

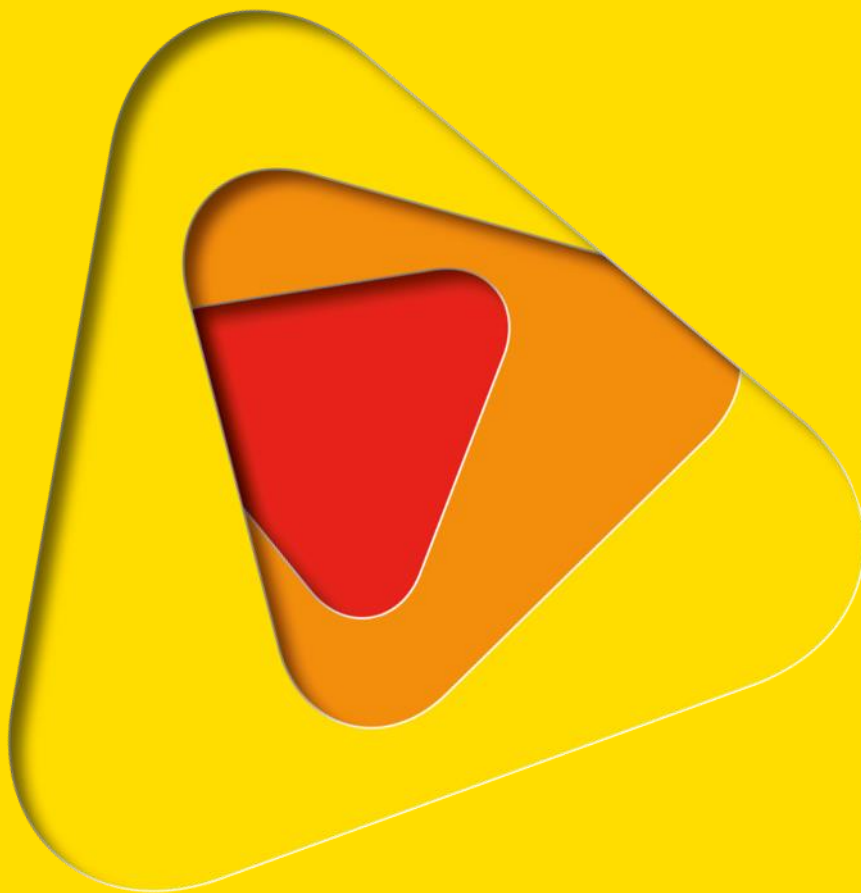


# IMPROVING FLOOD FORECAST SKILL USING REMOTE SENSING DATA

Non-peer reviewed research proceedings from the Bushfire and Natural Hazards CRC & AFAC conference  
Sydney, 4 – 6 September 2017

**Yuan Li, Stefania Grimaldi, Ashley Wright, Jeffrey Walker, Valentijn Pauwels**  
Monash University  
Bushfire and Natural Hazards CRC

Corresponding author: [valentijn.pauwels@monash.edu](mailto:valentijn.pauwels@monash.edu)





Version	Release history	Date
1.0	Initial release of document	04/09/2017



**Australian Government**  
**Department of Industry,  
 Innovation and Science**

**Business**  
 Cooperative Research  
 Centres Programme

All material in this document, except as identified below, is licensed under the Creative Commons Attribution-Non-Commercial 4.0 International Licence.

- Material not licensed under the Creative Commons licence:
- Department of Industry, Innovation and Science logo
  - Cooperative Research Centres Programme logo
  - All graphics.

All content not licenced under the Creative Commons licence is all rights reserved. Permission must be sought from the copyright owner to use this material.



**Disclaimer:**

Monash University and the Bushfire and Natural Hazards CRC advise that the information contained in this publication comprises general statements based on scientific research. The reader is advised and needs to be aware that such information may be incomplete or unable to be used in any specific situation. No reliance or actions must therefore be made on that information without seeking prior expert professional, scientific and technical advice. To the extent permitted by law, Monash University and the Bushfire and Natural Hazards CRC (including its employees and consultants) exclude all liability to any person for any consequences, including but not limited to all losses, damages, costs, expenses and any other compensation, arising directly or indirectly from using this publication (in part or in whole) and any information or material contained in it.

