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OBSERVATIONALLY-CONSTRAINED FLOOD FORECASTING

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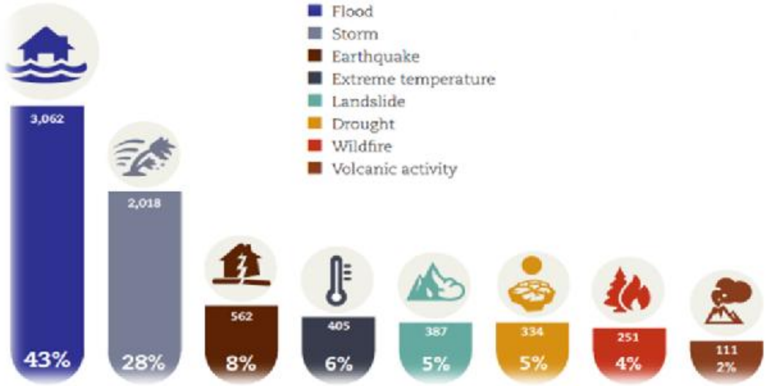
Australian Government Geoscience Australia
SES NSW STATE EMERGENCY SERVICE

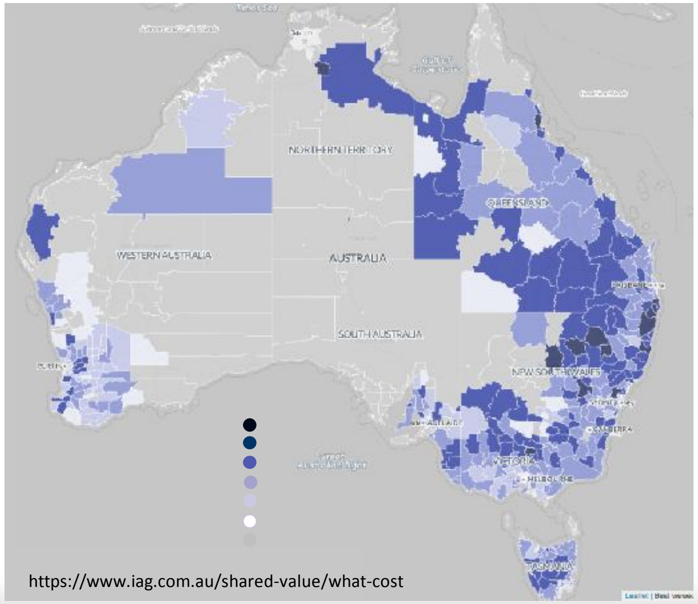
IMPACT OF FLOODING

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

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



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



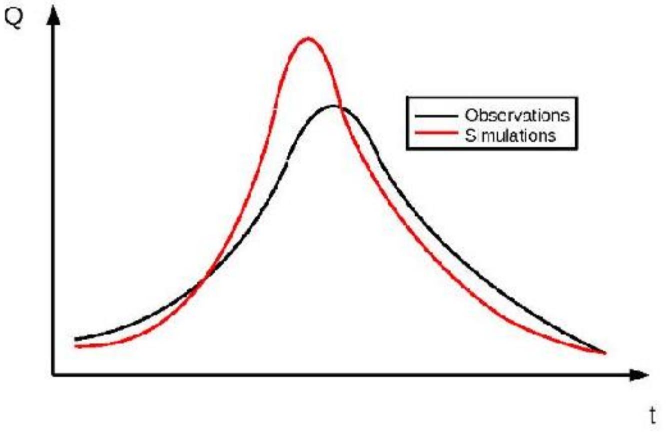
https://www.iag.com.au/shared-value/what-cost

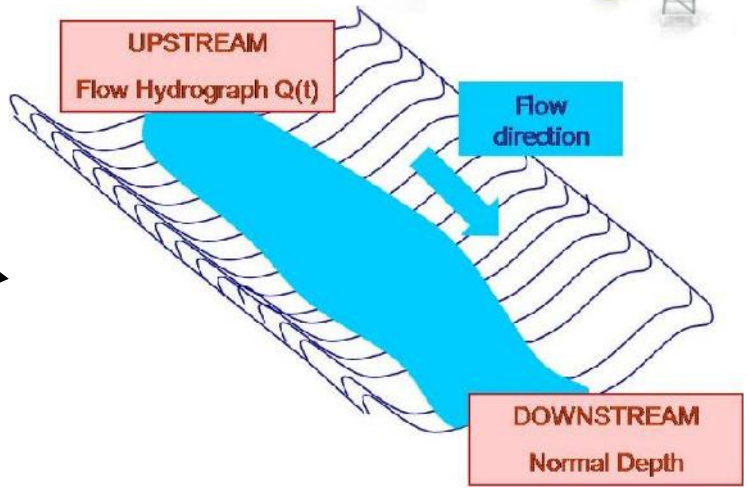
A **timely, accurate prediction** of the flood **wave arrival time, extent, depth and velocity** is essential to reduce flood related mortality and damages.

