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IMPROVING FLOOD FORECAST SKILL USING REMOTE SENSING DATA

Guidelines on the optimal use of remote sensing data to improve the accuracy of hydrologic and hydraulic models

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EXECUTIVE SUMMARY

Floods are among the most damaging natural disasters in Australia. In order to limit the personal and economic damage caused by floods, land and emergency managers need to rely on flood forecasting systems. These systems consist of a hydrologic model and a hydraulic model. The hydrologic model calculates the amount of water that enters the river network, while the hydraulic model computes how that water moves throughout the river and floodplain. The accuracy and reliability of flood forecasting systems has significantly improved in the last decades. However, errors and/or uncertainties in model structures and parameters, input data, and/or meteorological forcings often hamper the accuracy of predictions. This document confirms that remote sensing data can be used to improve the accuracy of hydrologic and hydraulic models and thus ultimately improve the flood forecast accuracy.

More specifically, remotely sensed soil moisture data are used to improve the hydrologic forecast skill of ungauged sub-catchment streamflow locations through multi-objective calibration. A pragmatic approach to select the optimal hydrologic model, optimized rainfall product, and remotely sensed soil product is outlined. Routines to assimilate and smooth streamflow and remotely sensed soil moisture observations over the length of a unit hydrograph are provided for improving forecast capability. Further, remotely sensed inundation extent and water level are used to improve the accuracy of the hydraulic model. This spatially distributed information is essential for understanding the floodplain inundation dynamics, adequately setting-up the hydraulic model and effectively constraining its parameters. The research underpinning these guidelines is consistent with the findings of ongoing research efforts worldwide and has contributed to the development of knowledge and a pragmatic framework for application in the Australian context.

The methodologies presented in these guidelines for optimal use of remotely sensed data to improve the predictive skill of flood forecasting models can be applied by operational agencies. Moreover, the techniques for the analysis of remotely sensed data support and complement the existing capabilities of Geoscience Australia, and the hydrologic model assimilation has been implemented by the Australian Bureau of Meteorology.

END-USER PROJECT IMPACT STATEMENT

Norman Mueller, *Geoscience Australia, Canberra, ACT*

Digital Earth Australia (DEA) is working with Monash University to implement its flood mapping system in the Open Data Cube code. The intention is to use Monash's code to map water from Sentinel-1 SAR data and incorporate the water extents into DEA's Water Observations from Space (WOfS) product. Success of this work will allow the WOfS product to continue mapping water during cloudy periods, filling a large gap in the supply of water information to several agencies in Australia including the Murray Darling Basin Authority and the Commonwealth Environmental Water Office.

Karen Hudson, Chris Leahy, *Bureau of Meteorology, Melbourne, VIC.*

The Bureau of Meteorology has taken a keen interest in the work of the Monash University team regarding the Bushfire Natural Hazards CRC project "Improving flood forecast skill using remote sensing data". The project has clearly demonstrated the potential for remote sensing data to assist in real-time flood forecasting applications, as well as highlighting some of the challenges. Over the past few years, the Bureau of Meteorology has made opportunistic use of available satellite-derived flood extent data during flood events, for example use of MODIS imagery to help communicate flood extent in tweets and to track flood progression in remote areas with little ground data.

1. INTRODUCTION

Floods have dire socio-economic consequences for Australia and much of the world. In just the last decade Australia has been the subject of numerous floods which have claimed multiple lives and caused damage in excess of a billion dollars. The average annual cost of floods over the last 40 years has been estimated to be $377 million dollars. Despite this, in March of 2018, the Insurance council of Australia declared 823,560 Queensland homes to be unprepared for flooding.

Water and emergency agencies use flood forecasting systems to limit the socio-economic exposure to floods. Current flood forecasting systems in Australia make use of state-of-the-art technology. However, the scientific landscape is constantly changing and new opportunities to enhance our flood forecasting systems into the future need to be explored.

These guidelines are based on new research that explored novel ways to combine remote sensing data and models to improve flood forecasting capability and skill. Key areas include:

- The use of remotely sensed soil moisture observations to constrain and update hydrologic model states,
- Remotely sensed flood extent mapping and its use to constrain hydraulic model estimates of flood extent, depth and velocity.

Hydrologic flood forecasting models compute the transition of rainfall and runoff into streamflow throughout a catchment by simulating key processes. The bulk processes represented include evaporation and transpiration of water along with the portioning of incident rainfall into surface and sub-surface runoff components. Catchment scale measurements of water storage above and below ground are scarcely available. Remotely sensed soil moisture observations provide hydrological models with additional data that can be used to constrain and/or update the model. New remotely sensed soil moisture missions provide a promising avenue to improve flood forecasting capability. To provide robust results, optimal usage of remotely sensed soil moisture in hydrological flood forecasting models is necessary.

Two-dimensional hydraulic models allow the prediction of water depth and velocity everywhere in a floodplain. These models account for flow connectivity in the floodplain, and between the floodplain and the river network, thus allowing an accurate representation of inundation dynamics at the catchment scale. Spatially distributed data are required for the adequate evaluation of a model's predictive performances. The increasing availability of remote sesnsing observations of inundation extent and water level provide a synoptic view of the flooding dynamics, thus opening opportunities for model verification at a large number of locations in the catchment.

This document provides guidelines for the use of remote sensing data to set-up and constrain hydrologic and hydraulic models for riverine flood forecasts in unregulated catchments. These guidelines were generated from an analysis of three case studies; the Clarence (NSW), the Condamine-Balonne (QLD), and the Fitzroy (WA) catchment. Nevertheless, the methodologies and guidelines were developed for application to any Australian catchment by incorporating the heterogeneity of Australian catchments and datasets available at the continental scale.

More specifically, Section 2 provides recommendations for the collection of the remote sensing datasets, Section 3 explains the features of the hydrologic and hydraulic models, and Section 4 lists guidelines for the use of remote sensing data to improve flood forecasting skill. The main sources of uncertainties when using remote sensing constrained hydrologic-hydraulic models for flood forecasts and the limitations for the application of the proposed guidelines are discussed in Section 5. Finally, Section 6 lists the recommended datasets and approaches for the case studies analysed within the research project. The guidelines presented by this document outline the pragmatic autcomes of an extensive research activity; the theoretical details and the full demonstration of the methodologies have been presented in the publications listed in Section 7.

2. DATA COLLECTION

The following sections detail the datasets required for the set-up, forcing, and evaluation of the hydrologic and hydraulic models. Recommendations are made based on the availability and quality of data.

2.1. HYDROLOGIC MODEL

This section details the datasets required for the implementation, forcing, and evaluation of a typical hydrologic model. For the purposes of flood forecasting within this document a lumped conceptual rainfall-runoff hydrologic model is used. The sub-sections below list recommendations for selection of the datasets and provide relevant examples. Table 1 provides a list of datasets that (i) meet the minimum requirements and (ii) are freely available under creative commons attribution 4.0 license (CC by 4.0).

2.1.1. Implementation data

The data sets used throughout this project are outlined in table 1 and described in the following sections.

2.1.1.1. *Catchment boundaries*

The Australian Geofabric data set details the spatial relationships between important hydrological features such as rivers, water bodies, aquifers, and monitoring points and can be used to delineate catchment boundaries.

2.1.1.2. *Fraction of vegetation cover*

The monthly fraction of vegetation cover aids in the calculation of water available for evapotranspiration processes. Consequently, the fraction of vegetation plays a role in determining the precipitation available to both infiltrate into the soil layers and runoff to form streamflow. As the fraction of vegetation generally does not change significantly within a month, the monthly data set made available through MODIS is adequate.

2.1.2. Forcing data

The successful implementation of any hydrologic model hinges upon the quality of forcing data used. The hydrologic model captures the key processes rainfall undergoes to become streamflow. Rainfall and potential evapotranspiration (PET) form the key data sets that are required and used to represent the evapotranspiration process, the partitioning of incident rainfall into surface and sub-surface flows, and sub-sequent river flows.

2.1.2.1. *Rainfall*

The three main sources of rainfall measurements come from: in-situ gauges, ground based weather radars, and satellite-based weather sensors. A robust calibration of rainfall-runoff models to historical data provides an essential foundation for a flood forecasting model. The calibration of rainfall runoff models has typically been conducted using measurements from in-situ gauges. The required rain gauge density depends on catchment size and consequently the spatial distribution of rainfall across the catchment. When available, the use of radar-based measurements to calibrate the rainfall-runoff model can be considered a suitable substitute for catchments with poor in-situ gauge density.

Regardless of the source of measurement, rainfall observations are prone to errors which can manifest for a number of different reasons. Using the Australian Water Availability Project (AWAP) Australian Bureau of Meteorology (BoM) gridded rainfall data as a benchmark, Robertson et al. (2015)[1] developed a quality control strategy to detect and remove in-situ rainfall observations which are:

- Anomalously large,
- Anomalously small,
- Not associated with the correct time stamp.

They demonstrated that pre-processing of in-situ rainfall data with the AWAP BoM gridded daily rainfall allows for improved runoff simulation skill in both calibration and validation periods.

In-situ rainfall data is commonly used for flood forecasting purposes throughout this project and recommended for future operational flood forecasting. The AWAP BoM gridded daily rainfall product is recommended for use in quality control purposes.

2.1.2.2. *Potential Evapotranspiration*

In conjunction with the fraction of vegetation cover, PET rates are necessary to determine the partitioning of rainfall into various runoff processes. Since PET predominantly influences seasonal water availability, a resolution finer than one month is unlikely to provide significant improvements to flood forecasting capability. Consequently, the AWAP PET data set is deemed to be more than adequate for flod forecasting purposes.

2.1.3. Evaluation data

Evaluation of the hydrologic model is typically conducted by calibrating the model to streamflow time series data. An independent data set of meteorological forcings and observed streamflow is then used to validate the calibration of the model. Research conducted as part of this project explored methods to improve the model calibration process using remotely sensed soil moisture data.

2.1.3.1. *Streamflow*

To forecast future flood events, which have similar characteristics to historic flood events, continuous rainfall runoff models are typically calibrated to historic streamflow records. Historic streamflow records typically estimate streamflow quantities based on rating curves, which translate a given water depth to a flow volume. Consequently, it is essential that the rating curve is up to date, and given practical limitations, provides a reasonable estimate of flood volume. Discharge and water level time series data are obtained from the BoM.

[1] Robertson, D. E., Bennett, J. C., & Wang, Q. J. (2015.). A strategy for quality controlling hourly rainfall observations and its impact on hourly streamflow simulations.

2.1.3.2. *Soil moisture*

Soil moisture data have been used throughout this project to improve rainfall-runoff models thereof by:

- Forming an additional data-set to be used in calibration,
- Improving the understanding of incident rainfall, and
- Updating model states.