**Publisher:**

Bushfire and Natural Hazards CRC

September 2017

Citation: Li, Y., Grimaldi, S., Wright, A., Walker, J. & Pauwels, V. (2017) Improving flood forecast skill using remote sensing data. In M. Rumsewicz (Ed.), *Research Forum 2017: proceedings from the Research Forum at the Bushfire and Natural Hazards CRC & AFAC Conference*. Melbourne: Bushfire and Natural Hazards CRC.



## ABSTRACT

Floods are among the most important natural disasters in Australia. The average annual cost of floods in the last 40 years has been estimated to amount to \$377 million, with the 2010-2011 Brisbane and South-East Queensland floods alone leading to \$2.38 billion in economic damage, and 35 confirmed deaths. Flood forecasting systems are the most important tools to limit this damage, but are prone to a considerable degree of uncertainty.

During the last decades, significant research focusing on the monitoring of the global water cycle through satellite remote sensing has been performed. The strength of remote sensing is the opportunity to provide information at large spatial scales, including areas that are difficult or impossible to monitor using on-ground techniques. For these reasons it is believed that the use of remote sensing data can improve the quality of operational flood forecasts.

Operational flood forecasting systems typically consist of a hydrologic model, which estimates the amount of water entering a river system, and a hydraulic model, which models the flow of water inside the river system. However, hydrological and hydraulic models are prone to a significant degree of uncertainty and error, caused by errors and uncertainties in the initial conditions, meteorological forcing data, topographic data, and model errors and/or oversimplification (*Li et al., 2016; Grimaldi et al., 2016*). In order to reduce this predictive uncertainty, we propose to constrain the models using remote sensing data. In particular, remotely sensed soil moisture data are being used to improve the hydrologic model results, while remotely sensed water levels and/or flood extent data can be used to support the hydraulic model implementation, calibration and real time constraint.

The project focusses on two test sites, the Clarence River in New South Wales and the Condamine-Balonne River in Queensland. Figure 1 shows an overview of these test sites.

Initial catchment soil moisture plays an important role in controlling runoff generation and infiltration processes, which consequently impact streamflow forecasting. Recent development in remote sensing techniques provide a new potential to monitor spatially distributed surface soil moisture. As a result, soil moisture assimilation for flood forecasting has been a hot research topic in the recent years. The ensemble Kalman filter (EnKF) has been widely used for soil moisture assimilation by the scientific and operational communities, due to its relatively satisfactory efficacy and efficiency. However, one of the challenge is that streamflow forecasts are calculated not only from current states, but also from antecedent states in many hydrologic models, while the EnKF updates the current states only, and so may not achieve an optimal performance. As an alternative, assimilation of surface soil moisture by the ensemble Kalman smoother (EnKS) has been demonstrated to give better soil moisture reanalysis (*Dunne et al., 2006*). Nevertheless, the impact of the EnKS-based soil moisture assimilation on flood forecasting remains a research question.

