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# Leveraging Earth Observation and Data Assimilation for Improved Flood Inundation Forecasts

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IITB-Monash  
Research Academy

An Indian-Australian research partnership



# What if most satellite-based flood observations could significantly improve flood forecasts?

BEFORE



AFTER

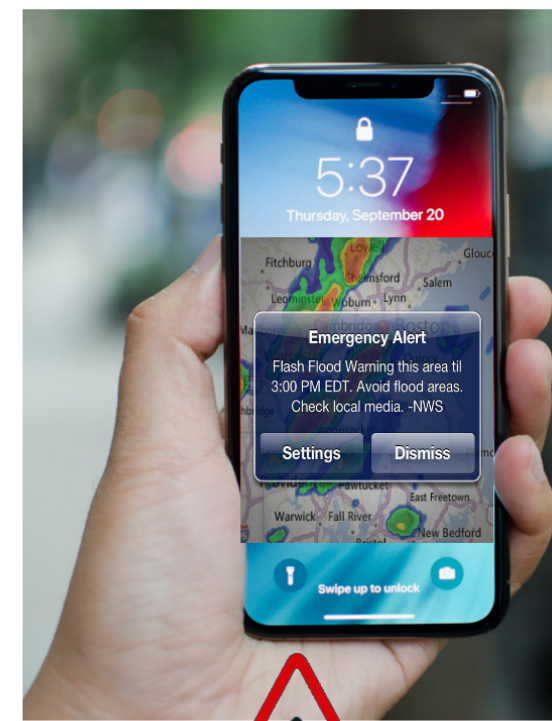
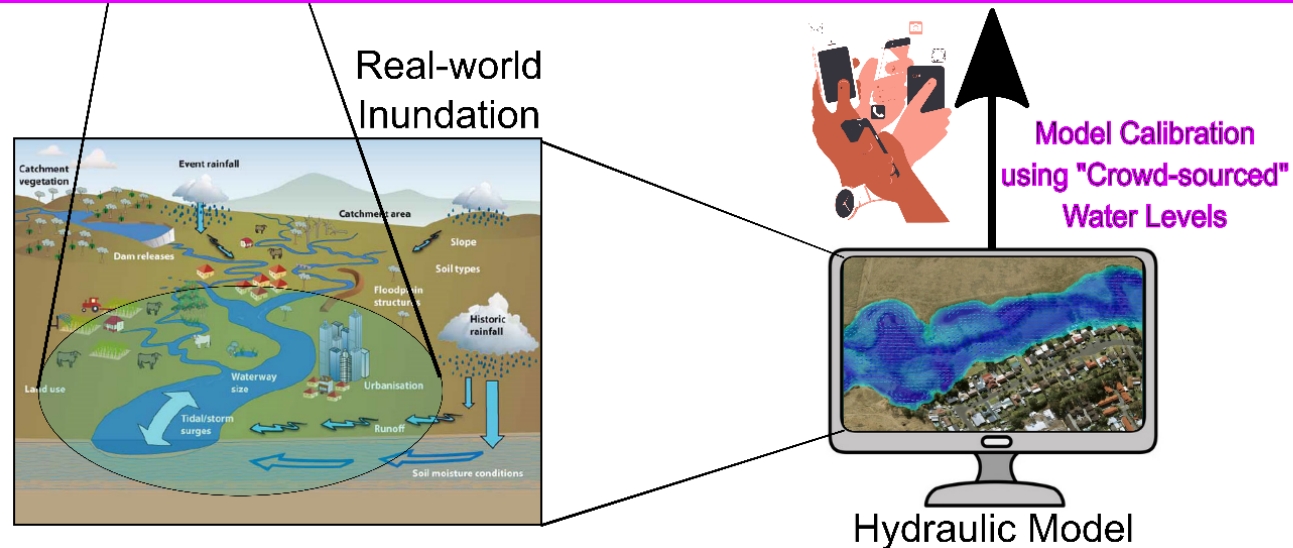
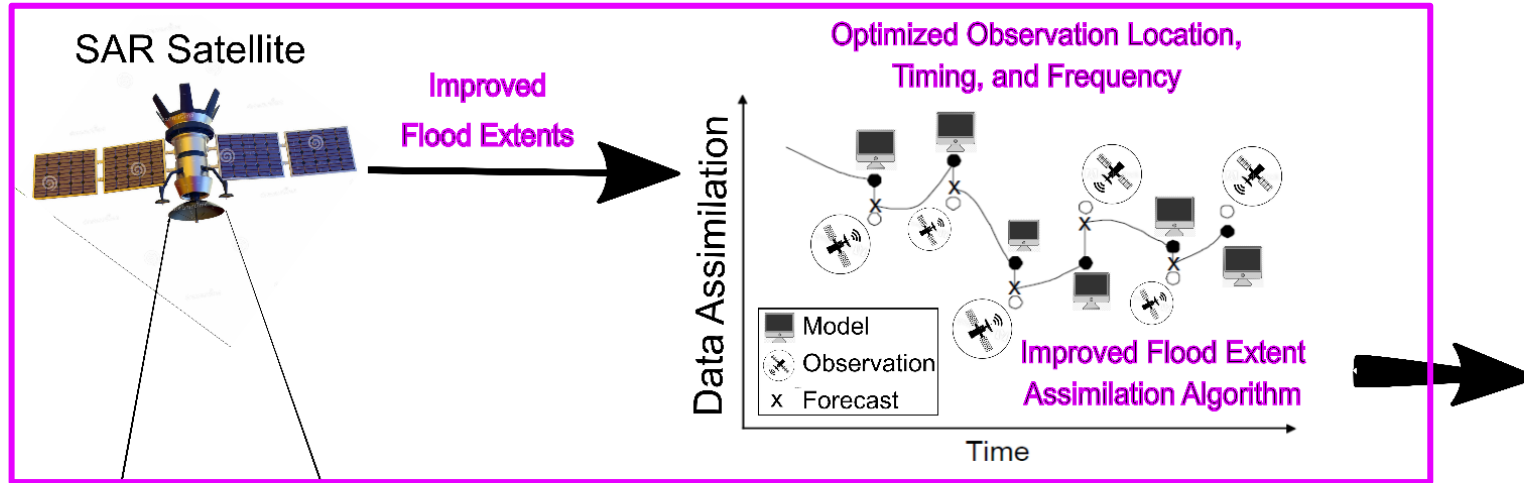


 Hits  
 False Alarms

This is the impact of integrating just one remotely sensed flood observation!!!

