IMPROVING FLOOD FORECAST SKILL USING REMOTE SENSING DATA

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Geoscience Australia

RATIONALE

In the **last decade of the 20th century**, floods caused **100,000 deaths** and affected almost 1.4 billion people **worldwide**.

Australia

- **1859 deaths from 1900 to 2015**
- average annual cost for the last 40 years: **$377M/year**

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

2010-2011 floods in Brisbane and South-East Queensland:

- 35 confirmed deaths
- $2.38 billion damage

June 2016 floods in East Australia and Tasmania

- 4 deaths
- approximately 14500 claims totalling $56M were lodged to the Insurance Council of Australia.

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

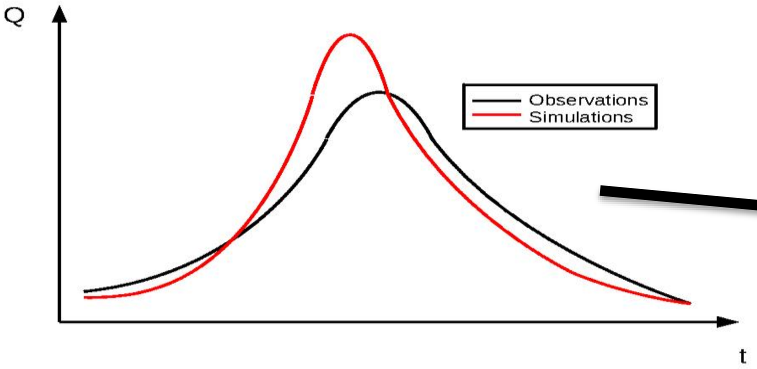
FLOOD FORECASTING SYSTEMS

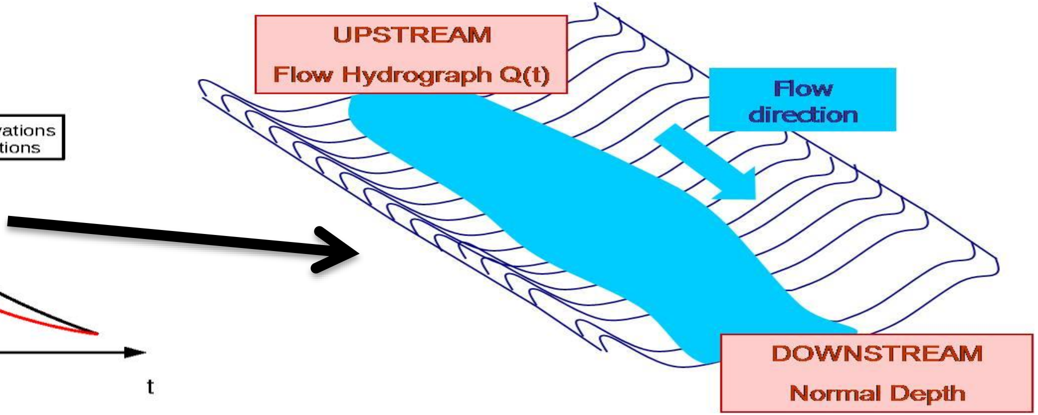
1. HYDROLOGIC MODEL:

Input: rain, PET

Output: discharge hydrograph

Model selected: GRKAL





2. HYDRAULIC MODEL:

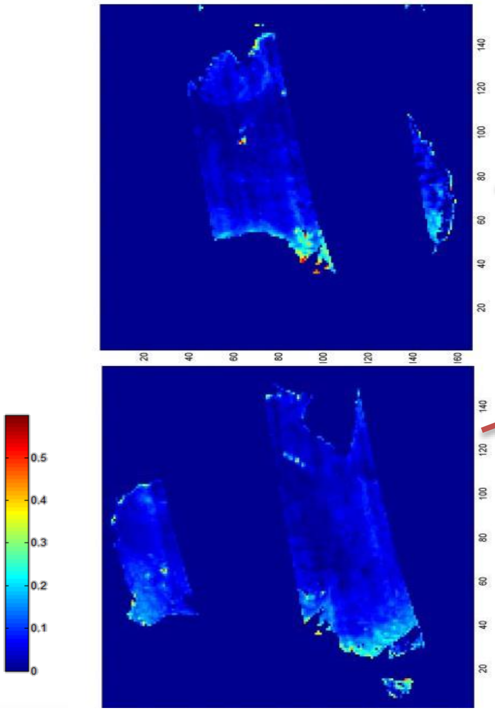
Input: discharge hydrograph

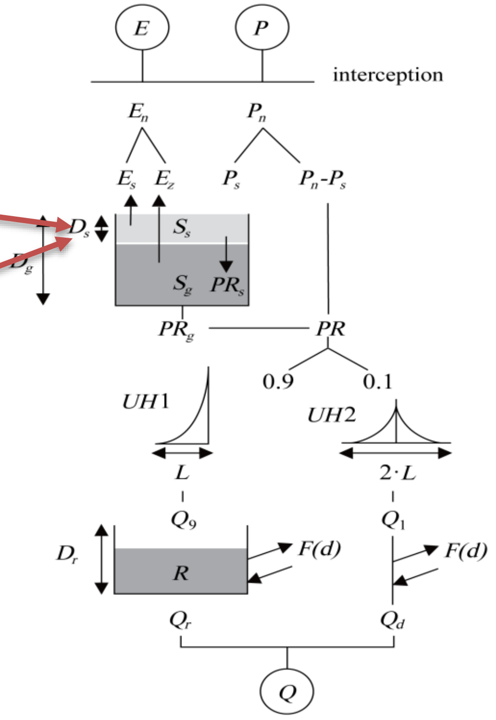
Output: water depth and velocity at each point of the flooded area

Model selected: LISFLOOD-FP

HYPOTHESIS:
REMOTE SENSING DATA CAN IMPROVE FLOOD FORECAST ACCURACY

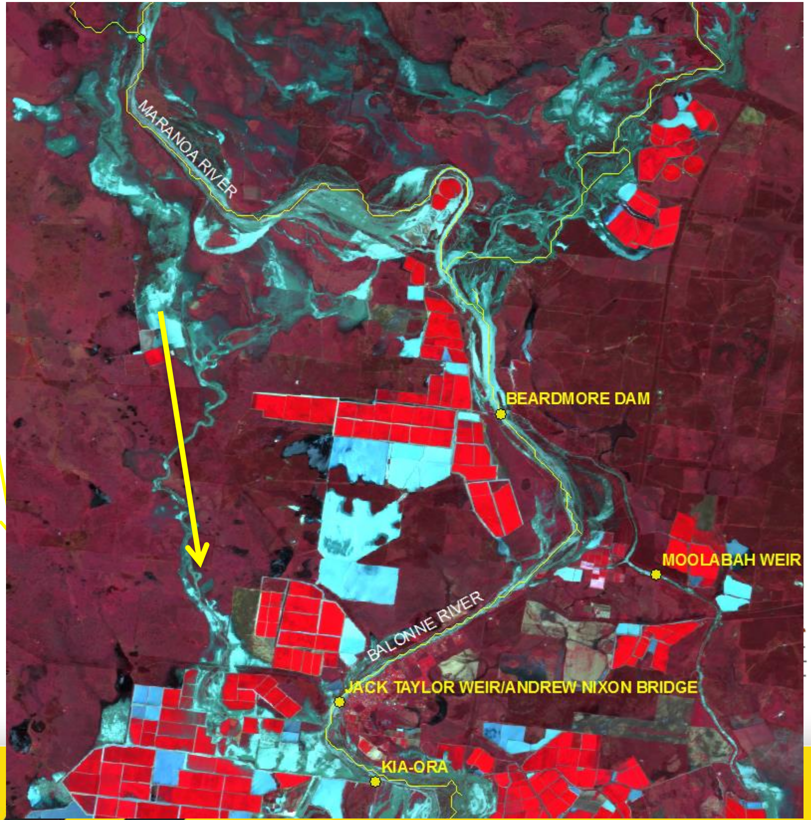
1. HYDROLOGIC MODEL: REMOTE SENSING SURFACE SOIL MOISTURE





SMOS coverage (morning pass) on 3rd and 5th July 2014

HYPOTHESIS:
REMOTE SENSING DATA CAN IMPROVE FLOOD FORECAST ACCURACY
2. HYDRAULIC MODEL: REMOTE SENSING-DERIVED FLOOD EXTENT and LEVEL

