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IMPROVING FLOOD FORECAST SKILL USING REMOTE SENSING DATA

Valentijn Pauwels, Jeffrey Walker, Ashley Wright, Stefania Grimaldi, Antara Dasgupta, Yuan Li
Department of Civil Engineering, Monash University, Clayton, Victoria

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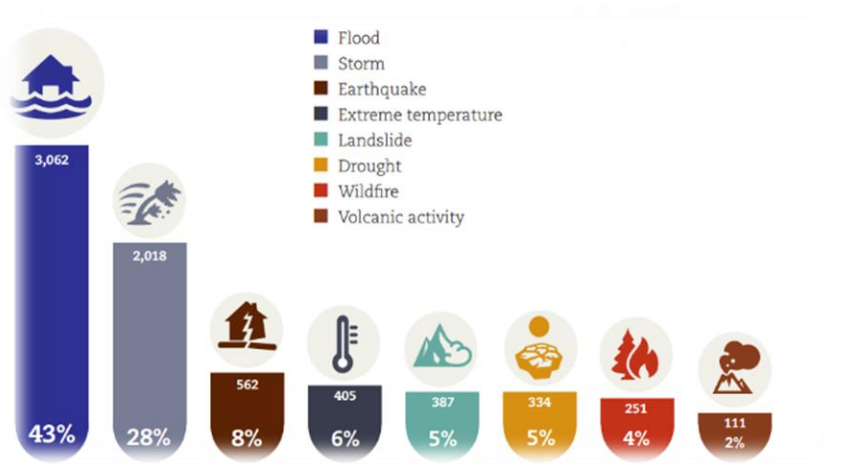
RATIONALE

Floods cause significant economic and ecological damages and account for approximately 40–50% of all disaster-related deaths worldwide



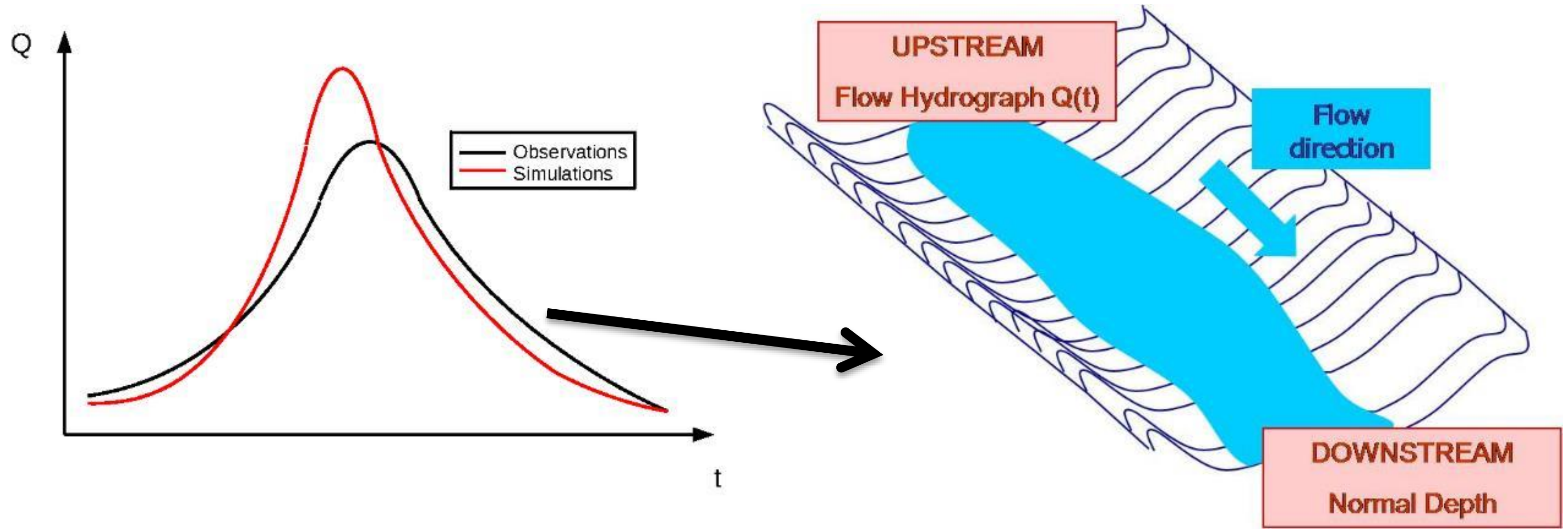
Percentage of occurrences of natural disasters by type worldwide(1995-2015) (World Economic Forum, 2016)

St. George (QLD, Australia), 2010 March 5th, http://www.abc.net.au

A **timely, accurate prediction** of
the flood **wave arrival time, depth and velocity**
is essential to reduce flood related mortality and damages.

FLOOD FORECASTING SYSTEMS

1. HYDROLOGIC MODEL:
Input: rain, PET
Output: discharge hydrograph

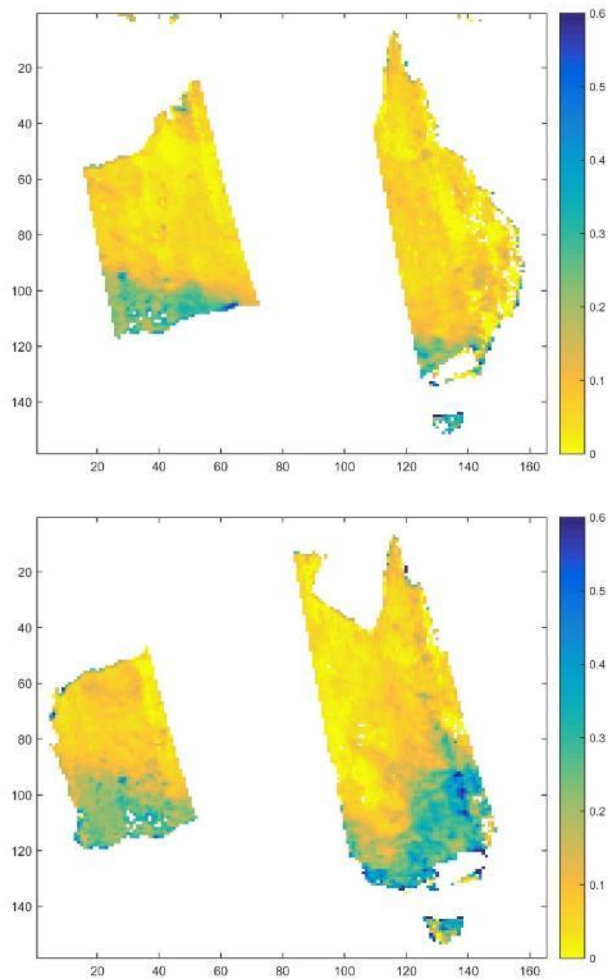


2. HYDRAULIC MODEL:
Input: discharge hydrograph
Output: water depth and velocity at each point of the flooded area

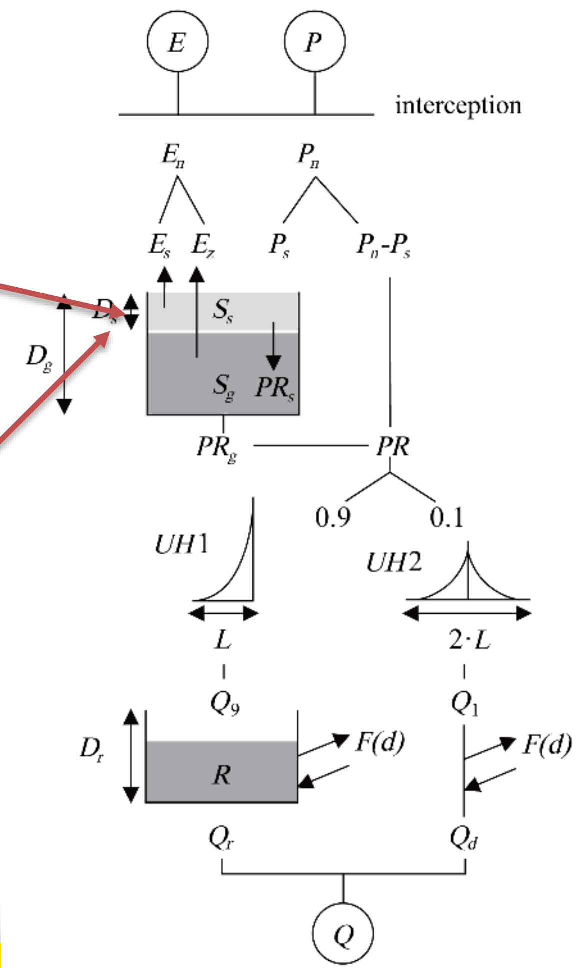
HYPOTHESIS:

REMOTE SENSING DATA CAN IMPROVE FLOOD FORECAST ACCURACY

1. HYDROLOGIC MODEL: REMOTE SENSING SURFACE SOIL MOISTURE



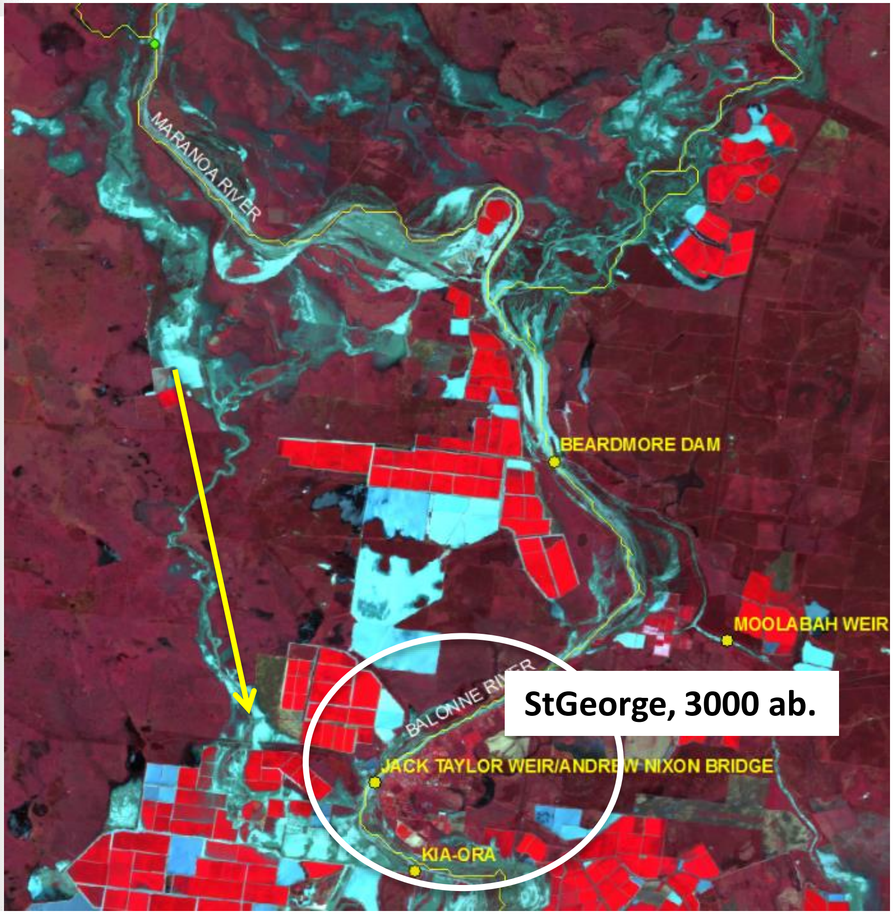
SMOS coverage (morning pass) on 14th and 16th Sep 2013



HYPOTHESIS:

REMOTE SENSING DATA CAN IMPROVE FLOOD FORECAST ACCURACY

2. HYDRAULIC MODEL: REMOTE SENSING-DERIVED FLOOD EXTENT and LEVEL



Condamine – Balonne catchment, Feb, 2012

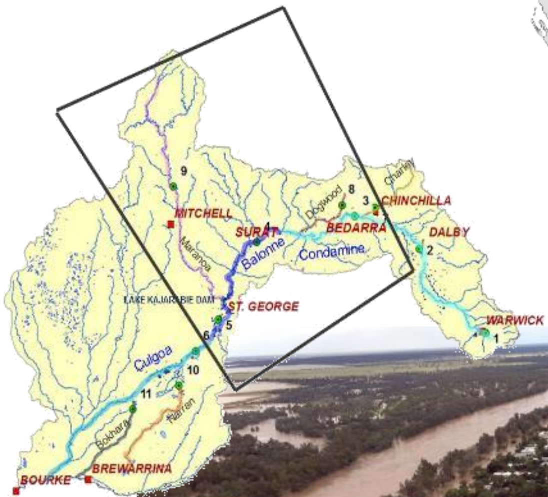
1) RS-derived maps of **flood extent** can be used to identify **gross errors** in the results of the numerical model or to detect unexpected events such as **levee breaches.**

2) RS-derived **water level** at selected locations can be used to fine tune the **parameters** of the hydraulic model.

STUDY BASINS

Condamine-Balonne (75370 sq. km)

Clarence (20730 sq. km)



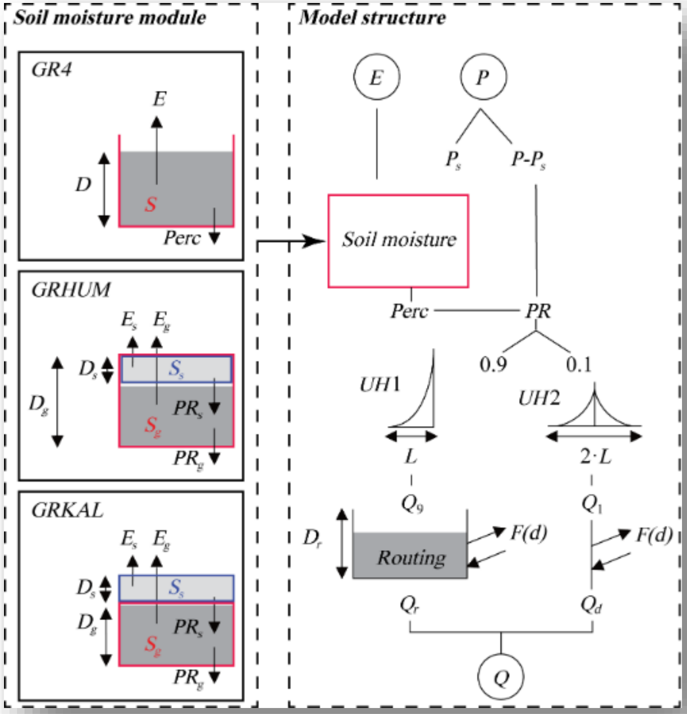
St. George, 2012 Feb 7th, http://www.abc.net.au