# How will it work?

Make improvements at every step of the process



**FLOOD WARNING**  
FLOODING IS EXPECTED. IMMEDIATE ACTION REQUIRED.

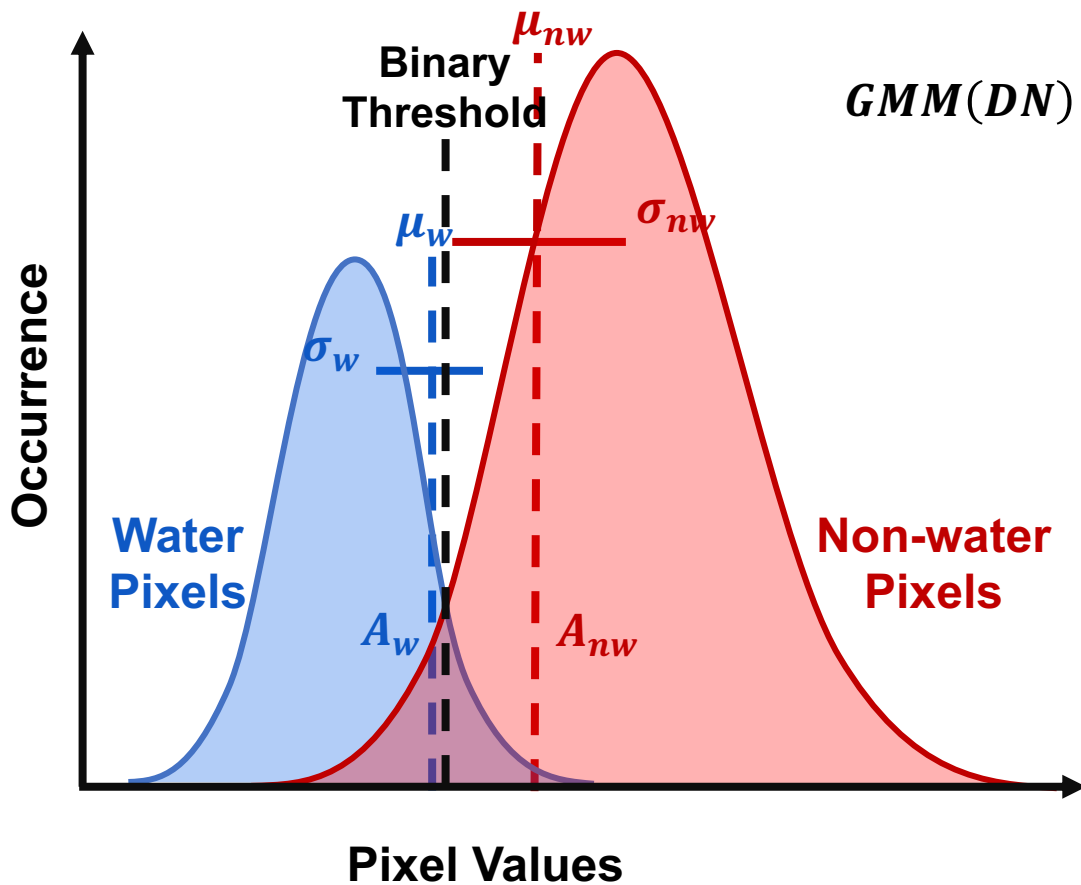
# IMPROVING RADAR- BASED FLOOD MAPPING

Dasgupta, A., Grimaldi, S., Ramsankaran, R., Pauwels, V. R. N., & Walker, J. P. (2018). Towards operational SAR-based flood mapping using neuro-fuzzy texture-based approaches. *Remote Sensing of Environment*, 215(15 September 2018), 313–329.  
<http://doi.org/10.1016/j.rse.2018.06.019>.

# Current Challenges

Histogram dependence and deterministic outcomes

Typical Flooded Image Histogram



$$GMM(DN) = A_w \exp \left[ -\frac{1}{2} \frac{(DN - \mu_w)^2}{\sigma_w^2} \right]$$

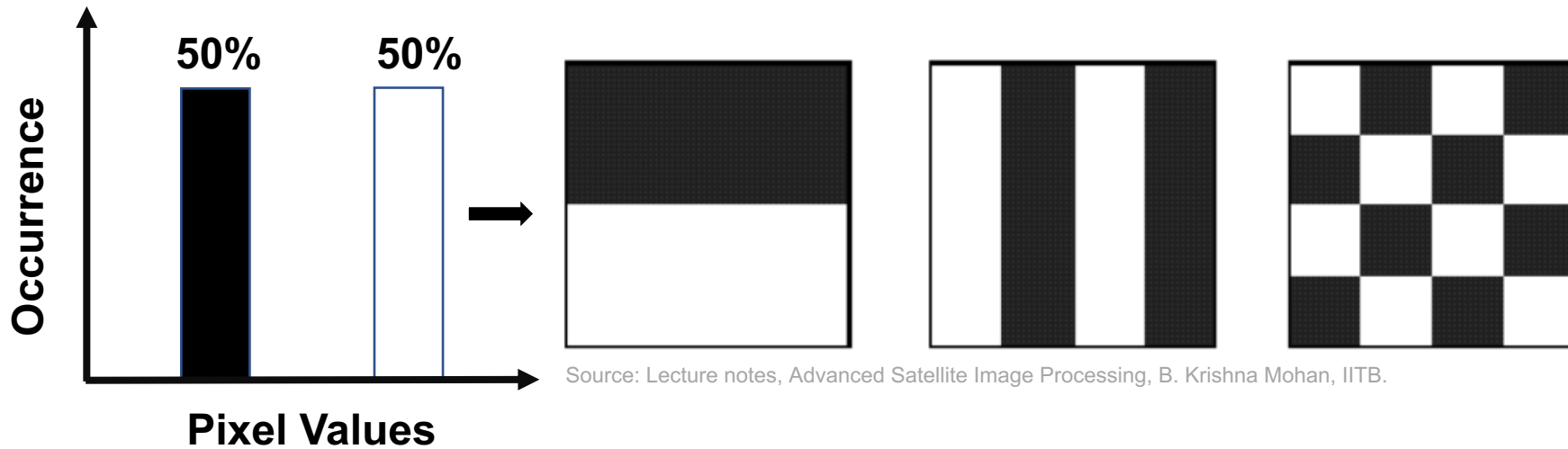
$$+ A_{nw} \exp \left[ -\frac{1}{2} \frac{(DN - \mu_{nw})^2}{\sigma_{nw}^2} \right]$$