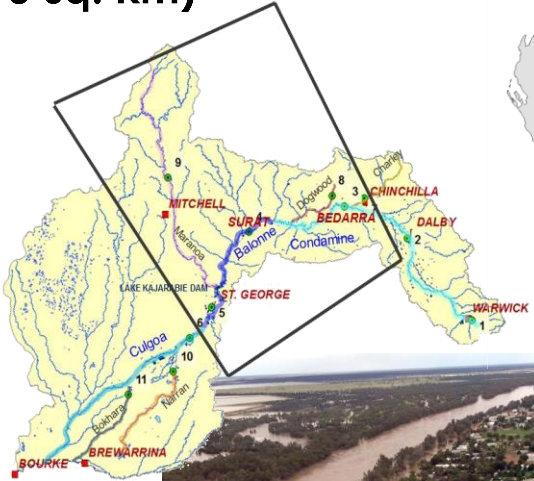


1) RS-derived maps of **flood extent** can be used to identify **gross errors** in the results of the numerical model or to detect unexpected events such as **levee breaches.**

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)



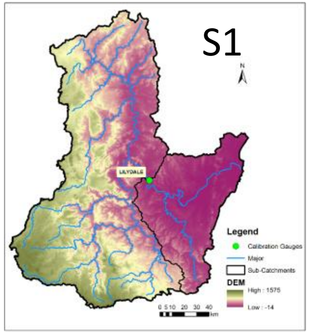
Clarence
(20730 sq. km)

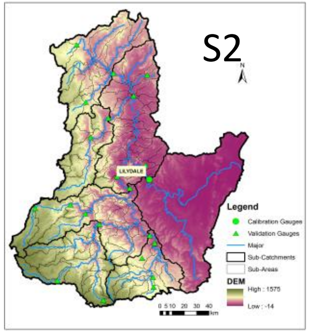
St. George, 2012 Feb 7th, http://www.abc.net.au

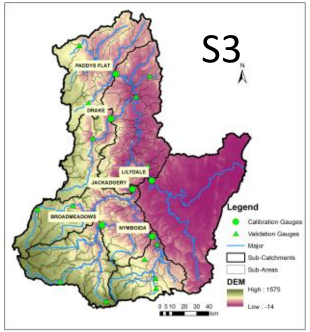
Grafton, 2013 Jan 30th, Mr. Williamson

HYDROLOGIC MODEL

CALIBRATION: Three catchment systems:







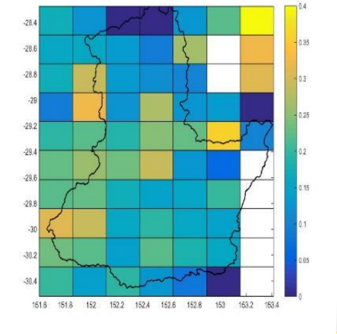
S1 - LUMPED SYSTEM
CALIBRATION @ ONE GAUGE

S2,S3 – DISTRIBUTED SYSTEM (144 SUB-AREAS)
CALIBRATION @ ONE GAUGE CALIBRATION @ SIX GAUGES

Two calibration scenarios:

- calibration using streamflow;
- calibration using streamflow and SMOS soil moisture.

Data : 2010 - 2012 calibration
2013 - 2014 validation



HYDROLOGIC MODEL

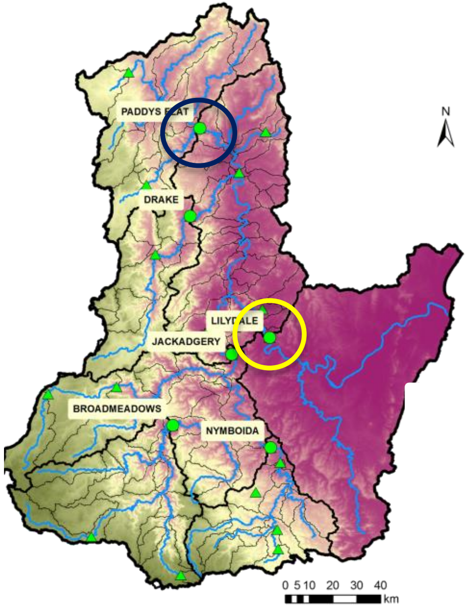
CALIBRATION USING STREAMFLOW DATA

- Performance at Lilydale (downstream gauge)

NS	S1	S2	S3
Cal.	0.81	0.83	0.83
Val.	0.67	0.74	0.76

- Performance at upstream gauges
  E.g. Paddys Flat

NS	S1	S2	S3
Cal.	-	0.59	0.85
Val.	-	0.56	0.76



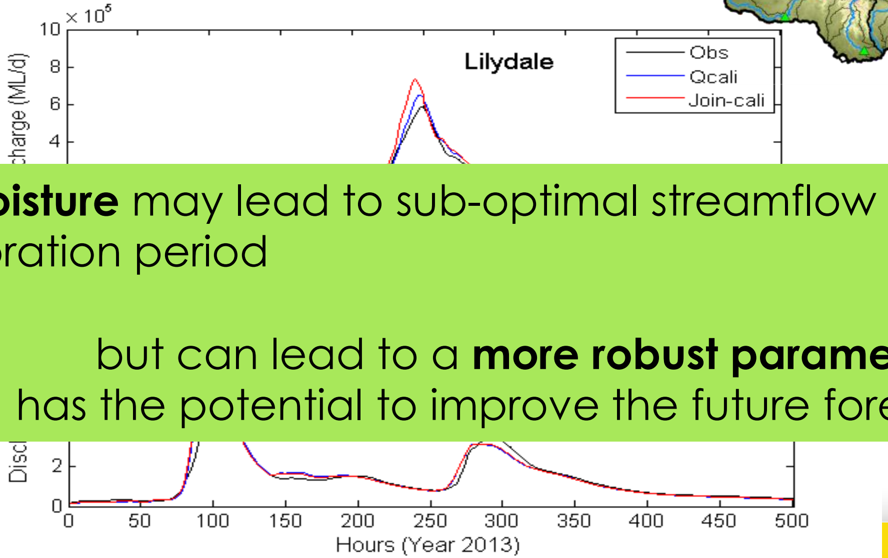
- ❖ **Distributed models** are recommended for large-scale catchments.
- ❖ Large **uncertainty** exists at **ungauged sub-catchments**, more data insertion is required --> RS soil moisture.