FLOOD FORECASTING SYSTEMS

1. HYDROLOGIC MODEL:

Input: rain, PET
Output: discharge hydrograph
Model selected: GRKAL



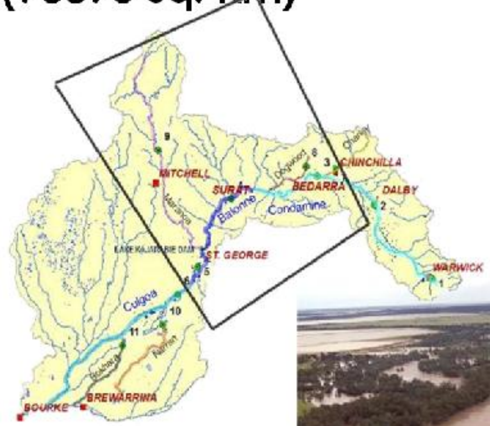


2. HYDRAULIC MODEL:

Input: discharge hydrograph
Output: water depth and velocity at each point of the flooded area
Model selected: LISFLOOD-FP

STUDY BASINS

Condamine-Balonne
(75370 sq. km)



Clarence
(20730 sq. km)

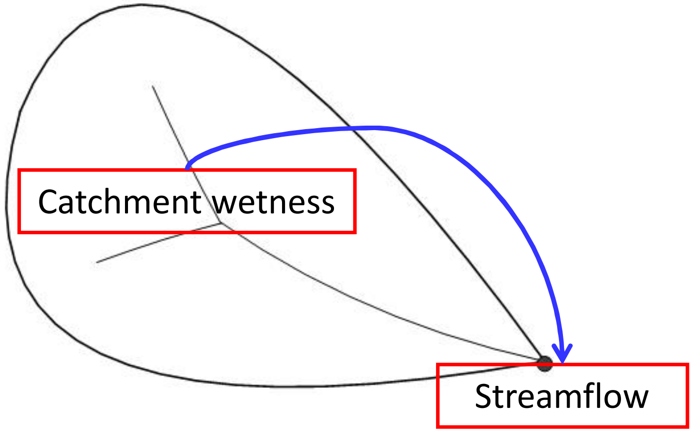
St. George, 2012 Feb 7th, http://www.abc.net.au

