Advances in Water Resources 92 (2016) 248–257

Contents lists available at ScienceDirect

Advances in Water Resources

journal homepage: www.elsevier.com/locate/advwatres

Moving horizon estimation for assimilating H-SAF remote sensing data into the HBV hydrological model

Rodolfo Alvarado Montero[a,*], Dirk Schwanenberg[a,b], Peter Krahe[c], Dmytro Lisniak[c], Aynur Sensoy[d], A. Arda Sorman[d], Bulut Akkol[d]

[a] Institute of Hydraulic Engineering and Water Resources Management, Department of Civil Engineering, University of Duisburg-Essen, Essen, Germany
[b] Deltares, Department of Operational Water Management, Delft, The Netherlands
[c] Federal Institute of Hydrology, Department of Water Balance, Forecasting and Predictions, Koblenz, Germany
[d] Department of Civil Engineering, Anadolu University, Eskisehir, Turkey

ARTICLE INFO

Article history:
Received 3 September 2015
Revised 15 March 2016
Accepted 19 April 2016
Available online 20 April 2016

Keywords:
Hydrological modelling
Remote sensing
Data assimilation
Moving Horizon Estimation
Variational methods

ABSTRACT

Remote sensing information has been extensively developed over the past few years including spatially distributed data for hydrological applications at high resolution. The implementation of these products in operational flow forecasting systems is still an active field of research, wherein data assimilation plays a vital role on the improvement of initial conditions of streamflow forecasts. We present a novel implementation of a variational method based on Moving Horizon Estimation (MHE), in application to the conceptual rainfall-runoff model HBV, to simultaneously assimilate remotely sensed snow covered area (SCA), snow water equivalent (SWE), soil moisture (SM) and in situ measurements of streamflow data using large assimilation windows of up to one year. This innovative application of the MHE approach allows to simultaneously update precipitation, temperature, soil moisture as well as upper and lower zones water storages of the conceptual model, within the assimilation window, without an explicit formulation of error covariance matrixes and it enables a highly flexible formulation of distance metrics for the agreement of simulated and observed variables.

The framework is tested in two data-dense sites in Germany and one data-sparse environment in Turkey. Results show a potential improvement of the lead time performance of streamflow forecasts by using perfect time series of state variables generated by the simulation of the conceptual rainfall-runoff model itself. The framework is also tested using new operational data products from the Satellite Application Facility on Support to Operational Hydrology and Water Management (H-SAF) of EUMETSAT. This study is the first application of H-SAF products to hydrological forecasting systems and it verifies their added value. Results from assimilating H-SAF observations lead to a slight reduction of the streamflow forecast skill in all three cases compared to the assimilation of streamflow data only. On the other hand, the forecast skill of soil moisture shows a significant improvement.

1. Introduction

An increasing number of satellite missions with dedicated remote sensing instruments for hydrological purposes have recently become available. Among this, the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) established the Satellite Application Facility on Support to Operational Hydrology and Water Management (H-SAF) in 2005. HSAF provides new satellite-derived products to satisfy the needs of operational hydrology and performs independent validation of the usefulness of these products. The currently operational H-SAF data include, among others, products for snow covered area (SCA), snow water equivalent (SWE), and soil moisture (SM). SCA, released as product H10 within H-SAF data, is generated from visible light and infrared images taken from low-earth and geostationary orbit (H-SAF, 2011). SWE product H13 is derived from microwave measurements (H-SAF, 2012a), whereas SM product H14 contains the profile index of the root-zone soil moisture generated by assimilating MetOp scatterometer observations in the European Centre for Medium-Range Weather Forecasts (ECMWF) Land Data Assimilation System (H-SAF, 2012b).

* Corresponding author: Rodolfo Alvarado Montero, Universität Duisburg-Essen, Institut für Wasserbau und Wasserwirtschaft, Universitätsstraße 15, 45141 Essen, Germany Tel.: +49 201 183 4303; fax: +49 201 183 2886.

E-mail addresses: rodolfo.alvarado-montero@uni-due.de (R.A. Montero), dirk.schwanenberg@uni-due.de (D. Schwanenberg), krahe@bafg.de (P. Krahe), lisniak@bafg.de (D. Lisniak), asensoy@anadolu.edu.tr (A. Sensoy), asorman@anadolu.edu.tr (A.A. Sorman), bltkkl@gmail.com (B. Akkol).

http://dx.doi.org/10.1016/j.advwatres.2016.04.011

The growing availability of remote sensing data has enabled the corresponding assimilation of this data in flow forecasting systems. Examples of these include the assimilation of snow products derived from the MODerate resolution Imaging Spectroradiometer (MODIS) (Andreadis and Lettenmaier, 2006; Nagler et al., 2008), SWE from the Advanced Microwave Scanning Radiometer (AMSR-E) (Andreadis and Lettenmaier, 2006), radar images of Envisat ASAR (Nagler et al., 2008), microwave radiance data from AMSR-E (Dechant and Moradkhani, 2011), SM from AMSR-E (Sahoo et al., 2013; Wanders et al., 2014), SM from Advanced Scatterometer (ASCAT) (Lu et al., 2015) as well as from the Soil Moisture and Ocean Salinity (SMOS) mission (Wanders et al., 2014), and snow depths from the Cold and Arid Regions Science Data Center (CARD) (Lu et al., 2015).

