HYDROLOGIC AND HYDRAULIC MODELING FOR RIVERINE FLOOD FORECASTING

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MOTIVATION

Queensland flood 2010-2011
(http://en.wikipedia.org/wiki/File:Long_and_Mackenzie_Streets_in_Toowoomba_flooded.jpg)

Flood Models

Forecasting

Warning

Operational control

Data Assimilation

Emergency response

Calibration

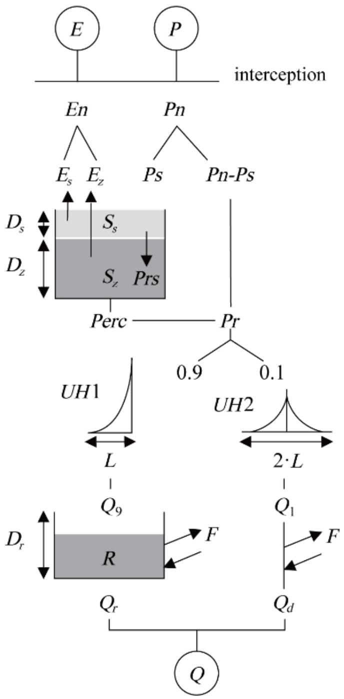
Historical Data

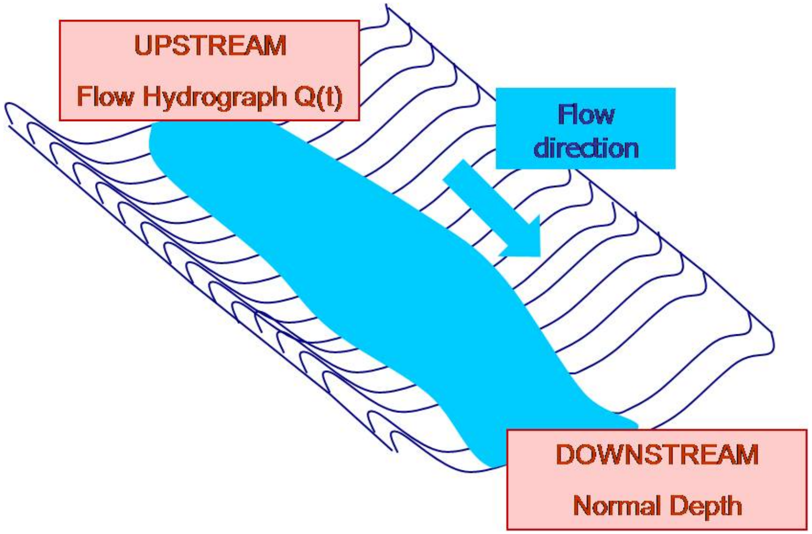
Real-time Data

Newcastle flood 2007
(http://en.wikipedia.org/wiki/File:Newcastle,_NSW,_Australia_Floods.jpg)

MODELING TOOLS

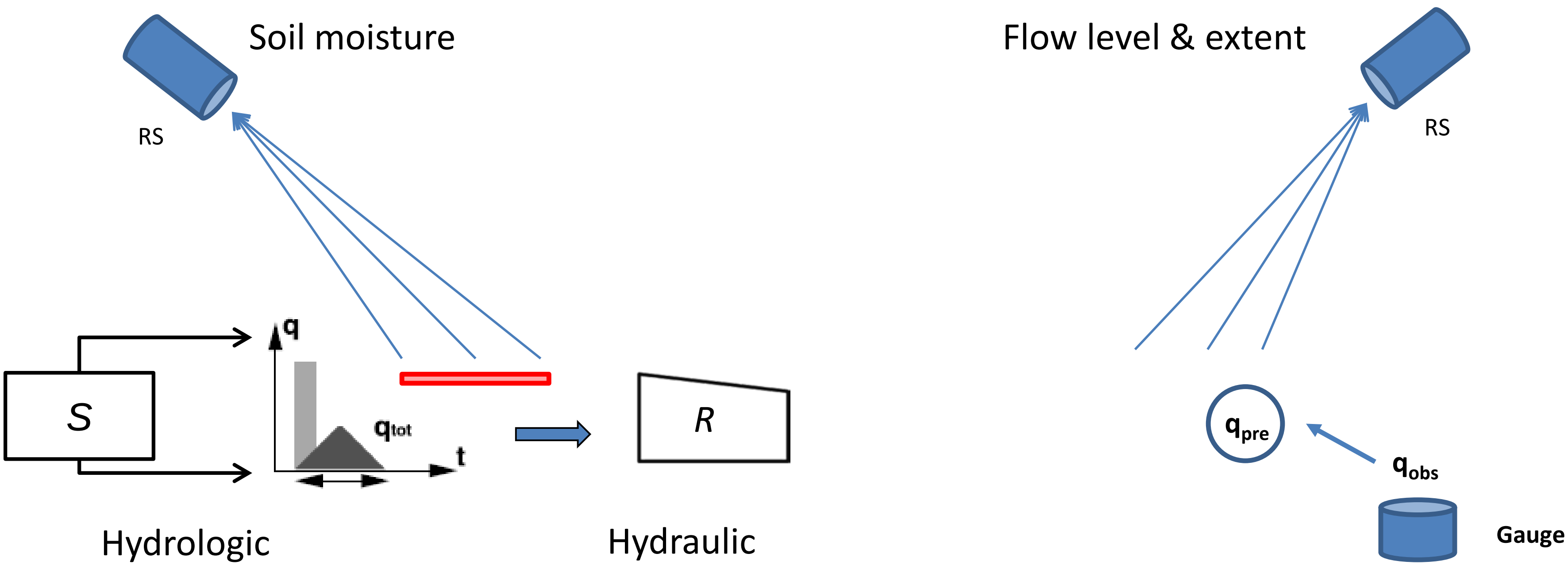
- Hydrologic models are widely used for operational flood forecasting, while hydraulic models are more implemented for flood related design.
- There is an increasing interest to use both types of models for flood forecasting.





- A **hydrologic model** computing the inflow into the river system.
- A **hydraulic model** computing the stream water level and flood extent.

