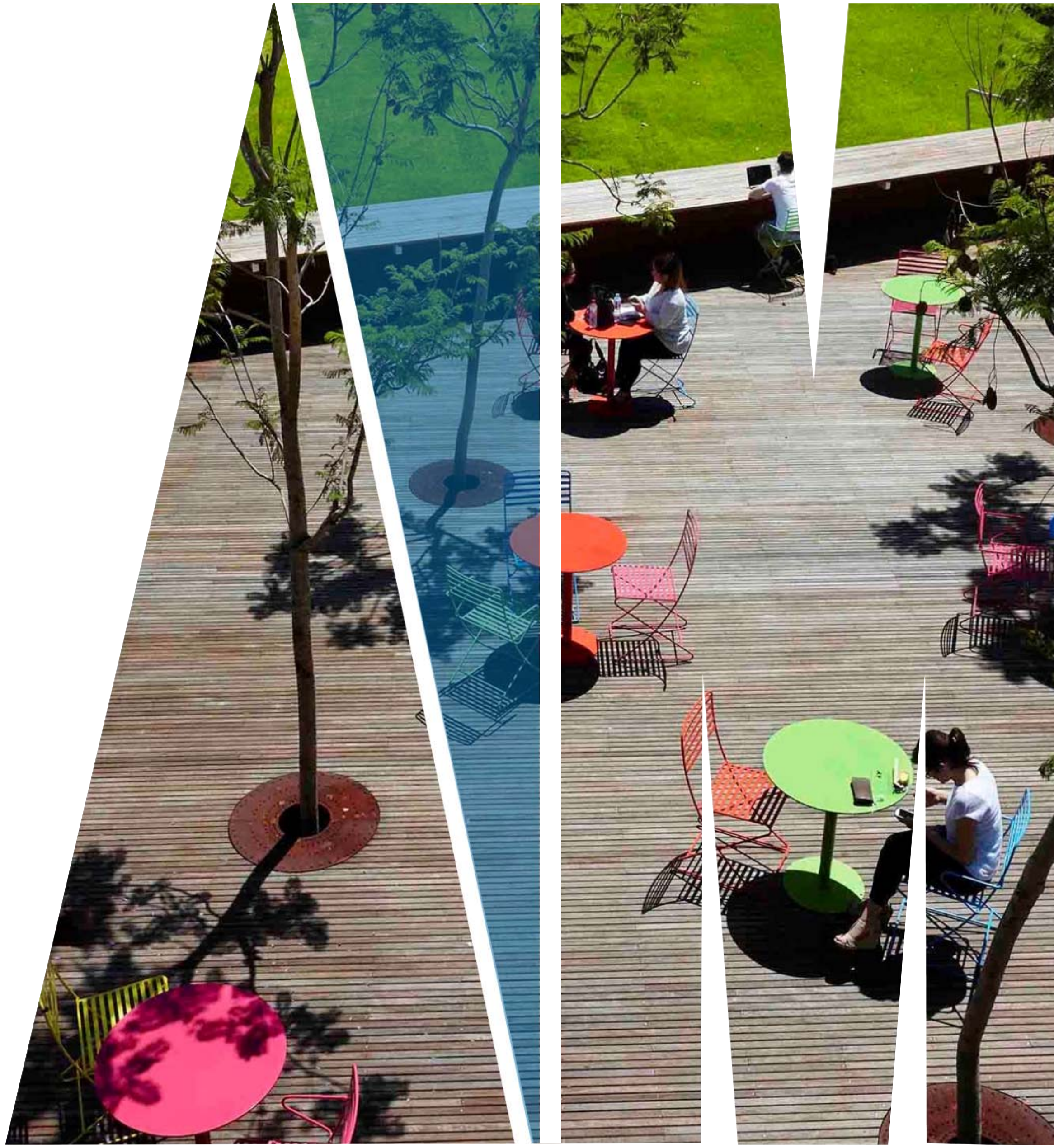
MONASH University

Modeling Activities to Support Flood and Drought Management in Australia

Valentijn Pauwels

May 21, 2019

CERFACS, Toulouse, France



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…

Monash University

- Member of the Go8.
- Founded in 1958.
- 50,000 undergraduate and 22,000 graduate students - 8,000 academic staff.
- Campuses:
    - Clayton
    - Caulfield
    - Peninsula
    - Parkville
    - Sunway (Malaysia)
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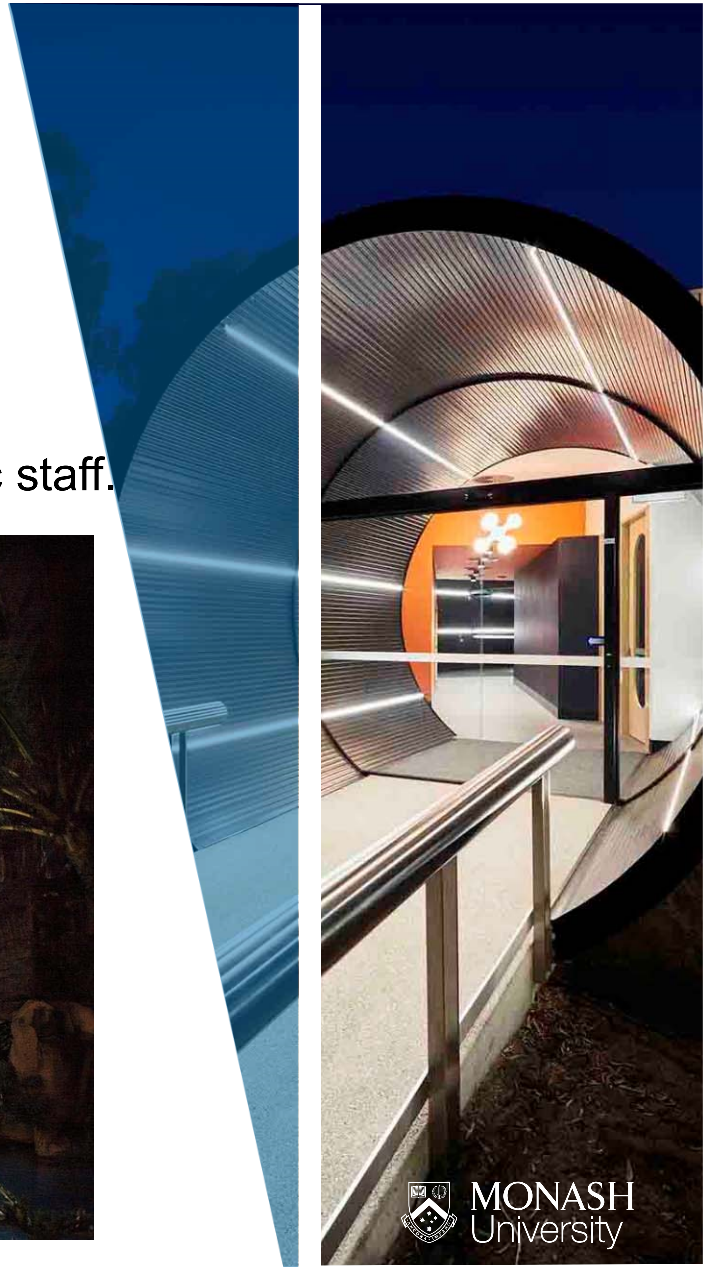


Department of Civil Engineering

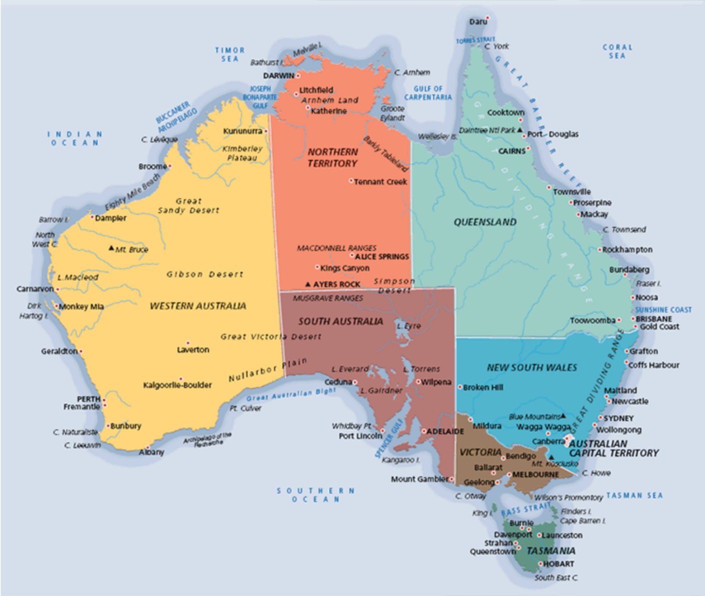
- 43 academic staff
  - 7 Lecturers
  - 14 Senior Lecturers
  - 6 Associate Professors
  - 16 Professors
- ~ 160 postgraduate students
- 5 groups:
  - Geomechanics
  - Structures
  - Transport
  - Water
  - Mining

Geographical Situation

Geographical Situation

MONASH University

Geographical Situation



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The Issue of Scale…

	BE	NL	DE	FR	TX	USA	Aus
Size (1000 sq. km)	30.5	41.5	357.4	643.8	696.2	9857	7692
Population (M)	11.2	17.2	81.5	66	26.9	318.9	23.1

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LA: 3.8 M

Chicago: 2.7 M

Sydney: 4.3 M

Melbourne: 4 M

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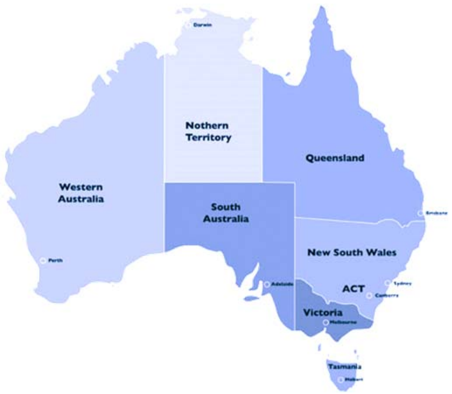

Northern Territory:

- 1.4 Million sq. km
- 244 000 residents

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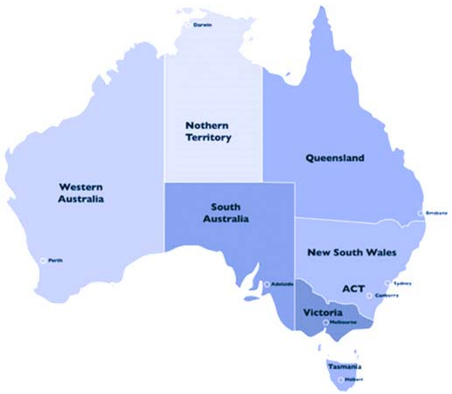

Northern Territory:

- 1.4 Million sq. km
- 244 000 residents

There are more square kilometres in the Northern Territory than arms, legs and heads of all its residents *combined*…

Motivation: Floods

- Floods are among the most important natural disasters in Australia
- Average annual cost of floods for the last 40 years: $377M.
- 2010-2011 floods in Brisbane and South-East Queensland:
    - 35 confirmed deaths.
    - $2.38 billion damage.

Wagga Wagga Flood 2010

Motivation: Droughts

- Australia is the driest of all inhabited continents, with droughts coming in clusters (9 in the 20th century).
- The 1911-1916 drought caused more WA men than expected to enlist into the Australian Imperial Forces during WWI.
- 2006-2007 resulted in a 23% drop in agricultural output and consequently cut 0.6% off GDP growth. The higher cost of food led to inflation standing at 3.5% in 2006.
- The millennium drought raised food prices by 25% in the world's poorest countries.

Who works on disaster management in Australia?