Soil moisture observations which are made in a way that they are representative of catchment soil moisture states can provide detailed information regarding antecedent soil moisture conditions and consequently are extremely beneficial. In-situ soil moisture observations exhibit good temporal resolution at a variety of depths within the soil layer. However, in-situ soil moisture observations commonly do not exist or represent the catchment average which is required. Alternatively, remotely sensed soil moisture observations can represent the catchment average soil moisture, albeit for a near-surface soil layer for a snapshot in time every few days. Furthermore, remotely sensed soil moisture observations are available for the majority of catchments. In this project the Soil Moisture Ocean Salinity (SMOS) remotely sensed soil moisture ascending product obtained from Centre Aval de Traitement des Données (CATDS) is used.

Example of datasets. This project primarily uses SMOS remotely sensed soil moisture data. However, depending on the application, location, and time period available for calibration this dataset may not be the most useful. The user should select a remotely sensed soil moisture product based on reported accuracy, application, and period of time for which the data is to be used. Both the SMOS and Soil Moisture Active Passive (SMAP) satellites are currently observing soil moisture remotely.

TABLE 1: RECOMMENDED DATASETS FOR THE IMPLEMENTATION AND EVALUATION OF THE HYDROLOGIC MODEL

	Data type	Freely available datasets throughout Australia	Features
Implementation	Australian Hydrologic Geofabric	http://www.bom.gov.au/water/geofabric/index.shtml	Spatial relationships between important hydrological features such as rivers, water bodies, aquifers, and monitoring points
	Fractional cover of vegetation	http://www.auscover.org.au/datasets/fractional-cover-modis/	500 m resolution, 1-month composite.
Forcing data	Rainfall	http://www.bom.gov.au/climate/data/	In-situ gauged rainfall observations at hourly intervals.
	Rainfall	http://www.bom.gov.au/climate/austmaps/metadata-daily-rainfall.shtml	Gridded daily rainfall data.
	PET	http://www.csiro.au/awap/	Gridded monthly PET data.
Evaluation data	Streamflow	http://www.bom.gov.au/waterdata/	In-situ gauged water levels converted to streamflow at hourly intervals.
	Remotely sensed soil moisture	https://www.catds.fr/	Ascending pass level 3 SMOS soil moisture data.

2.2. HYDRAULIC MODEL

This section details the datasets required for the implementation, forcing (boundary conditions), and evaluation of the hydraulic model. The paragraphs below list the recommendations for selection of the datasets and provide relevant examples. Table 2 provides a list of datasets that (i) meet the minimum requirements and (ii) are freely available under creative commons attribution 4.0 license (CC by 4.0) at the continental scale.

2.2.1. Implementation data

Hydraulic model implementation requires a representation of the morphology of the floodplain and of the river, and information on land cover. These datasets required for model implementation allow the analysis of different flood events and scenarios. The updating of these datasets is required only if the catchment undergoes relevant morphological and land cover changes. A change is defined relevant if the currently used morphological and/or land cover data are no longer reliable representations of the catchment conditions.

2.2.1.1. *Digital Elevation Model*

A Digital Elevation Model (DEM) is a raster in which each cell value represents its elevation. A DEM is hence a representation of the catchment morphology including valley slope and flow connectivity in the floodplain and between the floodplain and the river network. An accurate DEM is essential for the adequate modelling of inundation dynamics. The accuracy of a DEM is determined primarily by the resolution of the measurements (that is the distance between sampling points), the processing of the original dataset to remove bias and artefacts (e.g. vegetation canopies), and the complexity of the observed area. Albeit, in broad terms, the higher the resolution, the higher the accuracy. Selection of an adequate DEM resolution for the implementation of a hydraulic model must account for the following factors:

- Computational time. The finer the DEM resolution, the higher the number of cells used for the representation of the catchment area, the larger the computational time and the larger the memory usage. Consequently, it is imperative to achieve the optimal trade-off between DEM resolution and computational cost. The optimal DEM resolution is the pixel size that maintains enough morphological detail for the purpose of the modelling exercise while allowing its practical feasibility.
- Catchment morphology. The pixel size must allow the representation of the main catchment morphological features. In large, lowland, nearly flat catchments, floodplain features can be adequately represented by a pixel size up to 100 m; conversely, steep areas with a complex morphology require a finer resolution, with an upper boundary of 30 m.
- Purpose of the modelling study. Models used for flood forecast and land management planning generally require finer resolution than models used for scenario analysis under climate change conditions. A fine resolution terrain dataset may provide spurious results when the forcing data are affected by high uncertainty.
- Data used for model evaluation. The pixel size of the terrain data should be commensurate with the resolution of the observations used for model evaluation. Accurate evaluation of model predictions of floodplain

inundation extent can be difficult when only coarser observations are available (section 2.2.3).

Example of datasets. DEMs at the continental to global scale are derived from satellite measurements and have 10^1-10^2 m (order of magnitude difference) resolution. Notable examples are the Shuttle Radar Topography Mission (SRTM, NASA), the ASTER-DEM (ASTER GDEM, Ministry of Economy, Trade, and Industry of Japan in partnership with NASA), and the TanDEM-X DEM (German Aerospace Centre). The SRTM data where acquired in 2001 with a 3 arc-sec (~ 90 m) resolution. The post-processing of the SRTM-DEM led to terrain datasets widely used in hydraulic modelling such as the DEM-H (the Australian SRTM Hydrologically Enforced Digital Elevation Model [2]), and the Merit Hydro[3]. Airborne LiDAR data can have 10^{-1} -10^0 meter resolution, but their spatial coverage is limited. The reader is invited to verify the availability of LiDAR data for their area of interest using the webservice maintained by Geoscience Australia at https://elevation.fsdf.org.au/. A comparison between DEM-H, TanDEM-X DEM, LiDAR data, and field measurements and their potential impacts on flood modelling in the Condamine-Balonne catchment (QLD) showed that riparian vegetation can cause large errors in both the DEM-H and TanDEM-X datasets[4] .

2.2.1.2. ***River bathymetry***

Accurate modelling of river flow dynamics is essential to simulate floodplain inundation. Bathymetric data are thus critical to the application of hydraulic models. The implementation of hydraulic models for the prediction of floodplain inundation requires at least the following information:

- river network connectivity to adequately simulate the flow paths;
- river flow capacity to correctly estimate the start of floodplain inundation;
- river width to incorporate the impacts of geometrical complexity on flood wave routing.

Remote sensing data generally allow the detection of flow paths and of river width. The estimation of river flow capacity relies on information of river depth and shape. These latter quantities cannot be systematically retrieved from a remote location and require field data. Clearly, it is impractical to measure river bathymetry along the total river length, especially in large basins and when considering that river geometry can change over time.

[2] Gallant, J., Wilson, N., Dowling, T., Read, A., Inskeep, C. 2011. SRTM-derived 1 Second Digital Elevation Models Version 1.0. Record 1. Geoscience Australia, Canberra. http://pid.geoscience.gov.au/dataset/ga/72759

[3] Yamazaki, D., Ikeshima, D., Sosa, J., Bates, P. D., Allen, G. H., & Pavelsky, T. M. (2019). MERIT Hydro: A High-Resolution Global Hydrography Map Based on Latest Topography Dataset. *Water Resources Research, 55*(6), 5053-5073. 10.1029/2019wr024873

[4] Wang, A., Grimaldi, S., Shaadman, S., Li, Y., Pauwels, V., Walker, J.P., 2018. Evaluation of TanDEM-X and DEM-H digital elevation models over the Condamine-Balonne catchment (Australia). In, Hydrology and Water Resources Symposium (HWRS 2018): Water and Communities (pp. 989-1003). Melbourne: Engineers Australia.

The following guidelines were formulated to allow a cost-effective assessment of river bathymetry for the implementation of hydraulic flood forecasting models:

- A rectangular, width-varying shape with uniform longitudinal slope has been identified as the most effective simplified geometrical model. River width can be derived from remote sensing information.
- Where river width cannot be systematically retrieved from remote sensing-data (e.g. less than 30 m wide rivers covered by trees), a parabolic cross section shape can be used.
- For both the rectangular and the parabolic geometries, depth values can be assessed using a combination of continental/global studies and limited field data (at least three measurements). The limited field data can rely on gauging stations or targeted, cost-effective field collections. Figure 1 provides a graphical summary and the references to the continental/global studies required for the implementation of the proposed methodology[5]. In rivers a few hundred meters wide, the RiBEST method can be applied. This method requires a DEM as input and it is based on the analysis of the geometry of the floodplain for cross sections perpendicular to the main river stem. A sensible change of the floodplain slope allows the identification of the river banks and the estimation of the maximum river depth[6, 7].

Where field data are available, the rapid yet accurate interpolation of field samplings can be achieved using a two stage process. First, use of conformal mapping allows the development of a coordinate system fitted to the river geometry; second, use of a radial interpolation over this coordinate system yields to the three-dimensional representation of river bathymetry[8].

2.2.1.3. ***Land Cover information***

Different land cover types (e.g. grassland, bushes, and forests) have a different impact on surface flow dynamics. In hydraulic modelling, this effect is mimicked by the roughness parameter according to look up tables[9,10]. Land cover information at the catchment scale is routinely derived from optical remote sensing data. The following recommendations are provided:

- Resolution: the pixel size should be smaller than or equal to the pixel size of the DEM.

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5 Grimaldi, S., Li, Y., Walker, J.P., Pauwels, V.R.N., 2018. Effective Representation of River Geometry in Hydraulic Flood Forecast Models. Water Resources Research. 54, 1031-1057

6 Domeneghetti, A. (2016). On the use of SRTM and altimetry data for flood modeling in data-sparse regions. *Water Resources Research, 52*(4), 2901-2918. 10.1002/2015WR017967

7 Molari, G., Grimaldi, S., Paron, P., Walker, J., Pauwels, V., Domeneghetti, A., 2020/1. RiBEST – a tool for river bathymetry and hydraulic parameters estimation. In preparation

8 Hilton, J.E., Grimaldi, S., Cohen, R.C.Z., Garg, N., Li, Y., Marvanek, S., Pauwels, V.R.N., Walker, J.P., 2019. River reconstruction using a conformal mapping method. Environmental Modelling & Software. 119, 197-213

9 Chow, V. (1959). *Open-channel Hydraulics*. New York (USA): Mc Graw-Hill.

10 Sadeh, Y.; Cohen, H.; Maman, S.; Blumberg, D.G. Evaluation of Manning's n Roughness Coefficient in Arid Environments by Using SAR Backscatter. *Remote Sens.* 2018, *10*, 150

- Time: the land cover dataset should reflect the characteristics of the catchment for the selected modelling period.
- Land use information from local land management agencies might be useful to complement RS-derived land cover data (e.g. crops subject to flooded irrigation).

Catchment area, A	The catchment area can be retrieved from near global datasets (e.g. HydroSHEDS[11]) or computed using the Australian GEOFABRIC (Australian Bureau of Meteorology).	
Discharge at bank full, Q	Empirical formulation: $Q=\alpha A^{\beta}$; α and β are provided by studies at the near global scale[12], and at the continental scale[13].	
Depth, d; width, w,	Depth: empirical formulations	Remote sensing-derived width
	$d=\gamma Q^{\delta}$; γ and δ are provided by studies at the near global scale[14,15], and at the continental scale[16,17].	River width was derived from remote sensing data at the near global scale[18], and at the continental scale[19].