Grafton, 2013 Jan 30th, Mr. Williamson

HYDROLOGIC MODELLING

SUMMARY

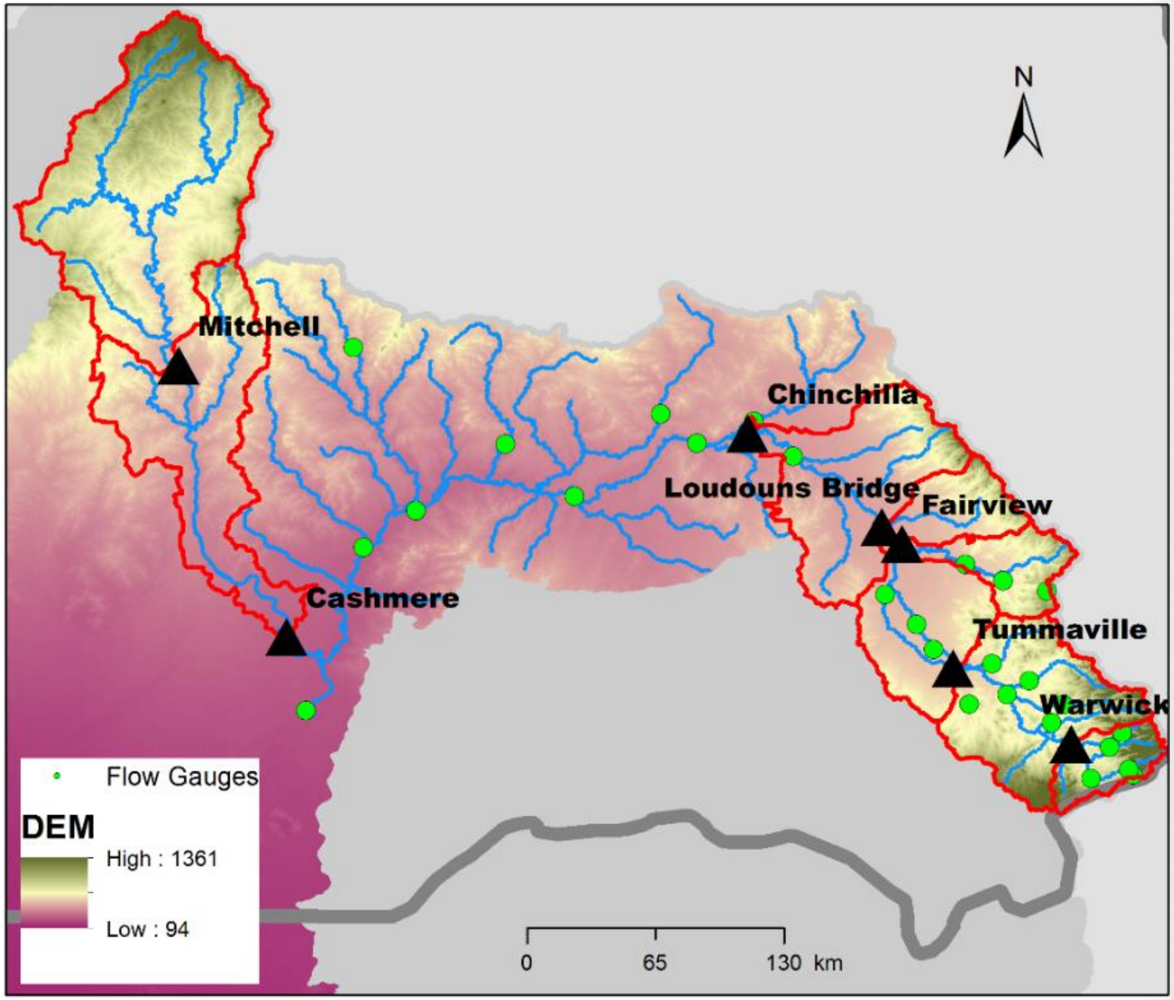
- Literature review (Li *et al.*, 2016, Remote Sensing)
- Data preparation
  - a) Forcing data
  - b) Remote sensing data
  - c) Other data
- Model comparison
- Model calibration
  - a) Impact of in-situ SM (Zhang *et al.*,
  - b) Impact of RS SM
    - Clarence
    - Balonne-Condamine
- Data assimilation
  - a) Preliminary experiment in Clarence



HYDROLOGIC MODELLING

CALIBRATION

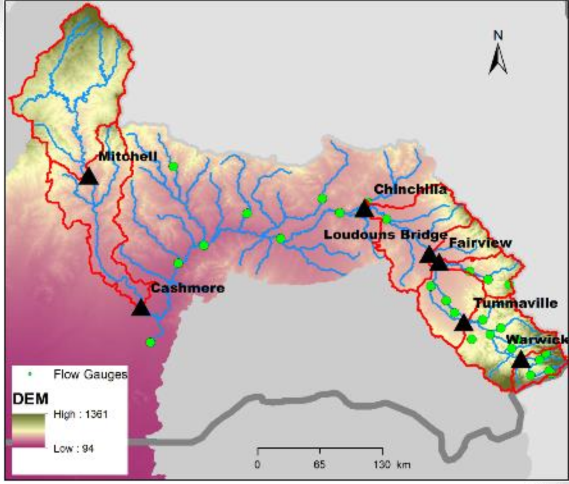
- Calibration scenarios
  - a) Streamflow only
  - b) Streamflow and SMOS SM
- Periods
  - a) Calibration (2010-2012)
  - b) Validation (2013-2014)
- Catchments
  - a) Lumped systems
  - b) Semi-distributed systems with outlet gauges
  - c) Semi-distributed systems with 7 gauges



Catchment system in Condamine-Balonne

HYDROLOGIC MODELLING

CALIBRATION USING STREAMFLOW



- Cashmere

NS	Lump	Semi-1	Semi-2
Cal.	0.63	0.71	0.73
Val.	0.55	0.64	0.66

- Mitchell

NS	Lump	Semi-1	Semi-2
Cal.	-	0.59	0.79
Val.	-	0.54	0.72

- Chinchilla

NS	Lump	Semi-1	Semi-2
Cal.	0.54	0.70	0.77
Val.	0.49	0.63	0.69

- Loudouns Bridge

NS	Lump	Semi-1	Semi-2
Cal.	-	0.62	0.76
Val.	-	0.55	0.69

- Tummaville

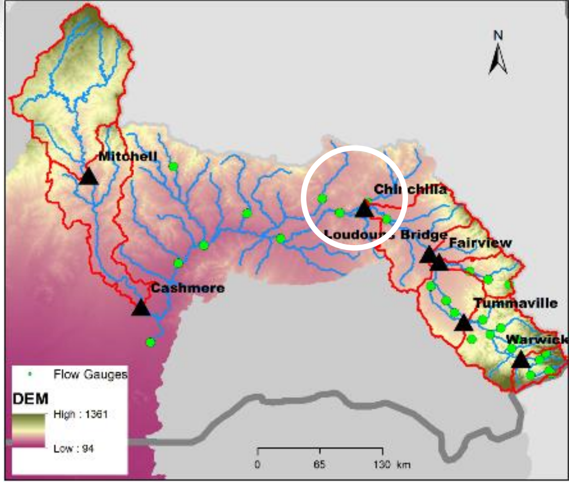
NS	Lump	Semi-1	Semi-2
Cal.	-	0.47	0.81
Val.	-	0.46	0.74

- ❖ **Distributed models** are recommended for large-scale catchments.
- ❖ Calibrating the model at a large number of streamflow gauges improves the simulation at the outlet (the more data are used, the more robust the model is).
- ❖ Large **uncertainty** exists at **ungauged sub-catchments**, more data insertion is required --> RS soil moisture.

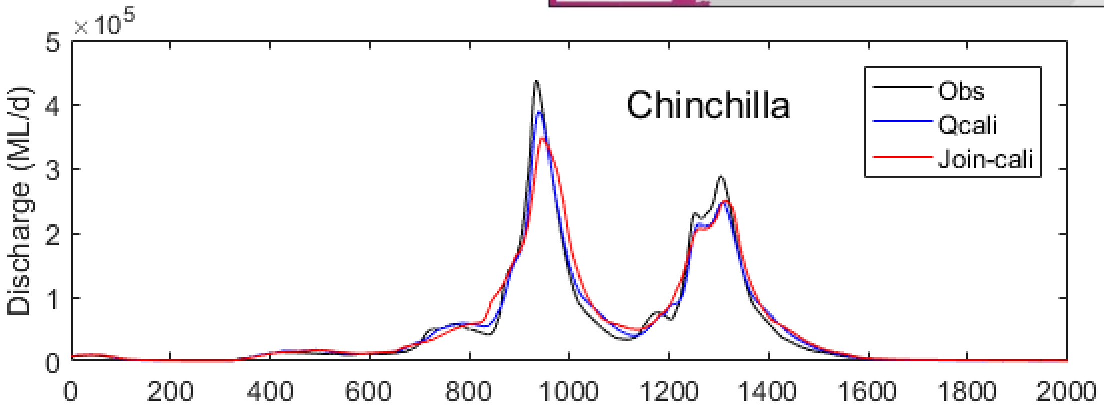
HYDROLOGIC MODELLING

CALIBRATION USING STREAMFLOW AND SM

- Chinchilla (downstream gauge)

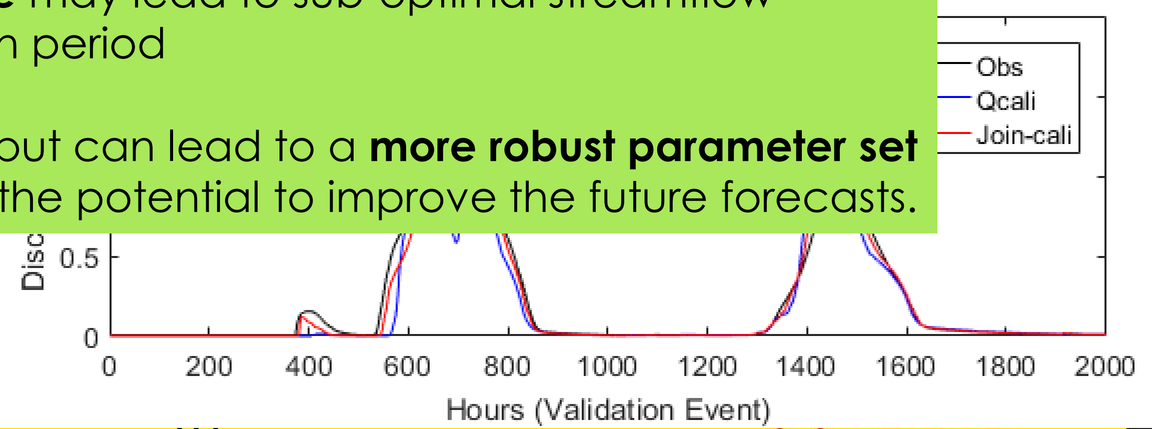


NS	Lump	Semi-1	Semi-2
Cal-Q	0.54	0.70	0.77
Cal-Joint	0.47	0.69	0.74
Val-Q	0.49	0.63	0.69
Val-Joint	0.44	0.65	0.70