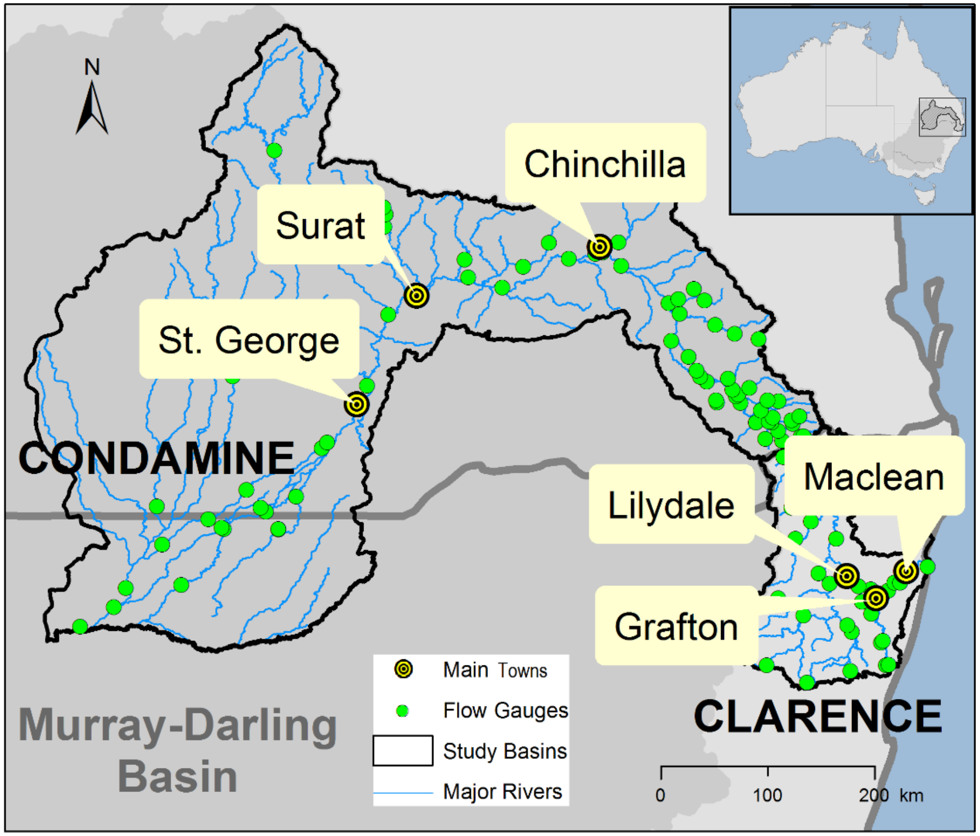
OBSERVATIONAL CONSTRAINTS

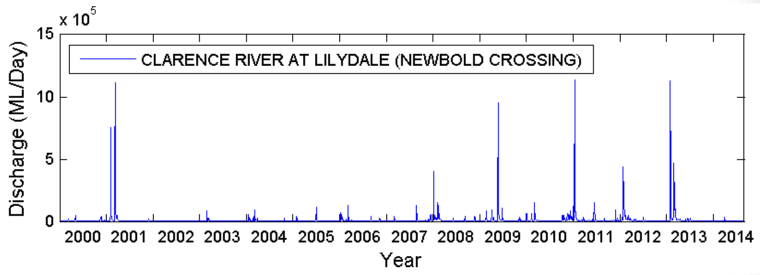


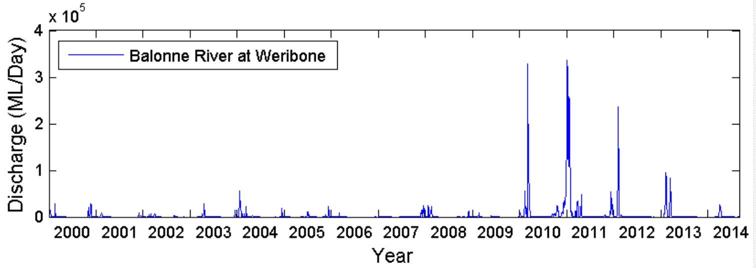
PROJECT OBJECTIVES

1) Select study basins, collect and process data.
2) Calibrate a hydrologic/hydraulic model using remote sensing data.
3) Understand and estimate various sources of uncertainties.
4) Develop data assimilation methods that work optimally for the hydrologic/hydraulic model sequence and types of data that will be used.
5) Construct a coupled hydrologic and hydraulic modeling system constrained by remote sensing data for improved flood forecasting.

STUDY BASINS







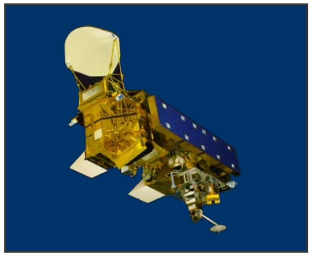
DATA

1) Streamflow/Water Level
    - Data from NSW and QLD water info databases
2) Rainfall
    - BoM archive gauged data 2007-2014
3) Potential Evapotranspiration
    - AWAP 5 km monthly data
4) Bathymetry
    - Data from BMT-WBM and QLD department of natural resources and mines (DNRM)
    - Planned field survey in November 2015
5) DEM
    - 30m DEM from Geoscience Australia (GA)
    - 1m DEM from Clarence Valley Council (CVC) and QLD DNRM
6) Land Cover
    - Land Cover from GA and QLD DNRM

REMOTELY SENSED SOIL MOISTURE

SMOS (Soil Moisture and Ocean Salinity) launched Nov 2009

40 km with 3 days repeat; synthetic aperture radiometer



AMSR-E/-2 (Advanced Microwave Scanning Radiometer) Jun 2002 – Oct 2011 / May 2012 –

50 km, 1-3days; “traditional” C-band radiometer

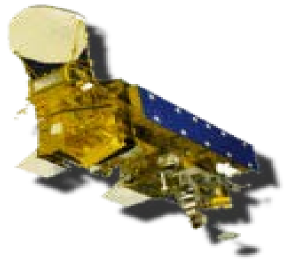
ASAR (Advanced Synthetic Aperture Radar) launched 2004