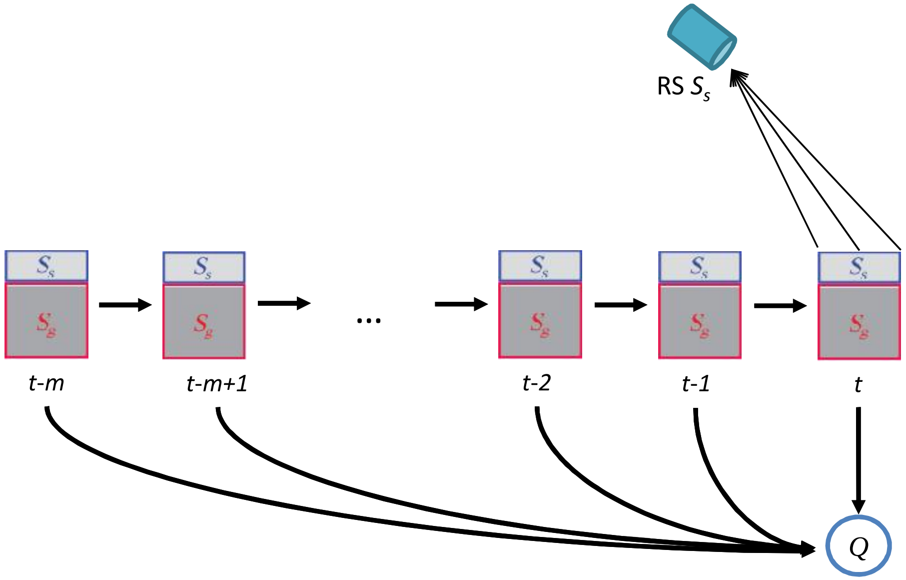
Grafton, 2013 Jan 30th, Mr. Williamson

HYDROLOGIC MODELLING – SYNTHETIC ASSIMILATION OF REMOTELY SENSED SOIL MOISTURE

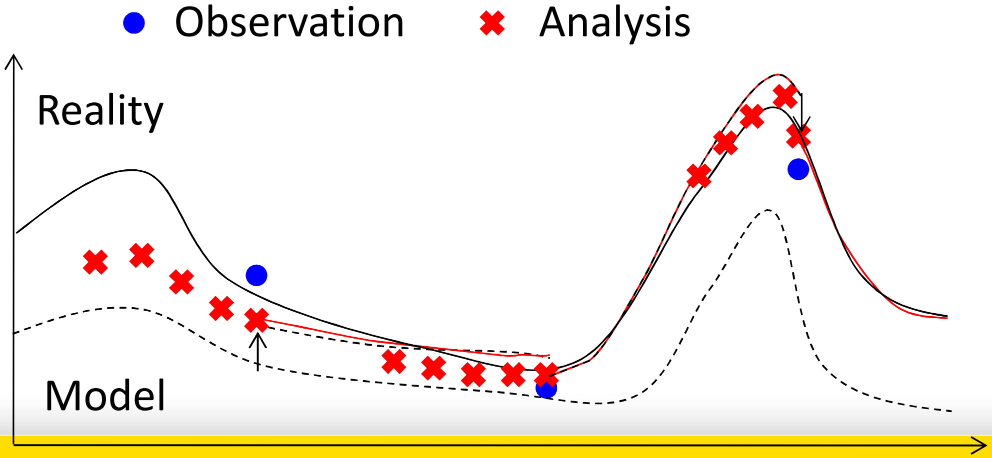
PROBLEM STATEMENT

1) Time lag – a forecasting issue



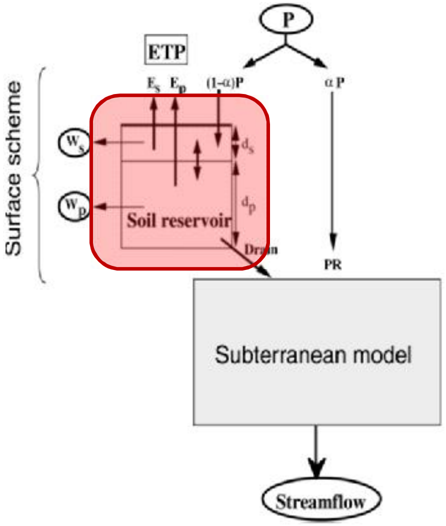


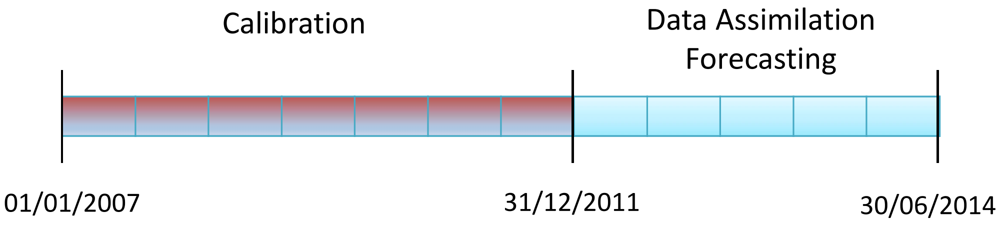
2) State updating



SYNTHETIC EXPERIMENT DESIGN

1) Catchment: lumped catchment of Warwick
2) Model: hourly GRKAL
3) DA algorithms: EnKS and EnKF
4) Observation: synthetic RS-SM
   (one image per day at 6am)