FIGURE 1: SCHEMATIC FOR THE ASSESSMENT OF RIVER BATHYMETRY (THE ARROWS INDICATE THE CONSEQUENTIAL STEPS)[5].

[11] Lehner, B., Verdin, K., & Jarvis, A. (2008). New Global Hydrography Derived From Spaceborne Elevation Data. *Eos, Transactions American Geophysical Union, 89*(10), 93-94. 10.1029/2008EO100001

[12] Andreadis, K. M., Schumann, G. J. P., & Pavelsky, T. (2013). A simple global river bankfull width and depth database. Water Resources Research, 49(10), 7164-7168. 10.1002/wrcr.20440

[13] Gordon, N. G. (1996). The Hydraulic Geometry of the Acheron River, Victoria, Australia.

[14] Moody, J. A., & Troutman, B. M. (2002). Characterization of the spatial variability of channel morphology. Earth Surface Processes and Landforms, 27(12), 1251-1266. 10.1002/esp.403

[15] Andreadis, K. M., Schumann, G. J. P., & Pavelsky, T. (2013). A simple global river bankfull width and depth database. Water Resources Research, 49(10), 7164-7168. 10.1002/wrcr.20440

[16] Stewardson, M. (2005). Hydraulic geometry of stream reaches. Journal of Hydrology, 306(1), 97-111. http://dx.doi.org/10.1016/j.jhydrol.2004.09.004

[17] De Rose, R. C., Stewardson, M. J., & Harman, C. (2008). Downstream hydraulic geometry of rivers in Victoria, Australia. Geomorphology, 99(1), 302-316. http://dx.doi.org/10.1016/j.geomorph.2007.11.008

[18] Yamazaki, D., O'Loughlin, F., Trigg, M. A., Miller, Z. F., Pavelsky, T. M., & Bates, P. D. (2014). Development of the Global Width Database for Large Rivers. Water Resources Research, 50(4), 3467-3480. 10.1002/2013WR014664

[19] Hou, J., van Dijk, A. I. J. M., Renzullo, L. J., Vertessy, R. A., & Mueller, N. (2019). Hydromorphological attributes for all Australian river reaches derived from Landsat dynamic inundation remote sensing. Earth Syst. Sci. Data, 11(3), 1003-1015. 10.5194/essd-11-1003-2019

2.2.2. Boundary conditions

Boundary conditions are required for modelling specific flood events. First, boundary conditions define how much water is entering the catchment; this information can be provided by discharge gauge stations, rain observations, or by the hydrologic model. This type of boundary conditions is often reffered to as input conditions. Second, boundary conditions define the flow routing at the edges of the computational domain (i.e. at the edges of the DEM). If the river mouth is included in the modelled area, the downstream boundary condition is given by measured or predicted (e.g. tidal model) water level time series. If the river mouth is not modelled, the slope of the downstream valley has to be assessed using the DEM to enable the application of normal flow boundary conditions. The following points provide recommendations for the selection of the datasets used to prepare the boundary conditions:

- The accuracy of these datsets, with specific regard to the input conditions, is crucial for the accuracy of the model (section "Uncertainties and limitations"), hence, extreme care must be taken to handle inaccuracies and gaps in the measurements.
- The temporal resolution of the dataset must allow for the representation of the relevant features of the time series: rising limb, flood peak, decreasing limb, tidal range. This resolution does not impact the model computational time; hence, the finest reliable resolution can be used.

2.2.3. Evaluation data

Evaluation of floodplain inundation prediction dynamics requires the quantitative comparison between model results and observations. Such a quantitative comparison allows the verification of the model implementation and/or to calibrate model parameters. Gauged data and high-water marks have been traditionally used for this purpose; crowd sourced data could also be used in densely populated areas. RS observations have gained extensive interest as they allow a synoptic view of large areas and the monitoring of remote locations. This section provides guidelines for the selection of the RS observations.

A) Remote sensimg sensor and remote sensing-derived observations.

- Optical and Synthetic Aperture Radar (SAR) instruments enable the mapping of inundation extents. These instruments can provide high to low resolution data. Remote sensing data spatial resolution is the size of the smallest object that can be resolved on the ground; the image pixel size quantifies the spatial coverage of a pixel in the real world. For instance, Sentinel-1 SAR data have ~20 m resolution and ~10 m pixel spacing. A sensors' resolution can be fine (~10^0 m), medium (~10^1 m), or low (~10^2 m).
- Passive microwave and radar altimeter instruments provide useful information only for large catchments (>10^3 m resolution and river width larger than 10^2 m), consequently, use of data from optical and SAR instruments is recommended for the purpose of constraining the hydraulic model in Australian catchments[20].

[20] Grimaldi, S., Li, Y., Pauwels, V.R.N., Walker, J.P., 2016. Remote Sensing-Derived Water Extent and Level to Constrain Hydraulic Flood Forecasting Models: Opportunities and Challenges. Surveys in Geophysics. 37, 977-1034

- Optical instruments allow flood monitoring only during day time, in cloud free conditions, and in areas without thick tree canopies; conversely, SAR instruments are not affected by these limitations. SAR sensors are then to be considered as the primary source of information. Optical sensors can provide relevant complementary information, nevertheless the user must be aware of potential omission errors (clouds, cloud shadows, vegetation canopies). Consequently, the user is advised to use optical data only to detect omission errors in the model results.
- SAR and optical sensors are used to derive floodplain inundation extent; this remote sensing-derived inundation extent can then be overlaid onto a DEM to extract the planar position and elevation of the points at edge between the flooded and the dry area (wet/dry boundary points).

B) <u>Resolution.</u>

- High resolution sensors (or sensor mode) have a lower acquisition frequency and target smaller areas than medium to low resolution sensors. Consequently, the use of medium resolution RS data allows to rely on a larger number of observations acquired over larger areas.
- Remote sensing-derived observations are compared with model results. The resolution of the hydraulic model is defined by the resolution of the terrain implementation data: fine resolution observation data are not strictly required to evaluate medium resolution results.
- Medium to coarse resolution observations can be used to monitor floodplain inundation dynamics in large, lowland floodplains; high resolution observations are strictly required in urban areas.

C) <u>Acquisition time.</u>

- Images acquired during the rising limb and close to the flood peak are expected to allow detecting sensible variations of inundation extent and level. The use of these observations is recommended for the evaluation of floodplain inundation models[20, 21, 22].
- Use of images acquired during the late stages of valley filling events require some further consideration. Variations of flood extent can be very difficult to detect when a valley is full, meaning that acquisitions at different times can provide similar information. In these scenarios, use of remote sensing-derived water level could allow the detection of the temporal dynamics of the flood event. Nevertheless, adequate estimates of remote sensing derived water level require high resolution and high accuracy DEMs.
- The measured or predicted flood hydrograph at the upstream location of the catchment can be used to assess the timing of the rising limb and flood peak and hence identify the optimal acquisition window.

D) <u>Spatial coverage.</u>

- The larger the footprint of the observed area, the higher the information content (at a lower spatial resolution, as explained in point B).

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[21] Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2020. Improving flood forecast using remote sensing data - annual report 2019-2020. Melbourne, in: Bushfire and Natural Hazards CRC.

[22] Dasgupta, A., 2020. Optimizing Flood Extent Assimilation for Improved Flood Inundation Forecasts. In. Mumbai: IITB Monash Research Academy.

- Use of images acquired over the upstream area of the catchment is recommended to improve the inundation modelling accuracy in the downstream areas of the catchment.
- Acquisitions targeting areas where a small variation of discharge/water level leads to a large variation of flood extent (thereafter referred to as *critical areas*) are preferred. Examples include: areas protected by levee systems, gorges, and large floodplains.
- Analyses of databases of historical observations of surface water such as Water Observations from Space[23] can support the identification of these critical areas.
- Analysis of the hydraulic behaviour of the catchment and of the model response to different parameter or input time series is an effective methodology to identify critical areas and morphological singularities. More specifically, it is recommended to complete a sensitivity analysis of the impact of different parameters and input time series on the prediction of flood extent and levels. The areas with morphological singularities can then be identified as the areas where small variations of the parameters' values or small discrepancies in the input datasets result in large variations of flood extents and levels. Targeted observations of such areas enable to effectively evaluate a model's performance. For instance, small variation of parameter values can lead to large variations in the prediction of flood extents in areas with levee systems[24]. Moreover, small discrepancies in the input flood hydrographs can result in sensibly different predictions of flood extents in presence of gorges and natural restrictions[25].

Examples of datasets. A notable example of remote sensing -derived inundation layers retrieved from optical data at the continental scale is Water Observations from Space; an example of a global dataset is provided at https://global-surface-water.appspot.com/ [26]. A number of algorithms have been proposed for the retrieval of flood extents from remote sensing data[27]. This BNHCRC project has focussed on the mapping of floods in areas with emerging vegetation using one SAR acquisition and commonly available datasets[28], that is, a common scenario in Australian applications. The proposed algorithm will be available via GitHub: https://github.com/GeoscienceAustralia/dea-sar-flood-veg (under development).

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23 Mueller, N., Lewis, A., Roberts, D., Ring, S., Melrose, R., Sixsmith, J., . . . Ip, A. (2016). Water observations from space: Mapping surface water from 25 years of Landsat imagery across Australia. Remote Sensing of Environment, 174, 341-352. http://dx.doi.org/10.1016/j.rse.2015.11.003

24 Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2019. Improving flood forecast using remote sensing data - annual report 2018-2019. Melbourne, in: Bushfire and Natural Hazards CRC

25 Grimaldi, S., Schumann, G.J.-P., Shokri, A., Walker, J.P., Pauwels, V.R.N., 2019b. Challenges, Opportunities, and Pitfalls for Global Coupled Hydrologic-Hydraulic Modeling of Floods. Water Resources Research. 55, 5277-5300

26 Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. Nature, 540(7633), 418-422. Doi: 10.1038/nature20584

27 Dasgupta, A., Grimaldi, S., Ramsankaran, R.A.A.J., Pauwels, V.R.N., Walker, J.P., 2018. Towards operational SAR-based flood mapping using neuro-fuzzy texture-based approaches. Remote Sensing of Environment. 215, 313-329

28 Grimaldi, S., Xu, J., Li, Y., Pauwels, V.R.N., Walker, J.P., 2020. Flood mapping under vegetation using single SAR acquisitions. Remote Sensing of Environment. 237, 111582

TABLE 2: RECOMMENDED DATASETS FOR THE IMPLEMENTATION AND EVALUATION OF THE HYDRAULIC MODEL.