Gaussian curve for water pixels

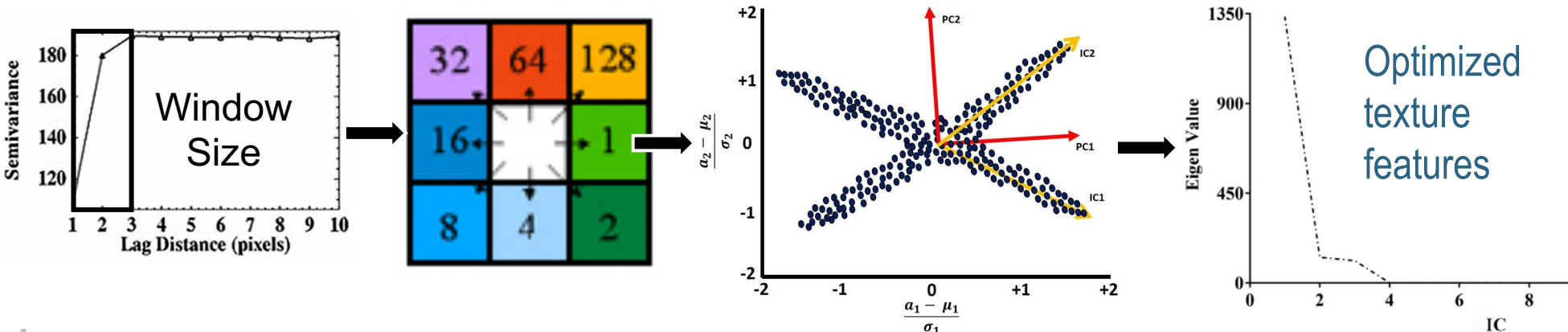
Gaussian curve for non-water pixels

# Proposed solutions

Image texture optimization and neuro-fuzzy flood mapping

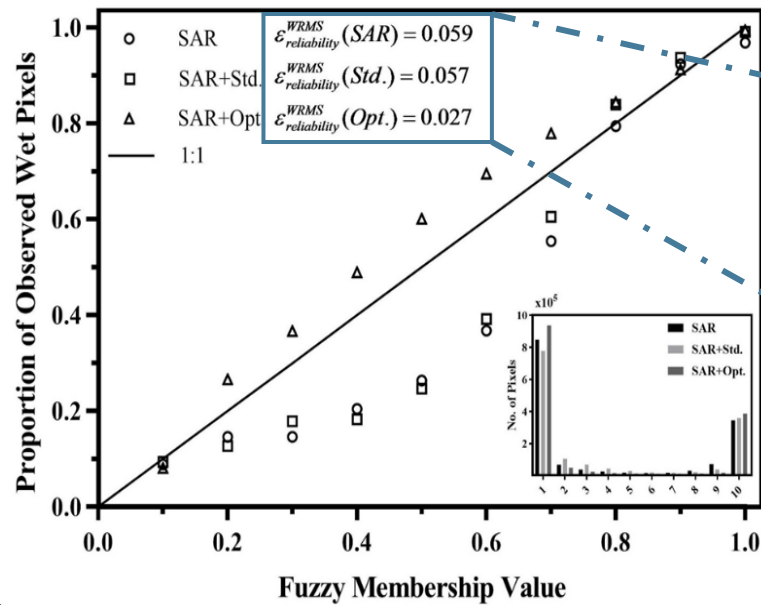
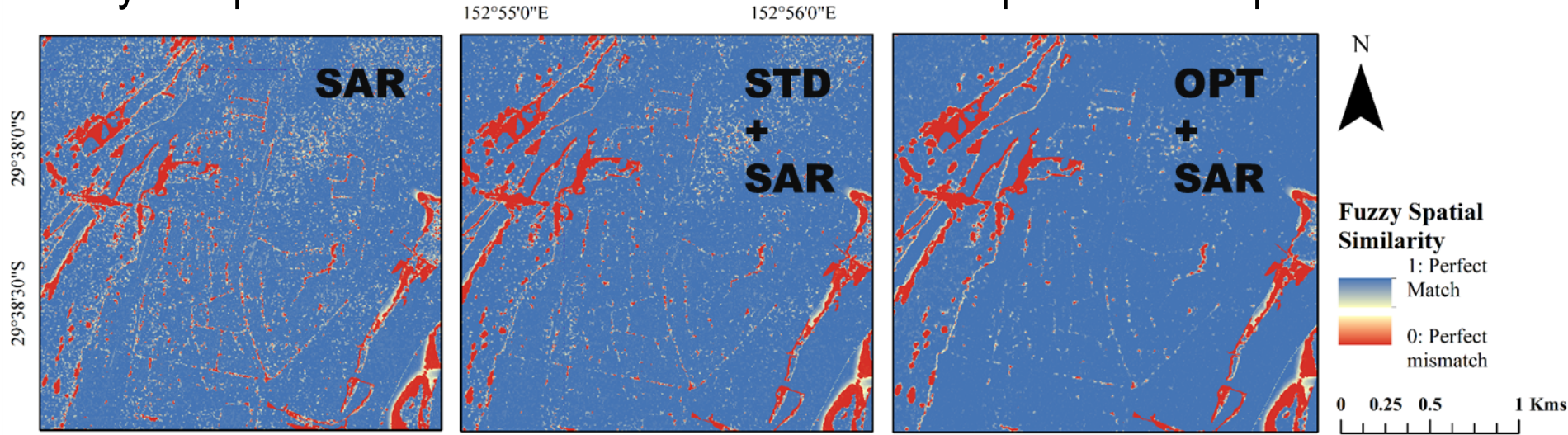