HYDROLOGIC MODEL

JOINT CALIBRATION USING STREAMFLOW AND REMOTE SENSING SOIL MOISTURE DATA

- Performance at Lilydale (downstream gauge)

NS	S1	S2	S3
Cal-Q	0.81	0.83	0.83
Cal-Joint	0.79	0.79	0.80
Val-Q	0.67	0.74	0.76
Val-Joint	0.68	0.76	0.77



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

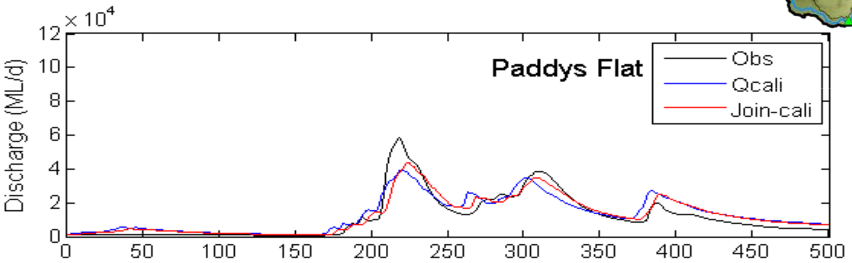
but can lead to a **more robust parameter set** which has the potential to improve the future forecasts.

HYDROLOGIC MODEL

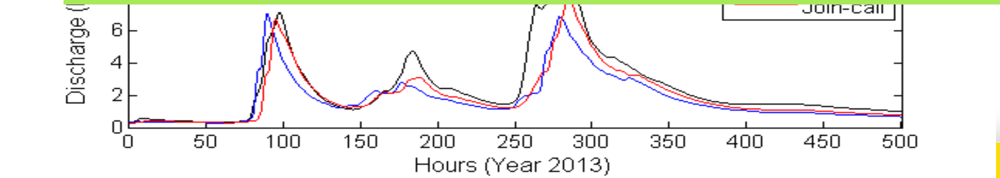
JOINT CALIBRATION USING STREAMFLOW AND REMOTE SENSING SOIL MOISTURE DATA

Performance at upstream gauges
E.g. Paddys Flat

NS	S1	S2	S3
Cal-Q	-	0.59	0.85
Cal-Joint	-	0.64	0.82
Val-Q	-	0.56	0.76
Val-Joint	-	0.61	0.76



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



HYDROLOGIC MODEL

JOINT CALIBRATION USING STREAMFLOW AND REMOTE SENSING SOIL MOISTURE DATA

- Scheme 2

NS	PADDYS FLAT	DRAKE	BROADMEADOWS	NYMBOIDA	JACKADGERY	LILYDALE
Cal-Q	0.59	0.41	0.43	0.58	0.65	0.83
Cal-Joint	0.64	0.43	0.59	0.55	0.66	0.80
Val-Q	0.56	0.45	0.50	0.57	0.64	0.74
Val-Joint	0.61	0.46	0.55	0.52	0.65	0.76

- Scheme 3 (refere

NS	PADDYS FLAT	D				
Cal-Q	0.85	0.74	0.77	0.81	0.83	0.83
Cal-Joint	0.82	0.69	0.76	0.81	0.79	0.79
Val-Q	0.76	0.68	0.68	0.70	0.75	0.76
Val-Joint	0.76	0.64	0.72	0.72	0.76	0.77

Four out of five upstream locations were **improved** through incorporating remote sensing **soil moisture** data in the calibration period.

HYDROLOGIC MODEL

CALIBRATION – *Some conclusions*

- **RS soil moisture** can **improve discharge** assessment during **forecasting periods** at **gauged locations.**
- **RS soil moisture** has **stronger impact** on discharge assessment during **calibration and forecasting** periods at **ungauged locations.**
- The impact of RS soil moisture decreases when the density of streamflow calibration sites increases.

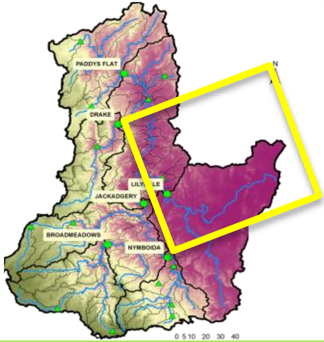
Hydrologic model

Prediction of the input discharge hydrograph

Hydraulic model

Flood extent and level in the lower Clarence catchment.

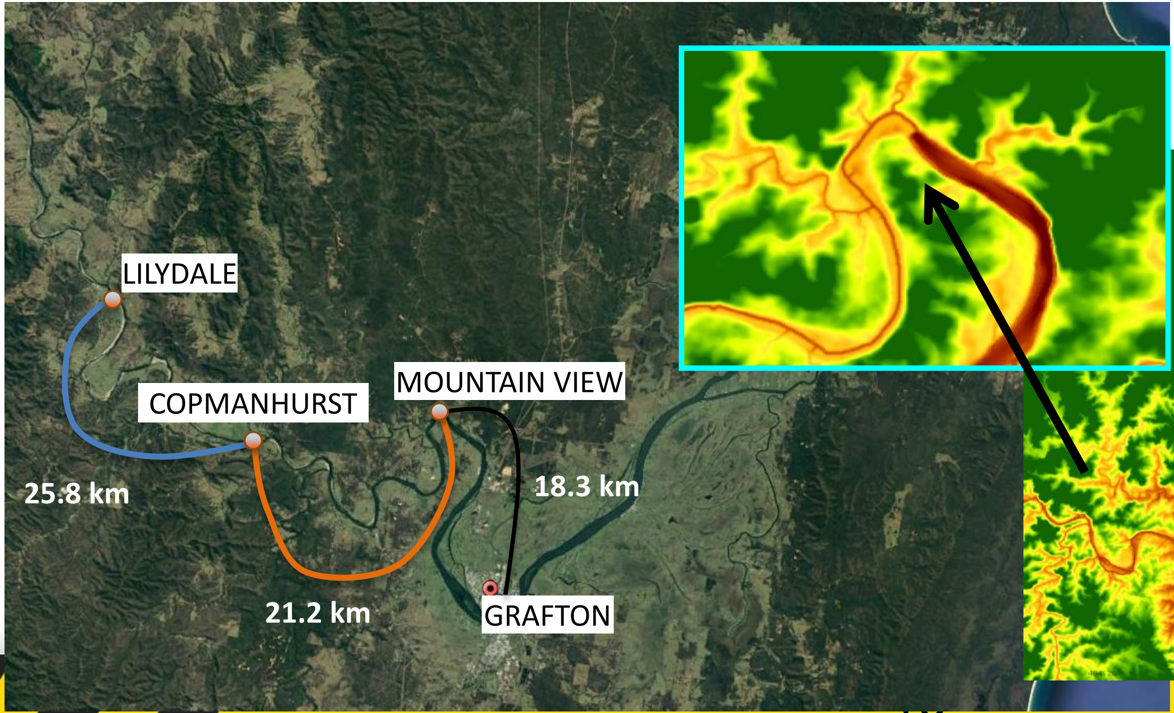
Historical flood event: Jan. 2011

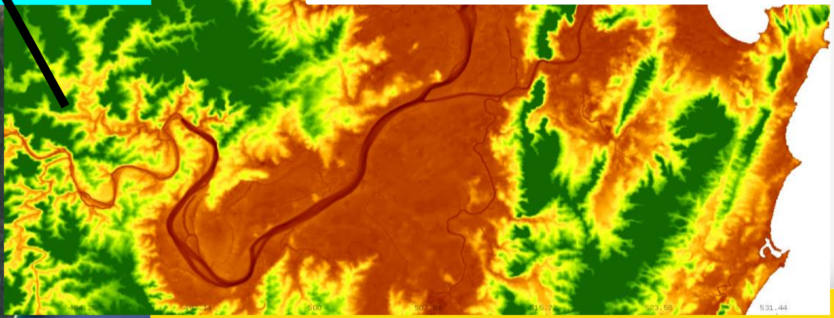


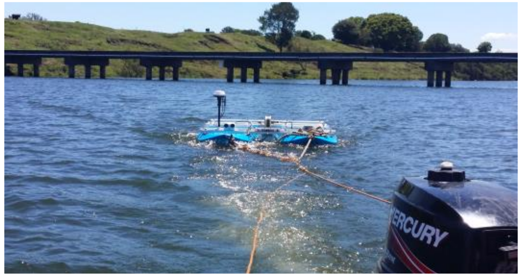
HYDRAULIC MODEL

IMPLEMENTATION DATA:

- DEM: 1m Lidar DEM (CVC, 2010)
- River bathymetry

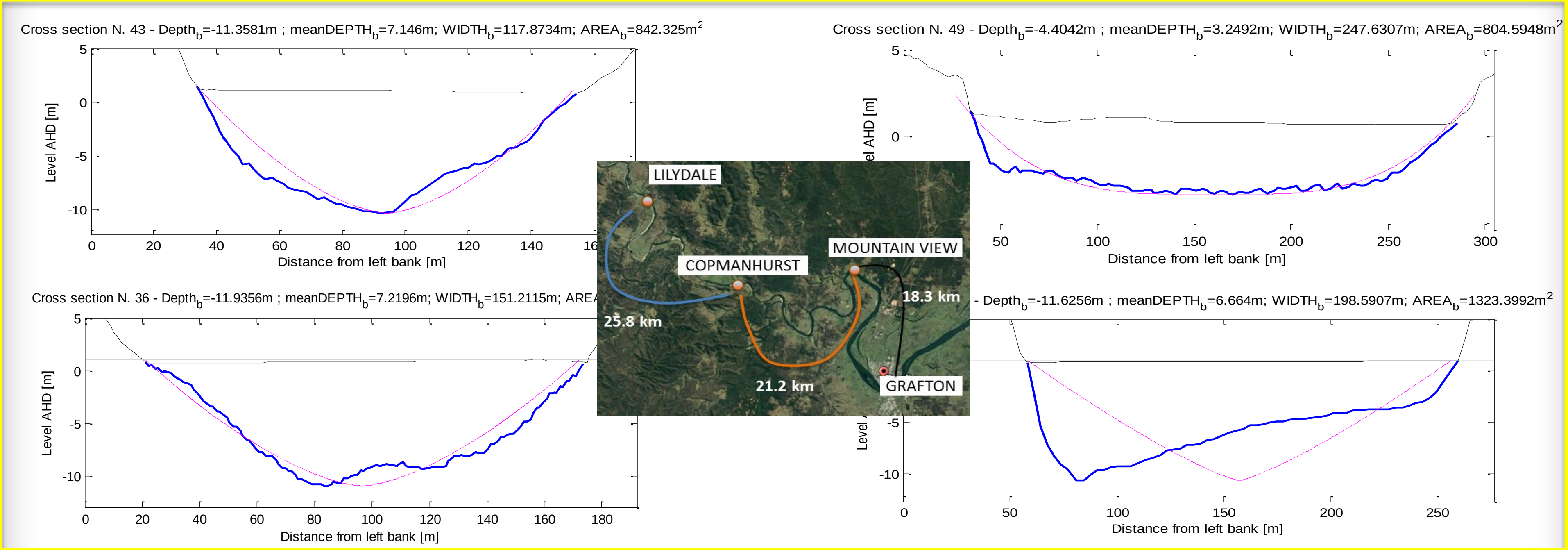






HYDRAULIC MODEL

RIVER BATHYMETRY: field data from Mountain View to Copmanhurst



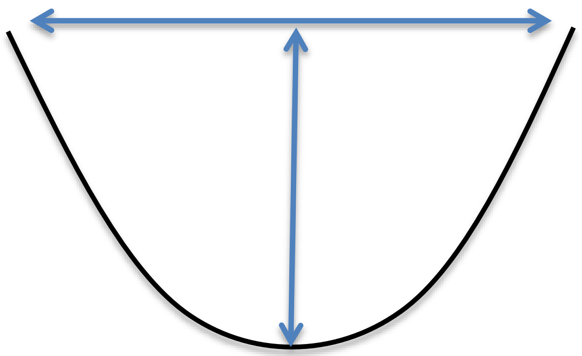
We analysed the new bathymetric dataset to extrapolate the bathymetry of the river **from Copmahurst to Lilydale**

HYDRAULIC MODEL

RIVER BATHYMETRY from Copmanhurst to Lilydale

"BASE" MODEL

- **Cross section shape:** $s = 1.8$ - **field data (Copmanhurst to Mountain View) ~ PARABULA**
- **Flow direction:** Yamazaki et al. (2014) - **Global Database**
- **Cross section Width at bankfull:** Water Observations from Space - **GA**



- **Cross section Depth at bankfull:**
  - Catchment Area, A_C, Yamazaki et al. (2014) - **Global Database**
  - Discharge at bankfull, Q_b, from Gordon et al. (1996) - **Victoria, NSW**
  - Mean Depth at bankfull, h_{mean}, from De Rose et al. (2008) - **Victoria, NSW**
  - Max Depth at bankfull, h_{max} - **field data (Copmanhurst to Mountain View)**