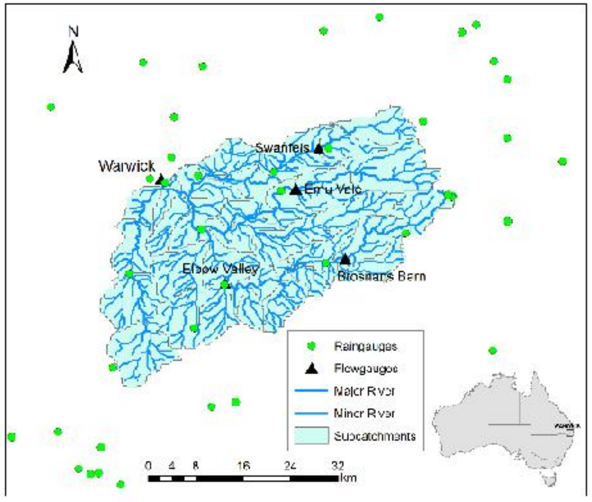
Calibration

Data Assimilation
Forecasting

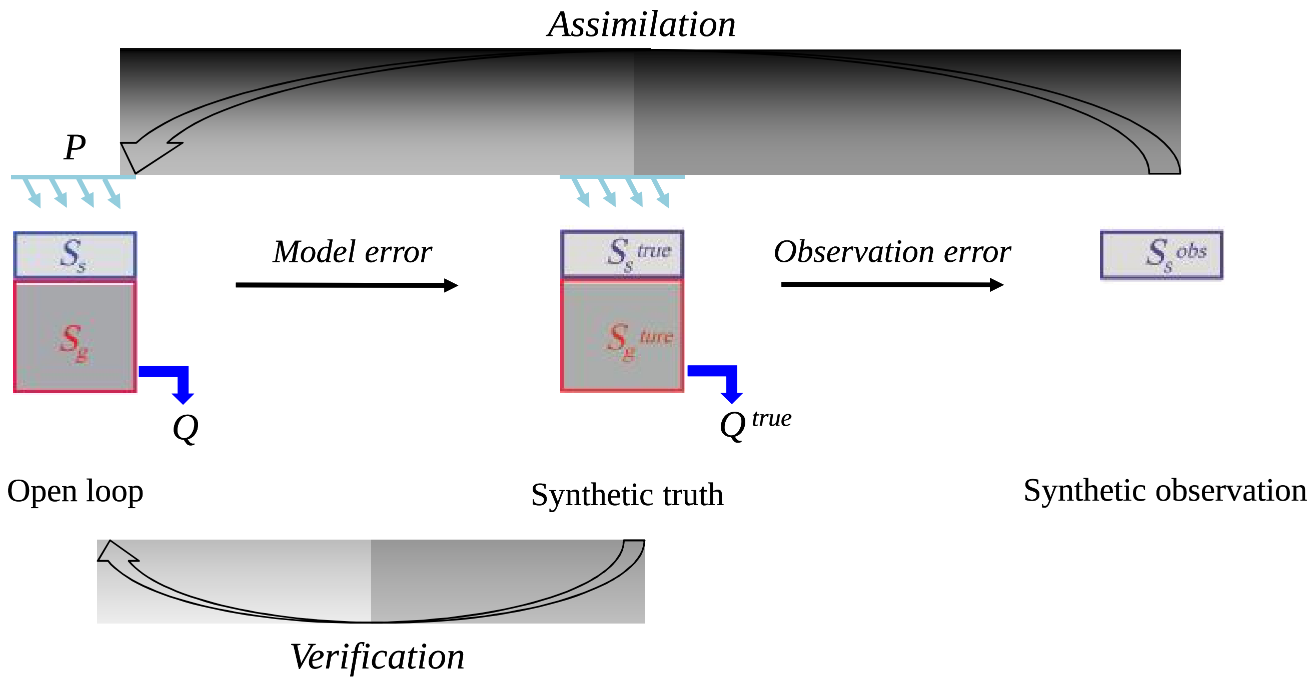
01/01/2007

31/12/2011

30/06/2014



SYNTHETIC EXPERIMENT DESIGN



1) Model error

a) Rainfall

$P_t^{true} = \xi_t \times P_t \qquad \mathrm{Ln}(\xi_t) \sim \mathrm{N}(\mu,\sigma^2)$

$\mathrm{Ln}(\xi_t) = \mu + \alpha\cdot(\mathrm{Ln}(\xi_{t-1})-\mu) + \varepsilon_t\cdot\sigma\cdot\sqrt{1-\sim^2}$

b) Soil moisture

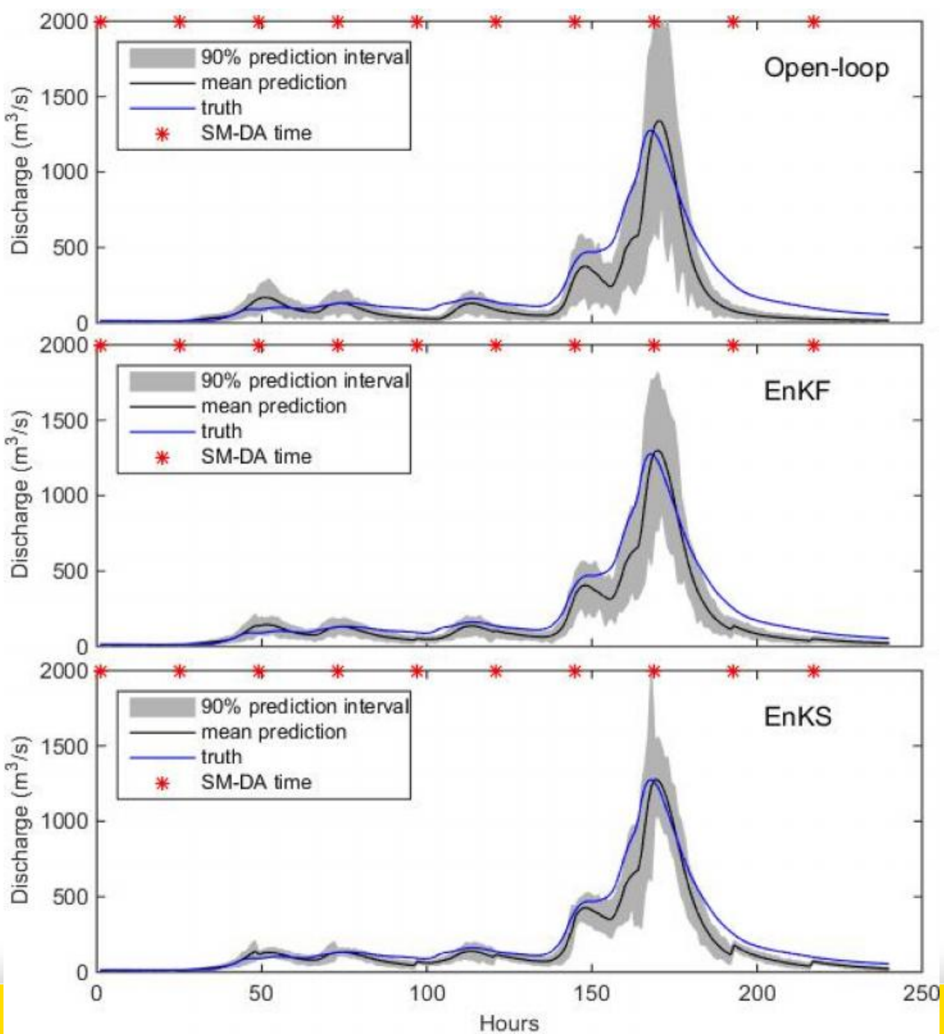
$\mathbf{S}_t^{true} = \mathrm{f}(\mathbf{S}_{t-1}^{true}, P_t^{true}, PET_t, \theta) + \boldsymbol{\omega}_t$