Minimizing errors in **soil moisture** may lead to sub-optimal streamflow simulation during the calibration period

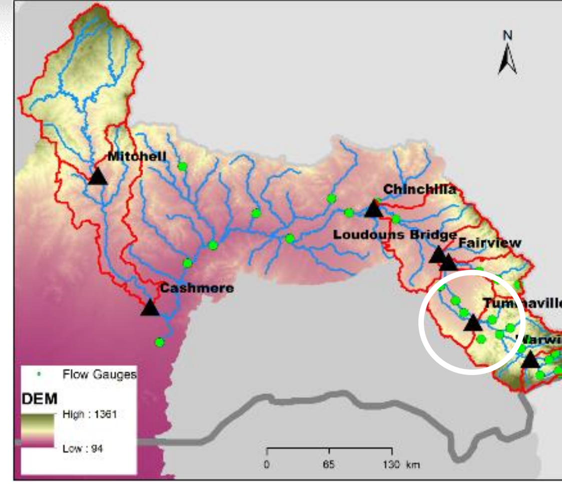
but can lead to a **more robust parameter set** which has the potential to improve the future forecasts.



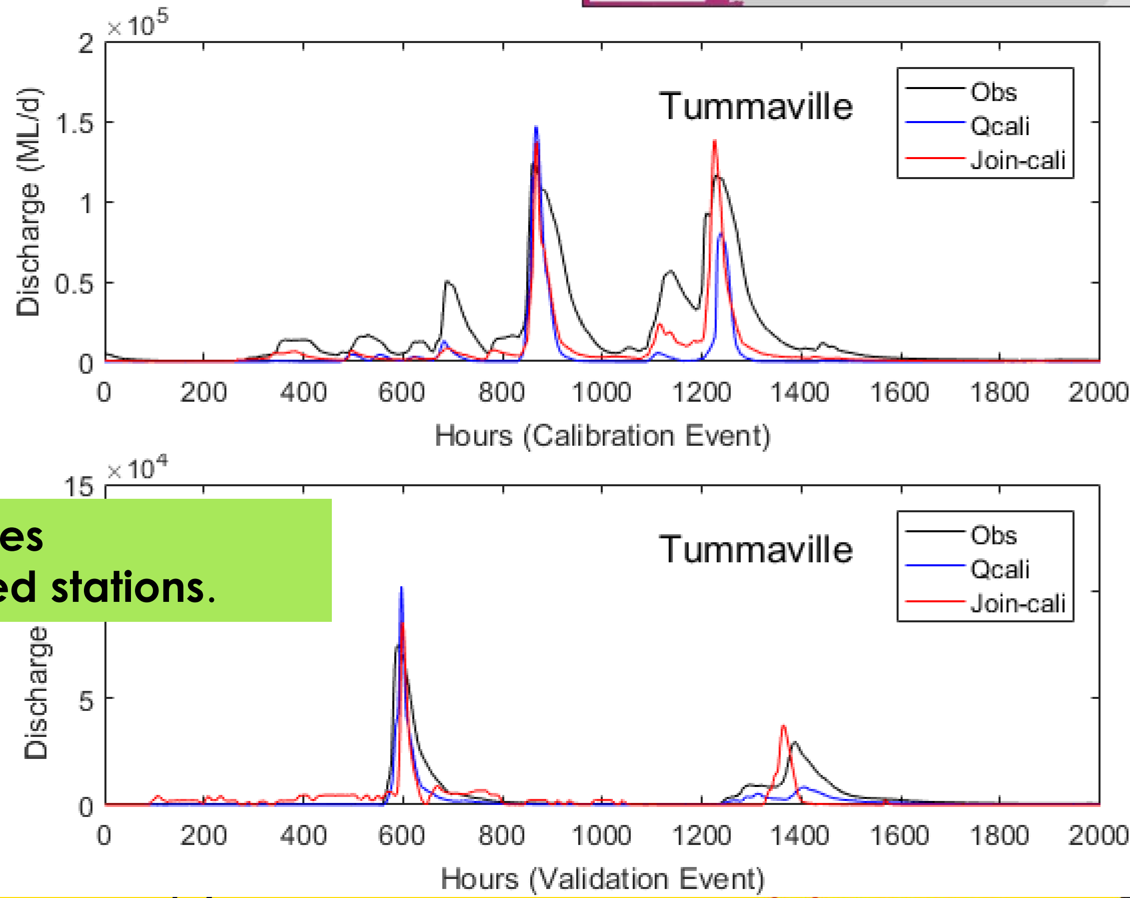
HYDROLOGIC MODELLING

CALIBRATION USING STREAMFLOW AND SM

- Tummaville (upstream gauge)



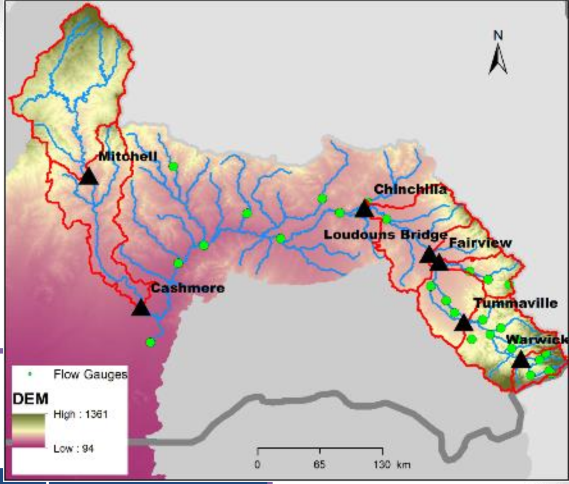
NS	Lump	Semi-1	Semi-2
Cal-Q	-	0.47	0.81
Cal-Joint	-	0.55	0.73
Val-Q	-	0.46	0.74
Val-Joint	-	0.51	0.71



Including **RS soil moisture improves** streamflow prediction at **ungauged stations**.

HYDROLOGIC MODELLING

CALIBRATION USING STREAMFLOW AND SM



- Semi-1

	Gauged	Ungauged			
NS	**Chinchilla**	**Loudouns**	**Fairview**	**Tummaville**	**Warwick**
Cal-Q	0.70	0.62	0.54	0.47	0.49
Cal-Joint	0.69	0.65	0.52	0.55	0.60
Val-Q	0.63	0.55	0.50	0.46	0.45
Val-Joint	0.65	0.59	0.47	0.51	0.55

- Sem

NS
Cal-Q
Cal-Joint
Val-Q
Val-Joint

Ungauged locations: 3/4 were improved through using remote sensing soil moisture data.