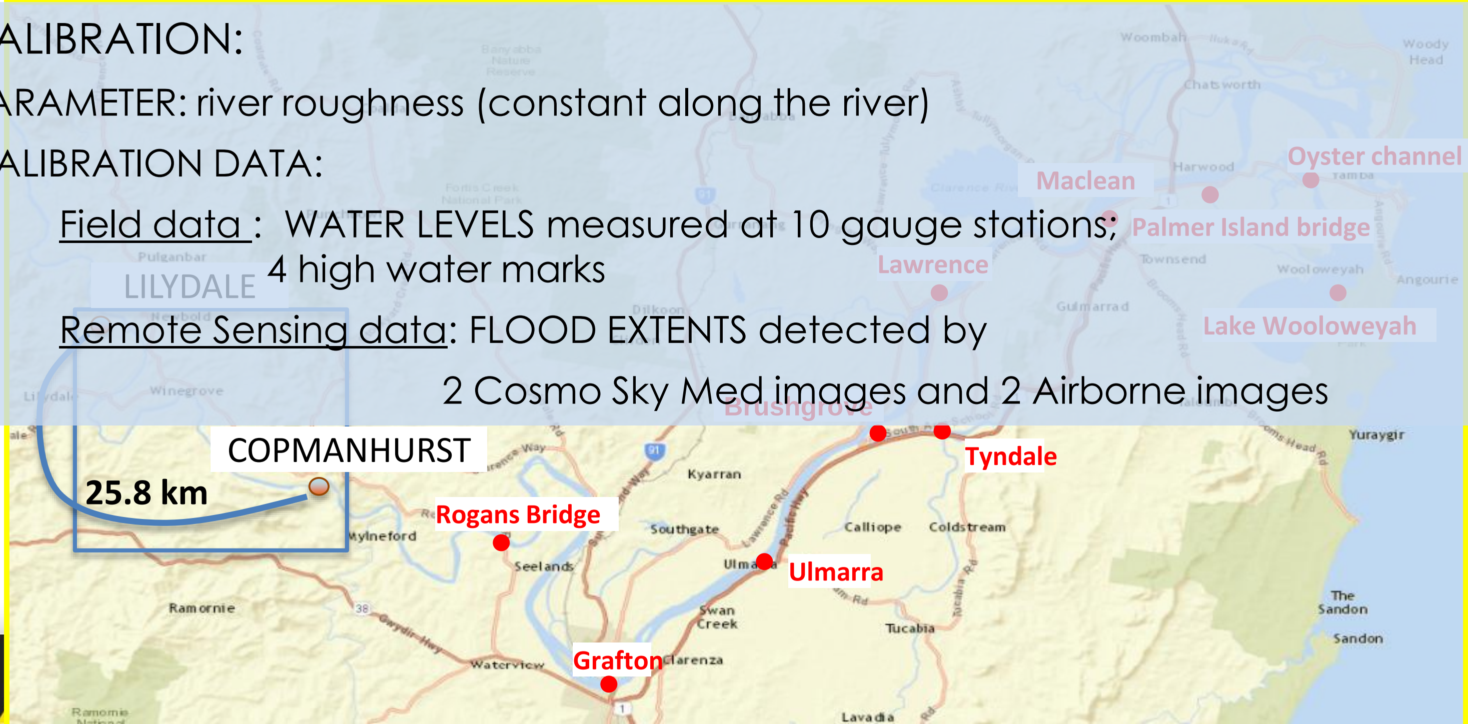
HYDRAULIC MODEL

2011, 2013 FLOOD EVENT

	Lilydale to Copmanhurst	Copmanhurst to Yamba
1	HDEM	Field data (Monash Univ. and CVC – BMT WBM)
2	Extrapolated bathymetric dataset	Field data (Monash Univ. and CVC – BMT WBM)

MODEL CALIBRATION:

- PARAMETER: river roughness (constant along the river)
- CALIBRATION DATA:
  - Field data : WATER LEVELS measured at 10 gauge stations; 4 high water marks
  - Remote Sensing data: FLOOD EXTENTS detected by 2 Cosmo Sky Med images and 2 Airborne images



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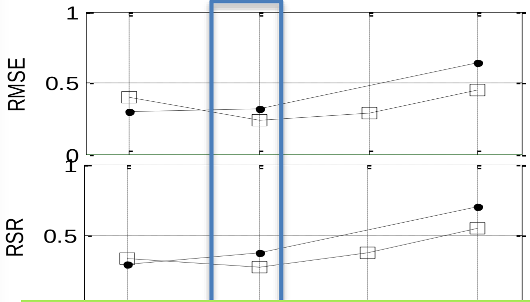
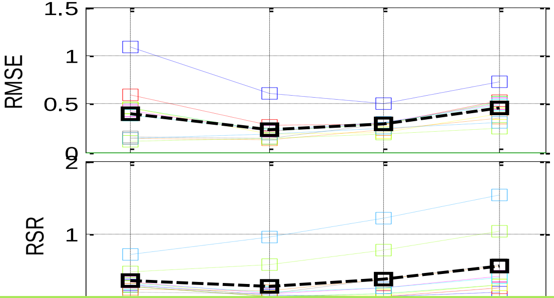
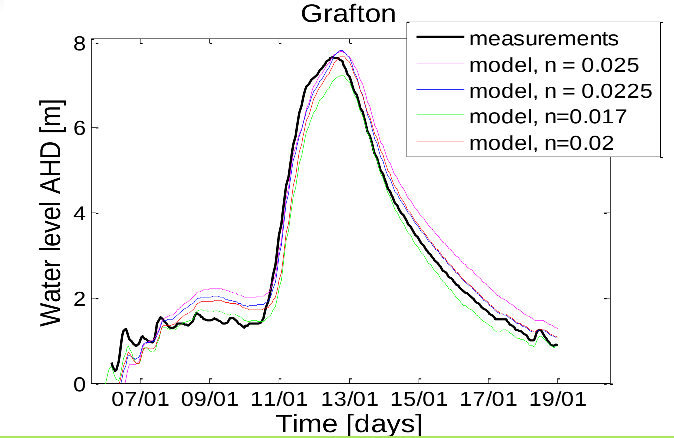
HYDRAULIC MODEL

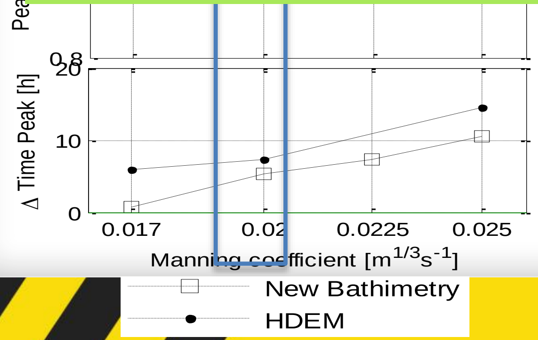
COMPARISON WITH GAUGED WATER LEVELS

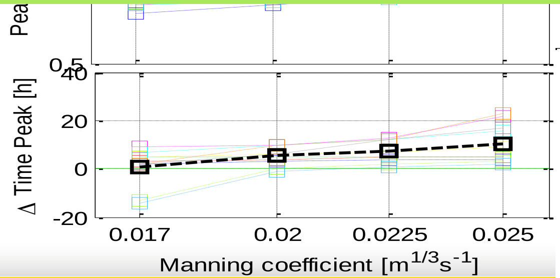






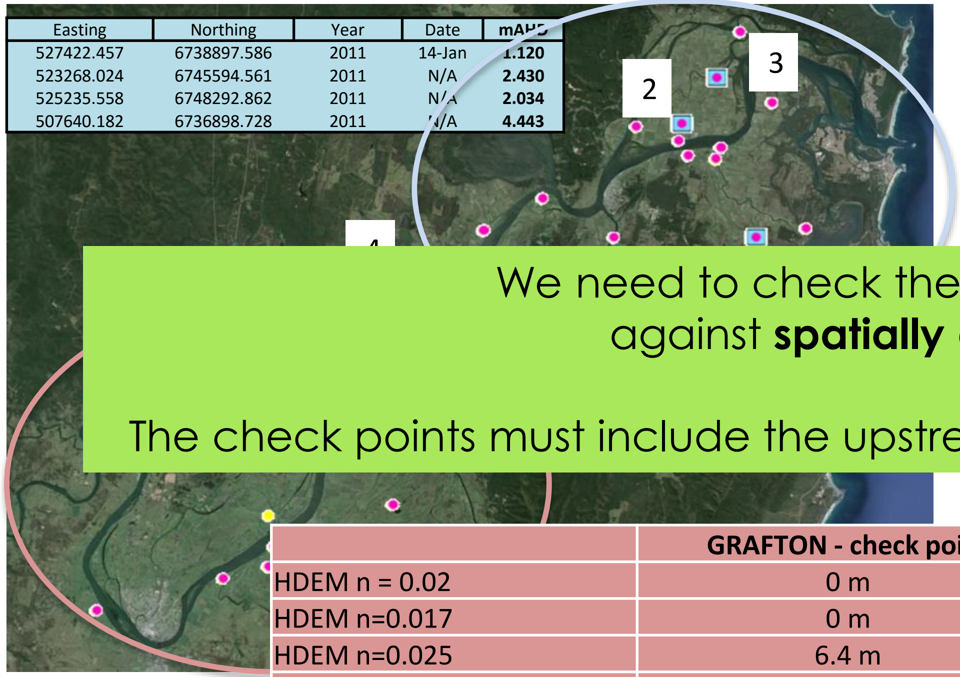
- ➢ A more precise description of the **river geometry** from Lilydale to Copmanhurst (25.8 km) improves the forecast accuracy over the total length of the river (125 km).
- ➢ Spatial variability of the catchment flooding behaviour → spatial variability of the river roughness parameter.