$\boldsymbol{\omega}_t \sim \mathrm{N}(\mathbf{0},\Sigma^2)$

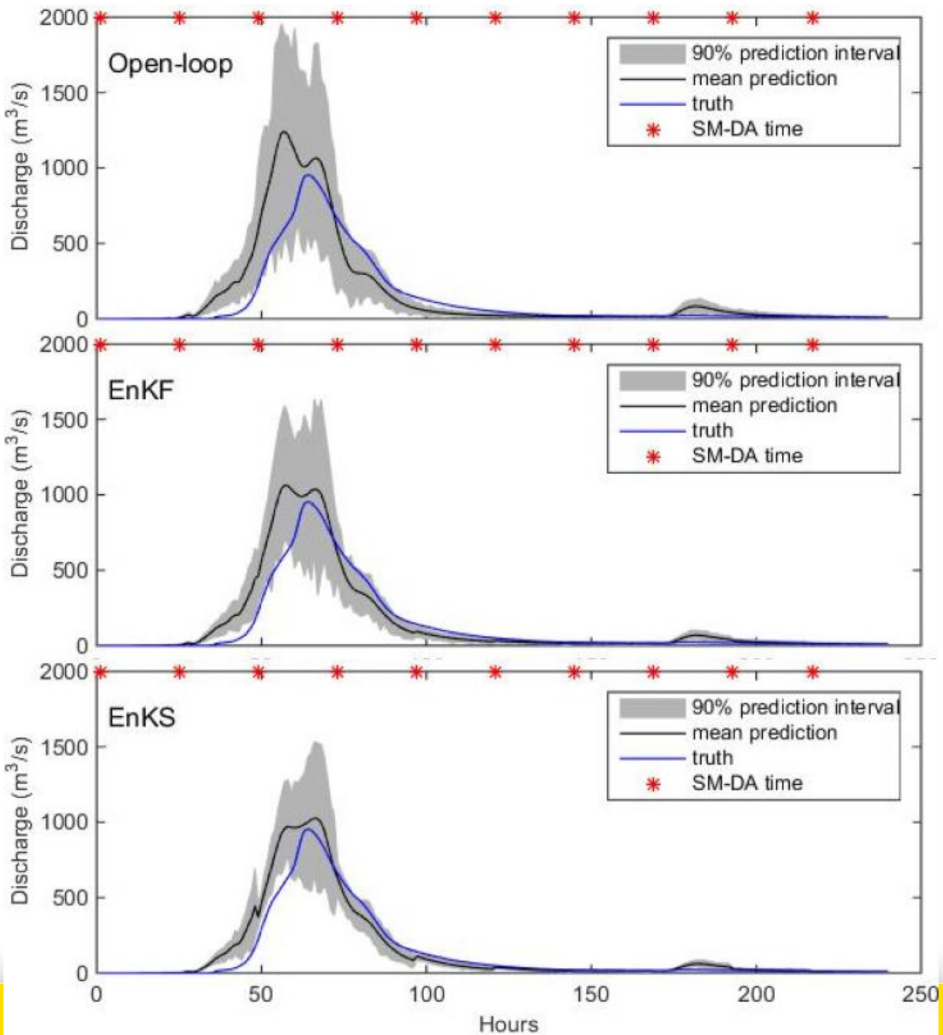
2) Observation error

$S_{s,t}^{obs} = S_{s,t}^{true} + \eta_t \qquad \eta_t \sim \mathrm{N}(0,\sigma^2)$

