hydrology

MDPI

Editorial

Editorial for Special Issue: "Multi-Source Data Assimilation for the Improvement of Hydrological Modeling Predictions"

Huidae Cho [1,*] and Lorena Liuzzo [2,*]

1 Institute for Environmental and Spatial Analysis, University of North Georgia, Oakwood, GA 30566, USA
2 Facoltà di Ingegneria ed Architettura, Università degli Studi di Enna Kore, 94100 Enna, Italy
* Correspondence: hcho@ung.edu (H.C.); lorena.liuzzo@unikore.it (L.L.)

Physically-based or process-based hydrologic models play a critical role in hydrologic forecasting. However, it has always been a challenge to estimate measurable physical parameters or unmeasurable abstract parameters for these models to make acceptable predictions because of many different sources of uncertainty [1]. The main interest of this Special Issue is on how to improve hydrological modeling predictions by assimilating data from multiple sources.

Data assimilation is a procedure in which data observed from a system are mathematically or statistically analyzed and integrated into models to improve their predictive performance. It has been recognized as a valuable and reliable tool for improving the predictive performance of hydrological models thanks to recent advances in technologies. Over the last 30 years, advances in remote sensing and Earth-observation technologies have enabled the collection of data at local and global scales at different spatial and temporal resolutions, improving the understanding and prediction of the Earth–ocean–atmosphere system. In addition, widespread communication infrastructures have made it possible for citizens to participate in scientific projects where they can contribute data as part of citizen science programs.

The aim of the Special Issue "Multi-Source Data Assimilation for the Improvement of Hydrological Modeling Predictions" was to collect contributions in which novel methodologies and approaches in the field of data assimilation were explored, with a particular focus on their advantages and limitations. In this Special Issue, researchers focused on the assimilation of data from radar [2], gauges [2–4], satellites [5,6], and crowdsourcing [6]. The ensemble Kalman filter (EnKF) was mainly used as a data assimilation tool [3,5,6]. Streamflow [3–5] and flood [2,6] predictions are the main focus of the issue. This issue also introduces a web application for streamflow services [4].

Jadidoleslam et al. [5] assimilated satellite-based soil moisture estimates including Soil Moisture Active Passive (SMAP) [7] and Soil Moisture and Ocean Salinity (SMOS) [8] for real-time streamflow predictions. They used a distributed hydrologic model called the Hillslope Link Model (HLM) and the same baseline parameter set that was determined a priori to isolate the impact of three different data assimilation approaches on streamflow predictions. Their assimilation approaches include (1) hard update (simple replacement) without accounting for potential observational errors, (2) the EnKF 27 with a zero mean and a constant error variance of data to incorporate observational and modeling errors, and (3) the EnKF with time-dependent observational error variances (EnKFV). These approaches were applied to an agricultural region of the state of Iowa over four years, and they were used to evaluate streamflow prediction performance using 131 United States Geological Survey (USGS) gauges. Using the Kling–Gupta Efficiency (KGE) and Peak Difference Ratio (PDR), they found that the EnKFV, EnKF, and hard update resulted in the most, intermediate, and least significant improvements, respectively. Overall, they successfully showed that assimilating satellite-based soil moisture data into streamflow predictions improved the performance of hydrological modeling.

check for updates

Citation: Cho, H.; Liuzzo, L. Editorial for Special Issue: "Multi-Source Data Assimilation for the Improvement of Hydrological Modeling Predictions". *Hydrology* **2022**, *9*, 4. https://doi.org/10.3390/hydrology9010004

Received: 30 November 2021
Accepted: 22 December 2021
Published: 24 December 2021

Bergeron et al. [3] investigated the importance of metrics chosen for hyper-parameter calibration in data assimilation methods and their impacts on discharge forecasting. Hyper-parameters are parameters of data assimilation methods such as the ensemble square root Kalman filter (EnSRF). They calibrated the EnSRF hyper-parameters over two catchments in Canada using a spatially distributed model called CEQUEAU and a lumped model called GR4J. They used EnSRF over EnKF because the former method uses the observation covariance matrix instead of an ensemble of observations and does not make a linear relationship assumption between observations and model states. Although EnSRF requires additional computational resources in general, the extra cost becomes negligible when the amount of data to be assimilated is small. The metrics they considered include the Nash–Sutcliffe efficiency (NSE), mean absolute flood bias (MAFB), continuous ranked probability score (CRPS), normalized root mean square ration (NRR), and consistency diagnostic on innovations (D1). They concluded that the optimal set of hyper-parameters depended on the selection of the metric, but it was not strongly affected by the hydrologic model, although their results may not be generalized in all cases.

Annis and Nardi [6] proposed a flood forecasting framework for rapid floodplain mapping. They used the GFPLAIN DEM-based hydrogeomorphic model for small- and large-scale flood hazard mapping and forecasting. In their framework, they used three components, including (1) physical modeling, (2) satellite image analysis, and (3) crowd-sourced data analysis to update flood model inputs, state variables, and parameters in real-time and near real-time during flood events. The hydrogeomorphic floodplain data set was used as a mask for all the three components to reduce computational time and improve computational efficiency. They discussed ensemble-based data assimilation filtering using EnKF and particle filtering (PF). This conceptualization of the data assimilation framework for flood forecasting is expected to provide ancillary information on the extension of critical areas during flood events and preprocess the computational domain of various flood detection methods.