	Data type	Freely available datasets at the continental scale; reference(s)	Features
IMPLEMENTATION	Digital elevation model	1 second SRTM Derived Hydrological Digital Elevation Model (DEM-H)[1]; Geoscience Australia https://elevation.fsdf.org.au/; http://www.ga.gov.au/scientific-topics/national-location-information/digital-elevation-data	Pixel size: 1arc-sec (~ 30m). The DEM-H captures flow paths based on SRTM elevations and mapped stream lines (ANUDEM software).
IMPLEMENTATION	River width	Temporal and spatial river width dynamics, flow regime, and river gradient for 1.4 million Australian river reaches[11], Australian National University. http://wald.anu.edu.au/data_services/data/hydromorphological-attributes-for-all-australian-river-reaches/	This dataset was developed based on surface water recurrence information from WOfS and GIS-based hydrological features from the Australian Geofabric.
IMPLEMENTATION	Land cover	National Dynamic Land Cover Dataset of Australia; Geoscience Australia. http://www.ga.gov.au/scientific-topics/earth-obs/accessing-satellite-imagery/landcover	Pixel size: 250 m.
FORCING	Discharge and water level time series	Gauged data: Water data online, Australian Bureau of Meteorology. http://www.bom.gov.au/waterdata/ Modelled data: hydrological model.	In-situ gauged water levels converted to streamflow at hourly intervals.
EVALUATION	Flood extent	OPTICAL DATA: Water Observations from Space (WOfS), Geoscience Australia. WOfS displays the detected surface water from the Australia-wide Landsat satellite imagery archive since 1987 to present. https://www.ga.gov.au/scientific-topics/community-safety/flood/wofs https://maps.dea.ga.gov.au/	Pixel size: 25 m. Acquisition frequency: 8 to 16 days.
EVALUATION		SAR DATA: https://github.com/GeoscienceAustralia/dea-sar-flood-veg (under development)	
EVALUATION	Wet/dry boundary points	There are no readily available datasets. The retrieval of the remote sensing-derived wet/dry boundary points in the Clarence catchment has been shown by published studies[29, 30]	Recommended when high resolution and accuracy DEMs are available.

[29] Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2020. Improving flood forecast using remote sensing data - annual report 2019-2020. Melbourne, in: Bushfire and Natural Hazards CRC.

[30] Mason, D.C., Schumann, G.J.P., Neal, J.C., Garcia-Pintado, J., Bates, P.D., 2012. Automatic near real-time selection of flood water levels from high resolution Synthetic Aperture Radar images for assimilation into hydraulic models: A case study. Remote Sensing of Environment. 124, 705-716

3. NUMERICAL MODEL SELECTION

Both the hydrologic and hydraulic models need to be carefully and correctly setup for the value of remote sensing data to be realised. The following sections outline possible steps to choose and setup hydrologic and hydraulic models.

3.1. HYDROLOGIC MODEL

3.1.1. Model structure, purpose and limitations

With a myriad of rainfall-runoff models available it is prudent to select a model that meets key requirements. To support the selection of a rainfall-runoff model which has the capability to take advantage of remotely sensed soil moisture for flood forecasting purposes the following recommendations are made:

- Use of a continuous model which simulates lumped catchment processes such as soil moisture dynamics, surface and sub-surface storage and flows, and interactions between PET and the associated water storages. It is this distinction between continuous rainfall-runoff models and event-based rainfall runoff models that makes continuous rainfall-runoff models well suited to take advantage of the information that remotely sensed soil moisture observations provide.
- The model should have proven ability to simulate streamflow amongst Australian catchments.
- The model can be used in real time to produce ensemble forecasts.
- The spatial representation of rainfall should be covered within a sub-catchment or grid.

The dominant processes need to be well represented[31]. A suitable model that fits these recommendations and has been implemented in forming these recomendations is the GRKAL variant of GR4J depicted in figure 2. GRKAL is a conceptual rainfall-runoff model that is designed to capture the essential surface layer soil moisture dynamics necessary to incorporate remotely sensed soil moisture observations.

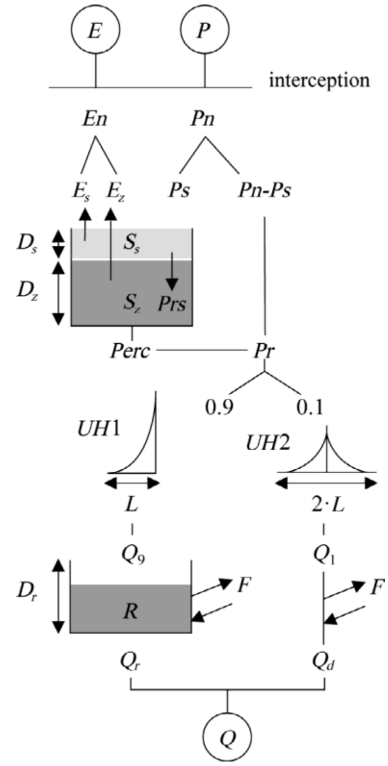

Figure 2: a representation of how GRKAL treats key rainfall runoff processes. Adapted from (Francois et al., 2003).

More complex physically based models may simulate rainfall-runoff dynamics with greater precision and generate more detailed output. However, as the model representation becomes finer and more distributed a larger number of parameters need to be calibrated. The computational time becomes cumbersome as well. Further, it is not realistic to expect historic streamflow records to always exhibit similar characteristics such as the timing, duration and peak flow to those which will be observed in future flood events. It is for this reason that conceptual or physically based rainfall runoff models are preferred to those models which provide little explanation or reasoning for the occurrence of events.

[31] Francois, C., Quesney, A., & Ottlé, C. (2003). Sequential Assimilation of *ERS-1* SAR Data into a Coupled Land Surface–Hydrological Model Using an Extended Kalman Filter. *J. Hydrometeorol.*, *4*(2), 473–487. https://doi.org/10.1175/1525-7541(2003)4<473:SAOESD>2.0.CO;2

3.1.2. Model outputs

The key output from rainfall-runoff models is the streamflow at any given time step. This streamflow volume can be converted to a depth in a forecasting situation using a rating curve or used to force a hydraulic model. Depending on the model, surface layer and root zone soil moisture profiles can also be extracted.

3.2. HYDRAULIC MODEL

3.2.1. Model structure, purpose, and limitations

With the large number of hydraulic models available[32], it is important to select a model that allows the accurate prediction of floodplain inundation dynamics and facilitates the comparison between modelled and observed inundation extents and level. For this purpose, the following recommendations are made:

- Use of a 2-dimensional (2-D) model is essential to adequately predict flow connectivity in the floodplain and between floodplain areas and the river network;
- The numerical code must adequately solve the shallow water equations and hence enforce the conservation of mass and momentum.
- Simplified formulations of the conservation of momentum, such as the diffusive and the inertial formulation, are adequate for the modelling of floodplain inundation (where the vertical gradient of flow velocity is negligible) and allow a reduced computational time compared to the numerical codes solving the full shallow water equations.
- Raster-based models have a higher practicality as DEMs can be used to implement the model without further post-processing and the output data have the same structure as the remote sensing observations.

The above points allow the selection of a model that can be used for the prediction of floodplain inundation dynamics. Nevertheless, it is imperative to state that such (relatively simple) models cannot be used for the investigation of:

- tsunamis;
- dam-breaks;
- solid transport, erosion, deposition, fluvial geomorphology, landscape evolution;
- bridge, levees, river banks scour;
- interaction with the groundwater table;
- manholes, sewage and aqueduct systems; or
- flow in buildings.

All the phenomena listed above require more complex (and time consuming) numerical models which are capable of solving the Navier-Stoke equations. One notable example of a numerical model formulated for the modelling of tsunamis

[32] Néelz, S., & Pender, G. (2013). Benchmarking the latest generation of 2D hydraulic modelling packages. *Environment Agency, Horison House, Deanery Road, Bristol, BS1 9AH*

and dam-breaks is ANUGA (https://anuga.anu.edu.au/). One notable example of a numerical model formulated for the modelling of fluvial geomorphology is Caesar Lisflood, (https://sourceforge.net/projects/caesar-lisflood/).

The model used in formulating these guidelines is based on LISFLOOD-FP[33] and uses the finite difference method to solve the inertial approximation of the shallow water equations. This model has proved to be accurate against analytical solutions and hydrodynamic models, while also being more computationally efficient than diffusive models. Nevertheless, the methodologies presented in these guidelines for the comparison between modelled and remote-sensing derived inundation extent and level can be applied when using any other 2-dimensional hydraulic model.

3.2.2. Model outputs

At any computational time step, 2-D hydraulic models compute water depth and discharge for each cell of the computational domain. Water levels are computed by adding water depth to the DEM elevation. The average cell flow velocity is the ratio between the discharge and the flow area (water depth multiplied by the cell size). Selection of the output data should be based on the following considerations:

- Scope of the study; e.g. is the maximum flood extent the only prediction of interest?
- Availability of evaluation data; remote sensing-derived acquisitions available at discrete (often larger than daily) time intervals.
- Features of the flood event; in many catchments, the receding phase is extremely slow and it can be studied using a few model predictions per day.

[33] Bates, P. D., Horritt, M. S., & Fewtrell, T. J. (2010). A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. Journal of Hydrology, 387(1–2), 33-45. http://dx.doi.org/10.1016/j.jhydrol.2010.03.027

4. USE OF REMOTE SENSING DATA TO IMPROVE MODEL FORECAST SKILL

These guidelines assert that remote sensing data can be been used to:

- Aid in the calibration of rainfall-runoff models for ungauged locations;
- Provide a pragmatic basis to choose between combinations of hydrologic model and remotely sensed soil moisture product;
- Update intermediate soil moisture states to improve forecast skill;
- Enhance performance metrics;
- Verify and optimise the implementation of the hydraulic model; and
- Calibrate the parameters of the hydraulic model.

The rest of this section provides the guidelines for the use of remote sensing data to improve the forecasting capability of hydrologic and hydraulic models.

4.1. HYDROLOGIC MODEL

4.1.1. Performance metrics

For streamflow simulation there is no widely regarded performance metric which consistently outperforms other performance metrics. The commonly applied approach in Australia the use an unweighted average of metrics which represent low, medium, and high flows and overall bias[34] is recommended.

4.1.2. Multi-objective calibration

Typically, rainfall runoff models are calibrated using historical streamflow to optimize streamflow simulations. Multi-objective calibration methods have been used to find a balance between competing objective functions which rank the rainfall-runoff models' ability to simulate streamflow and soil moisture[35]. By definition, multi-objective calibration will not improve the capability of the model to simulate streamflow at gauge locations for which calibration occurs.

In forming these recomendations, a study to discern the capability of using remotely sensed soil moisture in multi-objective calibration scenarios to improve

[34] Bennett, J. C., Robertson, D. E., Ward, P. G. D., Hapuarachchi, H. A. P., & Wang, Q. J. (2016). Calibrating hourly rainfall-runoff models with daily forcings for streamflow forecasting applications in meso-scale catchments. *Environ. Model. Softw.*, *76*, 20–36. https://doi.org/10.1016/j.envsoft.2015.11.006

[35] Li, Y., Grimaldi, S., Pauwels, V. R. N., & Walker, J. P. (2018). Hydrologic model calibration using remotely sensed soil moisture and discharge measurements: The impact on predictions at gauged and ungauged locations. *J. Hydrol.*, *557*, 897–909. https://doi.org/10.1016/j.jhydrol.2018.01.013

streamflow simulation skill in ungauged sub-catchments was conducted[36]. The study catchments and locations of internal gauges are shown in figure 3.