- A large number of stakeholders have strong interest in research on disaster prevention, prediction and mitigation:
- Joined forces to establish a Collaborative Research Centre (CRC)...

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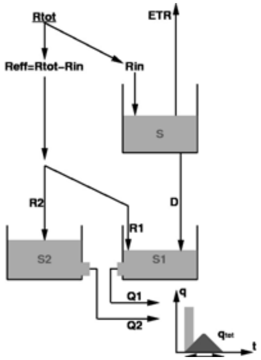
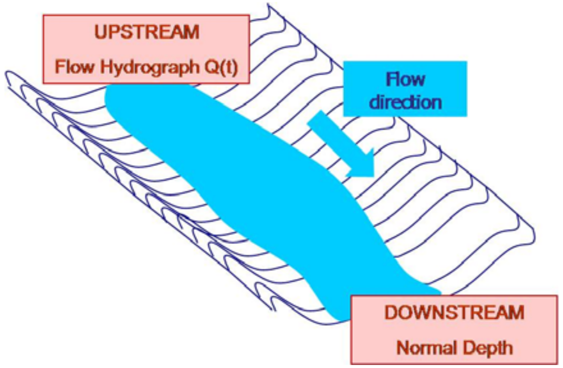
- A large number of stakeholders have strong interest in research on disaster prevention, prediction and mitigation:
- Joined forces to establish a Collaborative Research Centre (CRC)...
- The Bushfires and Natural Hazards CRC.

Improving Flood Forecasting Skill Using Remote Sensing Data

Objective: Develop an accurate flood forecasting system by using remote sensing data to the fullest extent.

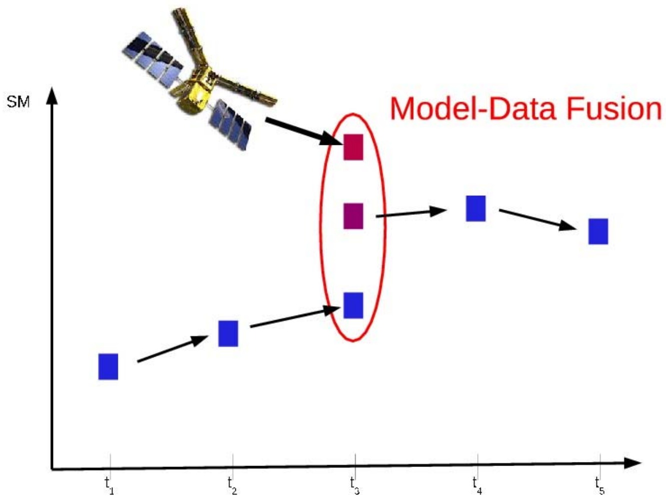




Improving Flood Forecasting Skill Using Remote Sensing Data

- Model predictions will be merged with satellite data to obtain the optimal predictions.

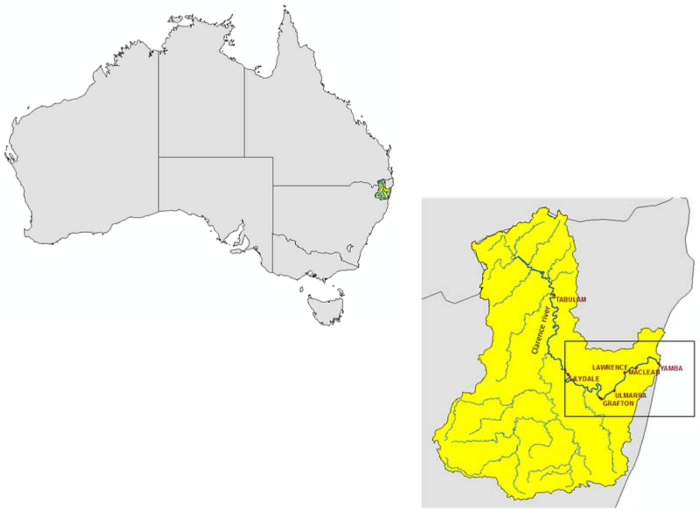
- Soil moisture data will be used for the hydrologic model.
- Flood extents and water levels will be used for the hydraulic model.



Improving Flood Forecasting Skill Using Remote Sensing Data

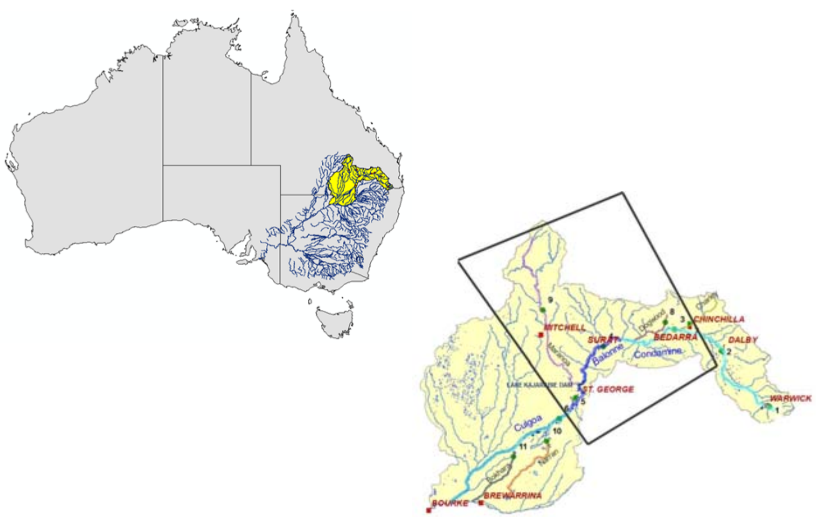
The Clarence Basin

(20730 sq. km)



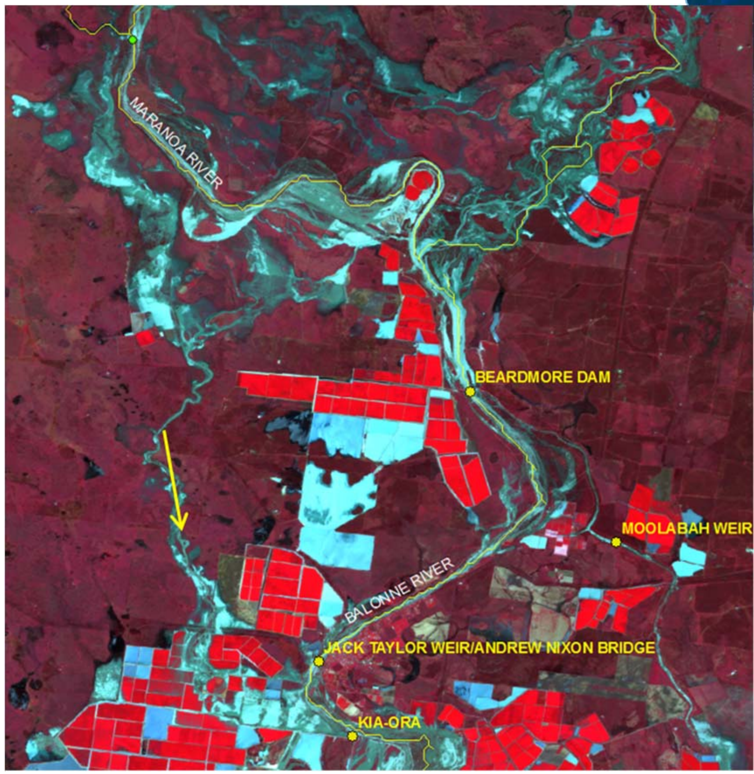
The Condamine Basin

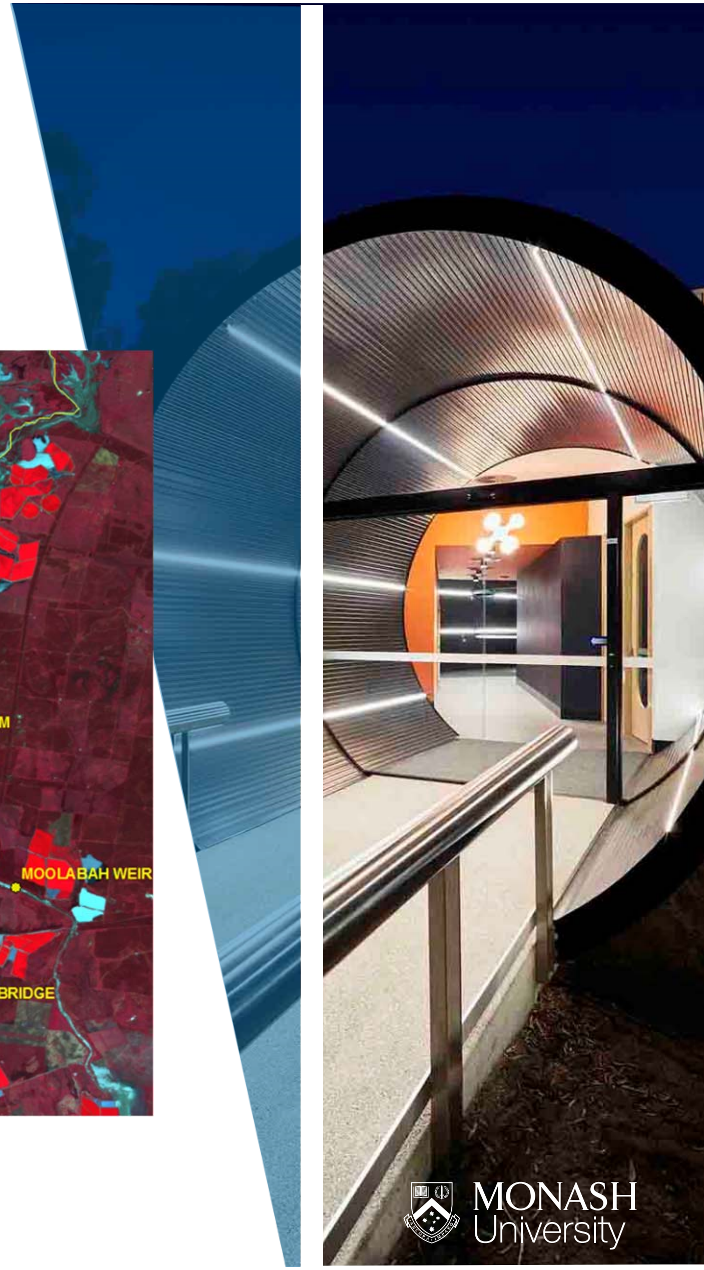
(75370 sq. km)



Improving Flood Forecasting Skill Using Remote Sensing Data

- The Clarence Basin:
  - Quickly evolving floods.
  - Permanent streams.
- The Condamine Basin:
  - Slowly evolving floods.
  - Streams are dry at many places for many months each year.
  - Temporary stream (the Glear) formed during the 2012 flood.