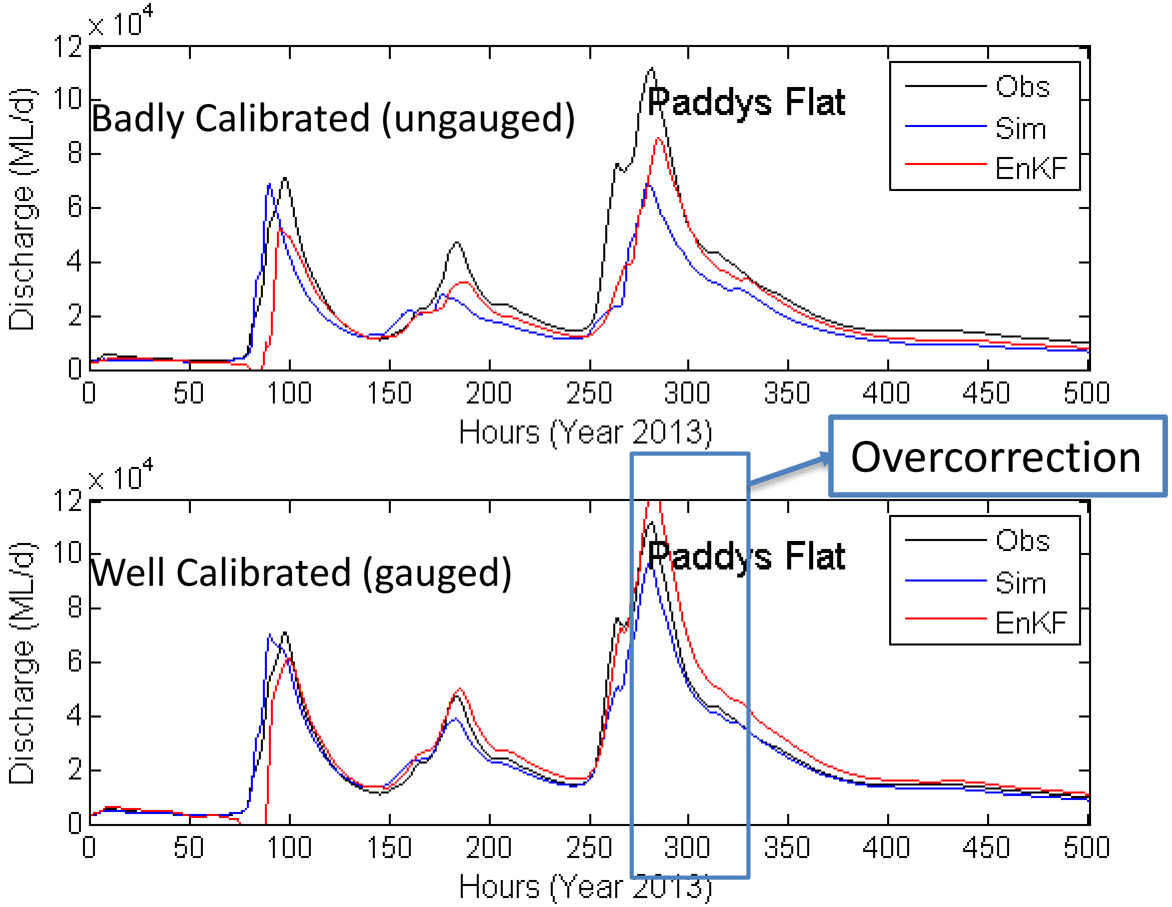
Gauged locations: 4/6 were improved in calibration periods, although degradation were found during validation periods.

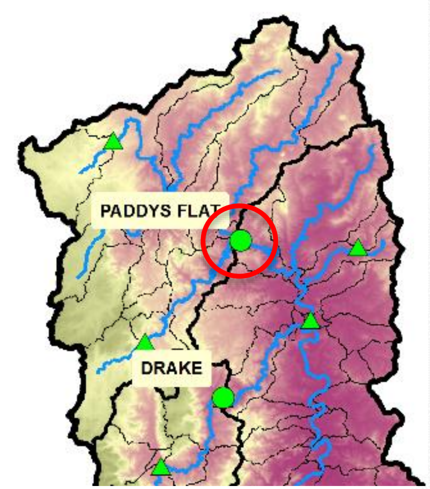
S1 vs S2: The availability of flow gauges are essential for constraining model calibration; however, the soil moisture can be alternative information when there is limited flow gauges.

HYDROLOGIC MODELLING

STATE UPDATING – *preliminary test*

- **EnKF is applied for a lumped catchment upstream of Paddys Flat**
- **Errors of model and observations are predefined based on previous studies**



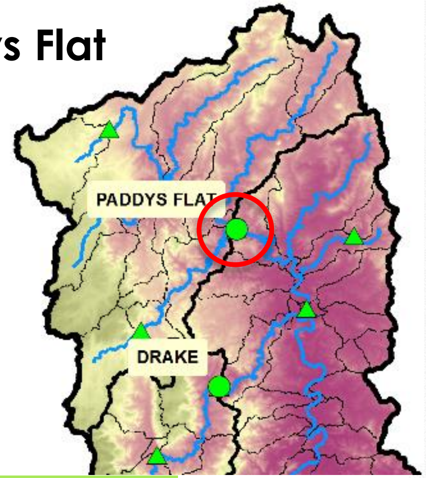


HYDROLOGIC MODELLING

STATE UPDATING – *preliminary test*

❖ **EnKF is applied for a lumped catchment upstream of Paddys Flat**

NS	Simulation	EnKF
Badly calibrated (ungauged)	0.61	0.70
Well calibrated (gauged)	0.76	0.78



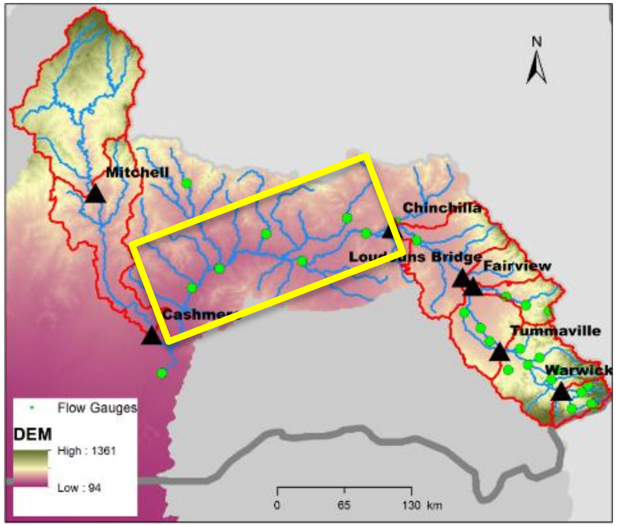
The assimilation of soil moisture brings benefit especially when the model is NOT well-calibrated, i.e., bias exists.

The assimilation improves prediction for some events but also causes over correction for some other events, when the model is well calibrated.

Improved results can be expected by joint assimilation of soil moisture and streamflow, as antecedent soil moisture updating cannot account for mass-balance errors due to poor rainfall data.

HYDROLOGIC MODELLING

LINKAGE TO HYDRAULIC MODELLING



Hydrologic model

Prediction of the input discharge hydrograph

Hydraulic model

Flood extent and level in the lower Balonne and lower Clarence catchment

HYDRAULIC MODELLING

SUMMARY

- Literature review (Grimaldi *et al.*, 2016, *Surv. Geophys.*)
- Model selection: LISFLOOD-FP
- River survey field campaigns
  a) Clarence (Nov 2015)
  b) Balonne-Condamine (May 2016)
- Data preparation
  a) Remote sensing water level/extent
  b) DEM, bathymetric dataset, land cover and land use data
- Hydraulic modelling
  a) Clarence: Numerical modelling of the 2011, 2013 flood events
  b) Balonne-Condamine: Preliminary bathymetric data analysis

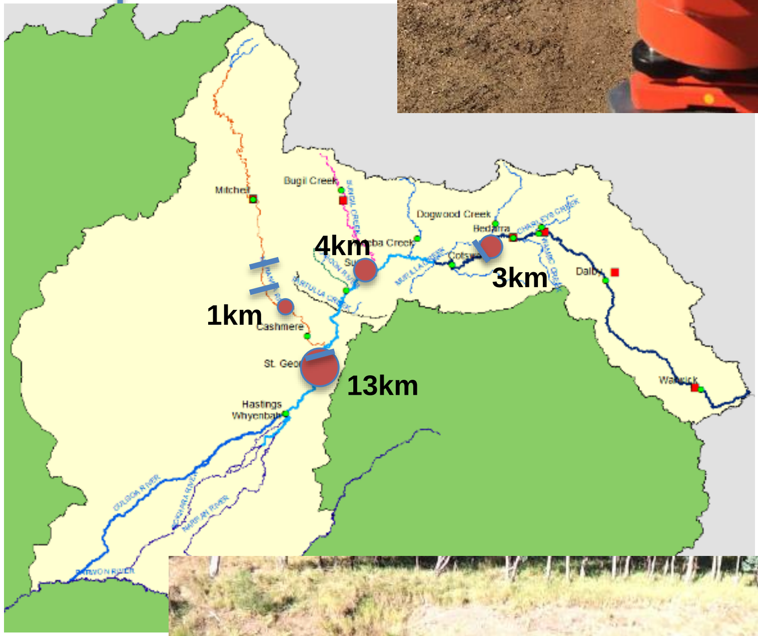
CHALLENGES

1 – Lack of bathymetric data

2 – Low accuracy of the DEM

3 – Densely vegetated, ephemeral, braided river

Hydraulic
RS image



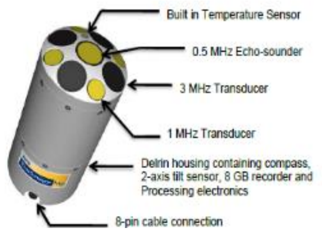
Bathymetric dataset

- QLD – DNRM: 16 cross sections (14 old/recent gauge stations + 2 transects) (CCBY)