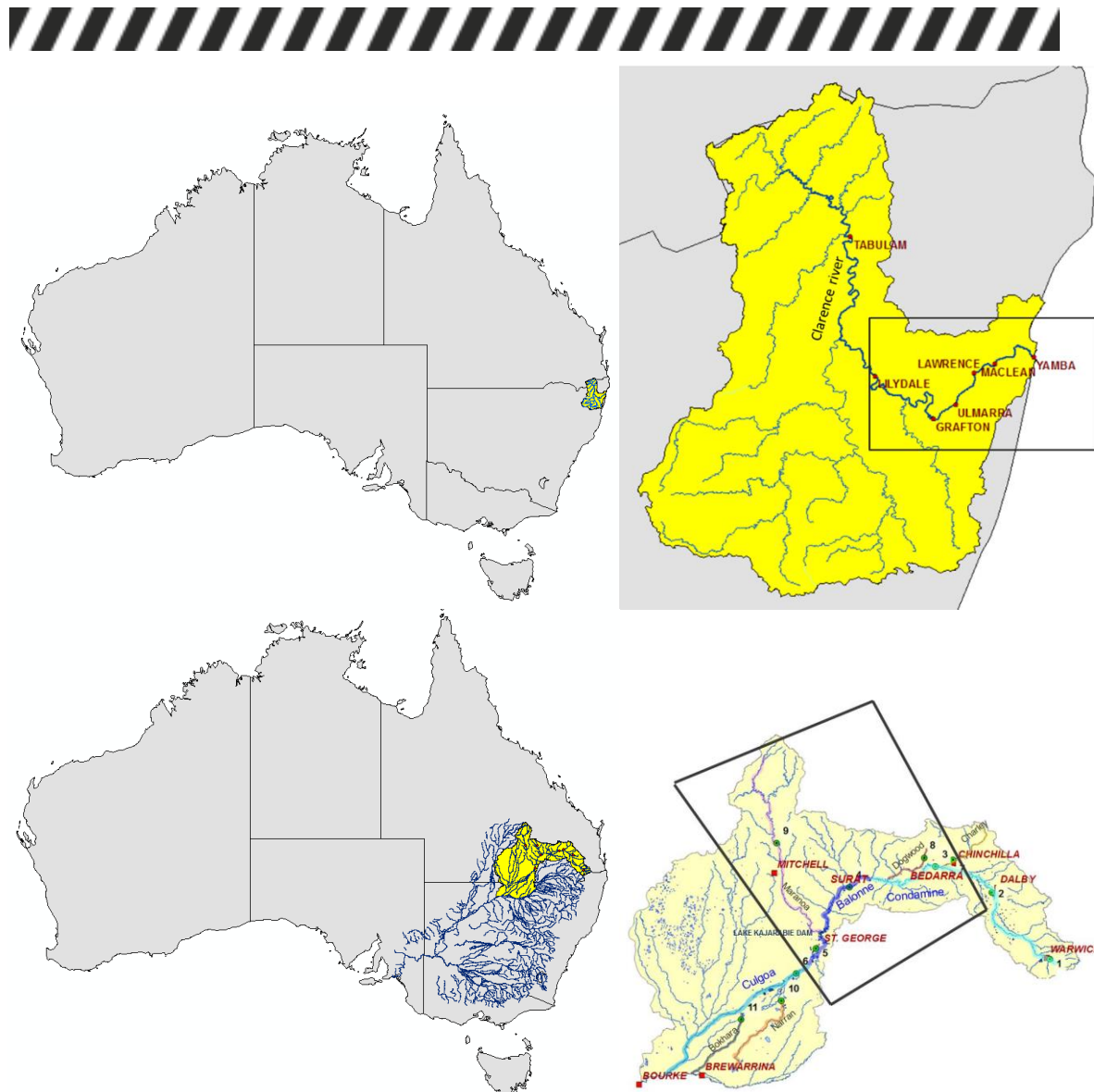


FIGURE 1. OVERVIEW OF THE TEST SITES. TOP LEFT HAND SIDE: LOCATION OF THE CLARENCE RIVER BASIN. TOP RIGHT HAND SIDE: DETAILED OVERVIEW OF THE CLARENCE RIVER BASIN. BOTTOM LEFT HAND SIDE: LOCATION OF THE CONDAMINE-BALONNE RIVER BASIN. BOTTOM RIGHT HAND SIDE: DETAILED OVERVIEW OF THE CONDAMINE-BALONNE RIVER BASIN.

In this study, the EnKF and EnKS were compared through a synthetic soil moisture assimilation experiment in the Warwick catchment, an upstream catchment in the Condamine-Balonne River Basin. A two-soil-layer conceptual hydrologic model, GRKAL, was adopted in this study. The model parameters were estimated through a joint calibration approach using gauged discharge and remotely sensed soil moisture, prior to the data assimilation experiment. The joint calibration was demonstrated to lead to a better match between observed and simulated surface soil moisture without degrading the predictability of streamflow, compared to the traditional streamflow calibration approach.