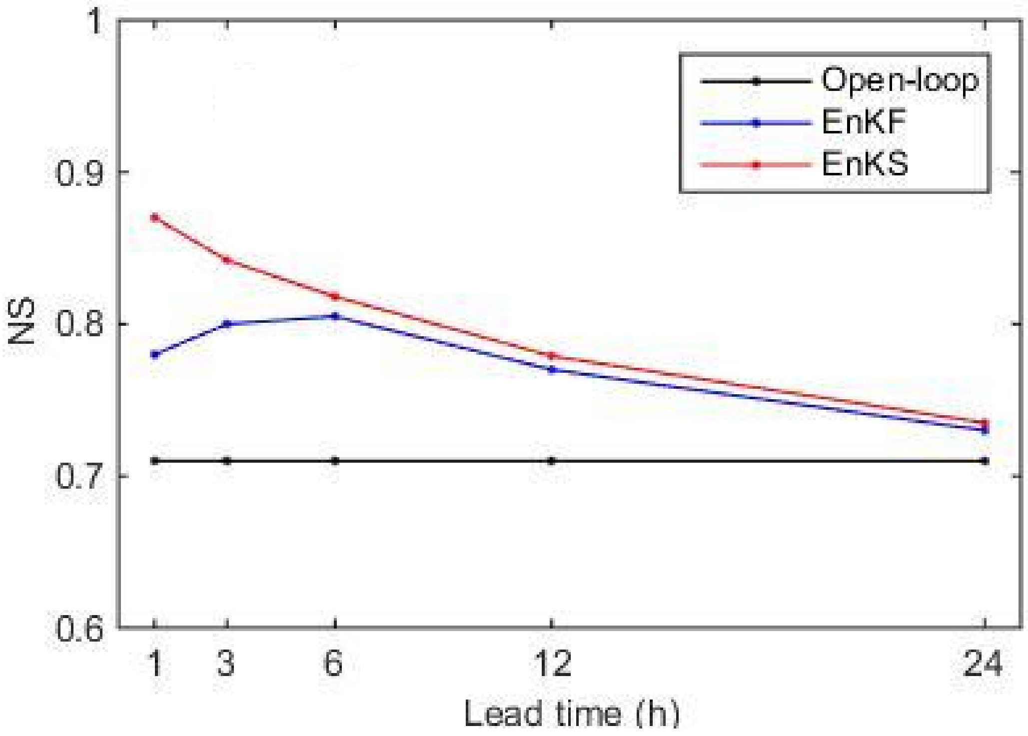
EVENT IN 2011



EVENT IN 2013



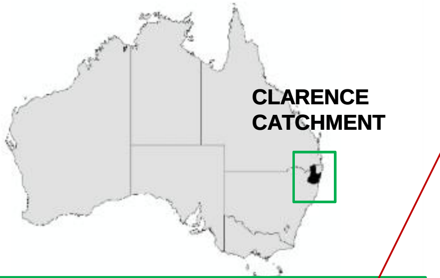
NASH-SUTCLIFFE MODEL EFFICIENCY

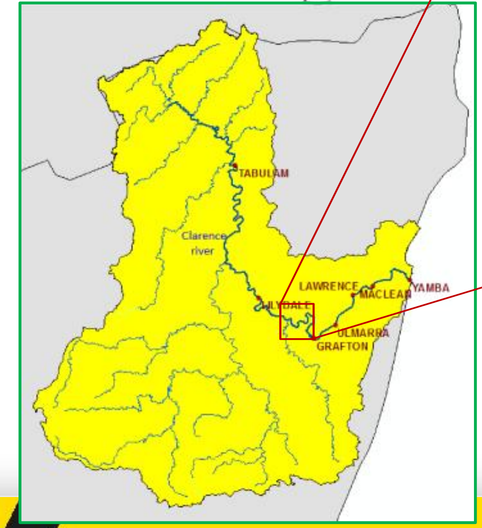


HYDRAULIC MODELLING

EFFECTIVE REPRESENTATION OF RIVER GEOMETRY

1) Information on **river bathymetry** is essential for the modelling of floodplain inundation
2) Field **data are scarce** and expensive; river depth and shape cannot be detected remotely
3) We investigated a parsimonious methodology for the **effective representation** of river geometry

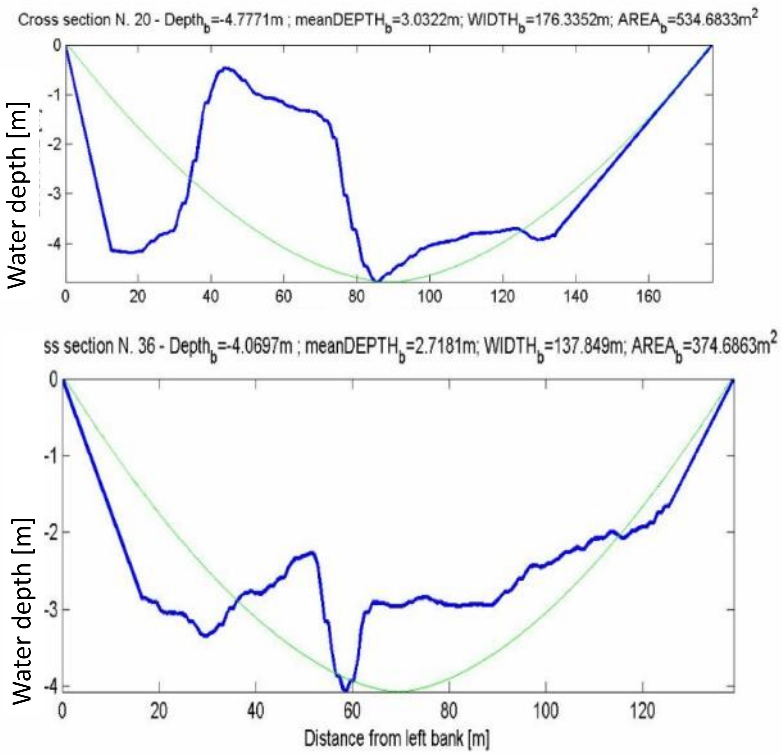




Numerical experiment based on detailed field data

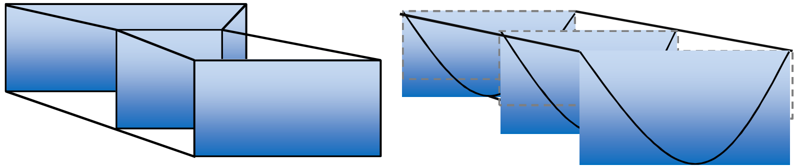
EFFECTIVE REPRESENTATION OF RIVER GEOMETRY