The main purpose of data assimilation is to provide updated model states at forecast time, based on recent observations. These updated states are used as a better estimate of initial conditions for the subsequent forecast, therefore improving the lead time accuracy of the forecast. In data assimilation, observations and model simulations are combined in an optimization problem that improves both observed and simulated data (Reichle, 2008). A more comprehensive definition is given by Liu and Gupta (2007), which consists of the merging of models with data, not only limited to the problem of state estimation but also to identify an appropriate model structure and parameter estimation.

Most data assimilation techniques applied in hydrology can be categorized as either sequential assimilation or variational assimilation. The former is commonly based on variants of Kalman Filters for which analytical solutions can be computed. Kalman filters estimate the best fit comprised by a true state and the model estimate, and between the true state and the observation (Reichle, 2008). This best state, or optimum value, is explicitly determined by the description of the model and the observation uncertainties, solved through the linear Kalman gain matrix. The dynamics of the system are partly captured by propagating the error from one time step to another. The Extended Kalman Filter (EKF) broadens the application to non-linear systems while the Ensemble Kalman Filter (EnKF) considers an ensemble of model states to determine the model uncertainties by perturbing the forcing variables using a Monte-Carlo approach (Reichle et al., 2002a,b). Alternatively, variational approaches depend on numerical approximations and optimization algorithms which iterate to find near-optimum solutions of a pre-defined objective function. Variational methods depend on adjoint models which compute the sensitivity of the model output to each of the inputs and states of the model (Seo et al., 2003). This is usually seen as their main drawback.

Sequential data assimilation has been used extensively in recent years partly because of its easy integration with existing models (Liu et al., 2012). While several authors have described the implementation of this approach to independently assimilate: i) SM (e.g. Chen et al., 2011; Han et al., 2012; Kumar et al., 2008; Sahoo et al., 2013); ii) snow (e.g. Andreadis and Lettenmaier, 2006; Clark et al., 2006; Kumar et al., 2008; Liu et al., 2015); and iii) streamflow (e.g. Clark et al., 2008; McMillan et al., 2013), few have attempted to simultaneously assimilate more than one observation variable type at a time (Trudel et al., 2014). Among these, Aubert et al., (2003) as well as Samuel et al., (2014) , assimilated both, in situ SM and streamflow data, into conceptual models using EKF and EnKF respectively and showed that the simultaneous assimilation of both observations gives more robust results than assimilating each observation individually. Other relevant studies, such as Mazzoleni et al., (2015) , presented the assimilation of dynamic and intermittent observations using the EnKF and improved model performance for several flood events by using additional uncertain observations associated to potential citizen measurements.

The assimilation of additional observations into the hydrological models seems a reasonable step towards the improvement of the forecast performance. Rakovec et al., (2012) assimilated streamflow observations from various sets of spatially distributed gauges using EnKF and obtained better performance when using an augmented observation vector. Together with Clark et al., (2008) , they recognized that hydrological forecasts could be improved by adding several previous time steps before the forecast time to the analysis, as opposed to using the instantaneous covariance between states and discharge. Rakovec et al (2015) then used the Asynchronous Ensemble Kalman Filter (AEnKF) approach to assimilate multiple streamflow observations from an assimilation window of approximately the same duration as the concentration time of the tested basin. Their results showed the benefits of adding these observations into the assimilation procedure.

On the other hand, variational methods, or the representer-based approach, use numerical approximations to minimize an objective function, also referred to as cost function, penalty function or misfit (Seo et al., 2003). The objective function uses distance metrics to penalize the introduction of noise into the model as well as the agreement between simulated and observed variables. Unlike sequential assimilation, variational methods do not rely on propagating the covariance matrix from one time step to the next but it is rather implicitly considered by simultaneously updating forcing and model states and propagating the effects in the model within the assimilation window. This makes it a very flexible method for the formulation of the objective function (Seo et al., 2003), which provides a simple approach to assimilate several types of data and deal with large assimilation windows. As mentioned before, a practical drawback of these methods is the requirement of a dedicated model in simulation and adjoint mode to apply the method in a computationally efficient way within operational applications. However, the availability of automatic adjoint code generators can overcome this problem (Seo et al., 2009). In the context of operational forecasting systems, the variational assimilation operates in a batch-processing manner over a time window (Liu and Gupta, 2007). The state estimation in this case becomes independent from previous runs as it optimizes over the complete assimilation window. The assimilation then repeats for the next time step in what is called the Moving Horizon Estimation (MHE) (Rawlings, 2013).

Due to its flexible formulation of observation terms, and congruently less computational effort compared to sequential equivalents, variational methods become a suitable method to simultaneously assimilate multiple observations. Seo et al., (2203) assimilated real-time observations of streamflow and precipitation, as well as climatological estimates of potential evaporation, through a variational approach using the soil moisture states at the beginning of the assimilation window, together with multiplicative adjustment factors to the precipitation and evaporation, as control variables. Seo et al., (2009) reported on the implementation of such a procedure in operational forecasting systems and compared the performance with the run-time modifications by human forecasters. Lee et al., (2011) implemented a variational approach to assimilate streamflow and in situ SM into a gridded Sacramento model by updating SM, precipitation and evaporation as in (Seo et al., 2003). Moreover, Lee et al., (2012) assimilated several streamflow observations in a distributed hourly model using observations at interior points. Abaza et al., (2014) compared sequential and variational assimilation of streamflow data in a conceptual model. The previous studies use assimilation windows of only a couple of days, in the range of the duration of the unit hydrograph. This is an insufficient window to properly handle hydrological processes with longer time lags such as snow deficits during winter period as driver for the snowmelt runoff in spring and early summer.