## Texture optimization process



# Key Results

Fuzzy comparison between SAR-based and aerial photo based probabilistic flood maps



**Errors**

$\mathcal{E}_{reliability}^{WRMS}(SAR) = 0.059$   
 $\mathcal{E}_{reliability}^{WRMS}(Std.) = 0.057$   
 $\mathcal{E}_{reliability}^{WRMS}(Opt.) = 0.027$

**-54%**

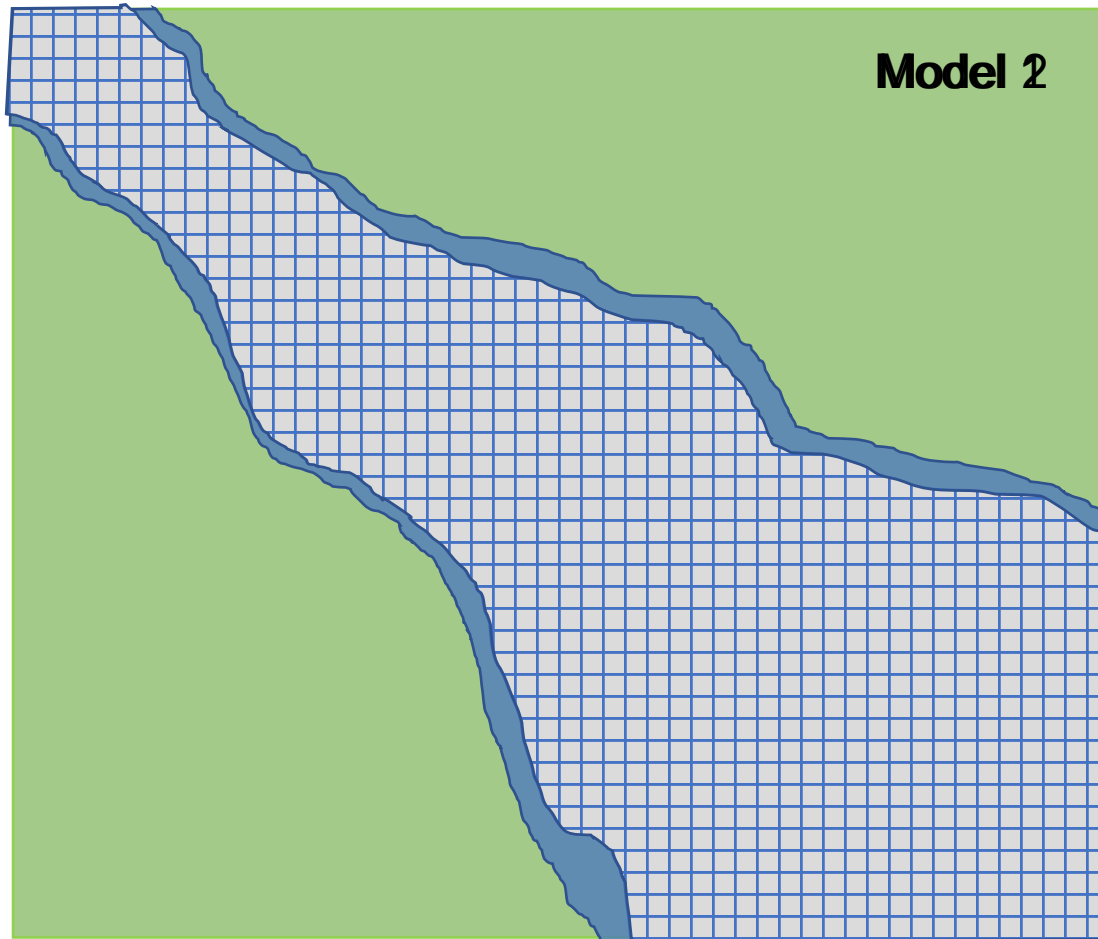
# A New Method to Combine Satellite- based Flood Maps with Models

Dasgupta, A., Hostache, R., Ramsankaran, R., Pauwels, V.R.N., Schumann, G.J.P., Grimaldi, S., and Walker, J.P. (2020) A mutual information-based likelihood function for SAR-derived flood extent assimilation using particle filters. *Water Resources Research* (In Review).