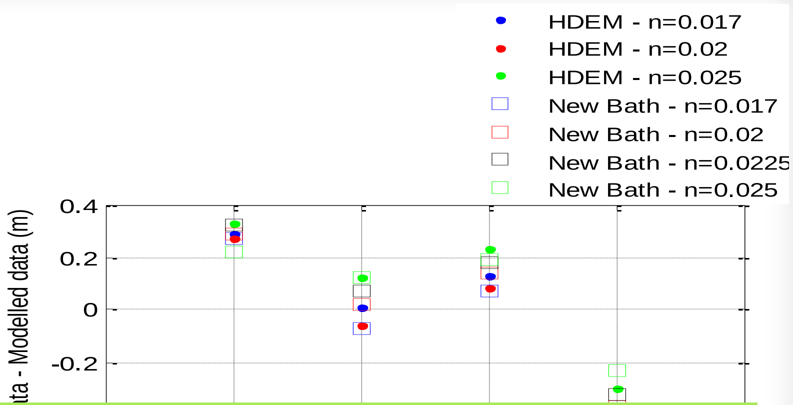


HYDRAULIC MODEL

COMPARISON WITH HIGH WATER MARKS



Easting	Northing	Year	Date	mAHD
527422.457	6738897.586	2011	14-Jan	1.120
523268.024	6745594.561	2011	N/A	2.430
525235.558	6748292.862	2011	N/A	2.034
507640.182	6736898.728	2011	N/A	4.443



We need to check the model performances against **spatially distributed data**.

The check points must include the upstream/central area of the model domain.

New Bath n=0.017	0.14
New Bath n=0.02	0.12
New Bath n=0.0025	0.12
New Bath n=0.025	**0.10**

	GRAFTON - check point
HDEM n = 0.02	0 m
HDEM n=0.017	0 m
HDEM n=0.025	6.4 m
New Bath n=0.017	0 m
New Bath n=0.02	0 m
New Bath n=0.0025	0 m
New Bath n=0.025	**3.9 m**

HYDRAULIC MODEL

COMPARISON WITH REMOTE SENSING-DERIVED FLOOD EXTENT

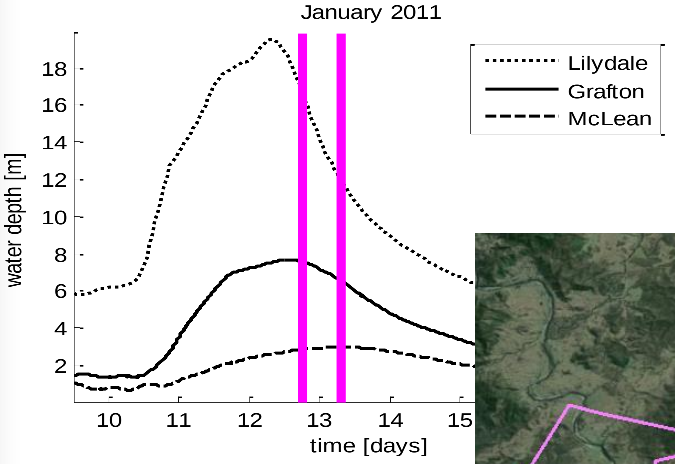
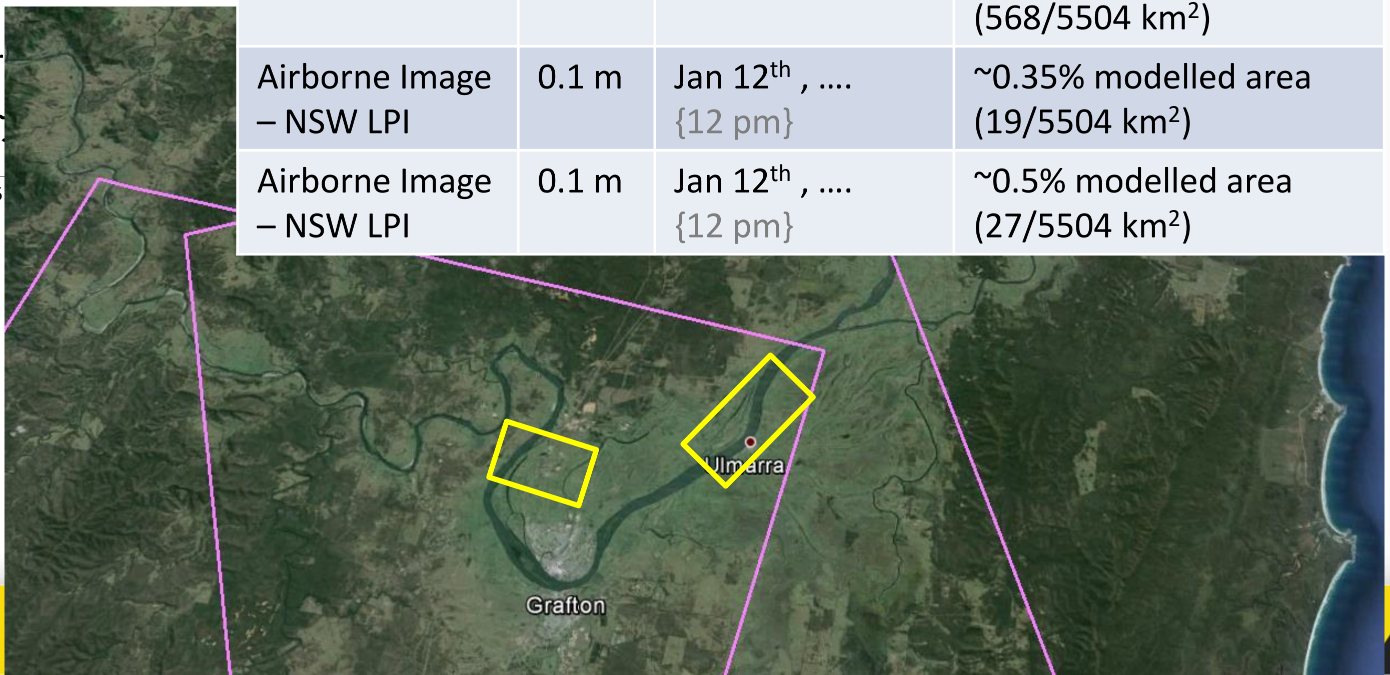
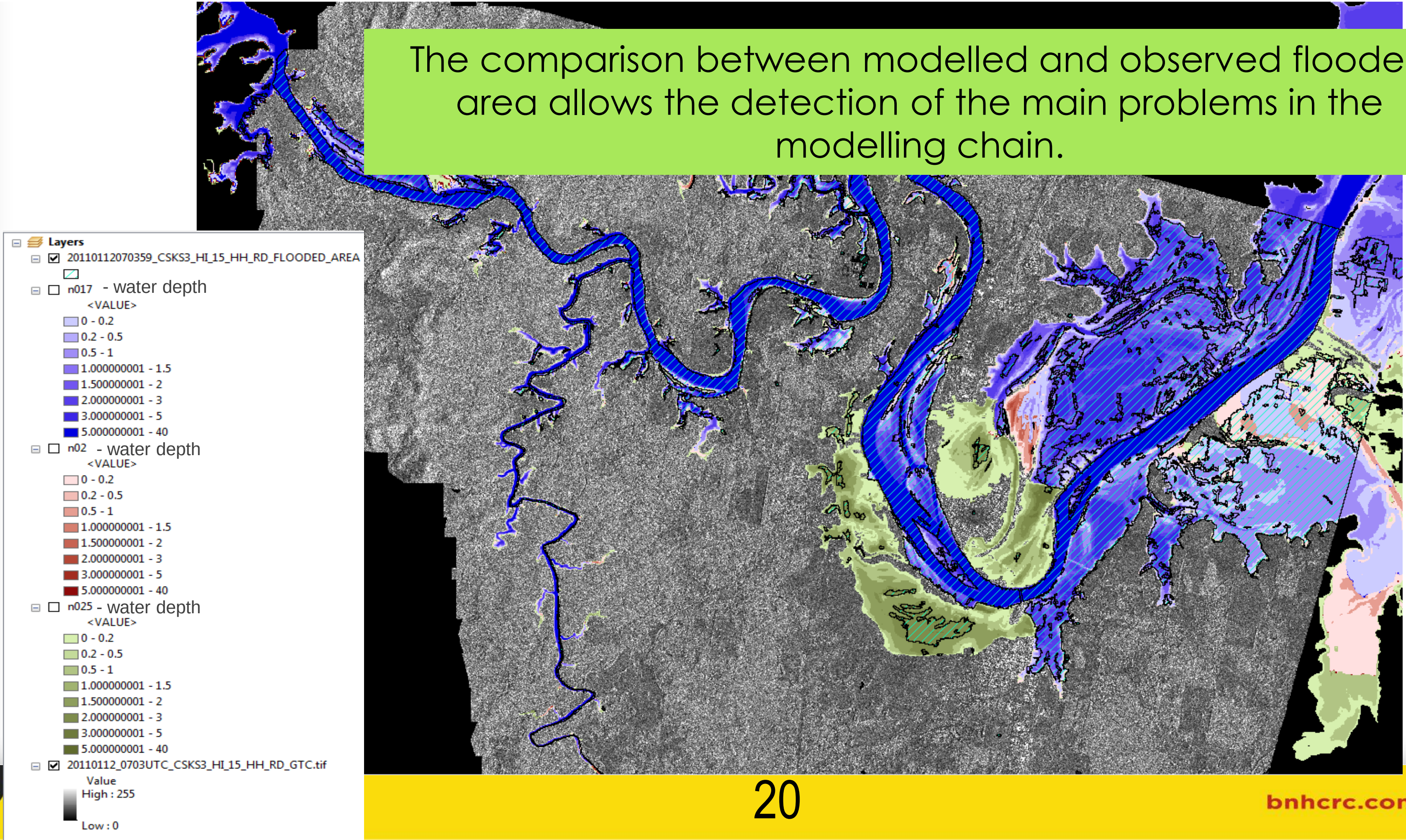