- QLD – DNRM: 30 waterholes between Chinchilla and Barrackdale

Our FIELD CAMPAIGN:
~ 21 km bathymetric data
5 transects

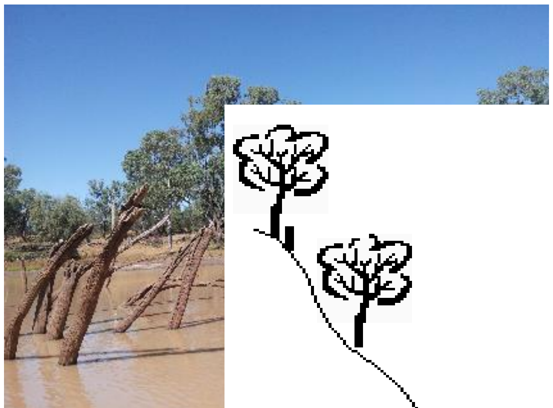
Combined analysis of field data and remote sensing data → new bathymetric dataset

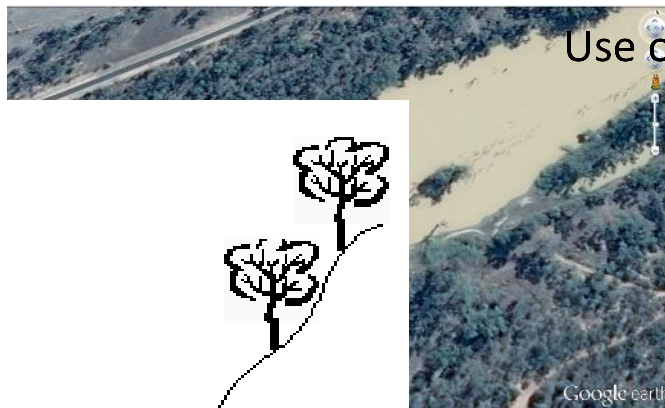


Acoustic Doppler Profiler , CastAway → field data

RS to complement field data where weeds and submerged obstacles impeded the measurement