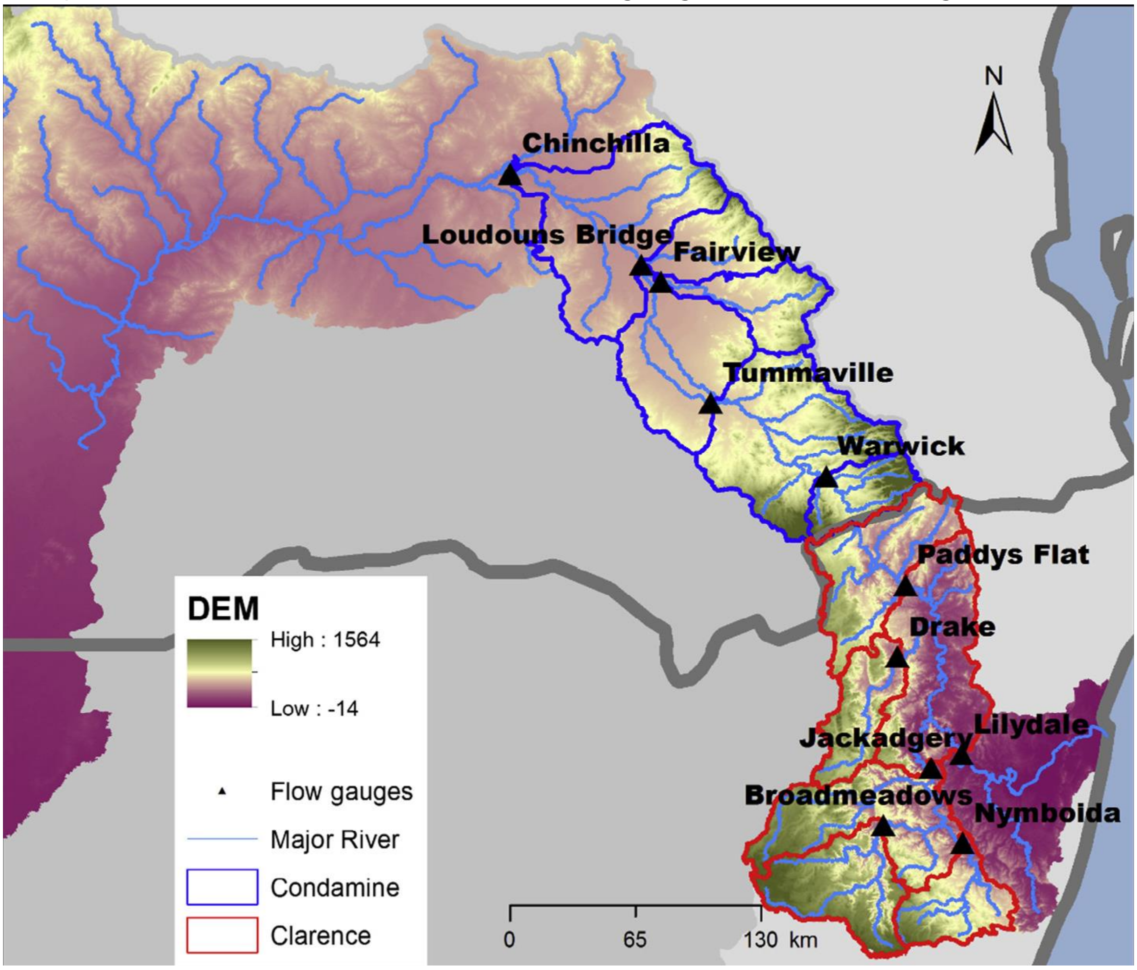

FIGURE 3: STUDY CATCHMENTS AND GAUGE LOCATIONS USED IN THE MULTI-OBJECTIVE CALIBRATION OF GRKAL USING REMOTELY SENSED SOIL MOISTURE AND STREAMFLOW. ADAPTED FROM (LI ET AL., 2018).

The GRKAL hydrologic model was setup in a semi-distributed fashion to simulate streamflow within the Condamine-Balonne and Clarence River catchments. Using a multi-objective calibration approach which utilizes remotely sensed soil moisture data for all sub-catchments and only streamflow at the downstream gauges, consistent improvements in streamflow simulation skill at internal sub-catchments was demonstrated. This finding indicates that remotely sensed soil moisture can be used to improve flood forecasts for ungauged locations upstream of a gauge.

4.1.3. Choosing between models and remotely sensed soil moisture data sets

A common problem hydrologists face is that different models and remotely sensed soil moisture data sets may be more useful in one catchment than another. Typically, choices between models are based on familiarity, past

[36] Li, Y., Grimaldi, S., Pauwels, V. R. N., & Walker, J. P. (2018). Hydrologic model calibration using remotely sensed soil moisture and discharge measurements: The impact on predictions at gauged and ungauged locations. *J. Hydrol.*, *557*, 897–909. https://doi.org/10.1016/j.jhydrol.2018.01.013

performance, and widespread usage. However, with the growing availability of soil moisture products it is prudent that hydrologists choose models that can take advantage of such observations and tailor the choice of hydrologic model to the characteristics of the catchment.

In forming these guidelines, a pragmatic approach was developed to aid in the decision-making process[37]. This approach built upon previous research to estimate rainfall time series and model parameter distributions using model input data reduction methods[38]. This approach evaluates the innovations of the Ensemble Kalman Filter (EnKF) using optimized rainfall products, three hydrological models, and two remotely sensed soil moisture products. When rainfall, simulated and observed soil moisture products are in agreement, innovations of the EnKF should display properties of white noise. As seen in figure 4 it is completely realistic for soil moisture simulations obtained from a given hydrological model and optimized rainfall product, to exhibit greater similarity to one remotely sensed soil moisture product than another.

A different hydrological model may produce soil moisture simulations with

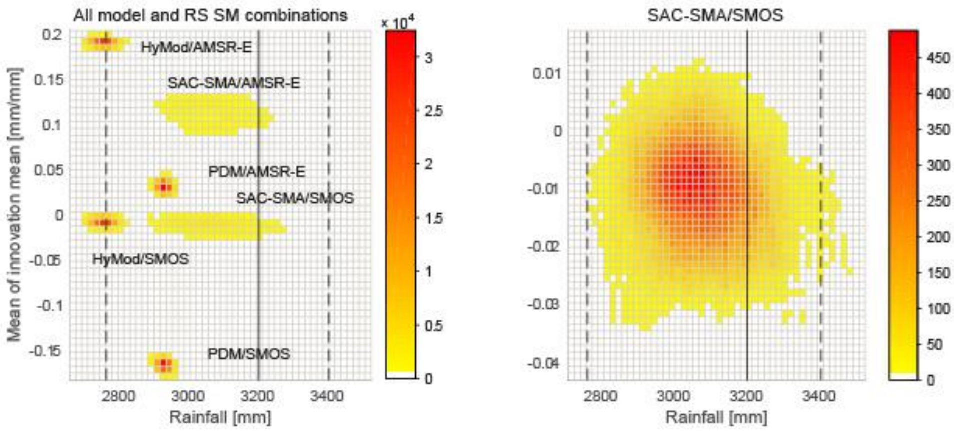

FIGURE 4: INNOVATIONS FOR A NUMBER OF HYDROLOGIC MODELS, OPTIMIZED RAINFALL, AND REMOTELY SENSED SOIL MOISTURE. ADAPTED FROM (WRIGHT ET AL., 2018).

greater similarity to an alternative remotely sensed soil moisture product. It is therefore recommended that hydrologists remain open to assessing different models and products for different catchments. As a rule of thumb, rainfall uncertainty should be represented with an ensemble, three hydrological models should be tested and two remotely sensed soil moisture products should be checked.

37 Wright, A.J., Walker, J. P., & Pauwels, V. R. N. (2018). Identification of hydrologic models, optimized parameters, and rainfall inputs consistent with in situ streamflow and rainfall and remotely sensed soil moisture. *J. Hydrometeorol.*, *19*(8). https://doi.org/10.1175/JHM-D-17-0240.1

38 Wright, Ashley J., Walker, J. P., & Pauwels, V. R. N. (2017). Estimating rainfall time series and model parameter distributions using model data reduction and inversion techniques. *Water Resour. Res.*, *53*(8), 6407–6424. https://doi.org/10.1002/2017WR020442

4.1.4. Data assimilation – Warwick and Paddys Flat

As part of a literature review conducted for developing these guidelines[39], strategies to improve the capability of rainfall-runoff models forecasting capability were outlined. The following two strategies have shown considerable potential:

- Addressing the bias between remotely sensed and modelled soil moisture, and
- Developing an assimilation procedure to utilize soil moisture and streamflow data together.

Biases between simulated and remotely sensed soil moisture have consistently been observed. Attempts to address this bias have come in the form of bias aware filtering processes, matching the cumulative distribution function (CDF) of the remotely sensed soil moisture product to the CDF of the simulated soil moisture, and incorporating the remotely sensed soil moisture observations into the calibration routine. The latter two approaches reduce the information content by attributing all bias to either the simulated or remotely sensed soil moisture observation. The quality of rainfall data and potential biases within are expected to contribute to biases within the modelled soil moisture. To effectively consider potential improvements assimilating remotely sensed soil moisture may have on flood forecasts, it is imperative that studies are performed with consistent and high-quality rainfall products. Data assimilation approaches which consider smoothing and filtering variants and independent and joint assimilation of remotely sensed soil moisture and streamflow were compared using the traditional CDF matching approach and an approach which optimized rainfall gauge weights[40]. The results can be seen in figure 5.

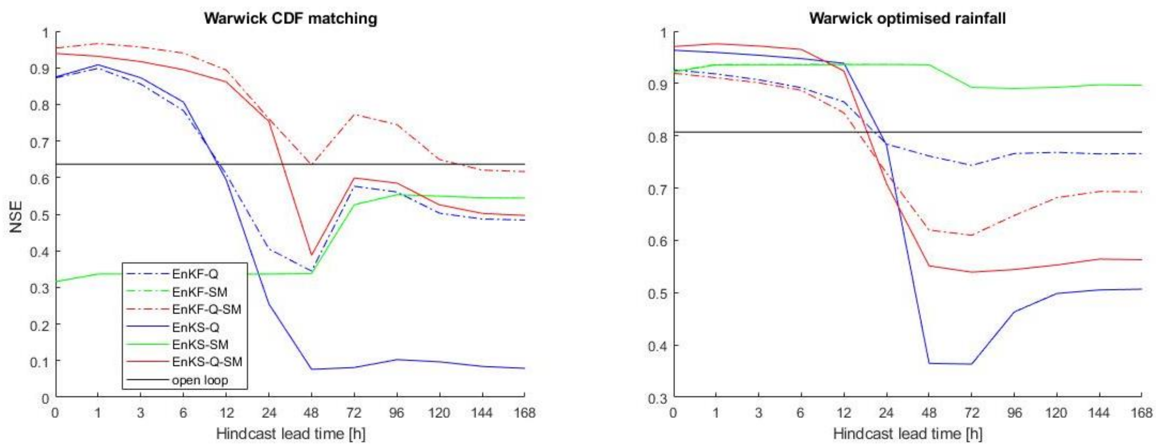

FIGURE 5: COMPARISON OF DATA ASSIMILATION SETUPS FOR A TRADITIONAL APPROACH AND OPTIMIZED RAINFALL APPROACH

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[39] Li, Y., Grimaldi, S., Pauwels, V. R. N., & Walker, J. P. (2018). Hydrologic model calibration using remotely sensed soil moisture and discharge measurements: The impact on predictions at gauged and ungauged locations. *J. Hydrol.*, *557*, 897–909. https://doi.org/10.1016/j.jhydrol.2018.01.013

[40] Wright, A., Robertson, D.E., Walker, J., Pauwels, V.R.N., 2020. Insights from a new methodology to optimize rain gauge weighting for rainfall-runoff models. In preparation.