The synthetic true soil moisture and streamflow were generated by running the model with errors imposed to the input rainfall and the two simulated soil moisture states. The rainfall error was assumed to follow a lag-one autoregressive multiplicative lognormal distribution. The soil moisture errors were assumed to follow Gaussian distributions truncated by the boundaries of the two soil moisture states. The synthetic remotely sensed soil moisture was generated at 6 AM everyday (i.e., under the assumption that



only one image per day is available) by adding an observational Gaussian error to the synthetic true surface soil moisture. The synthetic true surface soil moisture was assimilated into the open loop model and the results were evaluated by the synthetic truth.

The data assimilation experiment was conducted from Jan 2012 – June 2014. Figure 1 shows a flood event in 2013. It can be seen that both the EnKF and EnKS reduce the ensemble spread compared to the open loop. The flood peak is overestimated by the open loop model according to the ensemble mean, and this overprediction is reduced by the EnKF and EnKS. Comparing the EnKF and EnKS, it can be seen that the EnKS provides more accurate streamflow predictions immediately after data assimilation, compared to the EnKF. This is because the smoothing method can address errors in antecedent state variables more thoroughly and the improvement in antecedent state variable analysis can be further propagated to the streamflow forecasts through the routing process. Nevertheless, the difference between the EnKF and EnKS becomes less significant with the increase of the forecast lead time. This can be explained by the fact that the benefit of updating antecedent states has a decreased impact with the increase of the lead time. When the forecast lead time is longer than the catchment concentration time, the EnKF and EnKS should theoretically give equivalent forecasts as the antecedent states will not be used in streamflow calculation.

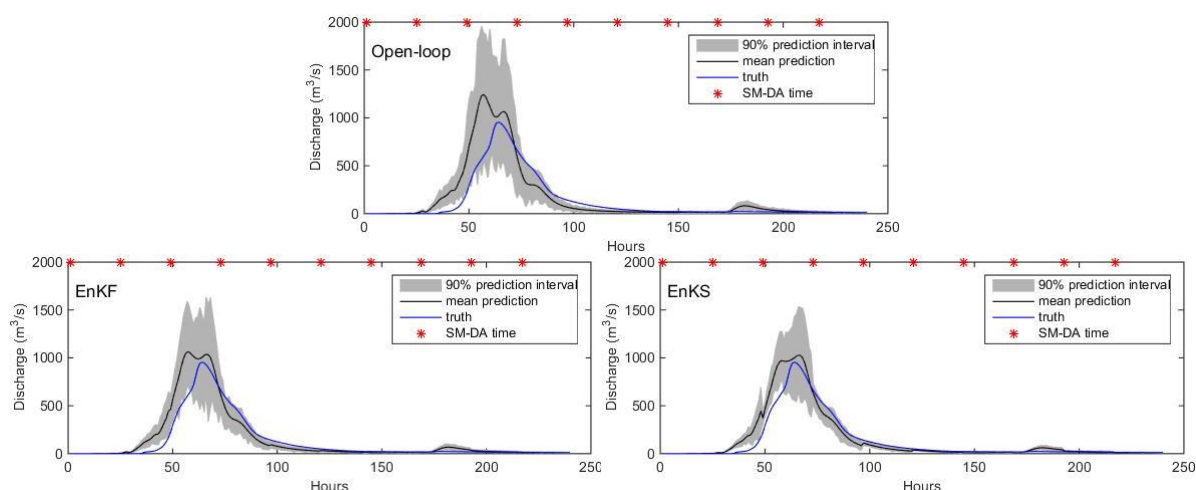


FIGURE 2. MODEL PREDICTIONS BEFORE AND AFTER DATA ASSIMILATION. THIS IS AN EXAMPLE FLOOD EVENT IN 2013.

The hydraulic model is based on LISFLOOD-FP (Bates *et al.*, 2010) and it uses the finite difference method to solve the inertial approximation of the shallow water equations.

Accurate modelling of river flow dynamics is essential to simulate floodplain inundation. Bathymetric data are thus critical to the application of hydraulic models. However, it is impossible to measure river bathymetry along the total river length, especially in large basins. While river width can generally be retrieved from space, river depth and channel shape cannot be systematically observed remotely. Where channel geometry is unknown, channel shape, depth, and friction can be estimated through calibration, but different parameter sets can often map model predictions to the observed data generating an equifinality problem. Conversely, even an approximated knowledge of river bathymetry can provide a more robust model setup.