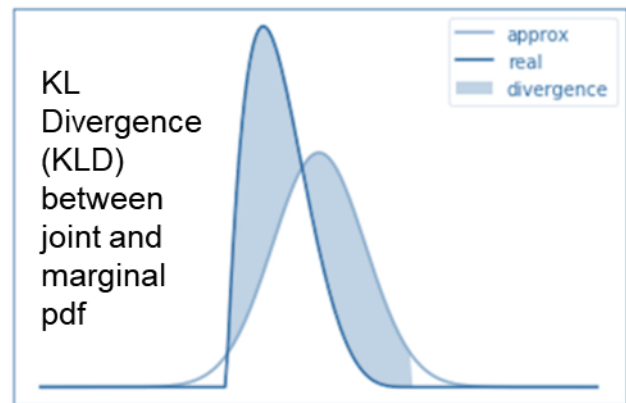
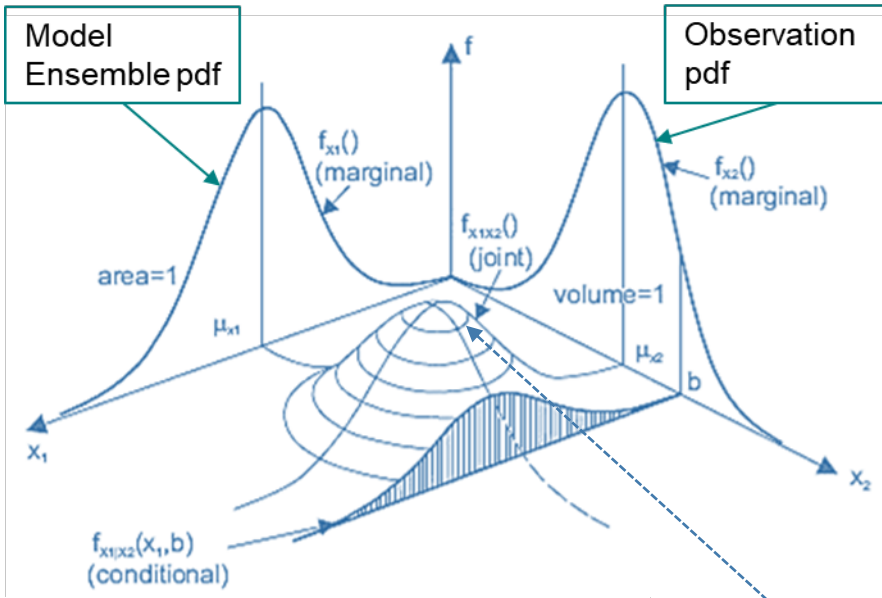
# Current Challenges

Likelihood sensitivity towards slightly varying extents

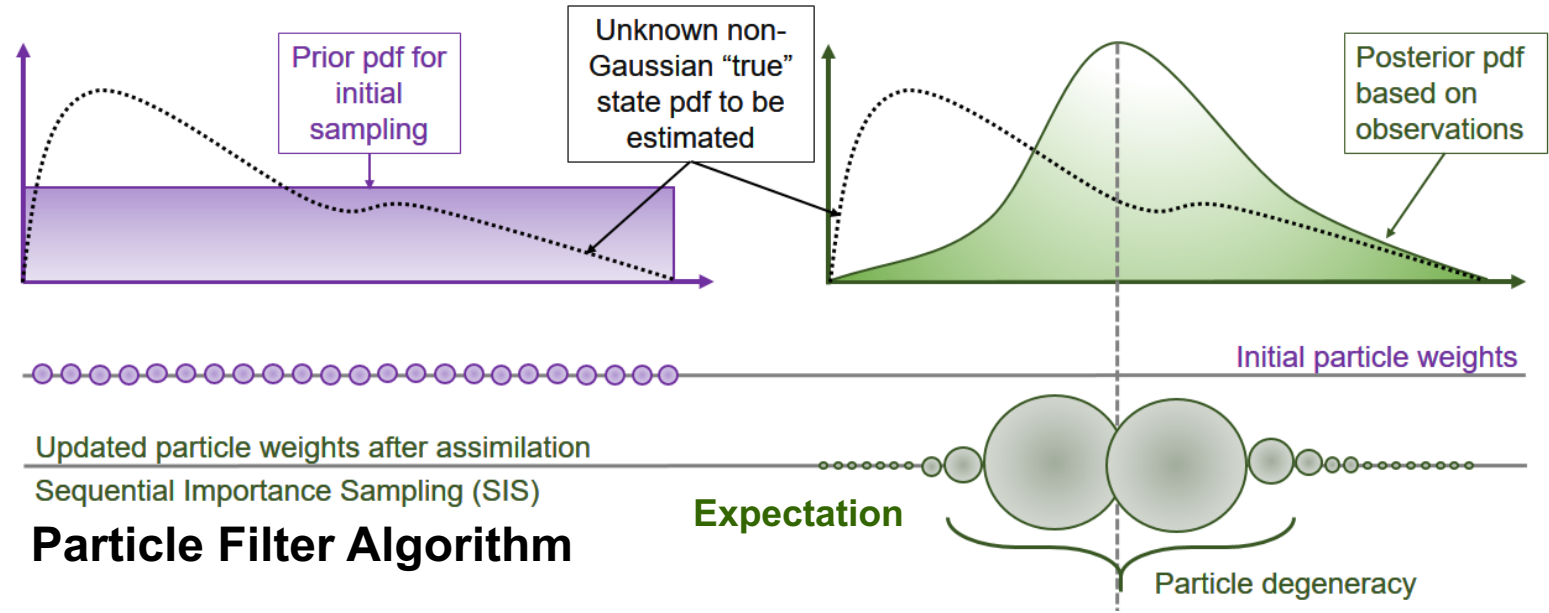


# Proposed Solution

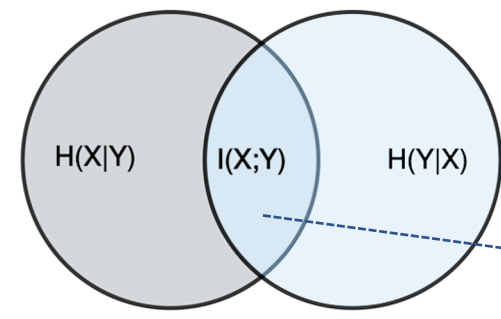
## Mutual Information (MI)



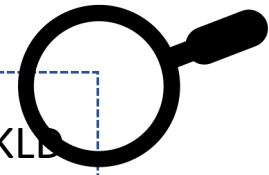
MI=0 iff the joint pdf is equal to the product of marginals