1 km ~10 days; C-band microwave scatterometer

SMAP (Soil Moisture Active Passive) launched Jan 2015

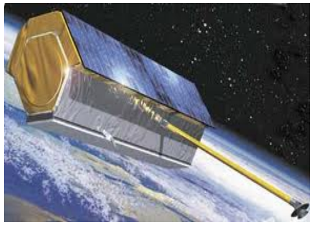
40-10 km with 3 days repeat; high resolution active

REMOTELY SENSED WATER EXTENT/LEVEL



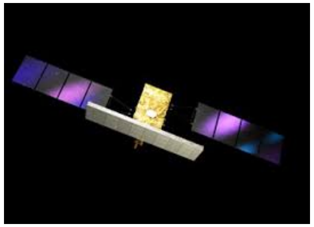
TerraSAR-X
launched June 2007

~1 m with 11 days revisit



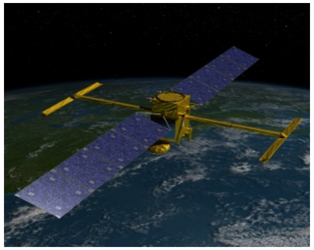
RadarSat-2
launched Dec 2007

~1 m with 24 days revisit



COSMO Skymed
launched June 2007

~1 m with 4 days revisit



SWOT (Surface Water and Ocean Topography)
launch 2020

~100 m with 10 days revisit

Plus many others on the horizon

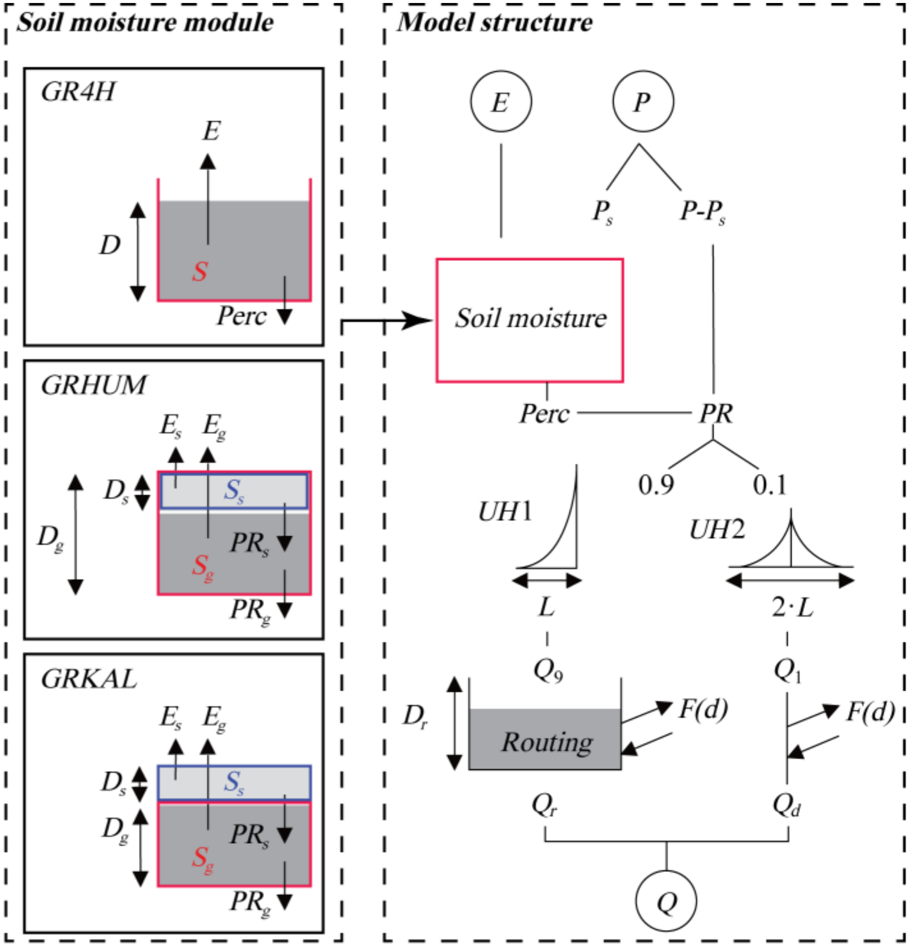
and

Visible data when unobstructed by clouds

PRELIMINARY STUDY IN CLARENCE RIVER BASIN

HYDROLOGIC MODELS

SM DA implication	***Water balance***
Need to have observation operator to convert RS SM (surface) to model SM (bulk)	$\frac{\partial S}{\partial t} = P_s - E - Perc$
Can propagate surface SM information to the bulk layer through cross covarience (EnKF)	$\frac{\partial S_s}{\partial t} = \frac{P_s - E_s - PR_s}{D_s}$ $\frac{\partial S_g}{\partial t} = \frac{P_s - E_g - PR_g}{D_g}$
Can propagate surface SM information to the bulk layer through cross covarience (EnKF) <u>and</u> vertical hydraulic process (infiltration)	$\frac{\partial S_s}{\partial t} = \frac{P_s - E_s - PR_s}{D_s}$ $\frac{\partial S_g}{\partial t} = \frac{PR_s - E_g - PR_g}{D_g}$



MODELING EXPERIMENTS

1) Model comparison:

- GR4 vs GRHUM vs GRKAL
- Calibrated using discharge

2) Test of using SM data:

- GRKAL
- Calibrated using discharge and SMOS SM product

Objective functions

- Flow: F2+V3+F5+F6 →
- Flow+SM: V3

F2: NS of log flows (low flows)

$$F2 = F_{\log NS} = \frac{\sum_{i=1}^{n} \alpha_i \left[\ln(Q_{sim,i} + \varepsilon) - \ln(Q_{obs,i} + \varepsilon)\right]^2}{\sum_{i=1}^{n} \alpha_i \left[\ln(Q_{sim,i} + \varepsilon) - \ln(\overline{Q}_{obs} + \varepsilon)\right]^2}$$

V3: Kling-Gupta Efficiency (variance and high flows)

$$V3 = F_{KGE} = 1 - \sqrt{(1 - r_\alpha)^2 + (1 - \frac{\sigma_{\alpha sim}}{\sigma_{\alpha obs}})^2 + (1 - \frac{\overline{Q}_{sim}}{\overline{Q}_{obs}})^2}$$