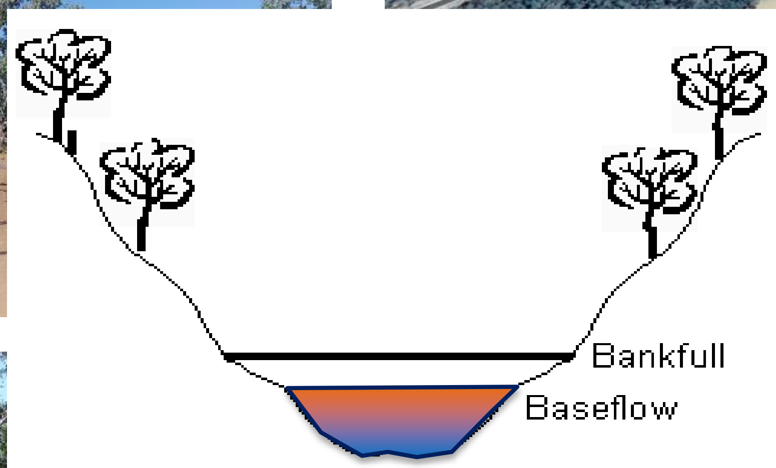
St. George





Use of RS imagery

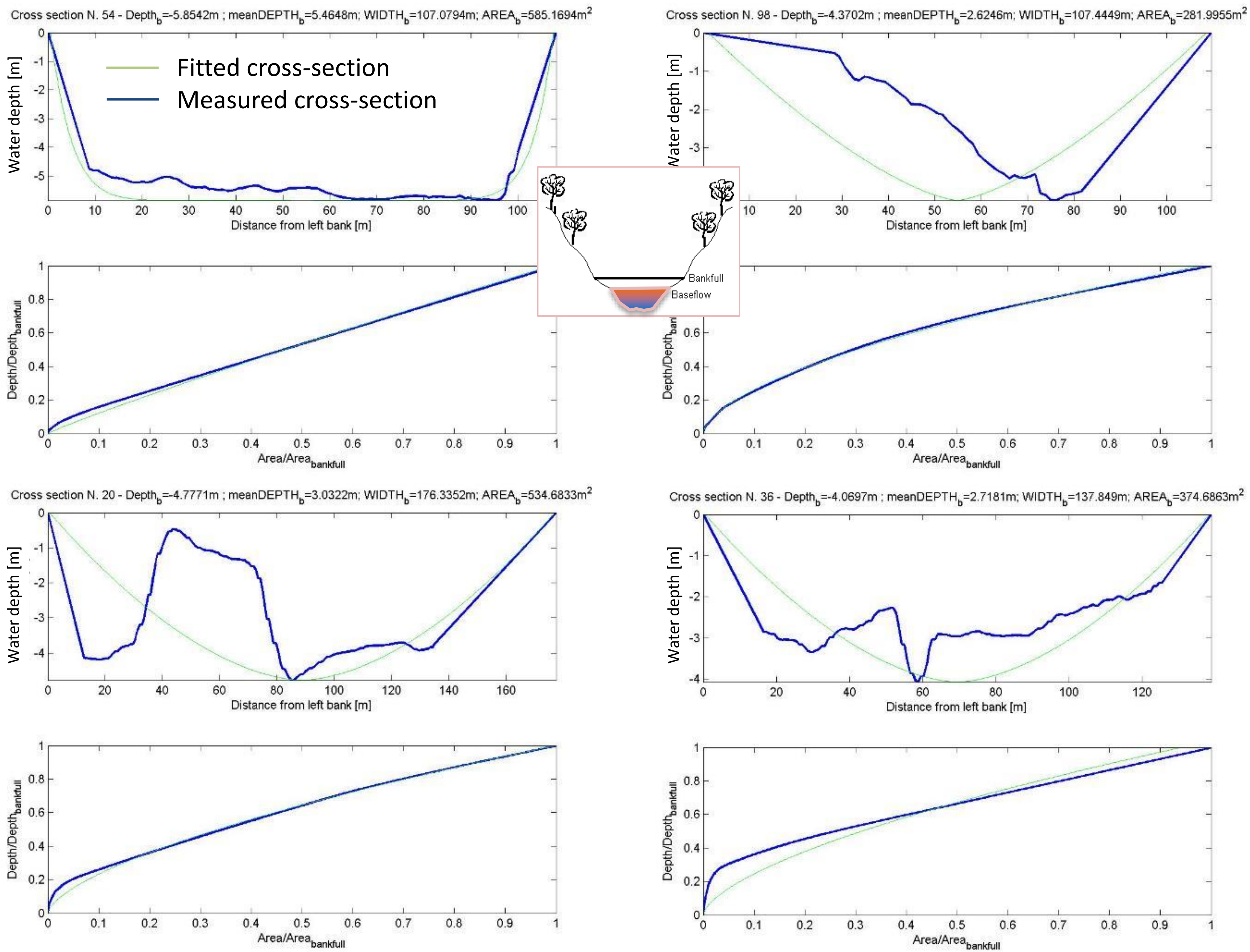
SPOT
2016/05/14



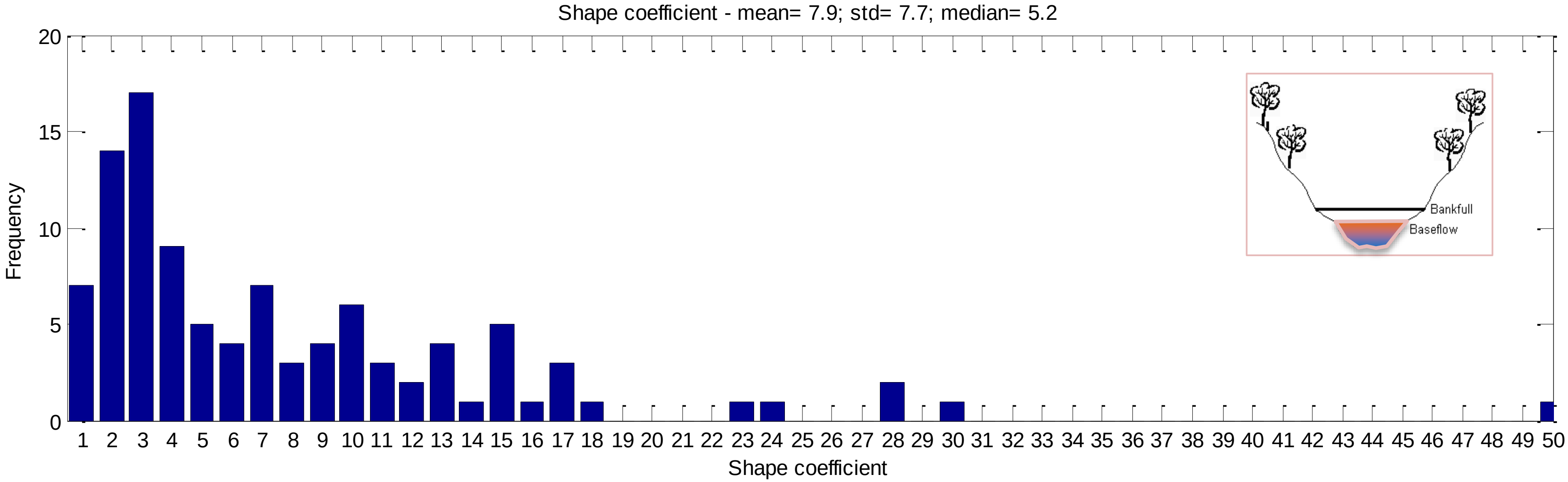
Condamine

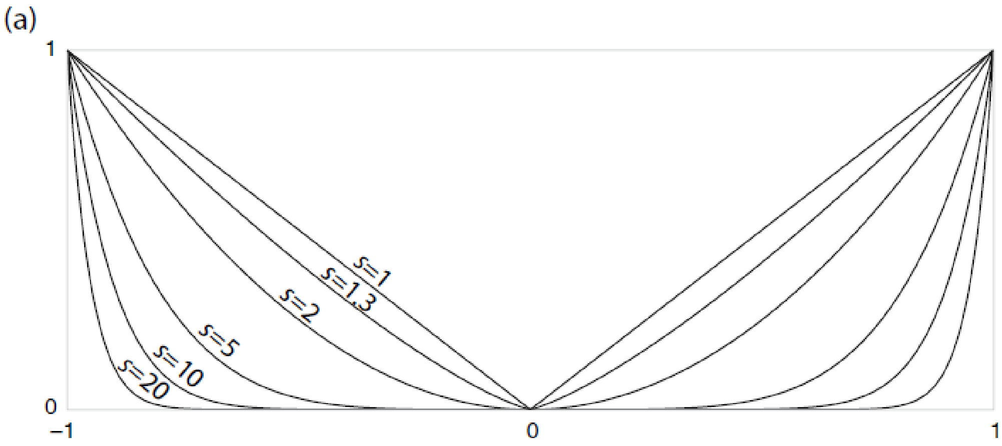
SPOT
2005/03/26
ASTER
2015/09/22

FIELD DATA: ST. GEORGE – 13 KM (101 CROSS SECTIONS)



FIELD DATA: ST. GEORGE – 13 KM (101 CROSS SECTIONS)





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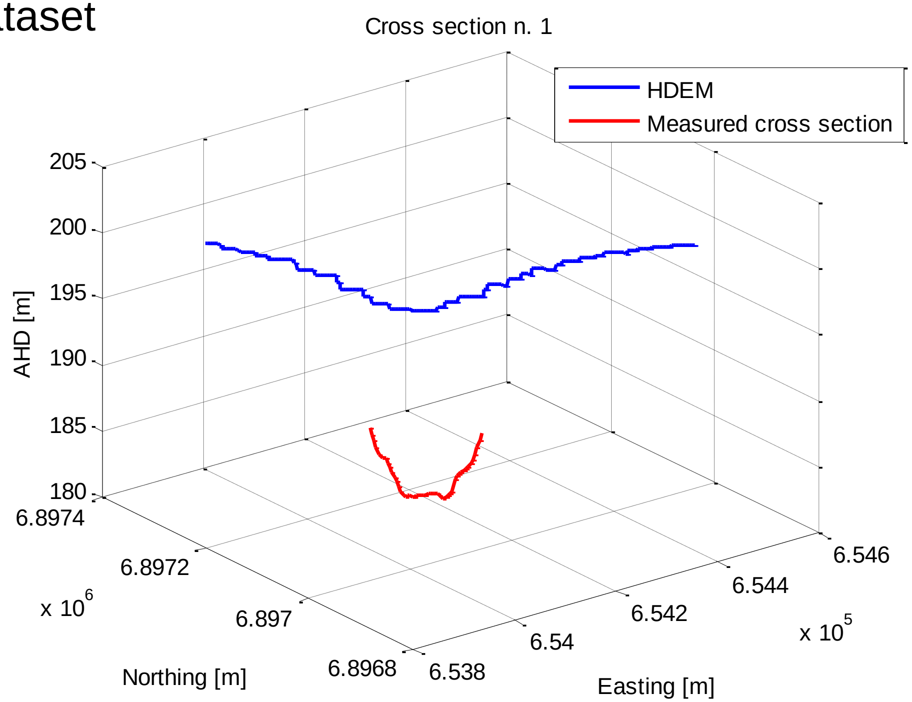
ST. GEORGE – BATHYMETRIC DATA AND HDEM

Integration of the new bathymetric dataset into the existing HDEM

The lowest point of the HDEM is ~9 m higher than the zero level (= water surface level) of our bathymetric dataset



SRTM derived DEMs are affected by systematic errors

Jarihani et al. (2015), Journal of hydrology
Diamantina/Cooper catchments → the SRTM DEM was higher than 2700 registered survey marks and 370500 ICESat points
Bias = +2.68 m; RMSD = 3.25 m, SD = 1.84 m

Definition of a strategy to model the geometry of the river

❖ Extrapolation of the bathymetric dataset:
analysis of field data, global database, Australian studies

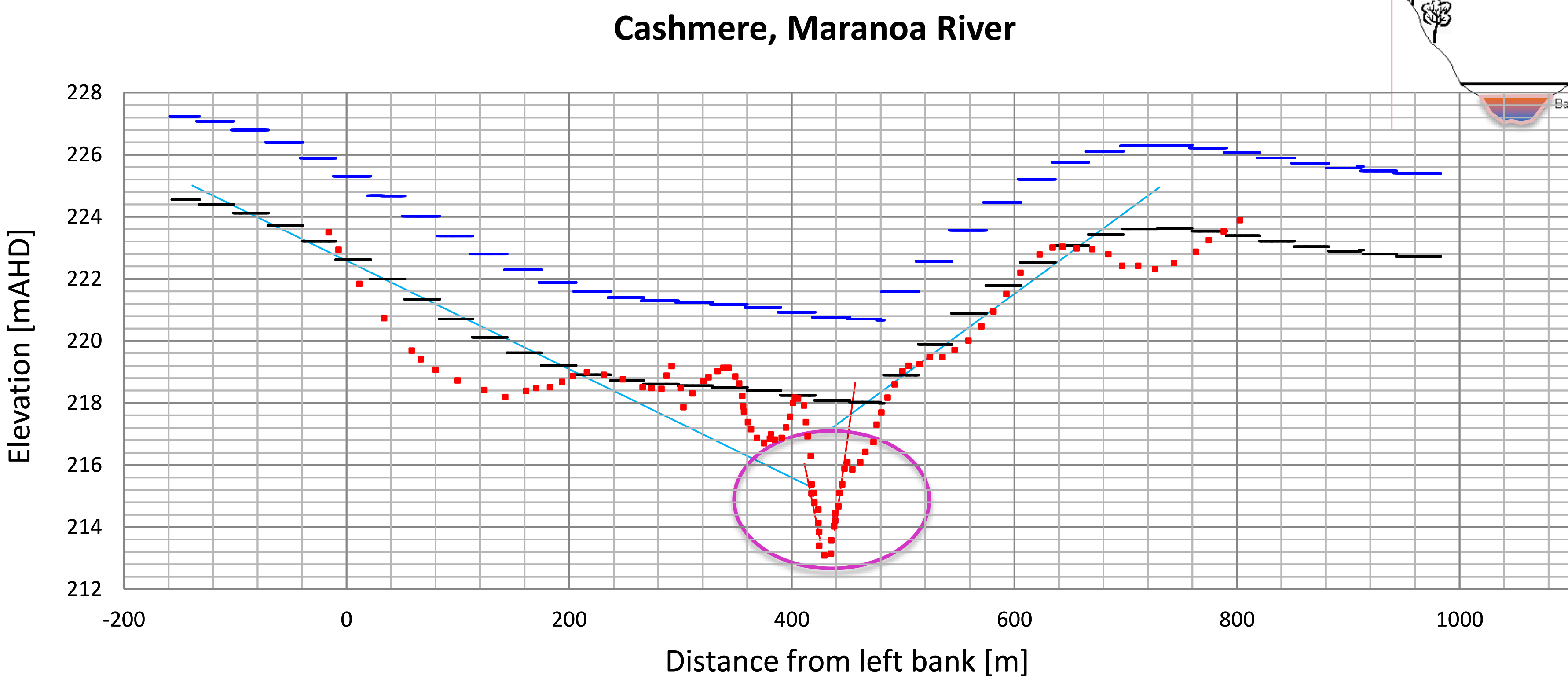
❖ Integration of the new bathymetric dataset with the existing HDEM