## Particle Filter Algorithm

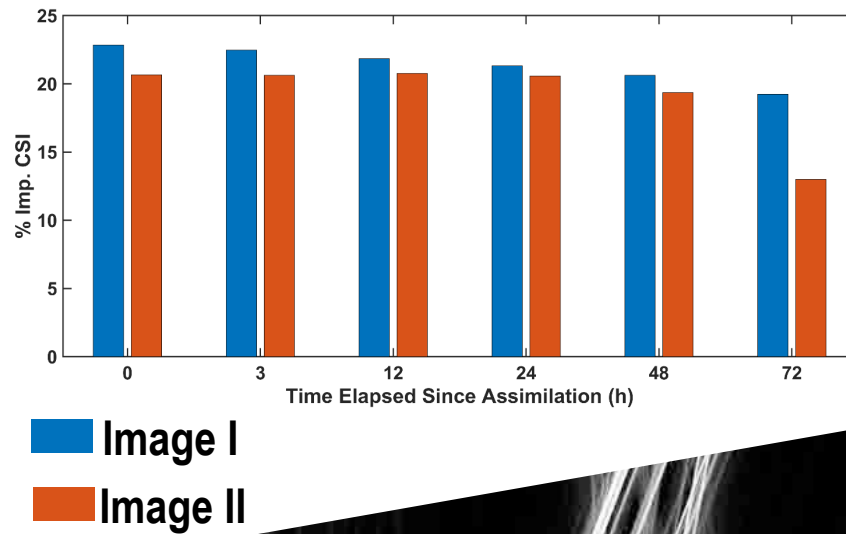
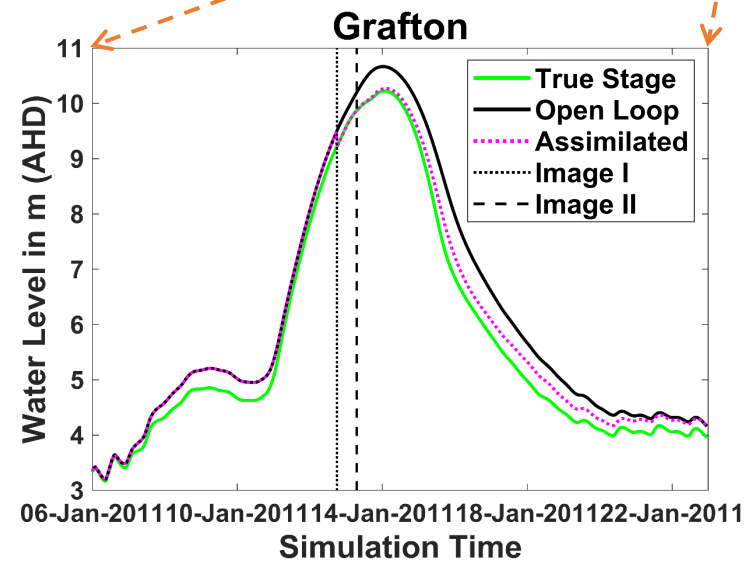
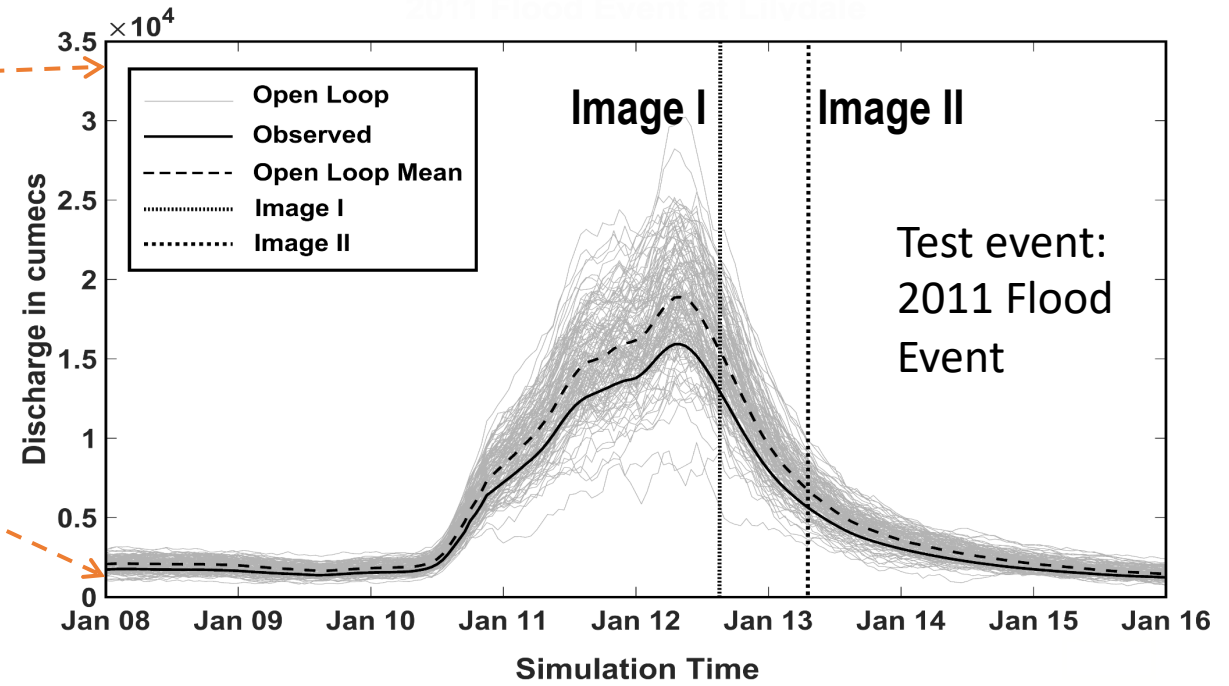
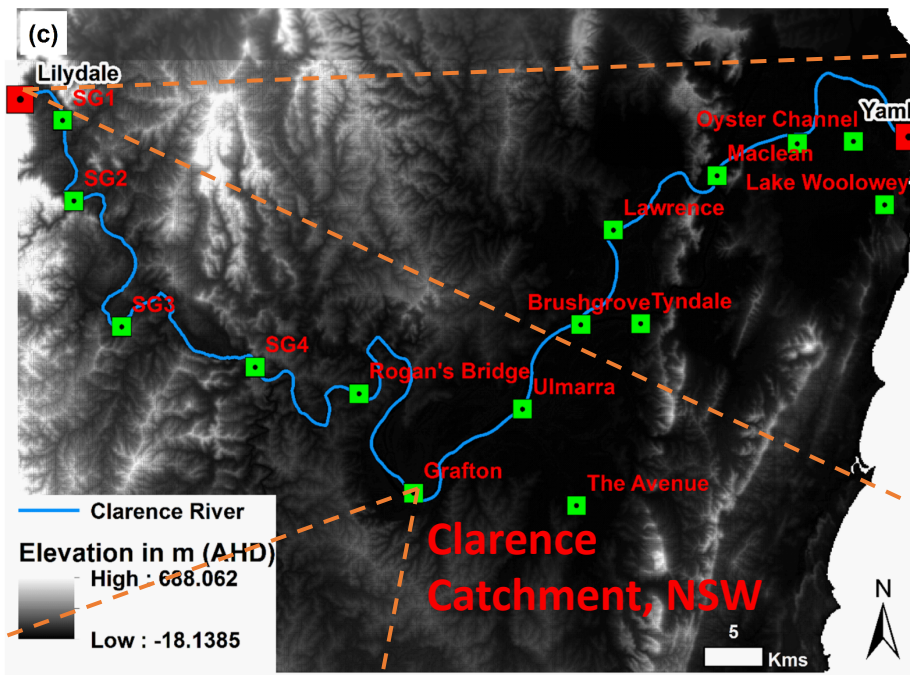
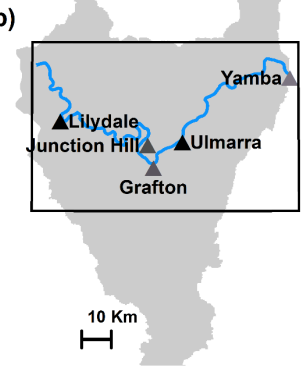