F5: Bias skill score

$$F5 = F_{bias} = \left[\max\left(\frac{\overline{Q}_{sim}}{\overline{Q}_{obs}}, \frac{\overline{Q}_{obs}}{\overline{Q}_{sim}}\right) - 1\right]^2$$

F6: NS of Box-Cox transformed flows (mid-range flows)

$$F6 = F_{box} = \frac{\sum_{i=1}^{n} \alpha_i \left(Q'_{sim,i} - Q'_{obs,i}\right)^2}{\sum_{i=1}^{n} \alpha_i \left(Q'_{sim,i} - \overline{Q'}_{obs}\right)^2}$$

$$Q' = \frac{(Q+1)^{0.3} - 1}{0.3}.$$

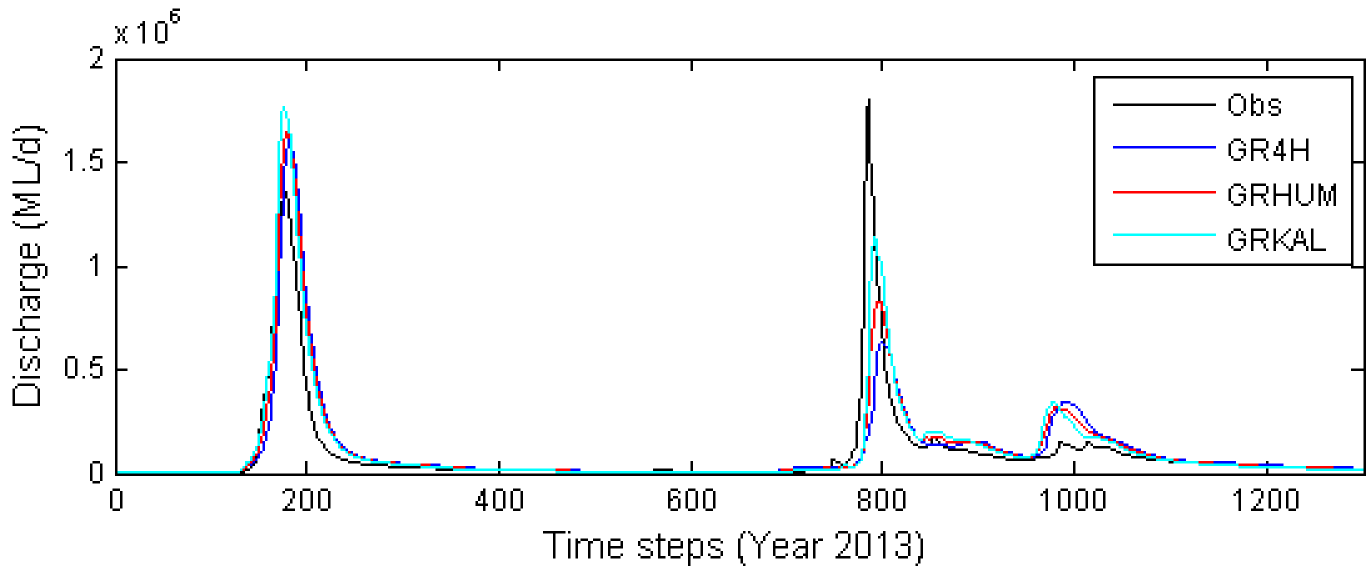
MODEL COMPARISON

Calibrated using discharge

a) Calibration (2010-2012)

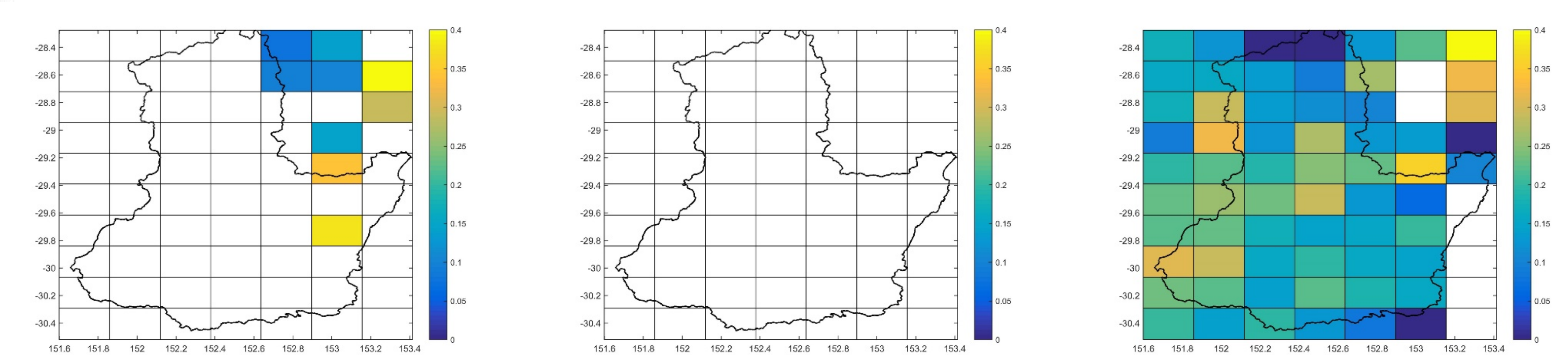
b) Validation (2013-2014)