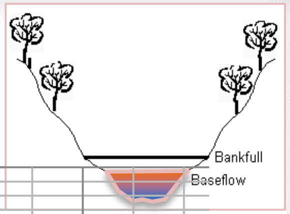
HDEM

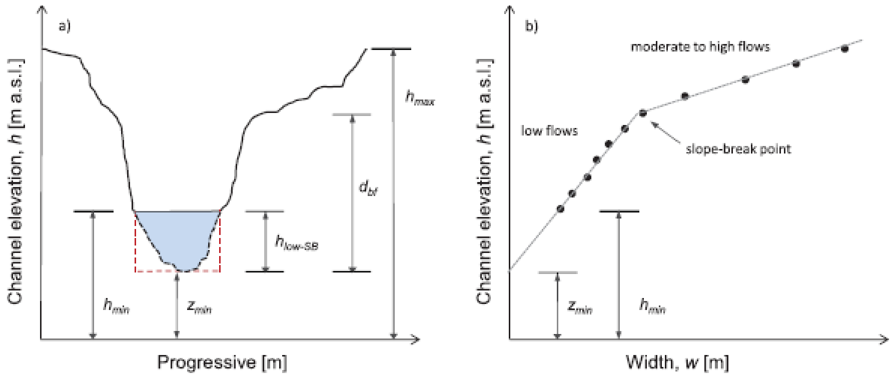
1. Simple, straightforward approach:

   HDEM *new* = HDEM – bias (Jarihani et al., 2015)

2. 1D Co-registration or 3D-coregistration



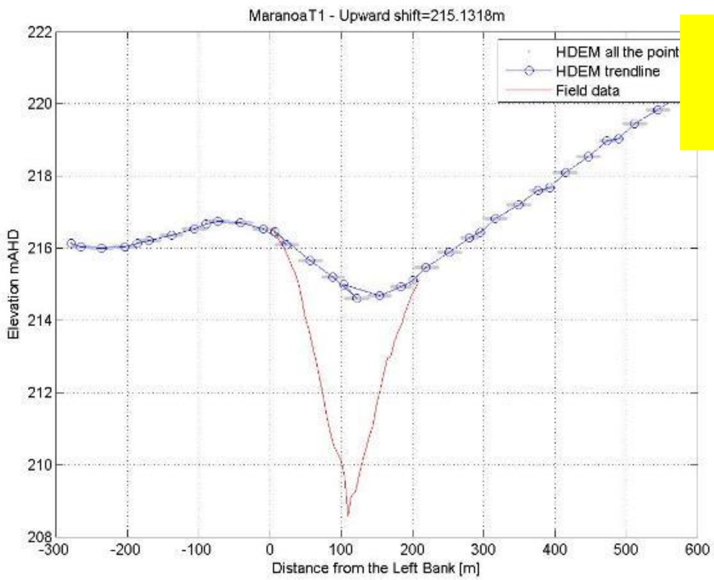


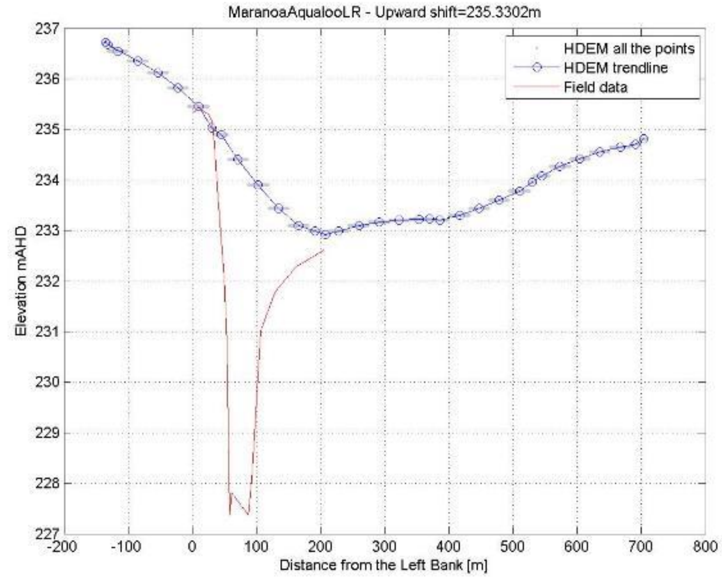


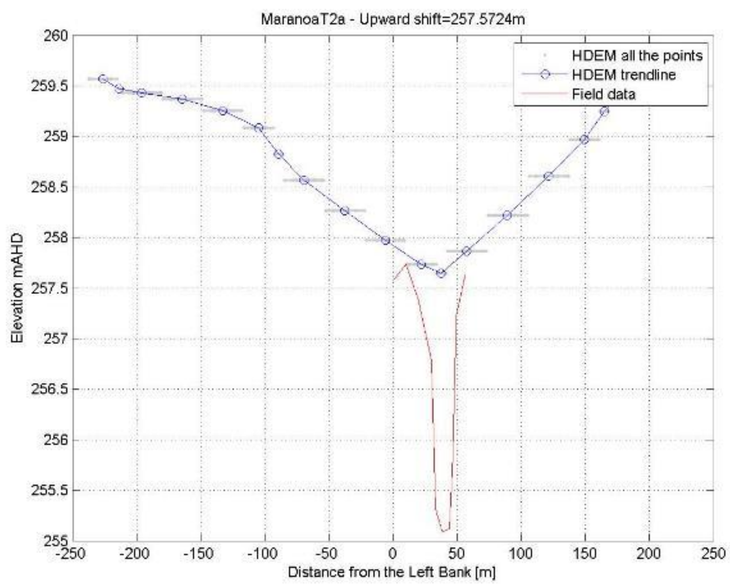
Mersel et al. (2013), Domeneghetti et al. (2016) suggested a break-slope method for depth estimation

Definition of a strategy to model the geometry of the river

The comparison between HDEM and field data will be extended to all the available cross sections







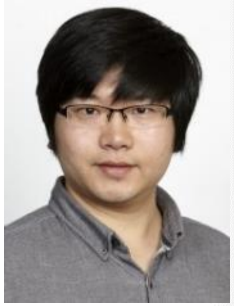
CONCLUSIONS

- **RS soil moisture** can improve streamflow prediction in **ungauged** catchments.
- **Soil moisture assimilation can improve flow predictions**; however, over correction has also been found for some events. Joint assimilation of soil moisture and streamflow is recommended to address errors in rainfall.
- A strategy to build a coherent **bathymetric dataset** needs to be developed.
- Integrated use of **field measurements, remote sensing imageries, and hydraulic modelling** will be investigated for improved flood inundation prediction.

THANKS FOR YOUR KIND ATTENTION!





Valentijn.Pauwels @monash.edu
Jeff.Walker@monash.edu
Ashley.Wright @monash.edu
Stefania.Grimaldi@monash.edu
Antara.Dasgupta @monash.edu
Yuan.Li2@monash.edu