Bathymetric data were available for ~80% of the total modelled length of the Clarence River. This peculiarly data rich case study provided the opportunity to investigate (1) the level of geometrical complexity required for the representation of river bathymetry in hydraulic flood forecasting models; (2) the definition of a data parsimonious methodology for the representation of river bathymetry in many data scarce catchments in Australia and worldwide.

A number of simplified geometrical models of river bathymetry were derived from cross sections sampled along the Clarence River. These simplified geometrical models had to be data-parsimonious. That is, each geometrical model was built from the combination of a limited number of measured cross sections selected from the complete field database, a global database and remote sensing data of river width.

The effectiveness of the proposed simplified geometrical models for flood prediction was tested using a numerical experiment. A high resolution model realization based on all available bathymetric field data was considered as truth. Subsequently, each simplified geometrical model of river shape was embedded into LISFLOOD-FP and the results compared against "true" water level hydrographs and maps of flood extent and levels. Based on this analysis, a data-parsimonious methodology for the definition of an effective river bathymetry representation in medium to high resolution raster-based flood forecasting hydraulic models was derived. A rectangular, width-varying shape was identified as the most effective simplified geometrical model, with width values derived from remote-sensing data; depth values assessed using a combination of global database and limited field data. Alternatively, an exponential cross section shape could be used; shape, depth and width were estimated using a combination of a global database and limited field data.

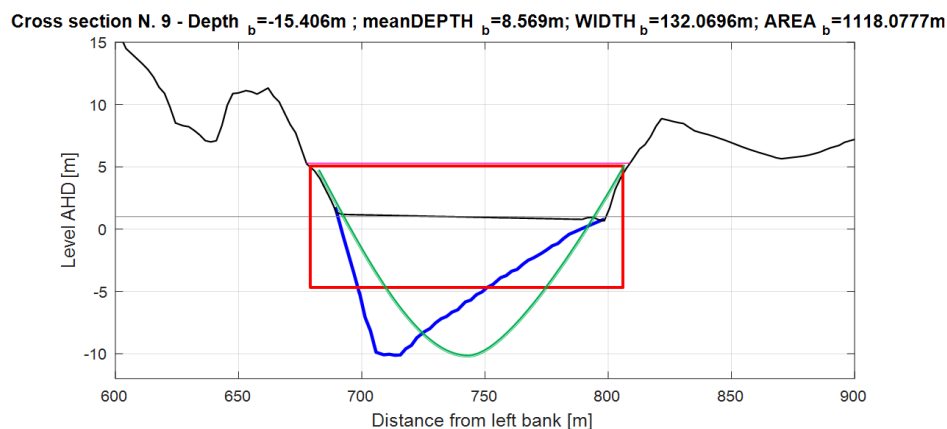


FIGURE 3. CLARENCE RIVER, EXAMPLE OF CROSS SECTION. BLUE: FIELD DATA; MAGENTA: BANKFULL LEVEL; RED: RECTANGULAR SIMPLIFIED GEOMETRY; GREEN: EXPONENTIAL SIMPLIFIED GEOMETRY.



## REFERENCES

- 1 Li, Y., S. Grimaldi, J. Walker, and V. Pauwels (2016), Application of Remote Sensing Data to Constrain Operational Rainfall-Driven Flood Forecasting: A Review, *Remote Sensing*, 8(6), 456, doi: 10.3390/rs8060456.
- 2 Grimaldi, S., Y. Li, V. R. N. Pauwels, and J. P. Walker (2016), Remote Sensing-Derived Water Extent and Level to Constrain Hydraulic Flood Forecasting Models: Opportunities and Challenges, *Surveys in Geophysics*, 37(5), 977-1034, doi: 10.1007/s10712-016-9378-y.
- 3 Dunne, S., and D. Entekhabi (2006), Land surface state and flux estimation using the ensemble Kalman smoother during the Southern Great Plains 1997 field experiment, *Water Resources Research*, 42, W01407, doi: 10.1029/2005wr004334.
- 4 Bates, PD, Horritt, MS, Fewtrell, TJ. (2010). A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. *Journal of Hydrology*, 387, 33-45. doi: 10.1016/j.jhydrol.2010.03.027.