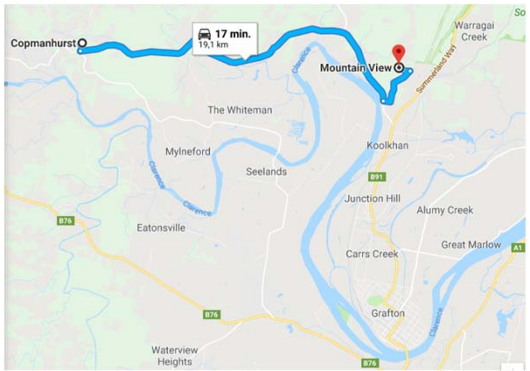




Challenge: Data Acquisition

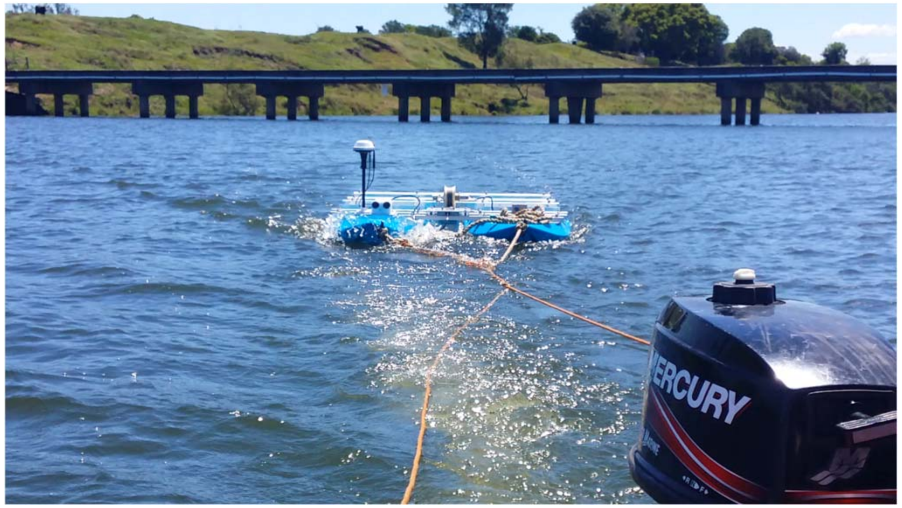
Field Campaign 1: November 8-15, 2015

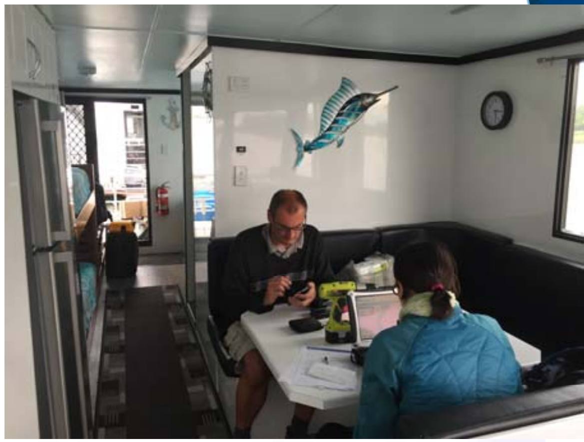
- Objective: Measure river bathymetry at strategic locations in the Clarence basin.
- Instruments: Acoustic Doppler profiler (RiverSurveyor) and temperature/salinity profiler (CastAway).



- Measuring the 21 km stretch from Mountain View to the Copmanhurst river head.

Field Campaign 1: Nov. 8-15, 2015





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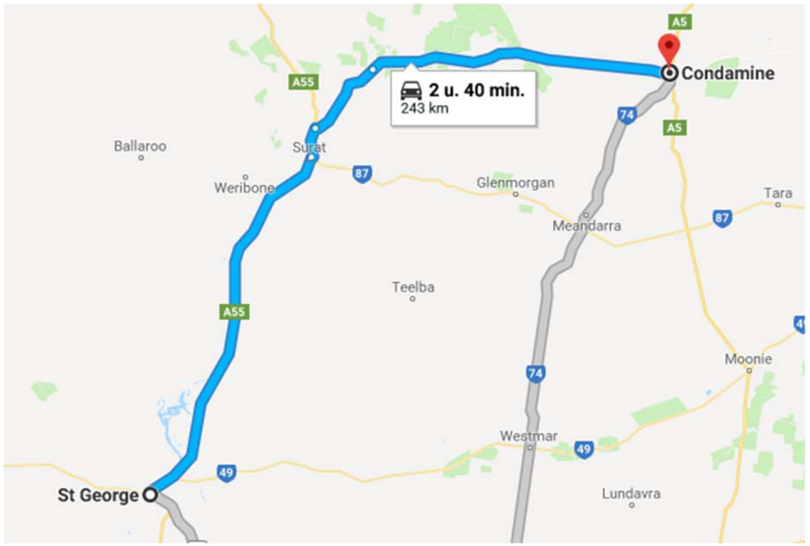
Field campaign 2: May 1-13, 2016

- Objective: Measure river bathymetry at strategic locations in the Condamine basin.
- Instruments: Acoustic Doppler profiler (RiverSurveyor) and temperature/salinity profiler (CastAway).
- Measuring the ±250 km stretch between St. George and Condamine.



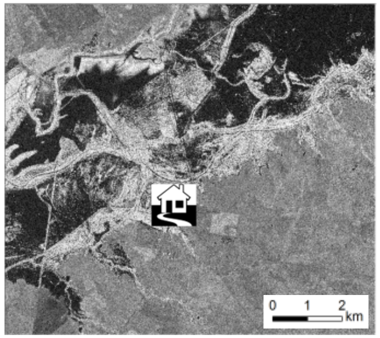
Field campaign 2: May 1-13, 2016

River width varying between 100’s of meters and completely dry:

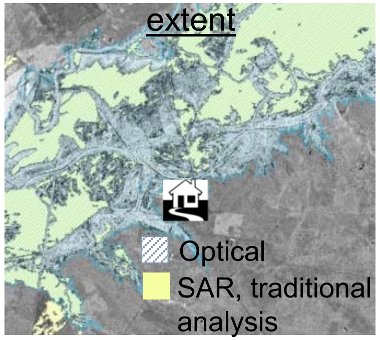
Field campaign 2: May 1-13, 2016

FLOOD MAPPING USING SAR DATA

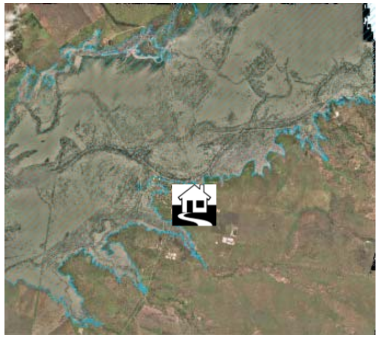
SAR (CosmoSkyMed)



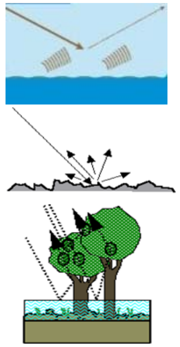
RS-derived flood extent



OPTICAL, evaluation data



RADAR BACKSCATTER



Open water: LOW

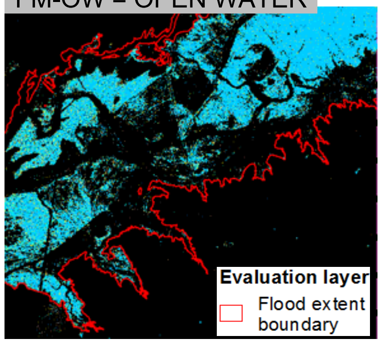
Dry surface: HIGH

Flooded vegetation: even HIGHER

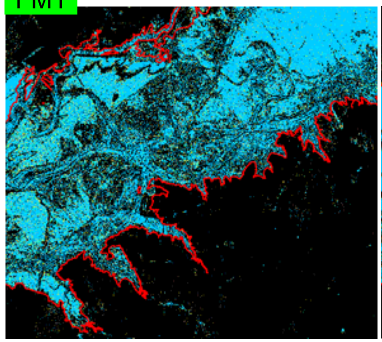
Flood mapping under vegetation using **single SAR** acquisitions and commonly **available ancillary data:**

- detection of open water areas → FM-OW
- statistical analysis of the backscatter response of wet and dry vegetation for different **land cover** types → FM1
- incorporation of information on **land use** and **morphology** within a fuzzy logic approach → FM2

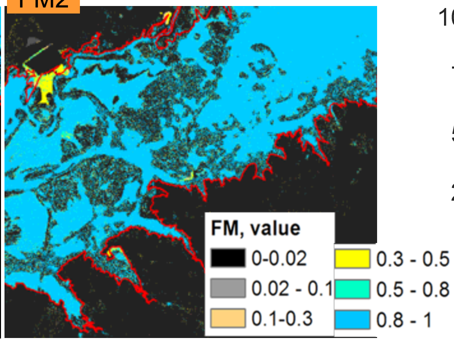
FM-OW = OPEN WATER

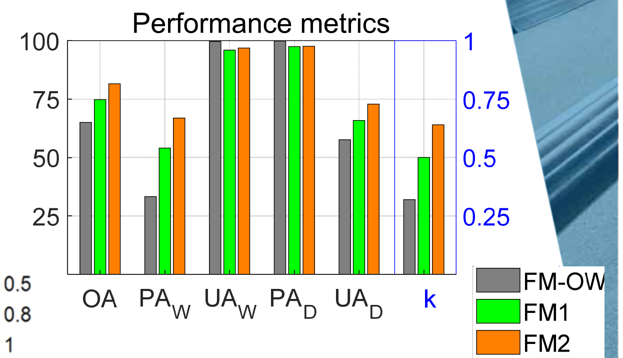


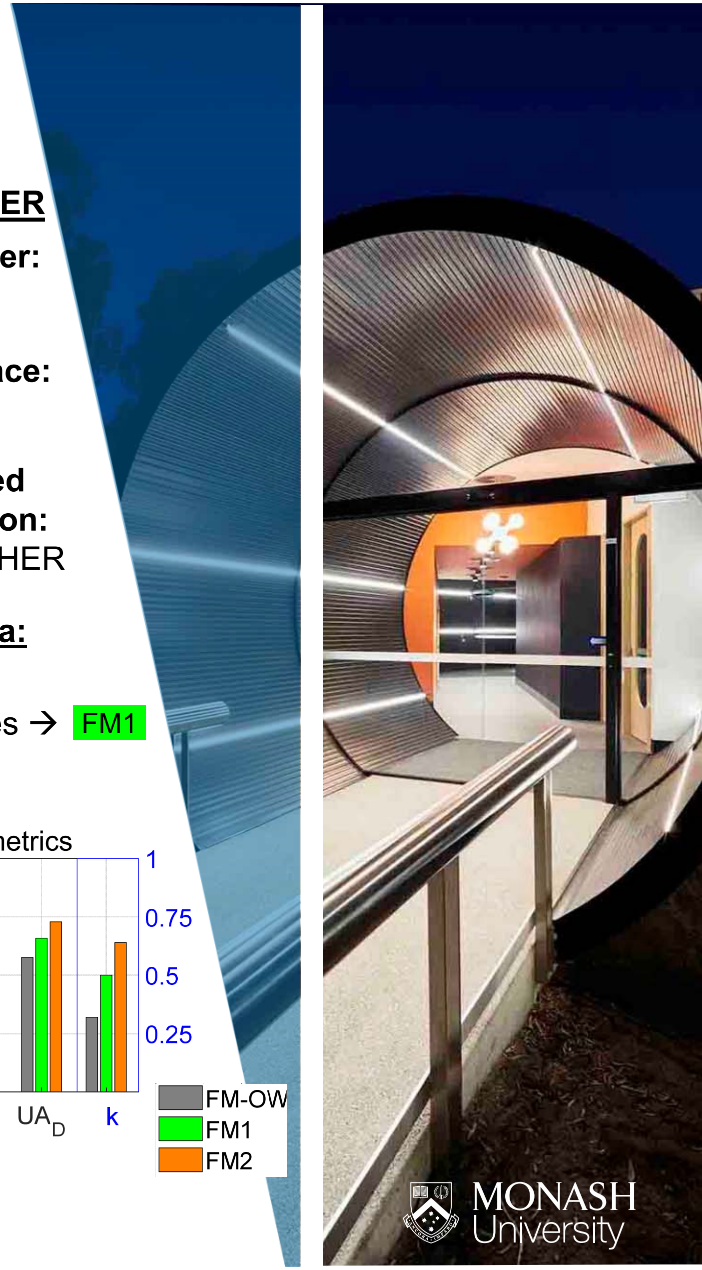
FM1



FM2







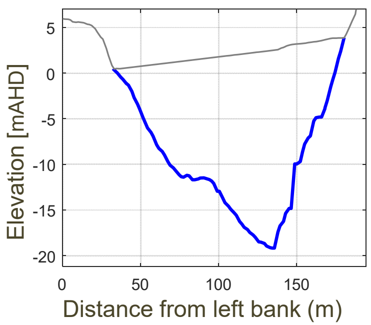
HYDRAULIC MODEL IMPLEMENTATION

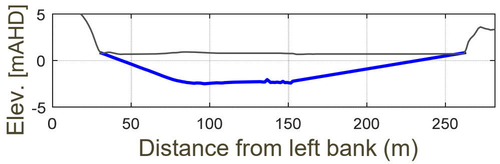
In many catchments, information on **river bathymetry** is essential for the modelling of floodplain inundation.