MI=KLD



Zoom in using rescaling factor to enhance sensitivity

# Key Results



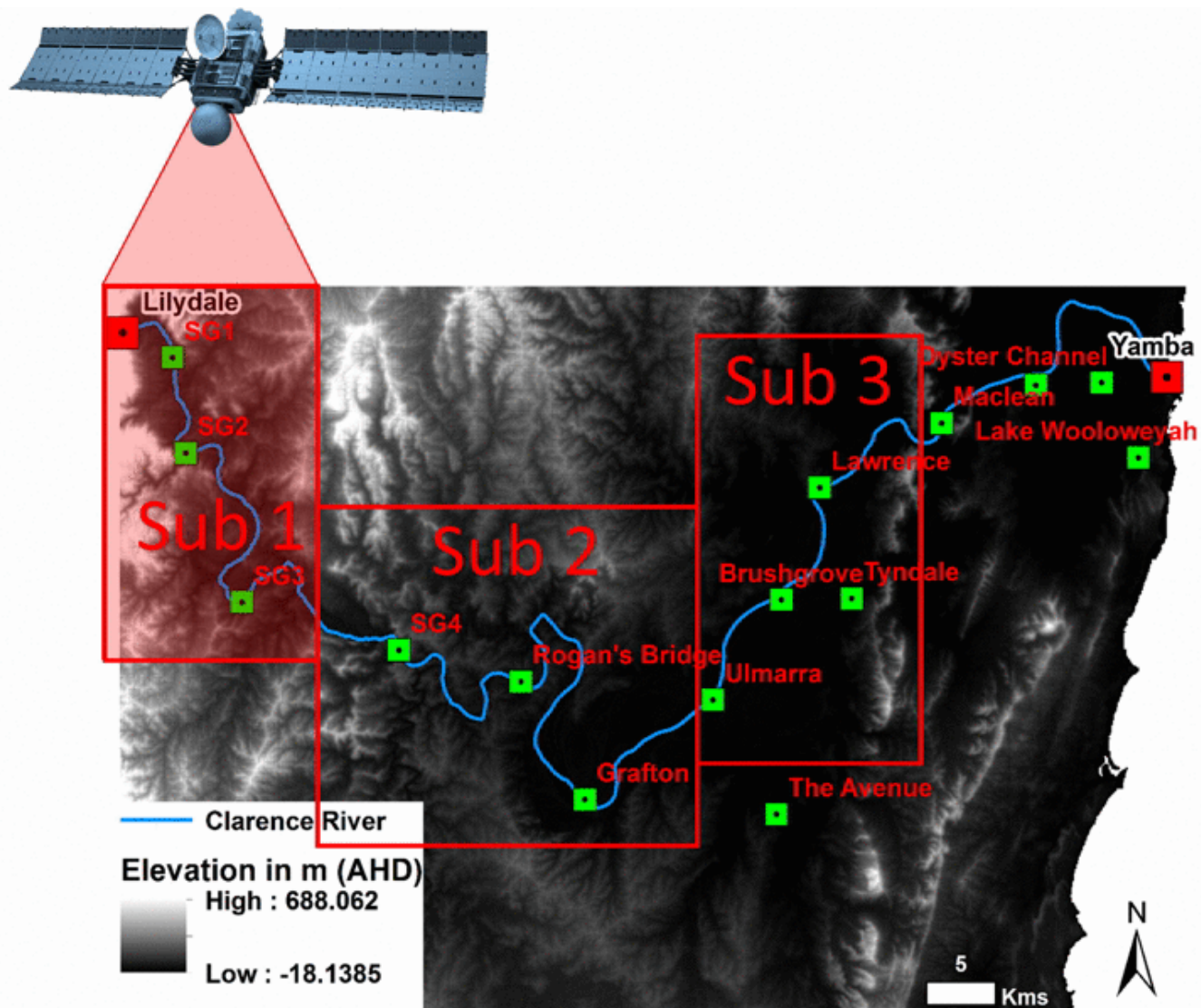
$$CSI = \frac{Hits}{Hits + Misses + False Alarms}$$

# Finding the Best Flood Observations to Correct Flood Forecasts

Dasgupta, A., Hostache, R., Ramsankaran, R., Pauwels, V.R.N., Schumann, G.J.P., Grimaldi, S., and Walker, J.P. On the impacts of observation footprint, timing, and frequency on flood extent assimilation performance. *Water Resources Research* (Accept after minor revisions).