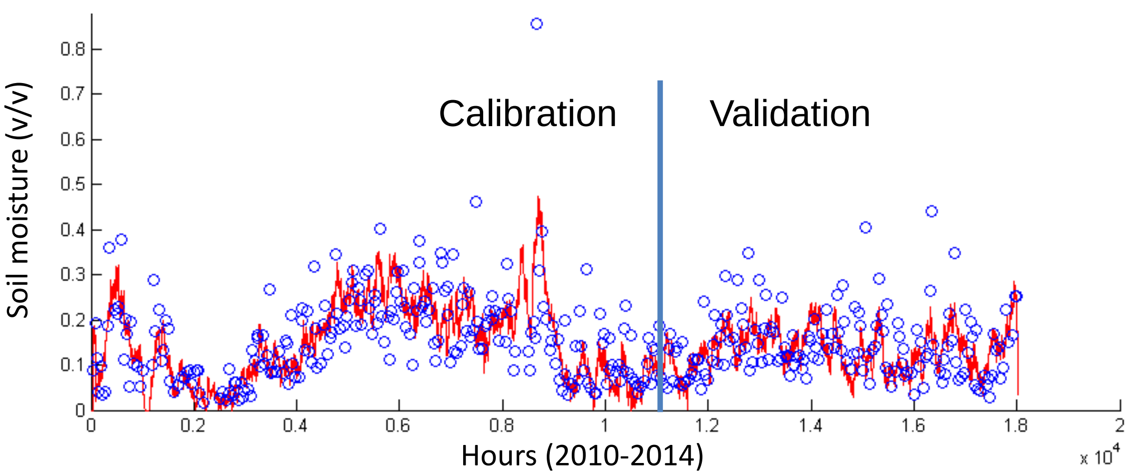
Statistics	NS	RMSE(m^3/s)	R^2
GR4H Cal.	0.78	2.3	0.79
GRHUM Cal.	0.79	2.2	0.83
GRKAL Cal.	0.81	2.1	0.82
GR4H Val.	0.70	3.5	0.77
GRHUM Val.	0.69	3.5	0.78
GRKAL Val.	0.70	3.4	0.76



JOINT CALIBRATION

GRKAL calibrated using SMOS SM and discharge





Statistics	NS	Relative Bias
GRKAL Cal.	0.59	18%
GRKAL Cal-RS	0.69	5%
GRKAL Val.	0.63	15%
GRKAL Val-RS	0.66	7%

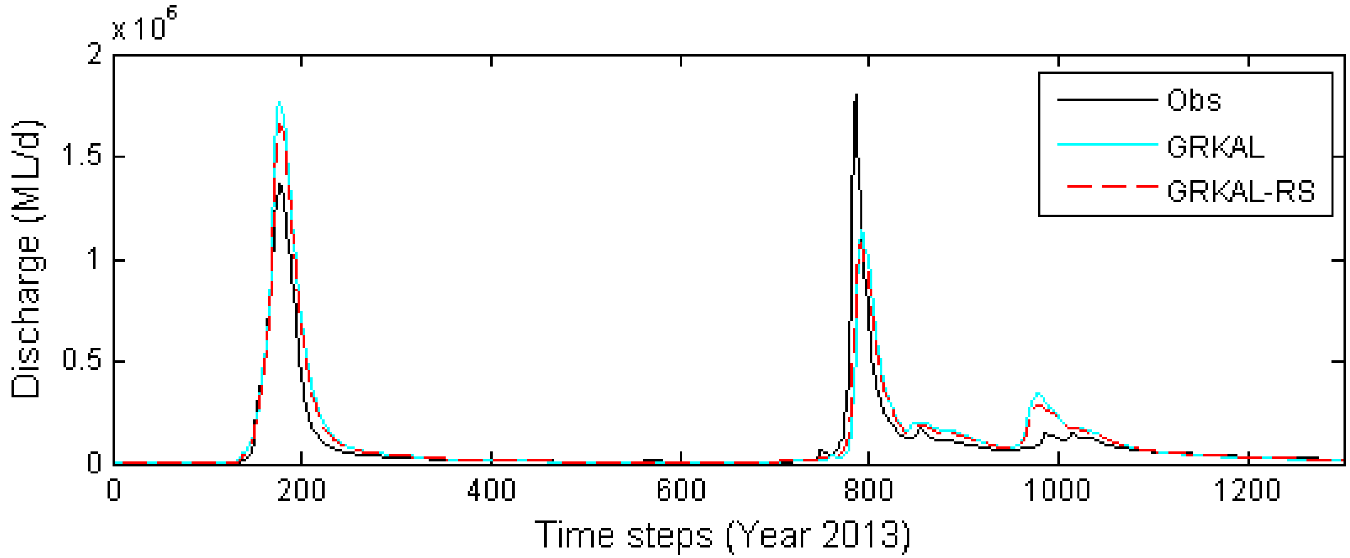
Blue dots are SMOS-SM; red line is calibrated model surface SM

JOINT CALIBRATION

GRKAL calibrated using SMOS SM and discharge

Streamflow prediction

Statistics	NS	RMSE(m^3/s)	R^2
GRKAL Cal.	0.81	2.1	0.82
GRKAL Cal-RS	0.76	2.5	0.78
GRKAL Val.	0.70	3.4	0.76
GRKAL Val-RS	0.71	3.2	0.76



HYDRAULIC MODEL

Flood waves are described by the shallow water equations (2D)

$$\begin{cases} \dfrac{\partial h}{\partial t} + \dfrac{\partial q_x}{\partial x} + \dfrac{\partial q_y}{\partial y} = 0 \\ \boxed{\underbrace{\dfrac{\partial q_x}{\partial t}}_{\substack{\text{local} \\ \text{acceleration}}}} + \underbrace{\dfrac{\partial}{\partial x}(uq_x) + \dfrac{\partial}{\partial y}(vq_x)}_{\substack{\text{convective} \\ \text{acceleration}}} + \boxed{\underbrace{gh\dfrac{\partial (h+z)}{\partial x}}_{\substack{\text{pressure}+ \\ \text{bed gradients}}} + \underbrace{\dfrac{gn^2 \|\mathbf{q}\| q_x}{h^{7/3}}}_{\text{friction}} = 0} \end{cases}$$

Conservation of mass

Conservation of momentum

Our model is based on the LISFLOOD-FP model (Bates et al., 2000; *2010*).

It solves the inertial approximation of the Shallow Water Equations using a finite difference scheme based on a rectangular grid.