- River width can be observed remotely.
- River **shape** and **depth** require **field data**.
- Field campaigns: Clarence (Nov.2015), Condamine-Balonne (May 2016).

NUMERICAL EXPERIMENT BASED ON FIELD DATA

Measured cross sections

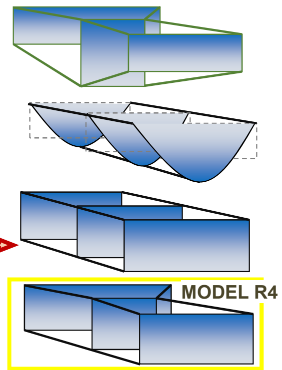


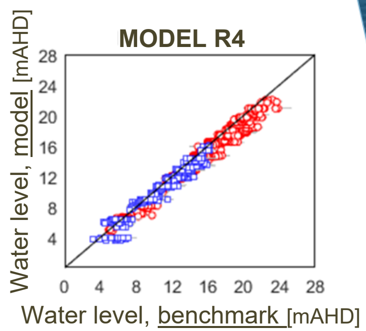


Simplified cross sections based on a combination of:

- a few measurements;
- Remote Sensing river width;
- global database.

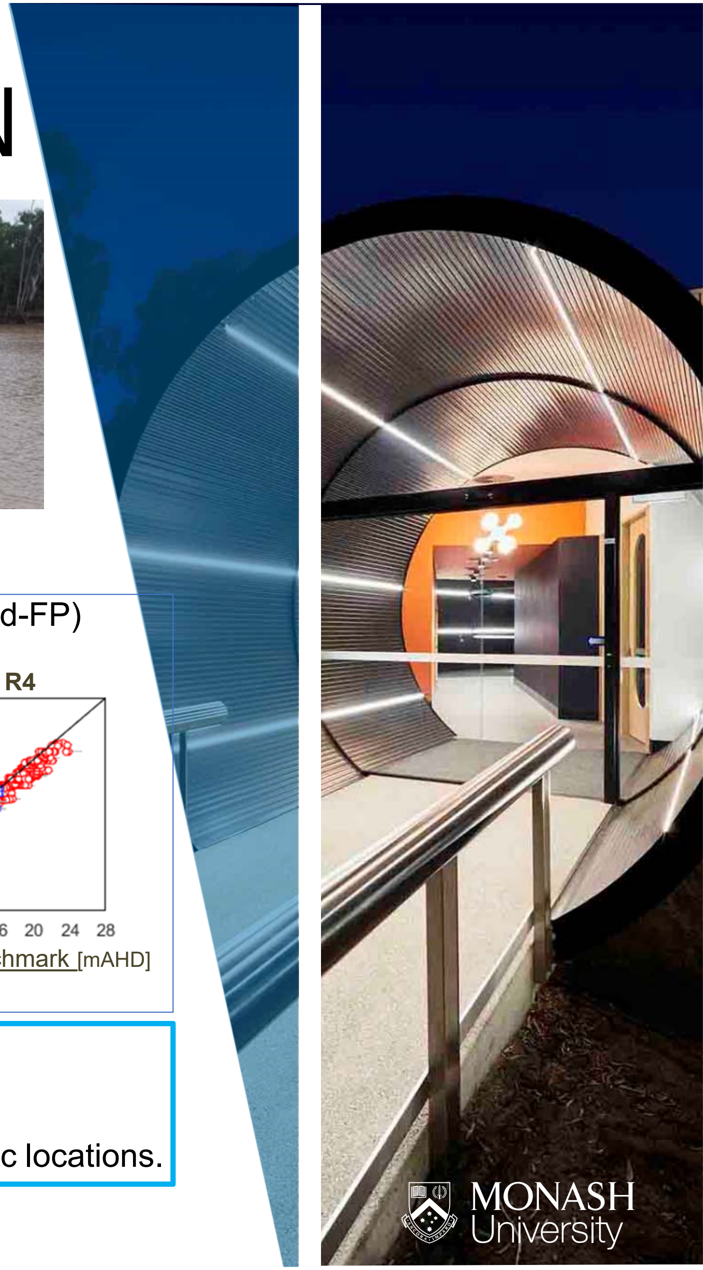
Numerical experiment (Lisflood-FP)





DATA PARSIMONIOUS IMPLEMENTATION METHOD:

- Width varying rectangular shape with uniform longitudinal slope.
- Remote Sensing-derived river width combined with a few (3) measurements of river depth at strategic locations.

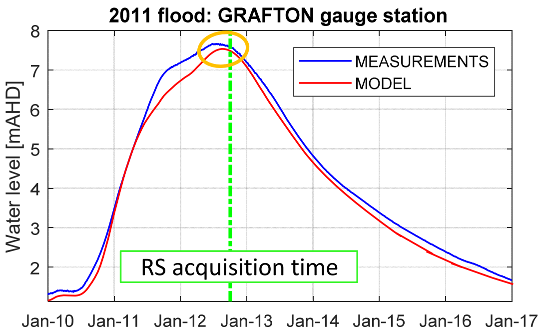


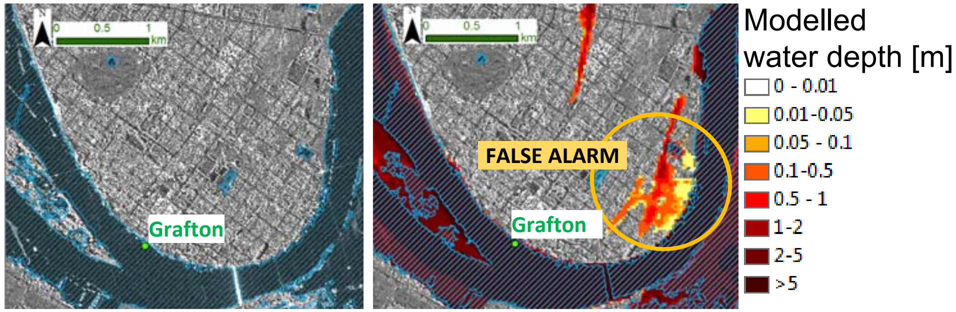
HYDRAULIC MODEL EVALUATION

Use of Remote Sensing-derived spatially distributed information

REMOTE SENSING-DERIVED FLOOD EXTENT

Gauged data ⟷ RS-derived flood extent





RS-derived flood extent

More effective evaluation of model performances.

REMOTE SENSING-DERIVED WATER LEVEL

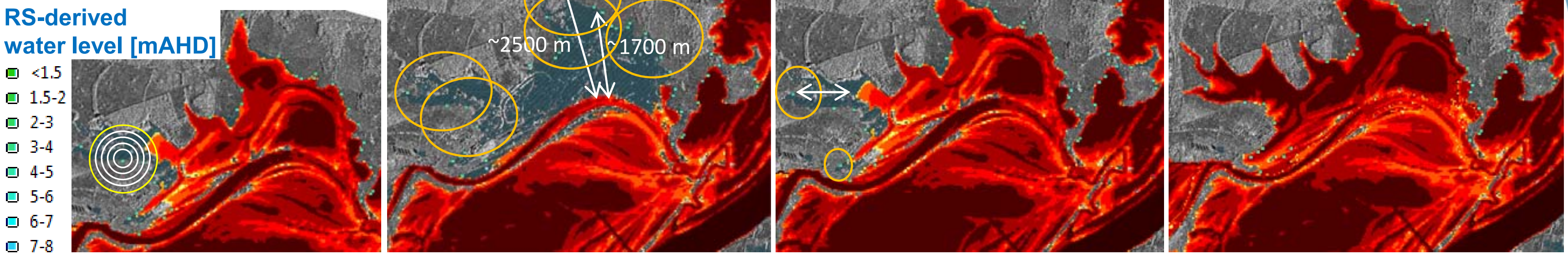
Use of RS data to evaluate modelled flood wave velocity.

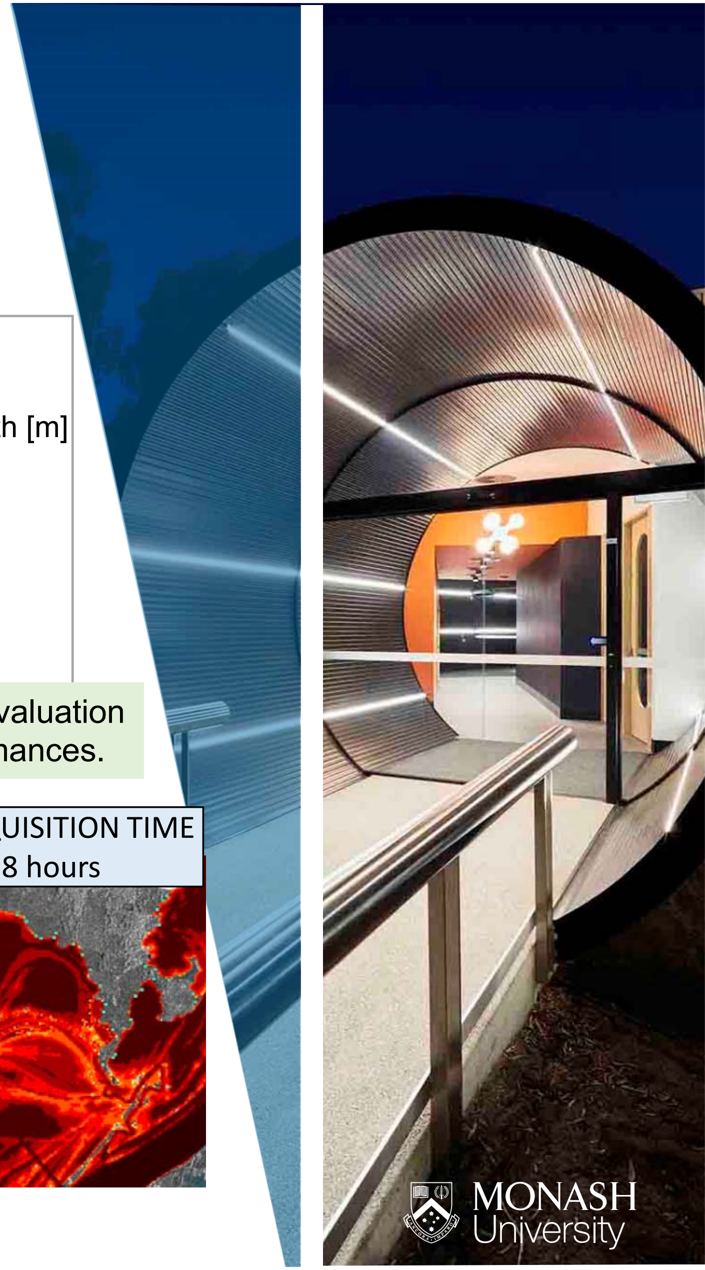
SAR ACQUISITION TIME

SAR ACQUISITION TIME + 3 hours

SAR ACQUISITION TIME + 8 hours

RS-derived water level [mAHD]

