptual hydrologic model using EnKF. But, the application of EnKF to a distributed hydrological model is computationally intensive due to ensemble executions. Furthermore, VIC LSM is selected in which more complex modeling components (such as interactions between land surface and atmosphere, vegetation dynamics, soil temperature and streamflow response) are explicitly incorporated with finer modelling timesteps to better estimate land-surface fluxes (Cox et al., 2000; Feddema et al., 2005; Bonan and Levis, 2006; Zeng, 2010).

The challenge in coupling VAR DA and VIC LSM is in incorporating the error in point measurements (i.e., observed streamflow at gauge) to correct the initial conditions of the gridded VIC states. To the best of our knowledge, there are limited efforts on assessing the application of VAR DA using in-situ streamflow observations in correcting VIC LSM initial conditions, and quantifying the resultant improvements in real-time long-range streamflow forecasts. Here, we propose a methodology that minimizes the errors in predicting the observed streamflow towards correcting the spatially varying VIC model's initial conditions. Our hypothesis here is that addressing the two sources of uncertainty - correcting initial conditions and utilizing month-ahead climate forecasts from GCM - will provide us with improved monthly streamflow forecasts, particularly for months with limited skill in climate forecasts (e.g.,summer season). For months with significant skill in climate forecasts arose from ENSO conditions (e.g., winter months), we expect the analyses to provide the added value of VAR DA in improving the monthly streamflow forecast over the climatological forcings of precipitation and temperature.

- How can the proposed assimilation scheme be extended in case of assimilation of distributed streamflow observations?

Response: If the distributed streamflow observations were available across the watershed, then the VAR framework could be performed for each station within the basin. We have added additional discussion regarding this. One approach would be to consider the constant multiplier as a spatial distribution with the ‘K’ to be correlated across space. A simplistic approach is to allow the “K” to vary based on the distance between streamflow observations. Alternately, this fits within a Bayesian framework by assuming a prior distribution on ‘K’, which could be used to update “K” simultaneously across the space to obtain the posterior distribution of the constant multiplier across the watershed that maximizes the joint likelihood of streamflow observations across the watershed. We have added these future opportunities under the discussion section on page 17.

is expected. In these conditions, multiple streamflow observations could be considered with spatially varying ‘K’ multiplier for implementing the VAR-DA framework. If distributed streamflow observations were available across the watershed, then the VAR framework could be adapted for each station/grid cell within the basin. One approach would be to consider the constant multiplier as a spatial distribution with the ’k’ to be correlated across space. A simplistic approach is to allow the ’k’ to vary based on the distance between streamflow observations. Alternately, this fits within a Bayesian framework by assuming a prior distribution on ’k’, which could be used to update ’k’ simultaneously across the space to obtain the posterior distribution of the constant multiplier across the watershed that maximizes the joint likelihood of streamflow observations across the watershed.

- As the authors properly stated, the skill of VIC in predicting low flows are particularly lower than normal. As a consequence, a strong improvement in low flow predictions is achieved. What could be the impact of calibrating the VIC model separately for low and high flows? How this will affect the assimilation performances?

Response: This is true, in the presence of a high bias in the predicted flows, DA application is more successful in improving the prediction skill, i.e. a better calibrated model decreases the positive role of VAR DA. Our previous studies have shown that calibrating models based on flow conditions tends to improve the model performance (Li and Sankar, 2012; Yapo et al., 1996). If we improve the model calibration, certainly it will reduce the role of VAR-DA. It’s also possible to apply a VIC model that has multiple parameter sets that optimize performance in different hydrologic regimes. In the VAR context, adjustments could be sought in simulations produced by each parameter set to potentially achieve higher performance than using just one parameter set. This approach is similar in some regards to a joint state/parameter estimation, which can be effected within EnKF and Particle Filter based methods.

The following is now added to the discussion section:

effect of DA in the absence of model bias. With the intention of applying bias correction as well as quantifying the sole role of DA in hydrologic forecasting, a recursive bias estimation should be coupled into the DA framework at each iteration resulting in a two-stage estimation algorithm, but this significantly increases the computational cost (Friedland, 1969; Dee and Da Silva, 1998). In the presence of a high bias in the predicted flows, DA application is more successful in improving the prediction skill, i.e. a better calibrated model decreases the positive role of VAR DA. Our previous studies have shown that calibrating models based on flow conditions tends to improve the model performance (Li and Sankarasubramanian, 2012; Yapo et al., 1996). Thus If the model calibration in this study improves, the positive role of VAR-DA will be reduced.

- *Li, Weihua, and A. Sankarasubramanian. "Reducing hydrologic model uncertainty in monthly streamflow predictions using multimodel combination." Water Resources Research 48.12 (2012).*
- *Yapo, Patrice O., Hoshin Vijai Gupta, and Soroosh Sorooshian. "Automatic calibration of conceptual rainfall-runoff models: sensitivity to calibration data." Journal of Hydrology 181.1-4 (1996): 23-48.*

- In all assimilation applications, it is important to provide adequate information regarding the estimation of model and observation error and their spatial correlation. These aspects can drastically affect the assimilation performance. Could the authors elaborate more on the assumption of daily observational error equal to 0.05% of the variance of observed daily flows over 62 years (1949-2010)?