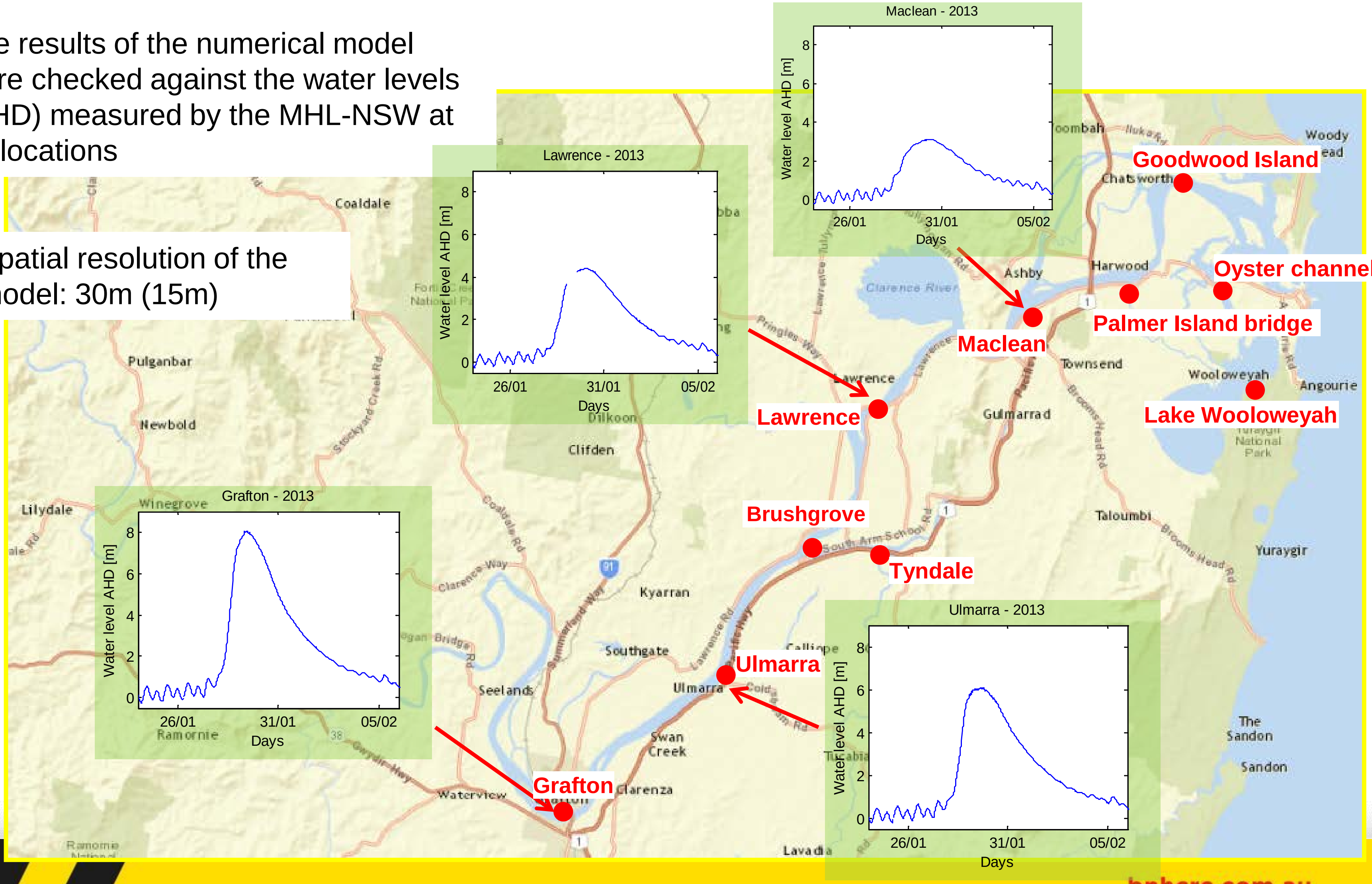
In order to optimise both modeling accuracy and computational time, our code (C#) uses an original <u>variable spatial discretization</u>:

- a "coarse" space discretization is used for the modeling of the flood wave in the floodplains;
- a "fine" spatial discretization is used for the modeling of the flood wave in the urban areas.

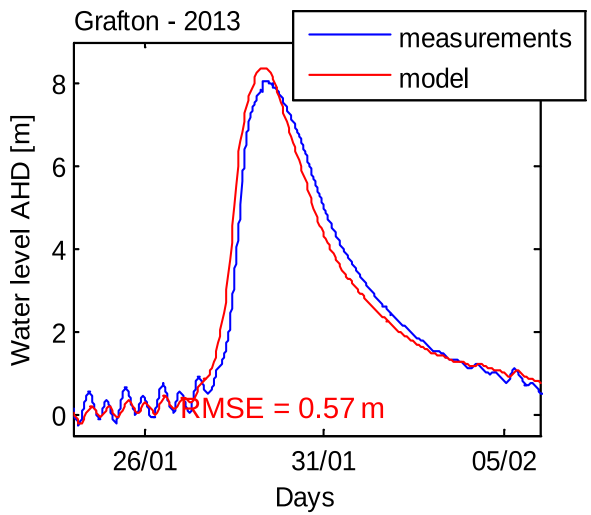
VALIDATION POINTS

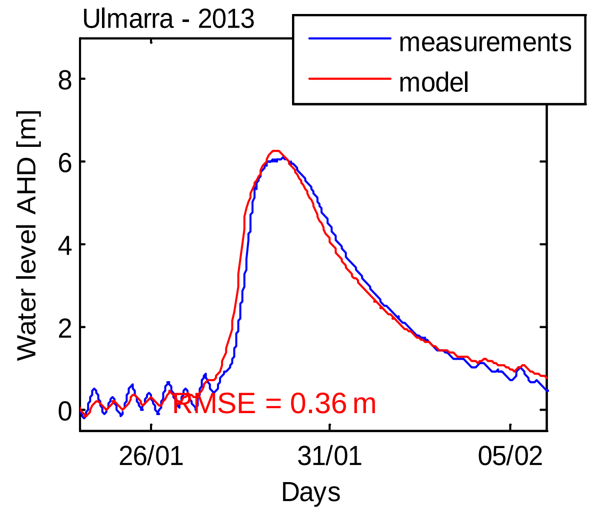
The results of the numerical model were checked against the water levels (AHD) measured by the MHL-NSW at 10 locations