These results demonstrate that improved rainfall products are likely to lead to improvements in remotely sensed soil moisture data assimilation and further improvements in flood forecasting skill. It should be noted that since different catchments commonly have poorer rainfall gauge density, these recommendations may not be generic.

4.2. HYDRAULIC MODEL

The comparison between model results and remote sensing-derived observations requires the use of adequate performance metrics to quantify the agreement between modelled and observed flood extents and wet/dry boundary points. The computation of these performance metrics then allows the evaluation of a model's performance and consequently supports the verification of model implementation, and the calibration of the parameters.

4.2.1. Performance metrics

4.2.1.1. *Flood extent*

Modelled inundation extent at the acquisition time of the remote sensing observation are extracted from the model results (section 3.1.2). Areas with modelled water depth higher than or equal to 0.01 m are considered as wet, with the remainder of the modelled domain considered as dry. Modelled inundation depths up to 0.01 m are excluded from the wet area to eliminate spurious numerical results. The use of a raster format for model output allows a straightforward comparison with remote sensing-derived inundation layers. Modelled and observed layers are divided into discrete categories of wet/dry cells (see section 5.3 for a discussion on remote sensing uncertainty and the deterministic approach) to build a contingency table which reports the number of pixels correctly and incorrectly predicted as wet or dry (Table 3). The agreement between modelled and observed inundation extent is then quantified using binary performance metrics such as the Critical Success Index, False Alarm Rate, Hit Rate, and Bias. However, each binary performance metric is affected by limitations such as the sensitivity to the magnitude of the flood, the shape of the valley, and the resolution of the model. Consequently, the conjunctive use of a number of performance metrics is recommended as a viable solution[41]. Table 3 reports the most commonly used metrics. Furthermore, model realizations can be ranked based on the conjunctive use of the metrics. More specifically, each one of the N model realizations is given a relative score ranging from 1 (highest agreement with the RS observations) to N (lowest agreement with the RS observations). The total score of each model realization is given by the sum of the relative scores. Hence, the higher the agreement between a model realization and the RS-derived flood extent, the lower the total score[42].

[41] Grimaldi, S., Li, Y., Pauwels, V.R.N., Walker, J.P., 2016. Remote Sensing-Derived Water Extent and Level to Constrain Hydraulic Flood Forecasting Models: Opportunities and Challenges. Surveys in Geophysics. 37, 977-1034

[42] Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2020. Improving flood forecast using remote sensing data - annual report 2019-2020. Melbourne, in: Bushfire and Natural Hazards CRC.

TABLE 3: PERFORMANCE METRICS TO QUANTIFY THE AGREEMENT BETWEEN MODELLED AND OBSERVED INUNDATION EXTENT AND WET/DRY POINTS.

<table>
<tr><td rowspan="5">Flood extent</td><td>Contingency table</td><td colspan="2"><table><tr><td></td><td>Observation wet</td><td>Observation dry</td></tr><tr><td>Model wet</td><td>A</td><td>B</td></tr><tr><td>Model dry</td><td>C</td><td>D</td></tr></table></td></tr>
<tr><td>Critical Success Index (CSI)</td><td>$\frac{A}{A+B+C}$</td><td>Optimal value: 1.</td></tr>
<tr><td>Bias</td><td>$\frac{A+B}{A+C}$</td><td>Optimal value: 1; bias>1 overestimation; bias<1 underestimation.</td></tr>
<tr><td>Hit Rate</td><td>$\frac{A}{A+C}$</td><td>Optimal value: 1.</td></tr>
<tr><td>False Alarm Rate</td><td>$\frac{B}{B+D}$</td><td>Optimal value: 0.</td></tr>
<tr><td>Wet/dry point</td><td>Point Score (WLS)</td><td>$WLpoint = Mod - Obs$
or
$WLpoint = \frac{Mod - Obs, median\ value}{0.5(Obs, maximum - \ Obs, minimum)}$
$WLS = \frac{\sum_{i=1}^{n} \sqrt{WLpoint_i^2}}{number\ of\ observations}$
$Mod = modelled\ water\ level$
$Obs = observed\ water\ level$
$WLpoint$ is defined to account for the possibility of several observations falling within the same modelled cell.
$WLpoint$ = 0 if the modelled water level is equal to the observed value or at the midpoint of the interval of the observed values.</td><td>Optimal value: 0.</td></tr>
</table>

4.2.1.2. *Wet/dry boundary points*

Remote sensing derived wet/dry boundary points have three coordinates: two planar coordinates (Easting and Northing) and one elevation coordinate. The complete set of coordinates is used when a high resolution and a high accuracy DEM is available. When only low to medium resolution and accuracy DEMs are available, only the planar coordinates are used.

A) Modelled and observed water level of the wet/dry boundary points.

Modelled water levels are extracted from the model results at the position of each remote sensing-derived wet/dry boundary point for the acquisition time of the remote sensing data. If a water level observation is located in a dry modelled cell, the modelled water level is retrieved from the nearest modelled wet cell. The agreement between modelled and observed water levels at the wet/dry boundary can be quantified using the RMSE, the point score[43] (Table 3), and the

[43] Savage, J. T. S., Bates, P., Freer, J., Neal, J., & Aronica, G. (2016). When does spatial resolution become spurious in probabilistic flood inundation predictions? Hydrological Processes, 30(13), 2014-2032. 10.1002/hyp.10749

Student t-test. Moreover, the scatterplot representing the modelled water level (y-axis) and the observed water level (x-axis) allows the identification of overestimation and underestimation errors[44].

B) Modelled and observed planar position of the wet/dry boundary points.

The planar position of the wet/dry boundary points represents the flood edge. The analysis of the planar distance and of the temporal discrepancy between the modelled and observed flood edge provides relevant information on the model's capability to represent inundation extent and dynamics[45].

4.2.2. Verification of the model implementation

Inaccurate representation of the river flow capacity and the floodplain morphological features unavoidably lead to inaccurate predictions of inundation dynamics. Remote sensing-derived observations can be used to detect and correct these inaccuracies:

- Remote sensing -derived water level can be used to identify and correct inaccurate representation of river bathymetry[46]. River geometry and roughness can be estimated through calibration, but different parameter sets can often map model predictions to the observed data generating an equifinality problem. Without an adequate representation of river geometry, the calibrated effective values can lead to spurious nonphysical effects[47].
- Remote sensing-derived inundation extent allows the detection of new flood paths that are not incorporated in the DEM (e.g. the SRTM mission was completed in 2001). Moreover, DEMs may not represent the levee systems or be affected by the inaccurate representation of catchment morphological features such as gorges[48]. These inaccuracies can be detected by the comparison between modelled and observed inundation extent and their impact on floodplain inundation dynamics can be introduced via inverse modelling in the catchment[49].

[44] Grimaldi, S., Li, Y., Walker, J.P., Pauwels, V.R.N., 2018. Effective Representation of River Geometry in Hydraulic Flood Forecast Models. Water Resources Research. 54, 1031-1057

[45] Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2020. Improving flood forecast using remote sensing data - annual report 2019-2020. Melbourne, In: Bushfire and Natural Hazards CRC

[46] Pauwels, V., Walker, J., Li, Y., Grimaldi, S., Wright, A., 2017. Improving flood forecast skill using remote sensing data: annual report 2016-17. Melbourne, in: Bushfire and Natural Hazards CRC.

[47] Grimaldi, S., Li, Y., Walker, J.P., Pauwels, V.R.N., 2018. Effective Representation of River Geometry in Hydraulic Flood Forecast Models. Water Resources Research. 54, 1031-1057

[48] Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2020. Improving flood forecast using remote sensing data - annual report 2019-2020. Melbourne, in: Bushfire and Natural Hazards CRC.

[49] Grimaldi, S., Schumann, G.J.-P., Shokri, A., Walker, J.P., Pauwels, V.R.N., 2019b. Challenges, Opportunities, and Pitfalls for Global Coupled Hydrologic-Hydraulic Modeling of Floods. Water Resources Research. 55, 5277-5300

4.2.3. Model calibration

4.2.3.1. *Calibration of a 2D hydraulic model using spatially distributed data*

The following considerations must be taken into account when calibrating a 2D hydraulic model using spatially distributed data:

- In 2D hydraulic models, roughness coefficients are considered to be the most important parameters controlling the flow characteristics and hence are used for model calibration.
- Roughness values have a two-fold function: they represent surface resistance to flow but they are also used as effective parameters to account for a large number of uncertainties including errors in input and implementation data, spatial discretization, and conceptual simplifications.
- Calibrated roughness values must then be physically plausible but their fine tuning might be event-dependent rather than strictly correlated to the real land cover.
- It is recommended to calibrate the model using two events of different magnitude.
- 2D hydraulic models can theoretically admit as many roughness values as the number of cells of the computational domain. The number of spatially distributed parameters has to be large enough to allow model flexibility while avoiding the overfitting and equifinality problem stemming from the use of too many parameters.
- Model calibration should primarily focus on river roughness (spatially distributed values along the river reach). Floodplain roughness can be assessed using land cover data.

4.2.3.2. *Calibration of a 2D hydraulic model using remote sensing data*

This section provides guidelines on the use remote sensing-derived spatially distributed data for the calibration of a 2D hydraulic model. More specifically, this section outlines which remote sensing-derived observation is best fitted for a specific purpose and for different catchment morphologies.

A) <u>Remote sensing-derived flood extent</u>

- Analysis of model behaviour at the large scale: the comparison between modelled and observed flood extent is recommended for any model implementation as it allows to gather an overall understanding of model performances and it is important to avoid overfitting problems.
- Analysis of the model behaviour for *critical areas* (section 2.2.3, point D). Here, a model exclusion rule based on a specific performance metric can be applied; e.g. the False Alarm binary metric can be used to avoid prediction errors in areas protected by a levee system.
- Analysis relying on observed inundation extents are effective in large, low slope floodplains.
- Observed inundation extents derived from acquisitions during the decreasing limb of valley filling flood events have limited information content; when using such data, model flexibility must be maintained to avoid errors.