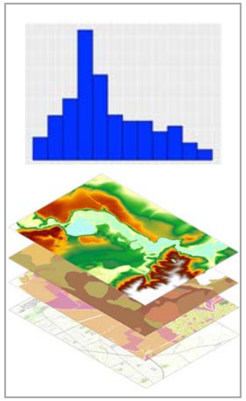




Efficient Simulation of Flood Events Using Machine Learning

Achieving two-dimensional flood modelling with deep learning (DL) techniques

Limited inputs



Hydrodynamic model

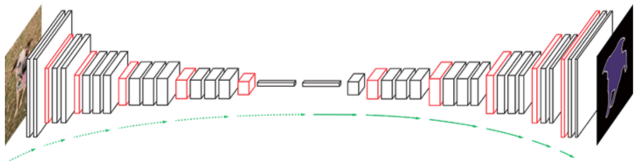
$$\frac{\partial H}{\partial t} + \frac{\partial}{\partial x}(H\bar{u}) + \frac{\partial}{\partial y}(H\bar{v}) = 0$$

$$\frac{\partial}{\partial t}(H\bar{u}) + \frac{\partial}{\partial x}(H\bar{u}^2) + \frac{\partial}{\partial y}(H\bar{u}\bar{v}) = -gH\frac{\partial \zeta}{\partial x} + \frac{1}{\rho}[\tau_{sx} - \tau_{bx} + F_x]$$

$$\frac{\partial}{\partial t}(H\bar{v}) + \frac{\partial}{\partial x}(H\bar{u}\bar{v}) + \frac{\partial}{\partial y}(H\bar{v}^2) = -gH\frac{\partial \zeta}{\partial y} + \frac{1}{\rho}[\tau_{sy} - \tau_{by} + F_y]$$

- Long computational time
- Numerical instability

Detailed spatio-temporal outputs



Deep learning neural network

Outcomes:

- New methodology for flood modelling
- **Fast-running models** for real-time applications

DATA 61

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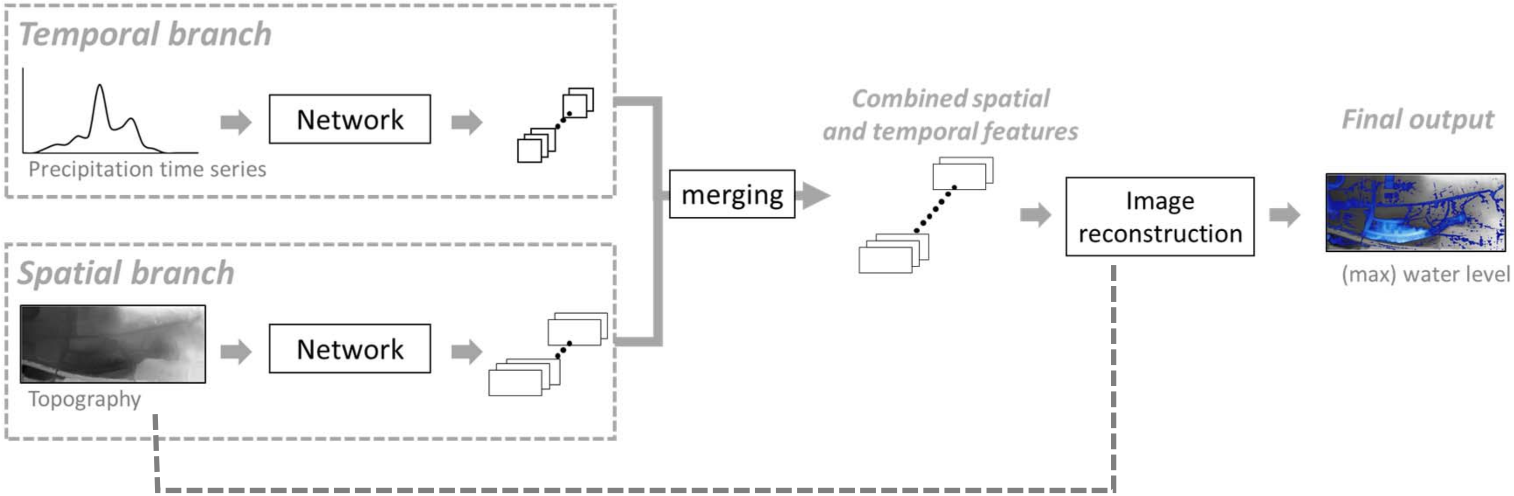
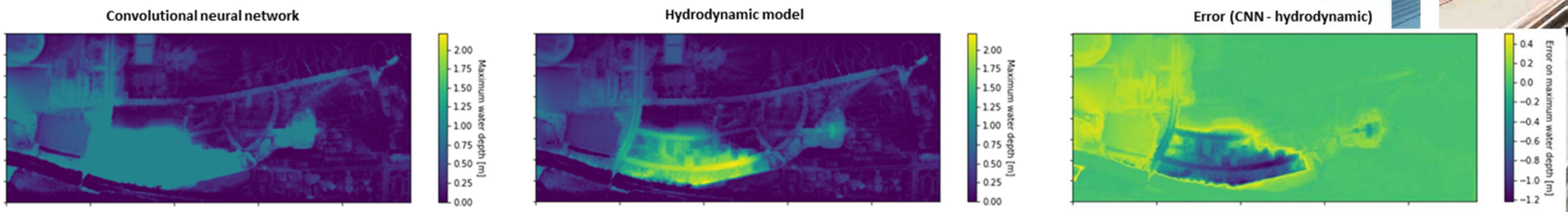
Efficient Simulation of Flood Events Using Machine Learning

Simplified model predicting the maximum water level





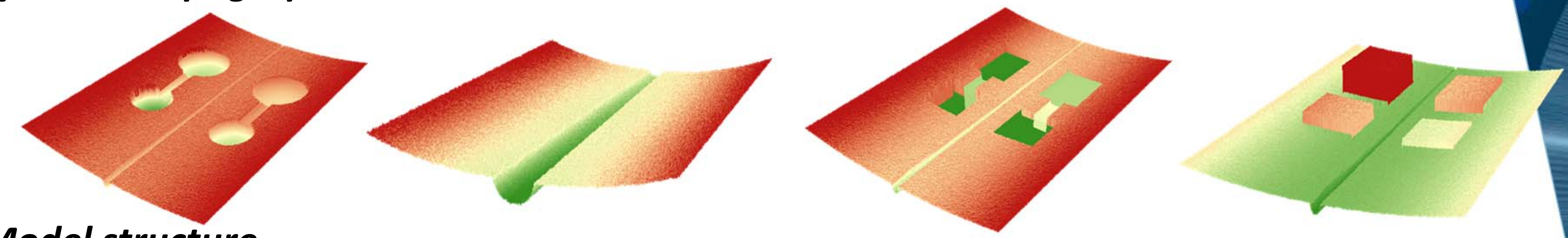
- Encouraging results from the simplified model
- Precision of the model is variable, error range too big for practical applications
- Running time much shorter than a hydrodynamic model → computationally more efficient

Efficient Simulation of Flood Events Using Machine Learning

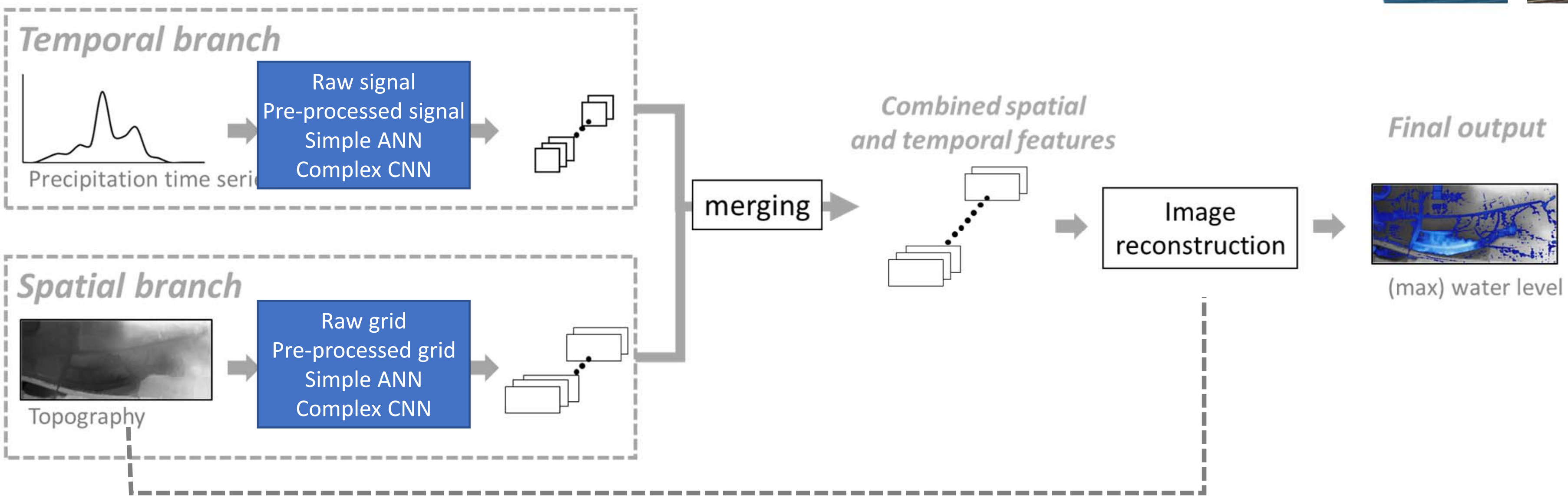
Simplified model predicting the maximum water level

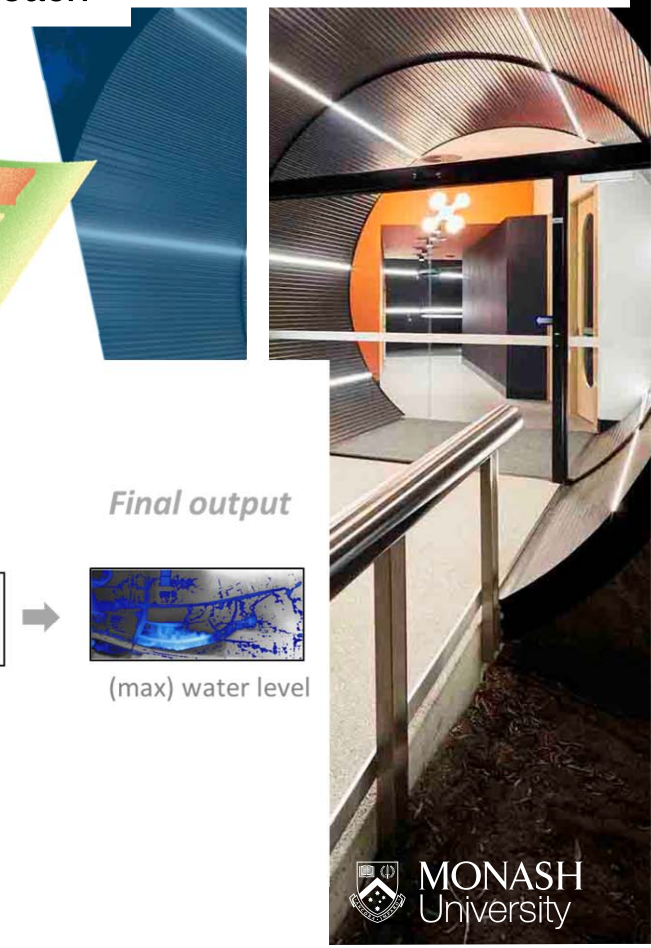
On-going work : testing more complex/simple DL architectures with a systematic approach