Image	Res.	Acquisition time	Spatial Coverage
Cosmo Sky Med	3 m	Jan 12th, 6pm	~7% modelled area (384/5504 km^2)
Cosmo Sky Med	3 m	Jan 13th, 7am	~10% modelled area (568/5504 km^2)
Airborne Image – NSW LPI	0.1 m	Jan 12th , …. {12 pm}	~0.35% modelled area (19/5504 km^2)
Airborne Image – NSW LPI	0.1 m	Jan 12th , …. {12 pm}	~0.5% modelled area (27/5504 km^2)



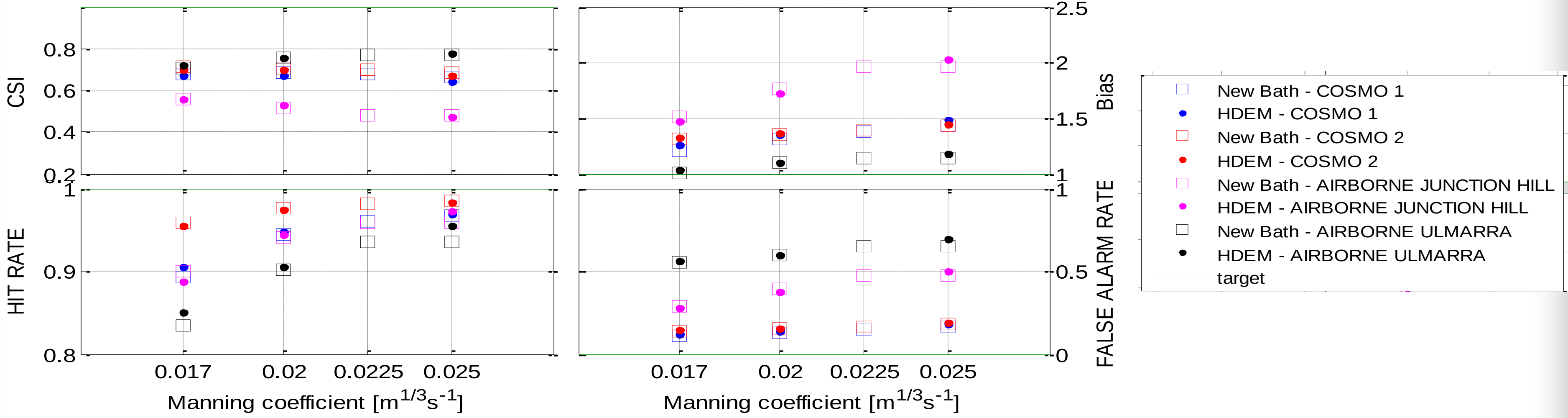
2011 flood – Comparison of RS-derived with computed flood extent

The comparison between modelled and observed flooded area allows the detection of the main problems in the modelling chain.