B) Remote sensing-derived flood extent and planar position of wet/dry points.

- Comparing the modelled and observed planar position of wet/dry points allows discriminating between underprediction and overprediction of inundation extent and flood wave arrival time[50,51]. It is underlined that high resolution DEMs are NOT required when comparing the planar position of wet/dry points.
- This analysis is effective in large, low slope floodplains with the exclusion of valley filling events.

C) Remote sensing-derived flood extent and water level at the wet/dry points

- A fine resolution and high accuracy DEM is strictly required to effectively compare modelled and observed water levels.
- Water level-based measures have a higher sensitivity to roughness parameters than binary performance metrics and can more effectively constrain the parameter space.
- This analysis is particularly useful in V-shaped areas and it can provide information for valley filling events. However, the use of water level at the wet/dry boundary is likely to return spurious results in nearly flat floodplains.

D) Key warnings:

- The capability of remote sensing observations to provide reliable information of flooding dynamics is crucial to the success of the calibration process.
- The use of remote sensing-derived flood extent and of the planar position of wet/dry boundary points is strongly recommended in low slope areas, in areas with levee systems, and in catchments with morphological singularities (e.g. gorges).
- The use of remote sensing-derived water level is recommended in narrow, V-Shaped valleys. However, the effective use of remote sensing-derived water level is bounded by the availability of high-accuracy and fine-resolution terrain data (i.e. Lidar data).
- The main obstacles for the routinely and effective use of remote sensing acquisitions to constrain the parameter space of a hydraulic model are the discrete acquisition time, the (sometimes) partial spatial coverage, and the uncertainty and errors in the inundation extent and wet/dry boundary points datasets (section 5.3).
- Critically combining information from multiple acquisitions can help to avoid overfitting and equifinality problems and errors stemming from uncertainty and errors in remote sensing acquisitions.

[50] Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2020. Improving flood forecast using remote sensing data - annual report 2019-2020. Melbourne, in: Bushfire and Natural Hazards CRC.

[51] Grimaldi, S., Wright A., Walker J., V., P., 2020/21. On the use of remote sensing-derived waterlines to calibrate hydraulic flood forecasting models. In preparation.

- It is recommended to make use of all the available observations, including the coarse-resolution data. Higher weights can be given to fine resolution data acquired during the rising limb and over critical areas.
- The conjunct use of gauged data and remote sensing data support the calibration exercise. Nevertheless, it is imperative to remember that gauged data informative value can have very limited spatial value[52].

The guidelines listed in this document were derived from the analysis of three selected case studies, specifically, the Clarence (NSW), the Condamine-Balonne (QLD), and the Fitzroy (WA). The research was conducted with the overarching aim to provide guidelines for application to any Australian catchment. For this reason, the case studies were specifically selected to represent different flooding dynamics. Moreover, all the analysis and methodologies were developed using datasets available at the continental scale. Albeit the conceptual findings hold, expert judgement is required when transferring the findings of this research to other catchments. Finally, the authors acknowledge that other datasets could be used to constrain the models but their analysis was not in scope.

[52] Pauwels, V., Walker, J., Li, Y., Grimaldi, S., Wright, A., 2018. Improving flood forecast using remote sensing data - annual report 2017-2018. Melbourne, in: Bushfire and Natural Hazards CRC.

5. UNCERTAINTIES AND LIMITATIONS

5.1. HYDROLOGIC MODEL

To evaluate the quality of flow forecasts it is important to determine if changes in land-use will significantly alter flow characteristics. This includes large intermittent extractions or regulation of water flowing through the catchment. Consequently, catchments that are minimally regulated are the focus of this study. The guidelines provided in this document can be applied to assist in the merging of remote sensing data with hydrologic rainfall-runoff models for the prediction of streamflow.

Topics relevant to flood forecasting, yet outside the scope of this research, were not investigated and are outlined as follows:

- Rainfall forecasting;
- Post-processing of rainfall forecasts;
- Impact of land-use changes on flood forecasting;
- Inclusion of ground or satellite-based rainfall observations;
- Comparison with event-based rainfall-runoff models.

Moreover, the following sources of uncertainty must always be considered:

A) Forcing data uncertainty.

The prevailing idiom known to all modeller's *garbage in, garbage out* cannot be avoided. By avoiding adequate quality control of forcing data a cascade of errors which nullifies the effectiveness of other modelling techniques becomes almost certain.

B) Model structure uncertainty.

All models have their limitations and make assumptions. Models which are built upon physical concepts still use quasi physical parameters, such as roughness, which are conceptually accurate. As such, users should chose a model with a structure that is most fit for purpose. Key considerations are:

1. Degree of physical representation for key processes,
2. Spatial resolution,
3. Temporal resolution,
4. Computational requirements.

C) Model parameter uncertainty.

Much focus has been paid towards model parameter uncertainty and the retrieval of an optimal parameter set. Since acknowledging the concept of *equifinality*, attention has shifted towards methodologies which return a parameter distribution that has maximum likelihood of representing the governing system given the observations. Such methodologies are recommended to incorporate an understanding of model parameter uncertainty into hydrological forecasts.

D) Initial state uncertainty.

It is common for hydrological systems, as for any system, to consist of states, such as groundwater storage, which are used to represent intermediate hydrological processes. These states are commonly not able to be measured across a catchment and consequently must be estimated upon initiating the model. For models with long hydrological records a warmup period which allows the states to reach an equilibrium is recommended. Alternatively, when the hydrological record is sufficiently short, the application of a warmup period may not be feasible. For situations such as this, the value of the initial state can be estimated in the calibration process.

E) Model output uncertainty.

It is common for hydrological models to provide deterministic outcomes, when in fact the uncertainty in the output is the culmination of a variety of error sources. In the past, deterministic outputs have been provided as a result of large computational requirements for hydrological models which impose long processing times. Fortunately, computers now have the capacity to run ensembles of hydrological models at the same time. Ensembles aim to represent the uncertainty in various processes and are becoming an increasingly popular way to represent forecasting uncertainty.

F) Observation data uncertainty.

Observations are used in to calibrate and update models. The inherent uncertainty in these observations contribute towards the total uncertainty in the system. Streamflow and remotely sensed soil moisture observations are both used in calibration and updating processes. The key sources of uncertainty in streamflow observations that need to be considered are the:

1. The instrumentation used to observe streamflow,
2. The development of streamflow rating curves,
3. The changes streamflow rating curves undertake over time.

Alternatively, the key sources of uncertainty in remotely sensed soil moisture observations are the:

1. Retrieval algorithm,
2. Quality of validation data set,
3. Accuracy of the sensor.

5.2. HYDRAULIC MODEL

The guidelines provided in this document can be applied to merge remote sensing information with a hydraulic model for the prediction of floodplain inundation.

This research did not investigate, as it was not part of the objectives:

- tsunamis;
- dam-breaks;
- solid transport, erosion, deposition, fluvial geomorphology, landscape evolution;
- bridge, levees, river banks scour;
- interaction with the groundwater table;
- manholes, sewage and aqueduct systems;
- flow in buildings;
- flood monitoring in urban areas.

Moreover, the following sources of uncertainty must always be considered:

A) Remote sensing-derived observations uncertainty.

The effectiveness of the methodologies explained in these guidelines rely on the capability of the RS acquisition to capture the essential features of the inundation process. RS-derived observations are inevitably affected by uncertainties and errors due to sensor characteristics, atmospheric conditions, and land cover. When overlaying a RS-derived flood extent to a DEM to retrieve water level at the wet/dry interface, the uncertainty in the DEM should also be considered. The accuracy of the algorithm for the retrieval of inundation extent and wet/dry boundary points must also be considered. An imperative feature of any protocol for the merging of RS data and numerical model is the delivery of results which are independent from RS data uncertainty.

- The use of multiple acquisitions and expert judgement are recommended.
- Probabilistic rather than deterministic analysis allows avoiding overfitting and blunders. Practical methodologies developed in the literature to account for remote sensing-derived observations uncertainty can be used[53, 54, 55].

B) Remote sensing observations discrete temporal coverage.

Remote sensing acquisitions provide spatially distributed information at a snapshot in time.

C) Implementation data.

Analysis of the flooding behaviour of the catchment based on a few model realizations[56] and historical datasets can effectively diagnose errors in the terrain data.

D) Input data.

Accurate time series of the volume of water entering the catchment are crucial to accurate predictions of floodplain inundation (section 5.3).

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[53] Schumann, G., Pappenberger, F., & Matgen, P. (2008b). Estimating uncertainty associated with water stages from a single SAR image. *Advances in Water Resources, 31*(8), 1038-1047. http://dx.doi.org/10.1016/j.advwatres.2008.04.008

[54] Hostache, R., Matgen, P., Schumann, G., Puech, C., Hoffmann, L., & Pfister, L. (2009). Water Level Estimation and Reduction of Hydraulic Model Calibration Uncertainties Using Satellite SAR Images of Floods. *Geoscience and Remote Sensing, IEEE Transactions on, 47*(2), 431-441. 10.1109/TGRS.2008.2008718

[55] Pappenberger, F., Frodsham, K., Beven, K., Romanowicz, R., & Matgen, P. (2007). Fuzzy set approach to calibrating distributed flood inundation models using remote sensing observations. *Hydrol. Earth Syst. Sci., 11*(2), 739-752. 10.5194/hess-11-739-2007

[56] Grimaldi, S., Schumann, G.J.-P., Shokri, A., Walker, J.P., Pauwels, V.R.N., 2019. Challenges, Opportunities, and Pitfalls for Global Coupled Hydrologic-Hydraulic Modeling of Floods. Water Resources Research. 55, 5277-5300

5.3. COUPLING OF THE HYDROLOGIC AND HYDRAULIC MODEL

The following challenges and pitfalls were identified by a study[57] on the implementation of coupled hydrologic-hydraulic models at the large scale:

- Discrepancies in the simulated and measured flood peak values highly affect floodplain inundation.
- Discharge-driven errors in the prediction of floodplain inundation peaks can increase from upstream to downstream. They are accentuated by a hydrological regime characterised by long dry spells and high magnitude floods and by peculiar morphological features.
- Discharge-driven errors in the prediction of floodplain inundation can accumulate in a continuous hydraulic modelling approach. Conversely, discrepancies could be reduced by using an event-based approach for the application of the hydraulic model.
- Based on the points above, it is hypothesized that assimilation of inundation extents and water level in both low and high flow periods may provide a pragmatic strategy to achieve acceptable skill in continuous flood modelling.
- Targeted acquisition of Lidar/high accuracy DEMs in strategic areas is advised.