Synthetic topographies

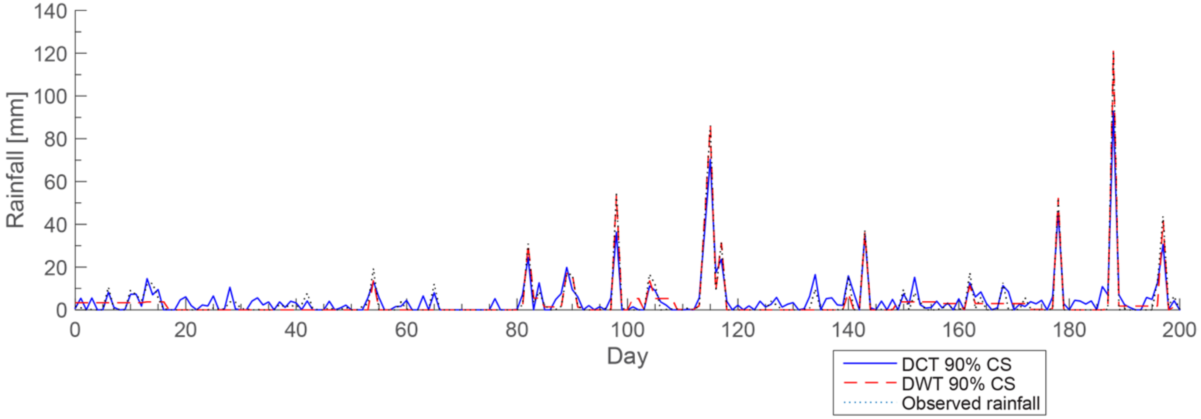


Model structure



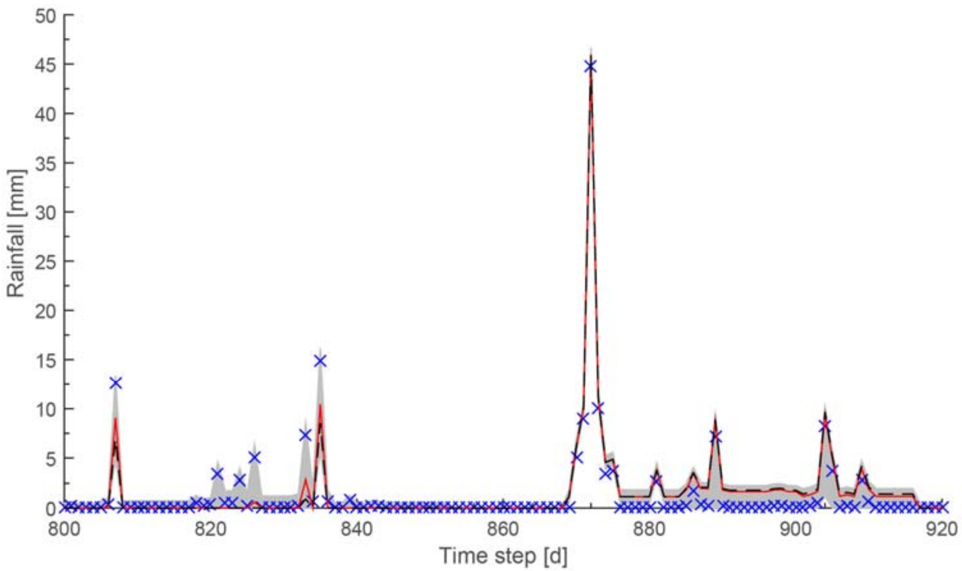


Estimating areal rainfall



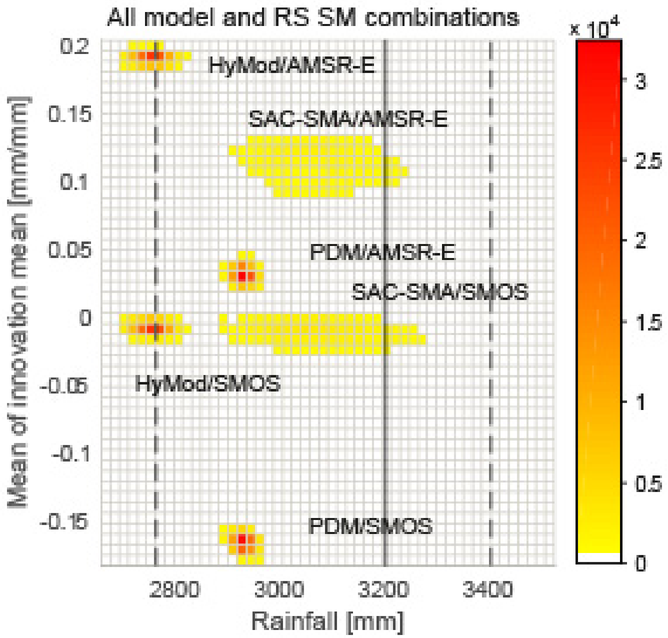
3 step process that involves

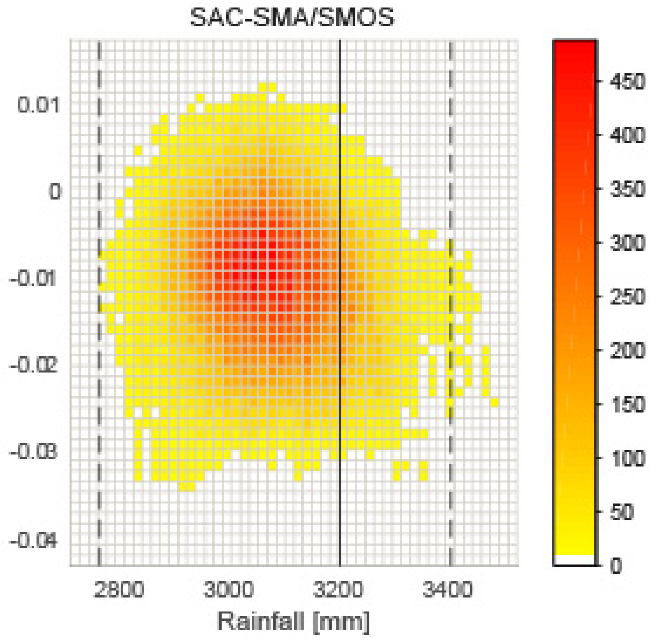
1. transforming rainfall into parameters to reduce model dimensionality,
2. including parameters in the model parameter optimisation process



Estimating areal rainfall

3. a multi model validation of process which analyses innovations from RS SM





Wright, A., Walker, J. P., Robertson, D. E., & Pauwels, V. R. N. (2017). A comparison of the discrete cosine and wavelet transforms for hydrologic model input data reduction. *Hydrol. Earth Syst. Sci.*, *21*(7), 3827–3838.

Wright, A. 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.

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), 1305–1320.

Adaptive Ensemble Kalman Filter

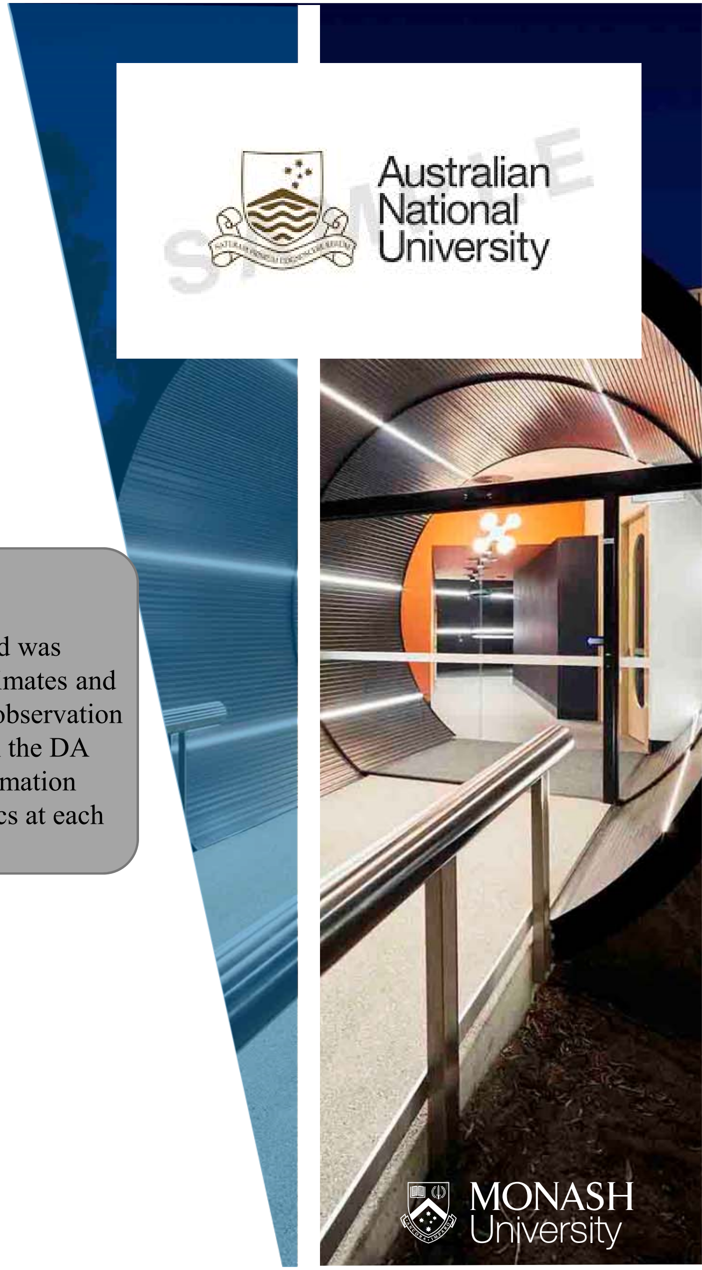
Problem:
Low skill to perfectly identify the error parameters for the EnKF

Objective: Improve the best(s) DA method(s) from the previous stage.