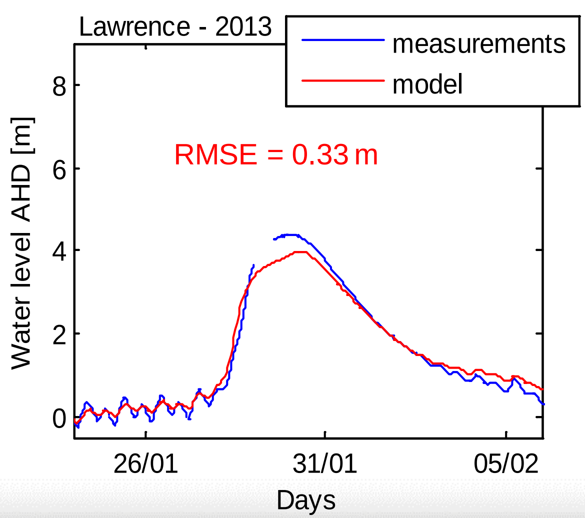
Spatial resolution of the model: 30m (15m)

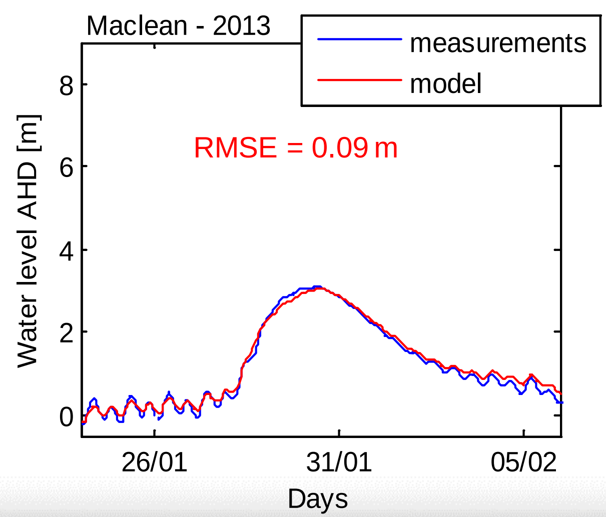


PREDICTED HYDROGRAPHS









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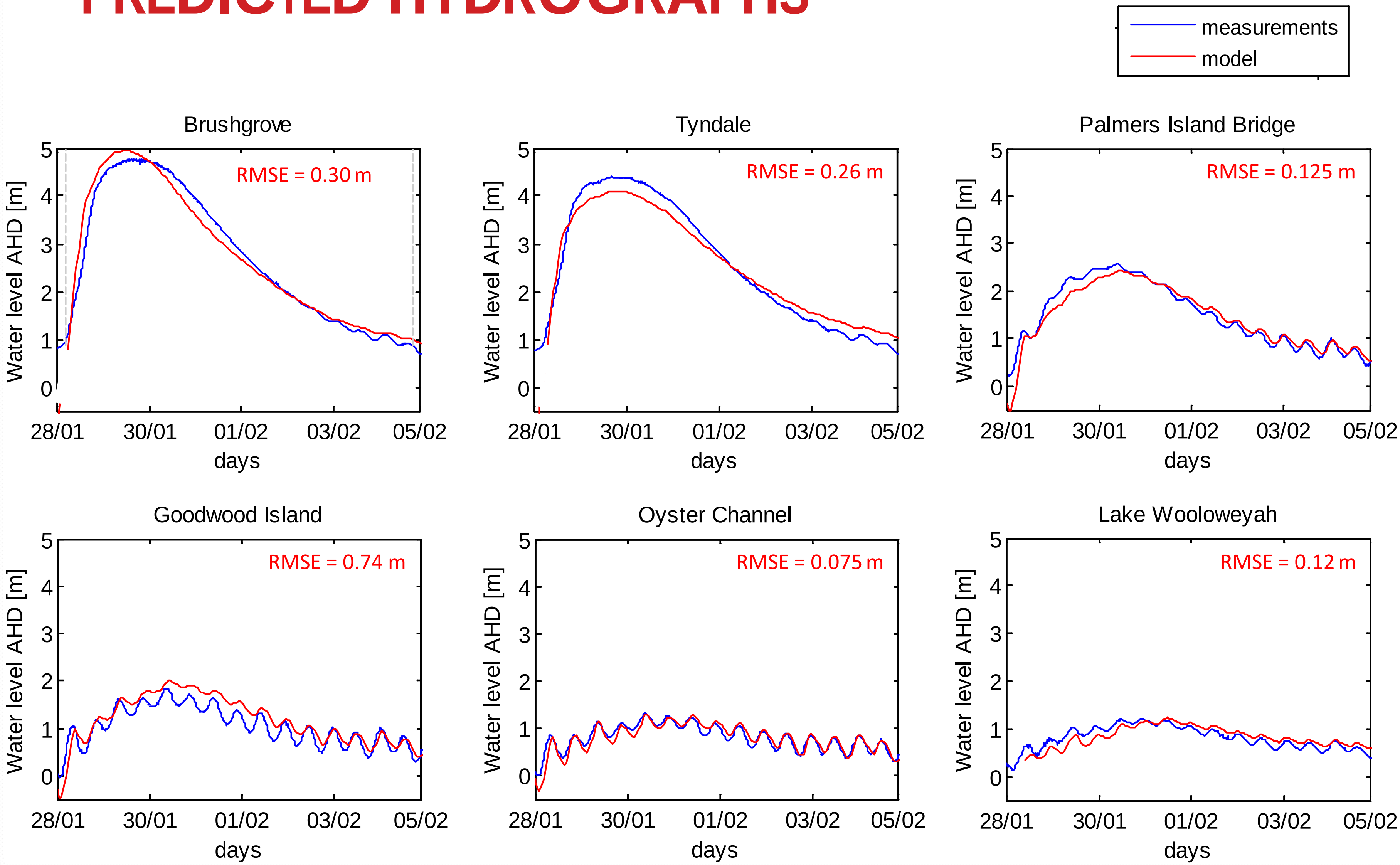
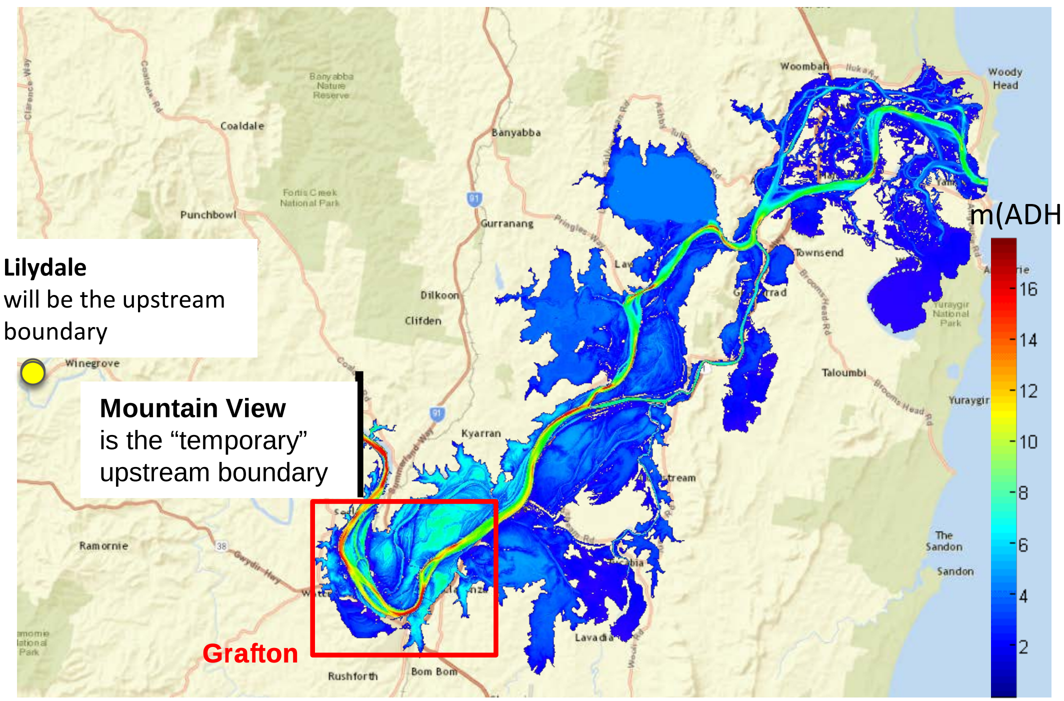