Response: The perturbation setup should add slight noise to the data, and this approach is adopted from Burgers et al 1998. Here we consider 0.05% variance of streamflow observations for perturbation purposes based on the uncertainties in the stage-discharge relationship (Herschy 1994). This is already explained in the draft Page7 Line23. Also this is in line with our other hydrologic DA study recently published (Mazrooei and Sankarasubramanian, 2019)

- *Burgers, Gerrit, Peter Jan van Leeuwen, and Geir Evensen. "Analysis scheme in the ensemble Kalman filter." Monthly weather review 126.6 (1998): 1719-1724.*
- *Herschy, Reg. "The analysis of uncertainties in the stage-discharge relation." Flow Measurement and Instrumentation5.3 (1994): 188-190.*
- *Mazrooei, Amirhossein, and A. Sankarasubramanian. "Improving monthly streamflow forecasts through assimilation of observed streamflow for rainfall-dominated basins across the CONUS." Journal of Hydrology 575 (2019): 704-715.*

- Can the authors provide more detail about the calibration method used with the VIC model? In addition, which range of model parameters is considered during calibration?

Response: The VIC LSM is calibrated for the Tar River basin over a 40-year period from 1951-1990 through estimating Nash-Sutcliffe Efficiency (NSE) by comparing the mean monthly simulated streamflows and the USGS #02083500 gauge observed monthly flows. The calibration is performed by manually adjusting the standard soil parameters of VIC model that control infiltration (i.e., Variable infiltration curve parameter "b_infilt" [0.00001,0.4]), and runoff and subsurface flows (i.e., Ws: fraction of maximum soil moisture where non-linear baseflow occurs [0.5,1] ,Dsmax: maximum velocity of baseflow [0,inf] ,Ds: Fraction of Dsmax where non-linear baseflow begins [0,1], depth: Soil depth of second and third layers [0,inf]). This calibration process is similar to what Sinha and Arumugam 2013 have done using VIC model over another river basin.

- *Sinha, T., and A. Sankarasubramanian. "Role of climate forecasts and initial conditions in developing streamflow and soil moisture forecasts in a rainfall–runoff regime." Hydrology and Earth System Sciences 17.2 (2013): 721-733.*

> - I suggest to include the dimension of the matrices of the VAR DA method (e.g. [nstate,nobs]). This will help the reader to better understand how to implement VAR DA in a generic hydrological model

Response: This information is fully given in the paper P.7 L.14. Nstate is equal to 804 , all the number of soil moisture elements in 3 soil layers over 268 sub-grids of the 40 grid cells covering Tar basin. and Nobs is the number of data points used within the assimilation window. Further, the following highlights are now added to the manuscript:

$$J(x_k) = J_o = \sum_{T_{-AW}}^{T_0} (y_t - H_t[x_k])^T R_t^{-1} (y_t - H_t[x_k]) \quad (2)$$

where in the above expression, $x_k \in \mathbb{R}^{3\times 268}$ refers to the analysis state, T_0 is the time of forecast, T_{-AW} is the beginning of the assimilation window, $y \in \mathbb{R}^{AW\times 1}$ is the vector of observations, and $H_t[x_k]$ is the simulated flow at time t when VIC is initialized with x_k. R_t is the daily observational error computed based on 0.05% of variance of observed daily flows over 62

> - Besides the simplification of the minimization function of Eq1, what are the other limitations of the current study and recommendations for future ones?

Response: The Tar river basin that is selected as our case study is categorized as a relatively small river basin. One limitation of this study is the application of our methodology in larger river basins. Since we are using downstream observed streamflow data in correcting the initial conditions of a distributed hydrologic model and taking into account that streamflow is an integrated product of all the physical processes over a basin with different time lags , thus selecting a larger river basin with a longer concentration time may result in a different behavior of VAR-DA and declined skill in VAR-aided forecasts/simulations is expected. In these conditions, multiple streamflow observations could be considered with spatially varying 'K' multiplier for implementing the VAR-DA framework. This is now added to the discussion section on page 17 and 18:

and parameter estimation. Finally, advances in hydrologic DA should be well communicated among researchers and forecasting centers in order to reach a transition strategy from hydrologic DA research into operational forecasting applications.

The Tar river basin that is selected as our case study here is categorized as a relatively small river basin. One limitation of this study is the application of our methodology in larger river basins. Since we are using downstream observed streamflow data in correcting the initial conditions of a distributed hydrologic model - taking into account that streamflow is an integrated product of all the physical processes over a basin with different time lags - thus selecting a larger river basin with a longer concentration time may result in a different behavior of VAR-DA and even declined skill in VAR-aided forecasts/simulations is expected.

If distributed streamflow observations were available across the watershed, then the VAR framework could be converted to a 3-D problem and be applied to each station/grid cell within the basin. In these conditions, multiple streamflow observations could be considered with spatially varying 'k' multiplier for implementing the VAR-DA framework. One approach would be to consider the constant multiplier as a spatial distribution with the 'k' to be correlated across space. A simplistic approach is to allow the 'k' to vary based on the distance between streamflow observations. Alternately, this fits within a Bayesian framework by assuming a prior distribution on 'k', which could be used to update 'k' simultaneously across the space to obtain the posterior distribution of the constant multiplier across the watershed that maximizes the joint likelihood of streamflow

observations across the watershed. Moreover, our VARDA framework is simplified to a 1-D problem along with excluding model background error term as it has a minimal impact on the VAR-aided forecasts and it is suggested for hydrological studies (Liu and Gupta, 2007; Seo et al., 2003). Here we apply a single 'k' multiplier to adjust the SM contents and minimize the observational error term J_o. In case of including the background error term J_b, matrix B could be computed as the variance of VIC LSM's SM simulations in an ensemble mode (e.g., by executing VIC LSM with perturbed observed forcings). Also, one could consider the spatial varying background SM values (X_b) across all the grid cells as the decision variables in the VARDA optimization problem, however this significantly increases the computational demand of the analysis.

Thank you for your review and constructive feedback!