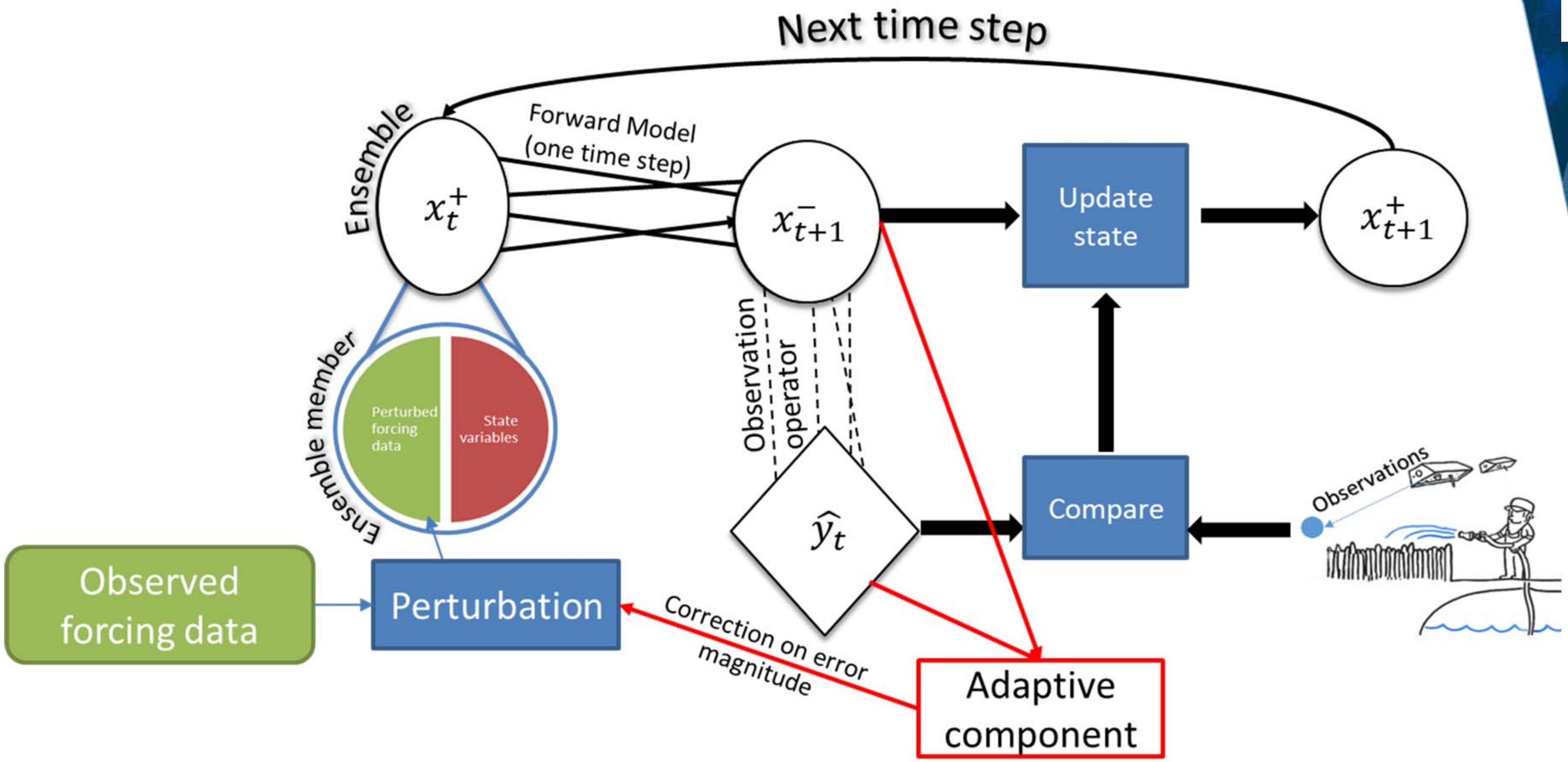
Part 1. Demonstrate the effects of error magnitude and misspecification on the results

Part 2. Employ the adaptive strategy to mitigate the error misspecification issue.

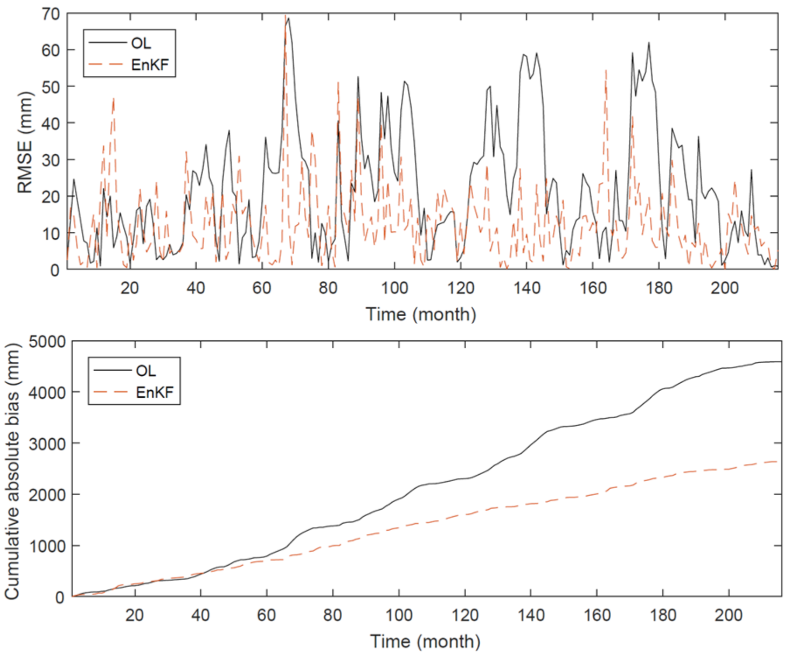
Outcome:
A more reliable DA
An adaptive DA method was developed so that it estimates and modify the model and observation error parameters within the DA iteration based on information from internal diagnostics at each step.

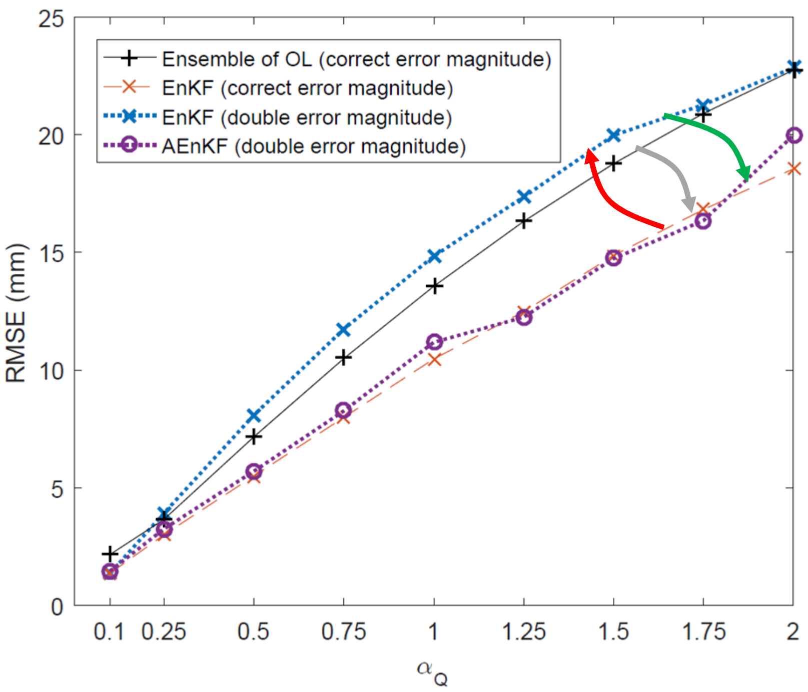


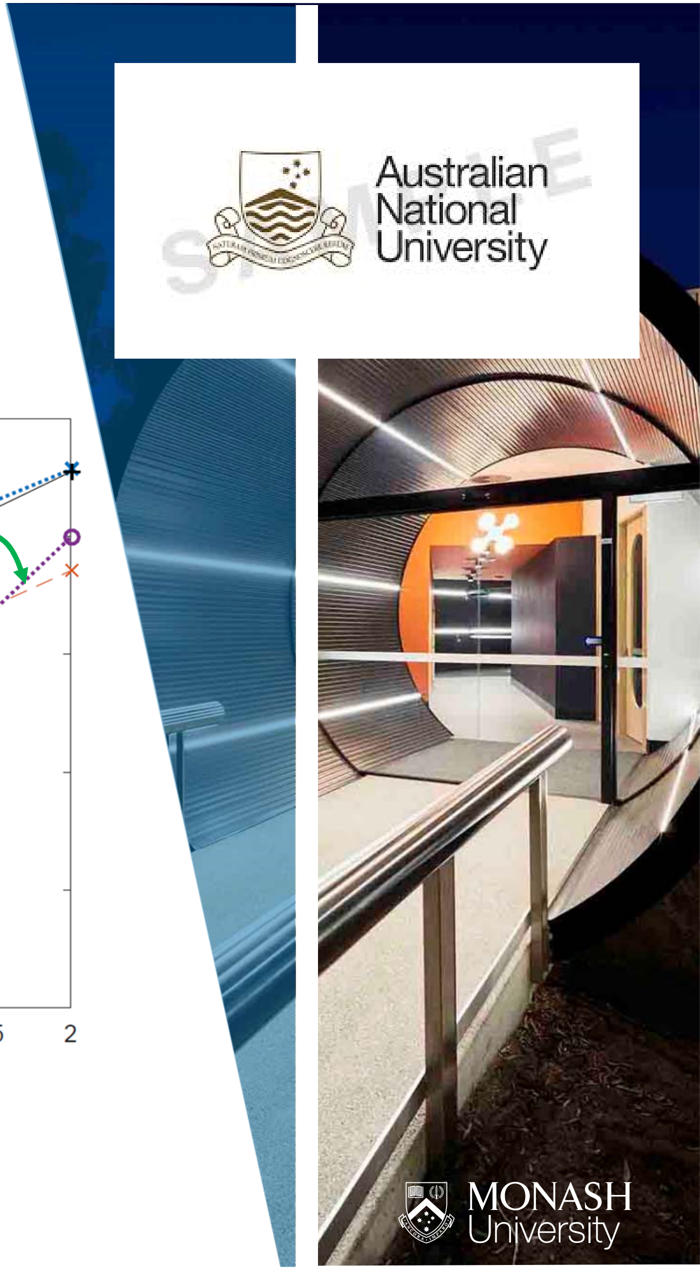
AEnKF - Method



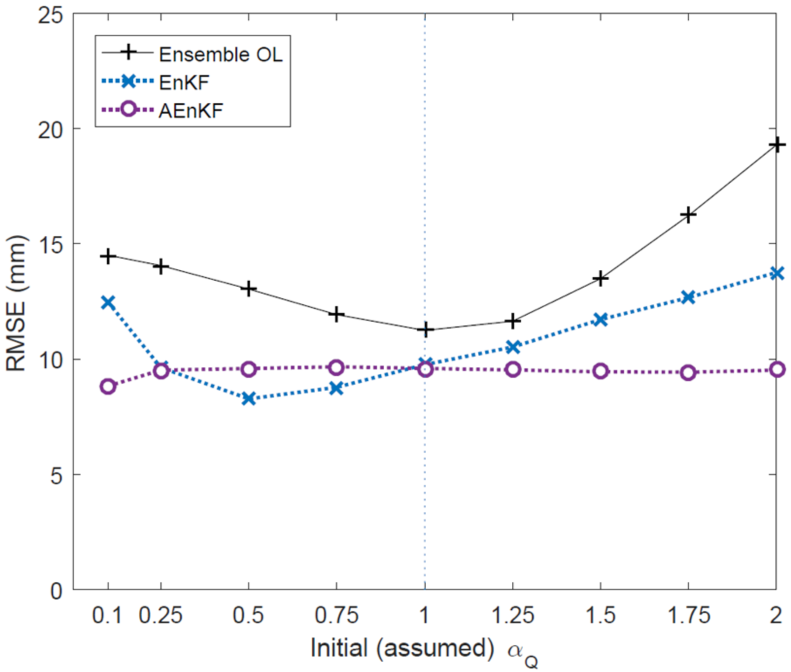
AEnKF - Results







AEnKF - Results



RS evapotranspiration assimilation into hydrogeological models

Objectives and questions

1) Explore the effects of the data assimilation of remotely sensed ET products into coupled unsaturated zone – groundwater models

   - *Does the ET assimilation improve the model products?*
   - *What is the required model/filter set up for ET to update the state variables?*
   - *Are the updated state variable improving modeled net-recharge and ET fluxes?*

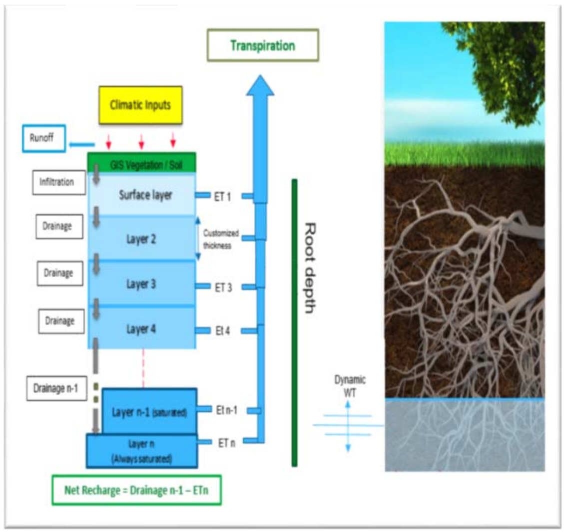
2) Quantify the complexity of the unsaturated zone model required for ET data assimilation