Grek and Zhuravlev [2] used weather radar data and ground-based observations of precipitation and runoff to simulate rainfall-induced floods in small catchments in north-west Russia where rain gauges are scarce. They used the Soil and Water Assessment Tool (SWAT) for hydrologic modeling. They adjusted radar data by fitting a linear relationship between rainfall depths measured at six gauges and derived from radar observations. Biases in radar-derived rain data were corrected using the residual interpolation method. They showed that the choice of the calibration period for radar data assimilation affected the simulation results. They concluded that, in general, gauge data, unadjusted radar data, and adjusted radar data performed well in that order using NSE. They also briefly discussed an issue in hydrologic calibration commonly known as “equifinality” [9] or multiplicity of solutions in their conclusions.

Lozano et al. [4] presented the development of a web application called the Historical Validation Tool (HVT) for global streamflow services. They used an open-source web application development framework called the Tethys Platform to build this application. The web application performs corrections of seasonally adjusted biases and forward biases on subsequent forecasts using observed hydrological data accessed using web services. HVT evaluates the performance of historic simulation data, while its bias correction allows it to improve the performance of the data. It provides the user with access to hydrological modeling and observation data as a web service. They demonstrated the effectiveness of their streamflow bias correction method in the use of global model results on a local scale.

As we discussed above, data assimilation involves a wide range of applications related to modelling uncertainties. Nevertheless, the articles published in this Special Issue provide a thorough overview of possible implementations involving data assimilation. Indeed, published contributions cover different data assimilation methods of different types of data for the improvement of hydrological modeling predictions. This issue also reviews challenges and limitations in data assimilation and presents a web service for streamflow forecasting.

Funding: This research received no external funding.

Acknowledgments: We want to thank the authors who contributed to this Special Issue on "Multi-Source Data Assimilation for the Improvement of Hydrological Modeling Predictions" and their anonymous reviewers who provided the authors with insightful and constructive comments.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Cho, H.; Park, J.; Kim, D. Evaluation of Four GLUE Likelihood Measures and Behavior of Large Parameter Samples in ISPSOGLUE for TOPMODEL. *Water* **2019**, *11*, 447. [CrossRef]
2. Grek, E.; Zhuravlev, S. Simulation of Rainfall-Induced Floods in Small Catchments (the Polomet' River, North-West Russia) Using Rain Gauge and Radar Data. *Hydrology* **2020**, *7*, 92. [CrossRef]
3. Bergeron, J.; Leconte, R.; Trudel, M.; Farhoodi, S. On the Choice of Metric to Calibrate Time-Invariant Ensemble Kalman Filter Hyper-Parameters for Discharge Data Assimilation and Its Impact on Discharge Forecast Modelling. *Hydrology* **2021**, *8*, 36. [CrossRef]
4. Lozano, J.S.; Bustamante, G.R.; Hales, R.C.; Nelson, E.J.; Williams, G.P.; Ames, D.P.; Jones, N.L. A Streamflow Bias Correction and Performance Evaluation Web Application for GEOGloWS ECMWF Streamflow Services. *Hydrology* **2021**, *8*, 71. [CrossRef]
5. Jadidoleslam, N.; Mantilla, R.; Krajewski, W.F. Data Assimilation of Satellite-Based Soil Moisture into a Distributed Hydrological Model for Streamflow Predictions. *Hydrology* **2021**, *8*, 52. [CrossRef]
6. Annis, A.; Nardi, F. GFPLAIN and Multi-Source Data Assimilation Modeling: Conceptualization of a Flood Forecasting Framework Supported by Hydrogeomorphic Floodplain Rapid Mapping. *Hydrology* **2021**, *8*, 143. [CrossRef]
7. O'Neill, P.E.; Chan, S.; Njoku, E.; Jackson, T.; Bindlish, R. Soil Moisture Active Passive (SMAP) Algorithm Theoretical Basis Document Level 2 & 3 Soil Moisture (Passive) Data Products. 2015. Available online: https://smap.jpl.nasa.gov/system/internal_resources/details/original/316_L2_SM_P_ATBD_v7_Sep2015.pdf (accessed on 30 October 2021).
8. Kerr, Y.H.; Waldteufel, P.; Wigneron, J.-P.; Delwart, S.; Cabot, F.; Boutin, J.; Escorihuela, M.-J.; Font, J.; Reul, N.; Gruhier, C.; et al. The SMOS Mission: New Tool for Monitoring Key Elements of the Global Water Cycle. *Proc. IEEE* **2010**, *98*, 666–687. [CrossRef]
9. Beven, K. A Manifesto for the Equifinality Thesis. *J. Hydrol.* **2006**, *320*, 18–36. [CrossRef]