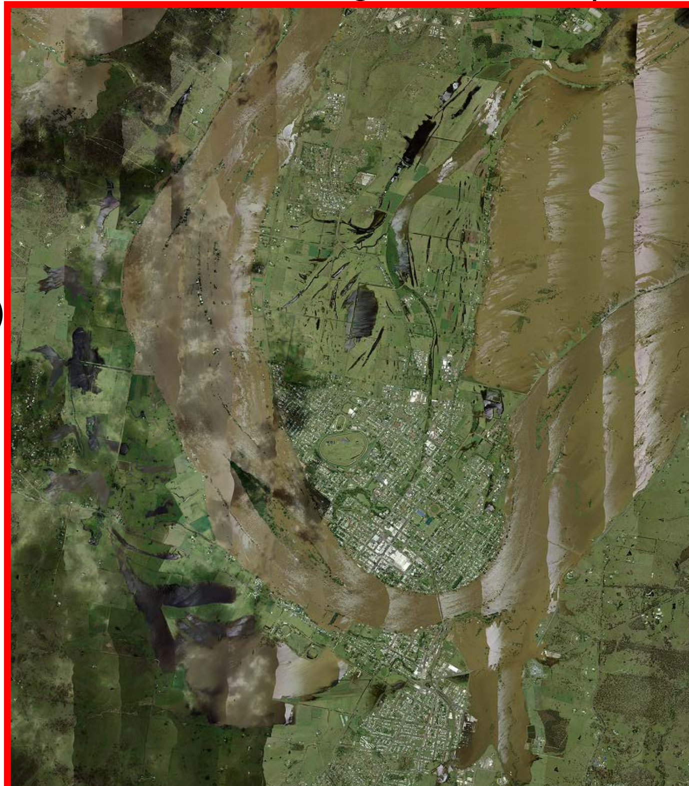
FLOODED AREAS

29 January 2013

Numerical Model, h 12PM



RGB airborne image – h 10am-3pm



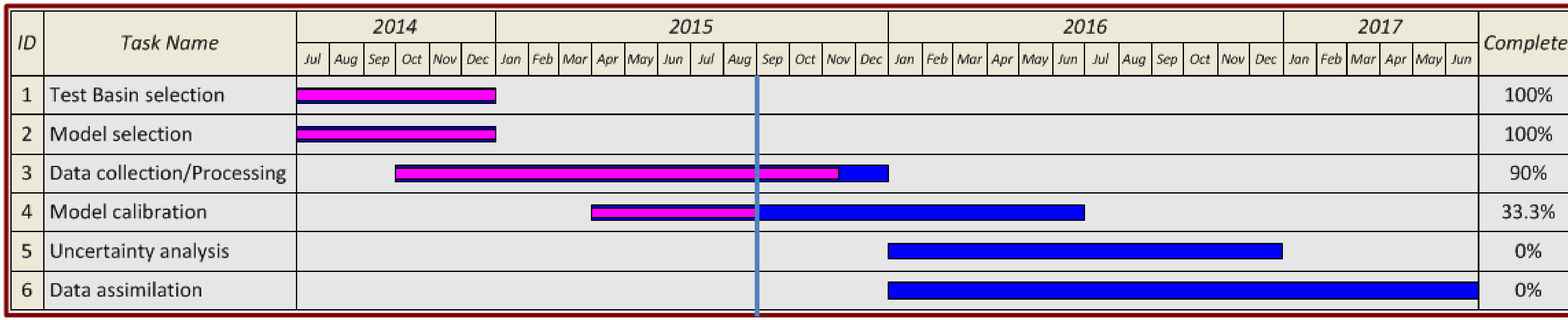
CONCLUSIONS

- Introducing remotely sensed soil moisture for model calibration leads to slightly degraded flow simulations in the calibration period but improved flow hindcasts in the validation period. The benefit of using soil moisture should be further investigated in real-time updating (DA).

- Validating a hydraulic model using only point measurements (in-situ water level) can lead to incorrect conclusions. It will be useful to incorporate spatial information (i.e., remotely sensed water extent/level) into model calibration, updating and validation.

PROGRESS AND PLAN

1) Progress



2) Future work

- Build a coupled system for streamflow and flood inundation forecasting
- Automatic integration of remote sensing products for an improved forecasting system
  - Multi-objective calibration using RS products
  - Assimilation of RS products for real-time updating

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