HYDRAULIC MODEL

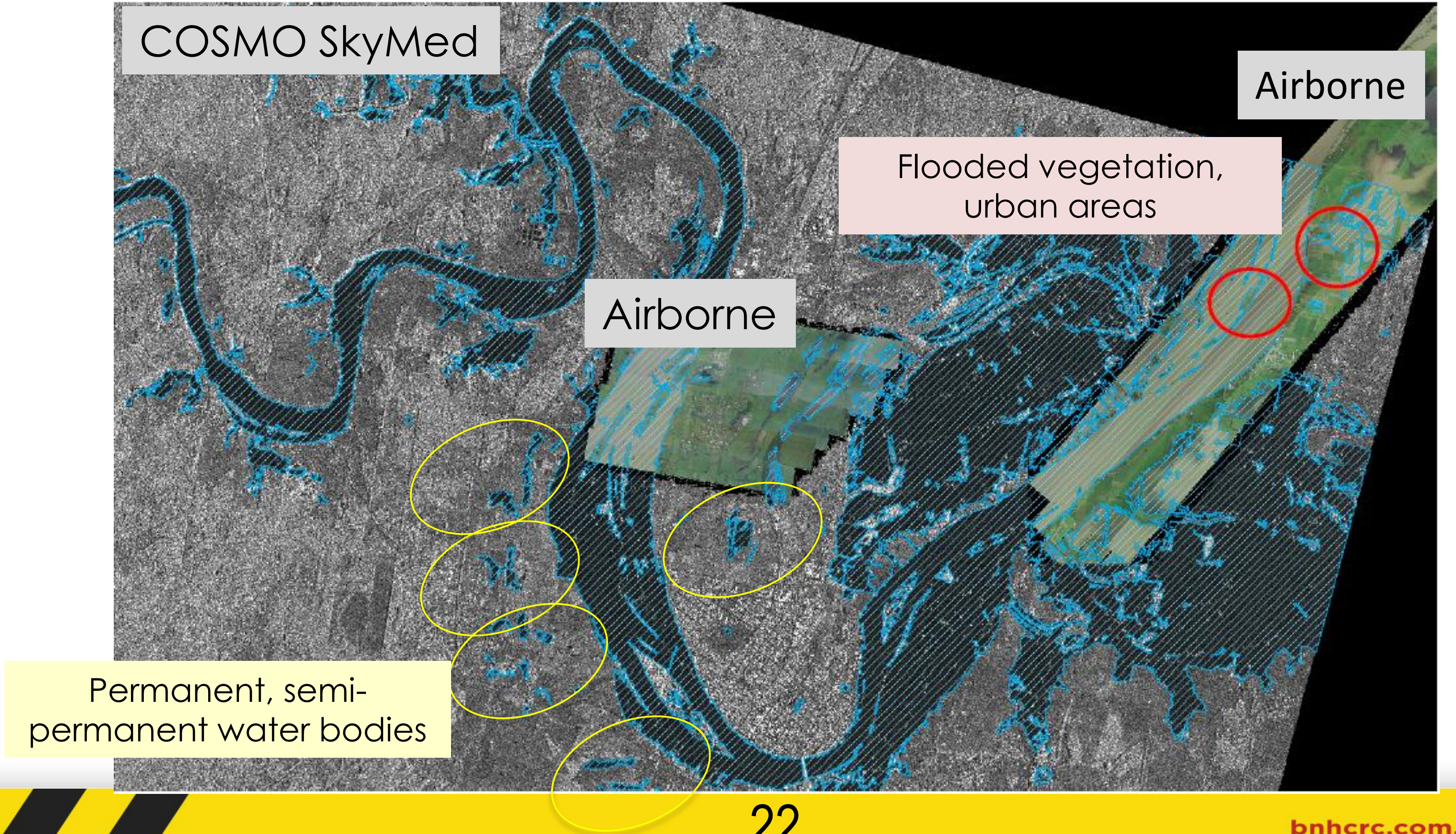
COMPARISON WITH REMOTE SENSING-DERIVED FLOOD EXTENT



The model **over-predicts** the flooded area.

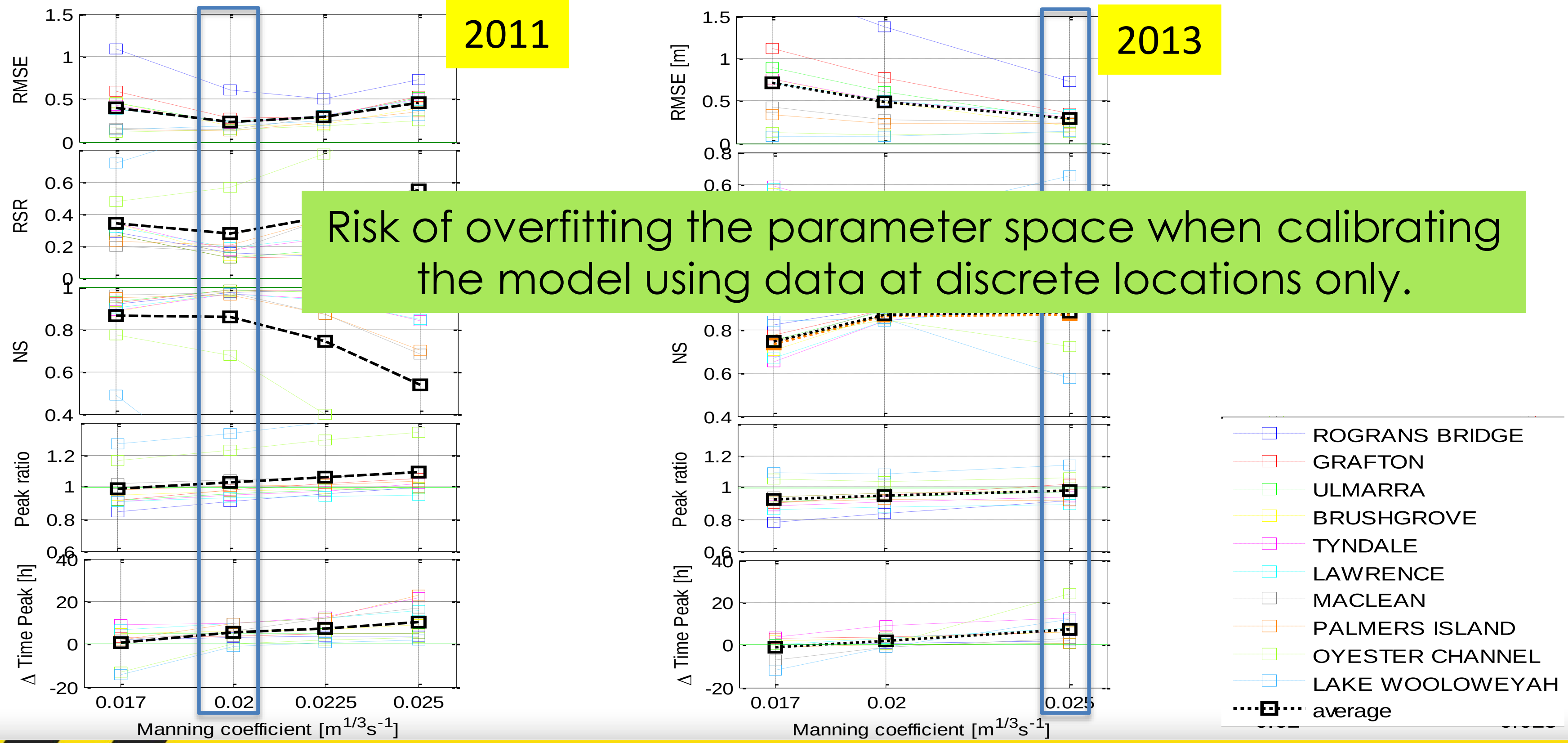
RS-derived water level at **selected**, spatially **distributed** locations can be used to constrain the model parameter space (e.g. Mason et al. 2009, Schumann et al. 2009, Stephens et al. 2012).

Uncertainty in the interpretation of the RS images



HYDRAULIC MODEL

CATCHMENT BEHAVIOUR: 2011 AND 2013 FLOODS, GAUGED LEVELS



Risk of overfitting the parameter space when calibrating the model using data at discrete locations only.

HYDRAULIC MODEL

CALIBRATION – *Some conclusions*

- These results underlined the limits of a punctual model-measurements comparison.
- **More coherent and explicative** modalities of comparison are possible thanks to the intrinsically two dimensional features of RS observations.
- The use of **spatially distributed information** can lead to a **more robust** parameter set which has the potential to improve both intra-event and inter-event forecast.
- A **multi-objective calibration** strategy able to exploit the temporal continuity of gauged data and the spatial distribution of RS observations is recommended.

FUTURE WORK:

Can we constrain a hydraulic model using **remote sensing data only**?

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Conclusions

- **RS soil moisture** can improve streamflow prediction in **ungauged** catchments.
- **RS-derived water extent and level** are **pivotal** for the constraining of the parameter space of hydraulic models.

THANKS FOR YOUR KIND ATTENTION!


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