Measured cross sections

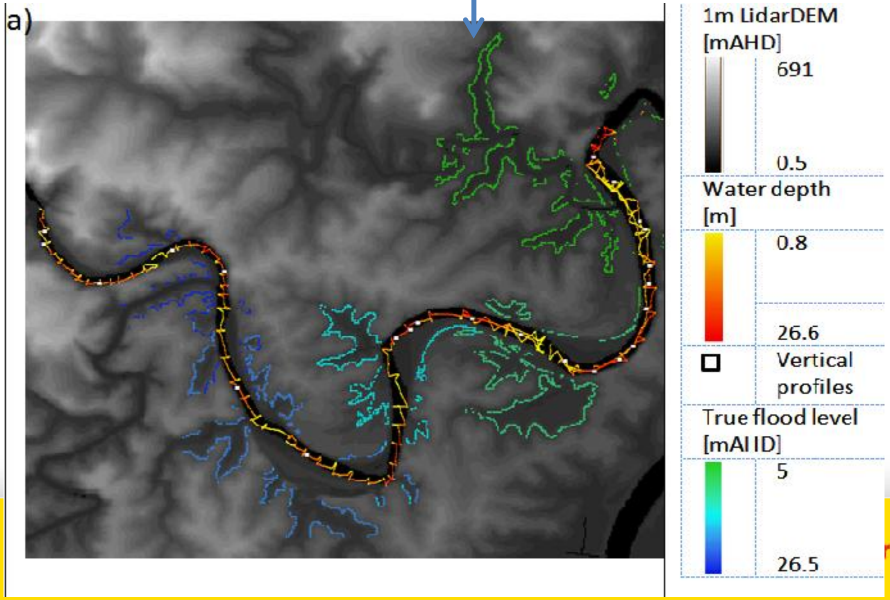


Simplified cross sections based on a combination of:

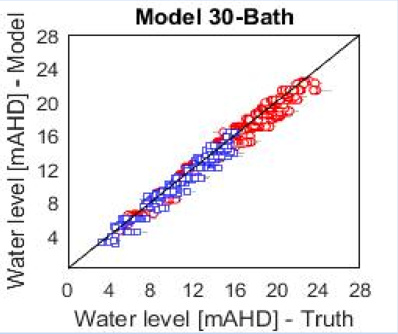
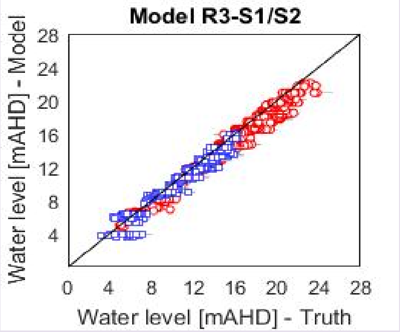
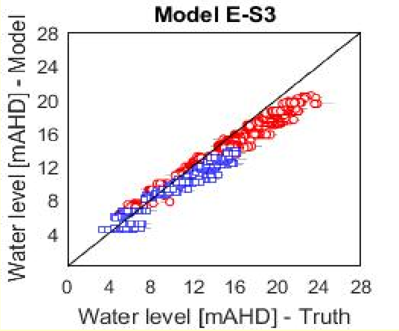
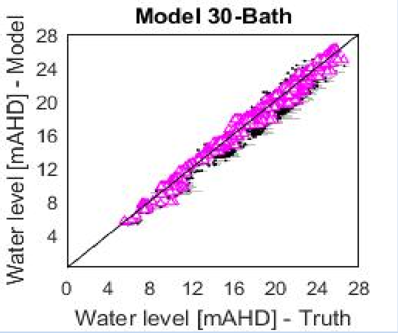
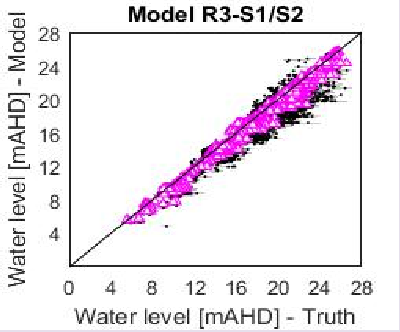
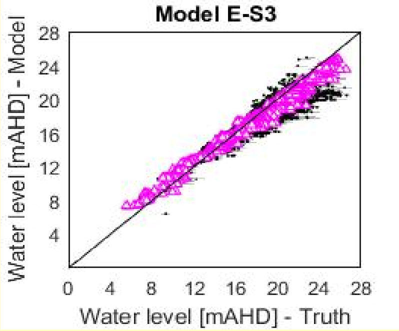
- Remote sensing data of river width
- A few measurements
- Global database



Numerical experiment (Lisflood-FP)



Analysis of Remote Sensing-derived water level at the catchment scale for the timely diagnosis of errors in the representation of river geometry.

	DESCRIPTION OF RIVER GEOMETRY		
	Field data (nf)	RS (WOfS) & global database & a few measurements. Flow area -24% (n<nf)	Global database & a few measurements. Flow area +29% (n>nf)
time			
			

□ $t_{Peak,l}$ - 24 h ○ $t_{Peak,l}$ - 12 h △ $t_{Peak,l}$ · $t_{Peak,l}$ + 12 h — interval of true values — 1:1

Importance of the appropriate representation of river geometry.

Analysis of Remote Sensing-derived water level at the catchment scale for the timely diagnosis of errors in the representation of river geometry.

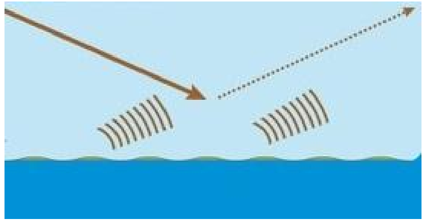
$$= \frac{\quad - \quad}{0.5 * (\quad - \quad)}$$

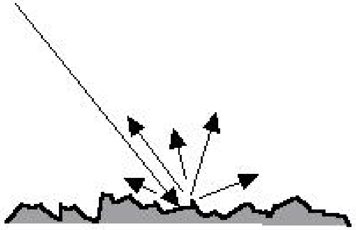
$$, \quad . \quad = \frac{\sum \sqrt{\quad}}{}$$

ANALYSIS OF SAR IMAGES OF FLOODS

1) SARs are active systems that emit microwave pulses at an oblique angle towards the target.
2) The amount of microwave energy scattered off an object or feature is mainly a function of its **surface texture**.