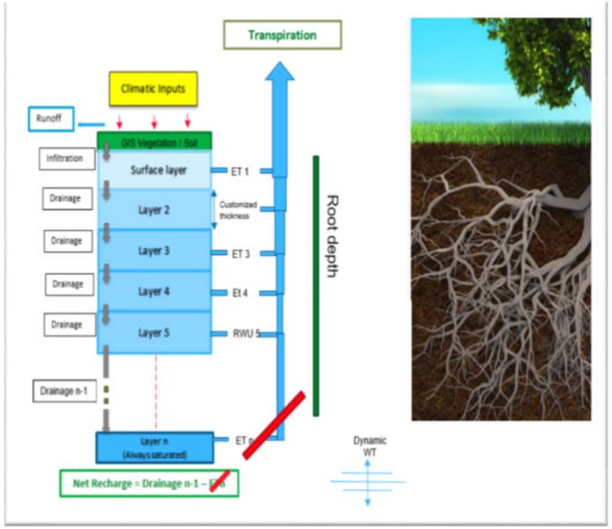
   - *Detailed Richard's equation model vs simplified ODE model, what is best?*

3) Identify areas where the ET data assimilation produces the greatest improvements on an operational regional scale groundwater model

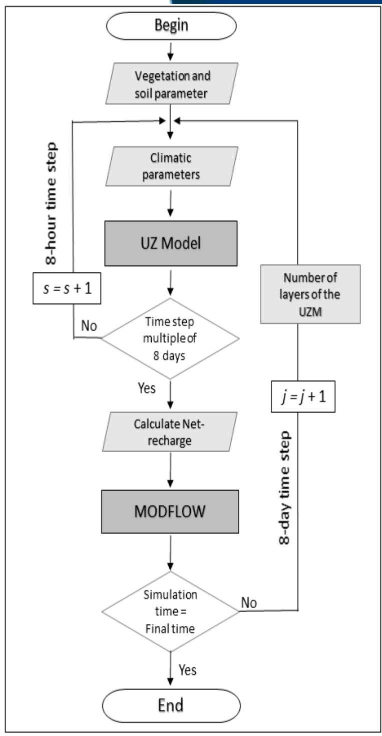
   - *Are shallow water table areas with direct transpiration seeing the highest improvements?*

Development of the unsaturated zone model and its coupling to MODFLOW-2005

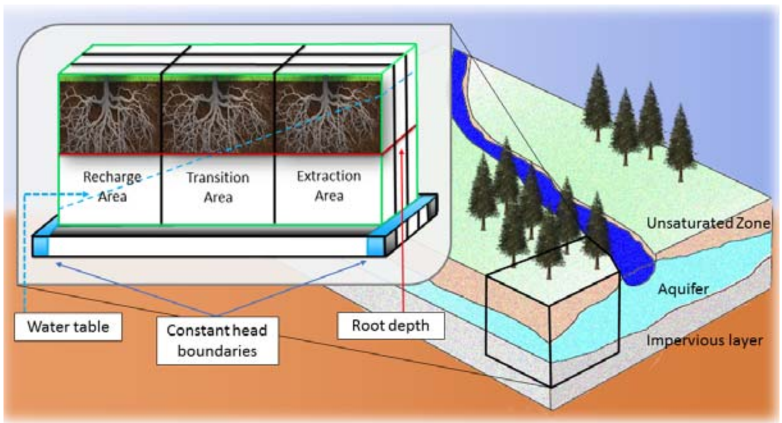




Two cases representing different water table depths and corresponding number and saturation of the modeled layers



Coupling schematic



The synthetic study domain

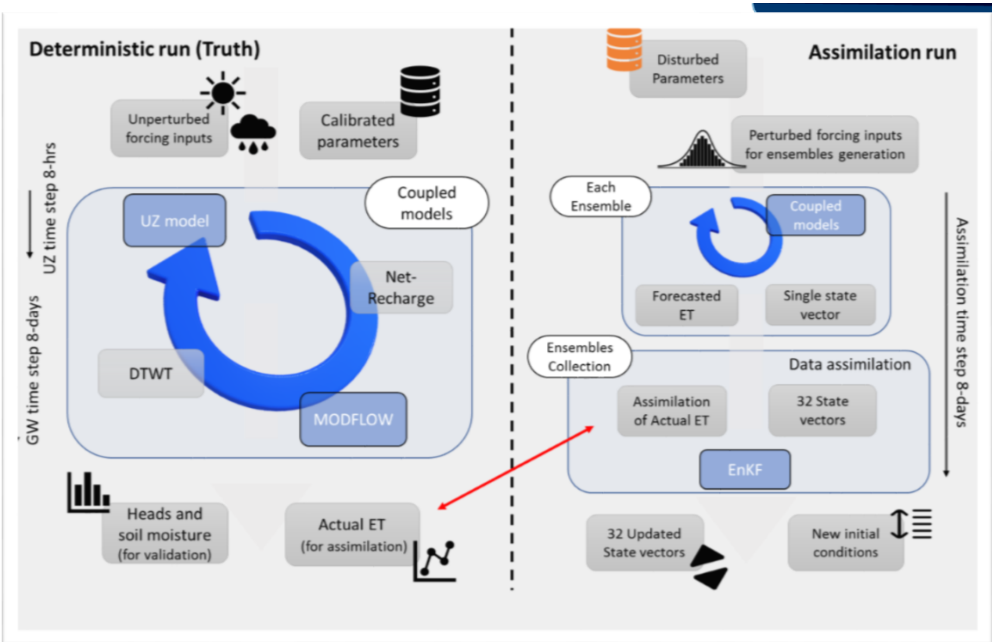
Losing river system

A gradually lowering water table identifies three areas of interaction between roots and water table

The data assimilation experiment set up

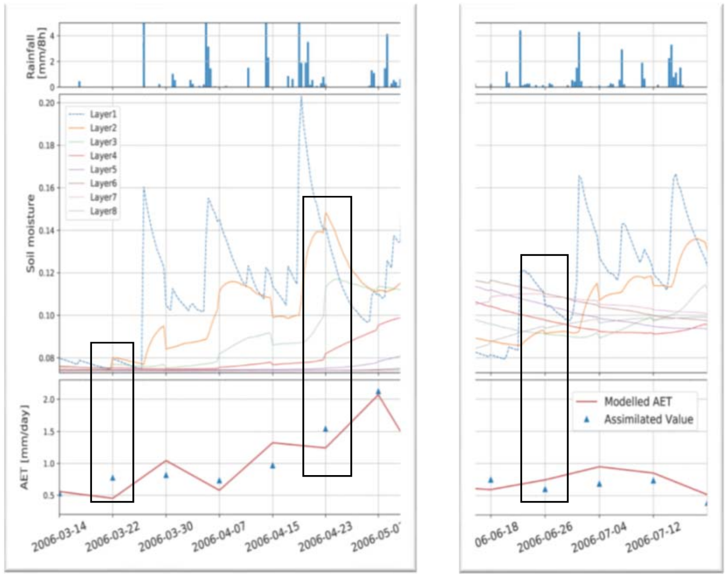
<u>Synthetic truth</u>
Optimal parameters calibration
Unperturbed forcing inputs
Generates Actual ET values for assimilation

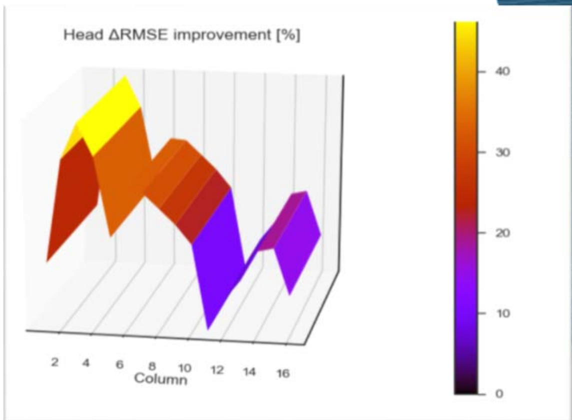
<u>Assimilation run</u>
Ensemble simulation (32 members)
Disturbed parameters
Perturbed forcing inputs



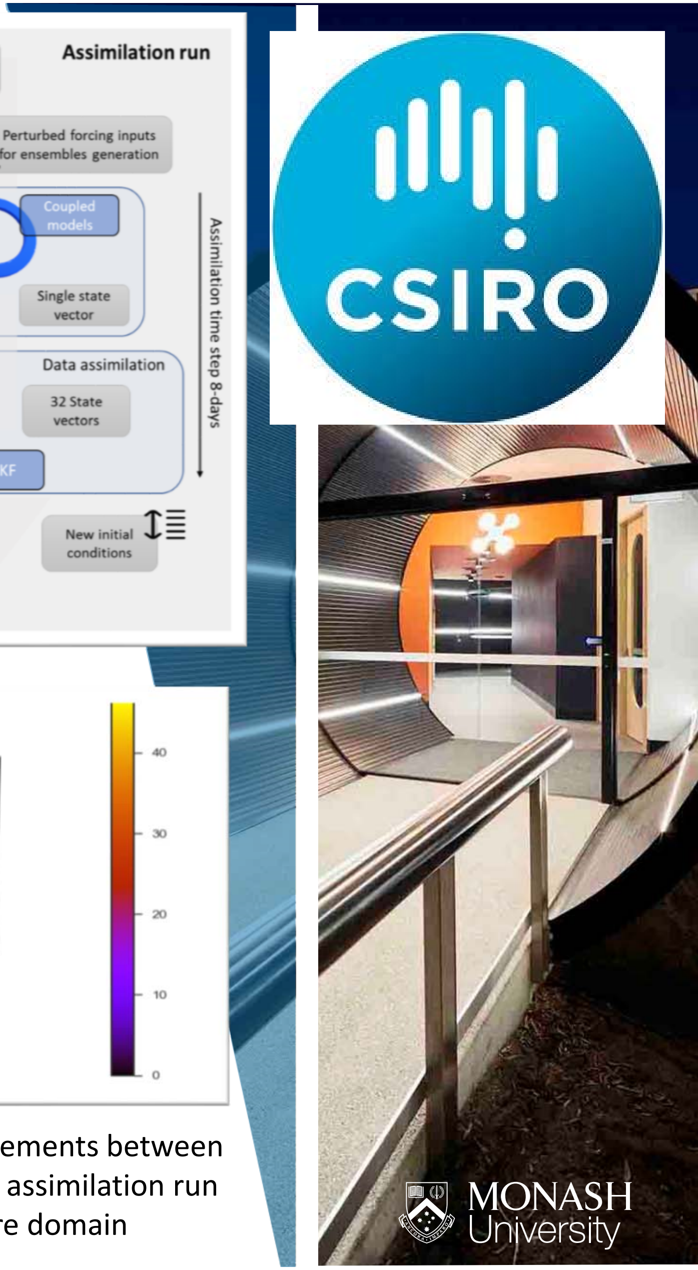
Results

Soil moisture content for a single member of the ensemble. Three boxes highlight cases with higher or lower observed ET than modelled and how the soil moisture content is updated by the filter





Head ΔRMSE improvements between the open loop and 1 assimilation run over the entire domain



Similarities Between Australia and France

Use of green energy

Public deficit (%GDP, 2017)

- France: 2.6
- Australia: 1.5

Similarities Between Australia and France

Cultural similarities

	Life Expectancy	Human Development Index	Literacy Rate
France	81.66	0.955	99%
Australia	82.07	0.965	99%

Similarities Between Australia and France

Cultural similarities

Similarities Between Australia and France

And of course flooding…

So there should be plenty of opportunity for further collaboration…


QUESTIONS ?
MONASH
University