[57] Grimaldi, S., Schumann, G.J.-P., Shokri, A., Walker, J.P., Pauwels, V.R.N., 2019. Challenges, Opportunities, and Pitfalls for Global Coupled Hydrologic-Hydraulic Modeling of Floods. Water Resources Research. 55, 5277-5300

6. RESULTS FOR SELECTED CASE STUDIES

The guidelines listed in this document were generated from the analysis of the selected case studies, which are the Clarence (NSW), the Condamine-Balonne (QLD), and the Fitzroy (WA) catchment. These case studies were selected to represent the heterogeneity of Australian catchments and the analyses relied on datasets available at the continental scale. This section presents the main hydrological and morphological characteristics of the selected case studies and provides detailed recommendations. The reader is encouraged to compare the hydrological and morphological features of their case study with the features explained in section 6.1 to infer indications on the appropriate datasets and methodologies. Expert judgement is required when transferring the findings of this research to other catchments.

6.1. CASE STUDIES

Table 4 provides a list of the main morphological and hydrological features of the three Australian catchments used as case studies.

TABLE 4: CASE STUDIES

Description	CASE STUDY		
	Clarence (NSW)	Condamine-Balonne (QLD)	Fitzroy (WA)
CATCHMENT AREA	22,716 km^2	75,370 km^2	93,829 km^2
CATCHMENT MORPHOLOGY	Upstream area (up to Rogans Bridge): U-shaped valley. Downstream area: large floodplain.	Large, low slope floodplains.	Upstream area: V-shaped valley. Downstream area: large, low slope floodplains.
RIVER NETWORK	Unicursal river.	Anabranching river system.	Unicursal river.
FLOODING BEHAVIOUR	Fast moving catchment. Flood events with magnitude larger than 5-year ARI often last less than 10 days. This catchment is subject to valley-filling events.	Slow moving catchment. Flood events can be triggered by intense precipitation in the north-east area (Condamine river, 2011 event) or in the north area (Maranoa river, 2012 event).	Slow moving catchment.
Annual rainfall	1111 mm	514 mm	552 mm
Climate	Humid sub-tropical	Humid sub-tropical	Hot semi-arid

6.2. HYDROLOGIC MODEL

Table 5 presents a summary of the key-findings for the three case studies including recommended implementation data and strategy, remote sensing data and methodologies used for model verification and calibration.

TABLE 5: DETAILED GUIDELINES FOR THE THREE CASE STUDIES.

	Description	CASE STUDY	
		Clarence (NSW)	Condamine-Balonne (QLD)
Implementation data	Delineation	Australian Hydrologic Geofabric	Australian Hydrologic Geofabric
	Fractional cover of vegetation	MODIS	MODIS
Forcing data	Rainfall	Streamflow and soil moisture simulation and forecasting skill are highly dependent upon capturing rainfall variability. Some sub-catchments have adequate gauge density.	Streamflow and soil moisture simulation and forecasting skill are highly dependent upon capturing rainfall variability. Only upstream sub-catchments have adequate gauge density.
	PET	AWAP. There is potential for finer temporal resolution to aid in the assimilation of remotely sensed soil moisture.	AWAP. There is potential for finer temporal resolution to aid in the assimilation of remotely sensed soil moisture.
	Quality control rainfall	AWAP/BoM	AWAP/BoM
Evaluation data	Remotely sensed soil moisture	Remotely sensed soil moisture can aid in model selection and be used to improve forecast skill for internal sub-catchments. SM time series are improved through assimilation. The impact this has on streamflow forecasting highly depends on the quality of rainfall forcing data.	Remotely sensed soil moisture can aid in model selection and be used to improve forecast skill for internal sub-catchments. SM time series are improved through assimilation. The impact this has on streamflow forecasting highly depends on the quality of rainfall forcing data.
	Streamflow	Not all flood peaks are captured in the rating curve. This is likely to impact the calibration of the model.	Not all flood peaks are captured in the rating curve. This is likely to impact the calibration of the model.

6.3. HYDRAULIC MODEL

Table 6 presents a summary of the key-findings for the three case studies including recommended implementation data and strategy, remote sensing data and methodologies used for model verification and calibration.

TABLE 6: DETAILED GUIDELINES FOR THE THREE CASE STUDIES.

	Description	**CASE STUDY**		
		Clarence (NSW)	**Condamine-Balonne (QLD)**	**Fitzroy (WA)**
Implementation data	DEM, recommended minimum resolution.	30 m	90 m	90 m
	River bathymetry, minimum representation.	HIGH FLOW: river flow capacity and river width. LOW FLOW: river flow capacity, river width, and river shape.	River flow capacity and river width. The DEM-H is recommended as it allows an accurate representation of river network connectivity.	River flow capacity and river width.
Evaluation data	Remote sensing sensor	SAR	SAR; optical data might allow the monitoring of the downstream area.	SAR; optical data might allow the monitoring of the downstream area.
	Acquisition time	Rising limb to flood peak at Grafton (important: 2011, 2013 were valley filling events).	Flood hydrograph at Surat, including the initial phase of the receding limb.	Flood hydrograph at Dimond Gorge, including the initial phase of the receding limb.
	Target area(s)	Grafton area (levee system).	Barrackdale Choke; St. George.	Geikie Gorge; Fitzroy Crossing.
Use of RS-derived	Verification of model implementation	Elevation of wet/dry boundary points: diagnosis and correction of erroneous representation of river geometry.	Flood extent: detection of inaccurate modelling of the Barrackdale Choke.	Flood extent: detection of inaccuracy in the terrain dataset (Geikie Gorge).
	Model calibration	Flood extent and planar position of the wet/dry boundary points.	Flood extent.	Flood extent.

7. PUBLICATION LIST

7.1. Peer-reviewed journal articles

Grimaldi, S., Xu, J., Li, Y., Pauwels, V. R.N, & Walker, J. P. Flood mapping under vegetation using single SAR acquisitions. *Remote Sensing of Environment*, Volume 237, 2020, 111582, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2019.111582

Hilton J.E., Grimaldi S., Cohen R.C.Z., Garg N., Li Y., Marvanek S., Pauwels V.R.N., Walker J.P. River Reconstruction Using a Conformal Mapping Method. *Enironmental Modelling & Software*, Volume 119, Pages 197-213, ISSN 1364-8152, https://doi.org/10.1016/j.envsoft.2019.06.006., 2019

Grimaldi, S., Schumann G.J-P., Shokri, A., Walker, J. P., and Pauwels V.R.N. Challenges, opportunities and pitfalls for coupled hydrologic/hydraulic modelling at the large scale. *Water Resources Research*, 55. https://doi.org/10.1029/2018WR024289 , 2019.

Grimaldi, S., Y. Li, J.P. Walker, and V.R.N. Pauwels, Effective Representation of River Geometry in Hydraulic Flood Forecast Models, Water Resources Research, 54, doi:10.1002/2017WR021765, 2018.

Wright, A.J., J.P. Walker, and V.R.N. Pauwels, Identification of hydrologic models, parameters and rainfall consistent with observed rainfall, streamflow, and remotely sensed soil moisture, *Journal of Hydrometeorology* 19.8, 1305-1320, 2018 .

Li, Y., S. Grimaldi, V.R.N. Pauwels, and J.P. Walker, Hydrologic model calibration using remotely sensed soil moisture and discharge measurements: the impact on predictions at gauged and ungauged locations, Journal of Hydrology, 557, 897-909, 2018.

Liu, S., Y. Li, V. R. N. Pauwels, and J. P. Walker, Impact of Rain Gauge Quality Control and Interpolation on Streamflow Simulation: An Application to the Warwick Catchment, Australia, Frontiers in Earth Science, 5(114), 2018.

Dasgupta, A., Grimaldi, S., Ramsankaran, R.A.A.J., Pauwels, V.R.N., Walker, J.P. Towards operational SAR-based flood mapping using neuro-fuzzy texture-based approaches. Remote Sensing of Environment. 215, 313-329, 2018.

Wright, A.J., Walker, J.P., and V.R.N. Pauwels, estimating temporal rainfall and model parameter distributions using model data reduction and inversion techniques, Water Resources Research, 53, doi:10.1002/2017WR020442, 2017.

Wright, A.J., J.P. Walker, D. Robertson, and V.R.N. Pauwels, A Comparison of the Discrete Cosine and Wavelet Transforms for Hydrologic Model Input Data Reduction, Hydrology and Earth System Sciences, 21(7), 3827-3838, 2017.

Grimaldi, S., Y. Li, V.R.N. Pauwels, and J.P. Walker, Remote sensing-derived water extent and level to constrain hydraulic flood forecasting models: opportunities and challenges, Surveys in Geophysics, 37(5), 977-1034, 2016.

Li, Y., S. Grimaldi, J.P. Walker, and V.R.N. Pauwels, Application of Remote Sensing Data to Constrain Operational Rainfall-Driven Flood Forecasting: A Review, Remote Sensing, 8(6), 456, doi:10.3390/rs8060456, 2016.

7.2. Journal articles in preparation

Wright, A., Robertson, D.E., Walker, J., Pauwels, V.R.N., 2020. Insights from a new methodology to optimize rain gauge weighting for rainfall-runoff models. In preparation.

Grimaldi, S., Wright, A., Walker, J., Pauwels, V., 2020/21. On the use of remote sensing-derived waterlines to calibrate hydraulic flood forecasting models. In preparation.

Molari, G., Grimaldi, S., Paron, P., Walker, J., Pauwels, V., Domeneghetti, A., 2020/1. RiBEST – a tool for river bathymetry and hydraulic parameters estimation. In preparation.

7.3. Conference papers

Wang, A., Grimaldi, S., Shaadman, S., Li, Y., Pauwels, V.R.N., and Walker, J. P. Evaluation of TanDEM-X and DEM-H digital elevation models over the Condamine-Balonne catchment (Australia). In: *Hydrology and Water Resources Symposium (HWRS 2018): Water and Communities*. Melbourne: Engineers Australia, 2018: 989-1003. ISBN: 9781925627183, 2018

Nguyen, T.P.C., S. Grimaldi, and V. Pauwels, Use of remote sensing observations for improved understanding and modelling of flood waves routing, Oral Presentation at the AFAC Conference, Brisbane, August 30-September 1, 2016

Zhang, Y., Y. Li, J. Walker, V.R.N. Pauwels, and M. Shahrban, Towards operational hydrological model calibration using streamflow and soil moisture measurements, Oral Presentation at MODSIM 2015, 21th International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, Broadbeach, QLD -Australia, November 29- December 4, 2015.

7.4. Technical Reports

Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2020. Improving flood forecast using remote sensing data - annual report 2019-2020. Melbourne, in: Bushfire and Natural Hazards CRC.

Pauwels, V., Walker, J., Grimaldi, S., Wright, A., Li, Y., 2019. Improving flood forecast using remote sensing data - annual report 2018-2019. Melbourne, in: Bushfire and Natural Hazards CRC.

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Pauwels, V., Walker, J., Li, Y., Grimaldi, S., Wright, A., 2017. Improving flood forecast skill using remote sensing data: annual report 2016-17. Melbourne, in: Bushfire and Natural Hazards CRC.

Grimaldi S., Pauwels V., Bathymetric field campaign of the Balonne River in St. George (QLD) – data analysis, prepared for SunWater Ltd, November 2016.