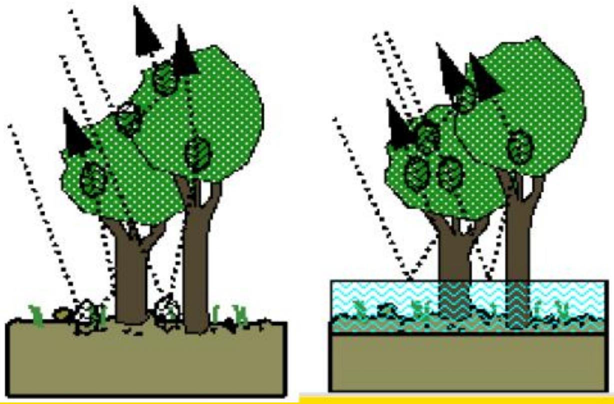
Flooded surface:
LOW backscatter





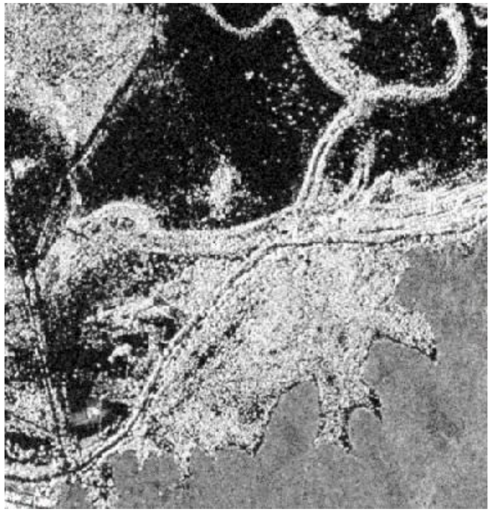
Dry surface:
HIGH backscatter

3) In **vegetated areas, flooded conditions** may cause an **INCREASE in radar return** because of the enhancement of the double bounce backscattering mechanism, which involves the specular water surface and vertical structures such as stems, trunks.



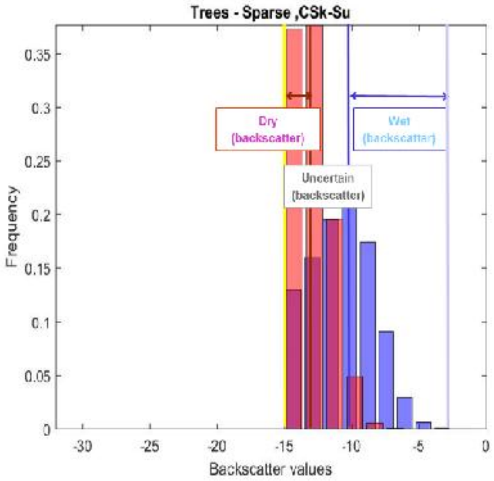
ANALYSIS OF SAR IMAGES OF FLOODS

1) Classification algorithm based on the statistical analysis of backscatter response from different vegetation types (land cover classes) in dry and wet conditions
2) The accuracy of this algorithm is being assessed using airborne optical imagery

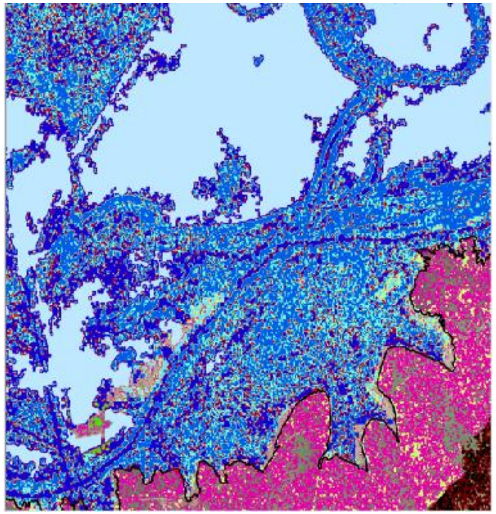


SAR image
Cosmo SkyMed
Jan 4th, 2011, 6 pm
Surat (QLD)

OPTICAL image
QLD-DNRM
Jan 4th, 2011, 2 pm
Surat (QLD)



Statistical analysis of backscatter values
(performed for each land cover)



Classification

Wet : traditional classification method
Wet: new classification method
Dry

CONCLUSIONS

1) The EnKS outperforms the EnKF in streamflow prediction;
2) The benefit of using EnKS is relatively significant within several hours after assimilation, and decrease over time;
3) We suggested a data-parsimonious methodology for the preliminary assessment of river geometry;
4) In our numerical experiment the analysis of Remote Sensing-derived water level at the catchment scale allowed the timely diagnosis of errors in the representation of river geometry;
5) We are developing an algorithm for the detection of floods in vegetated areas using SAR data.

THANKS FOR YOUR KIND ATTENTION!