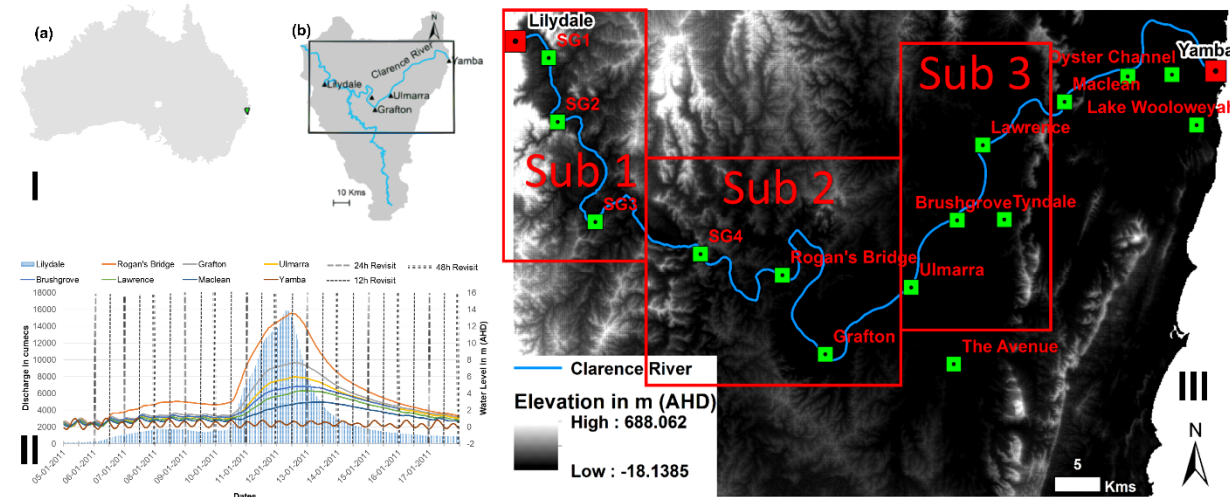
# Current Challenges

Only partial coverage for large catchments using high-res satellites



# Potential Solution

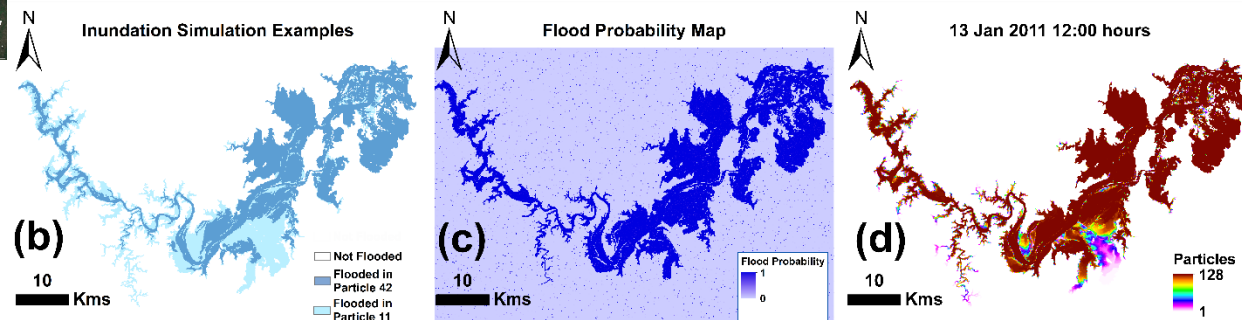
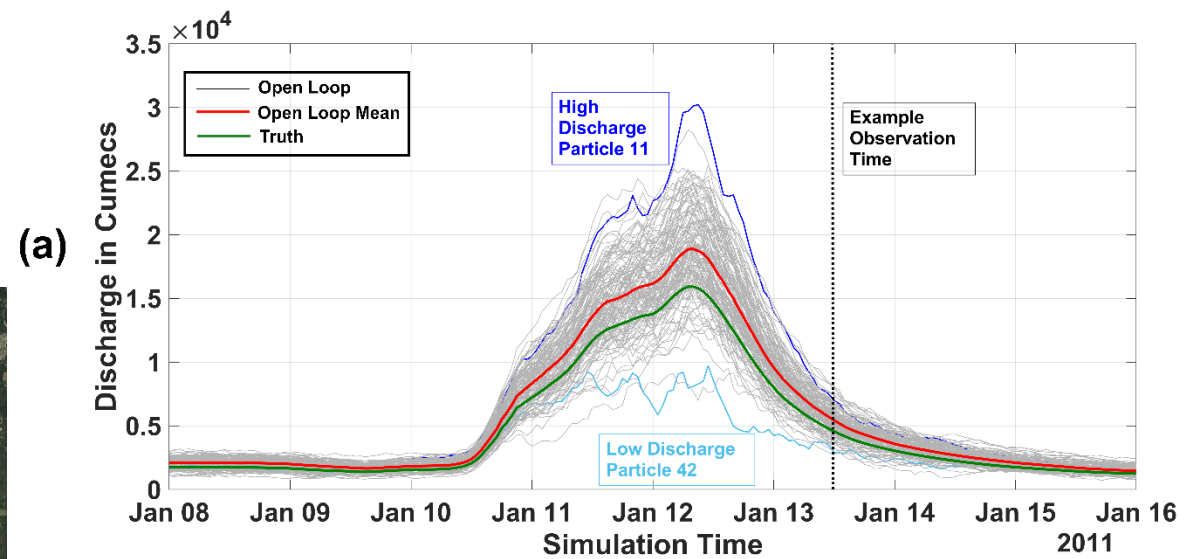
Targeted observations based on river reach characteristics



Narrow steep valley, no backwater

Flat gentle valley, little backwater

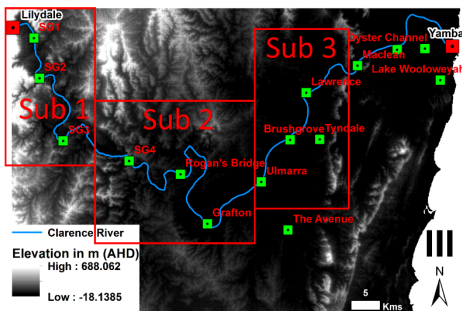
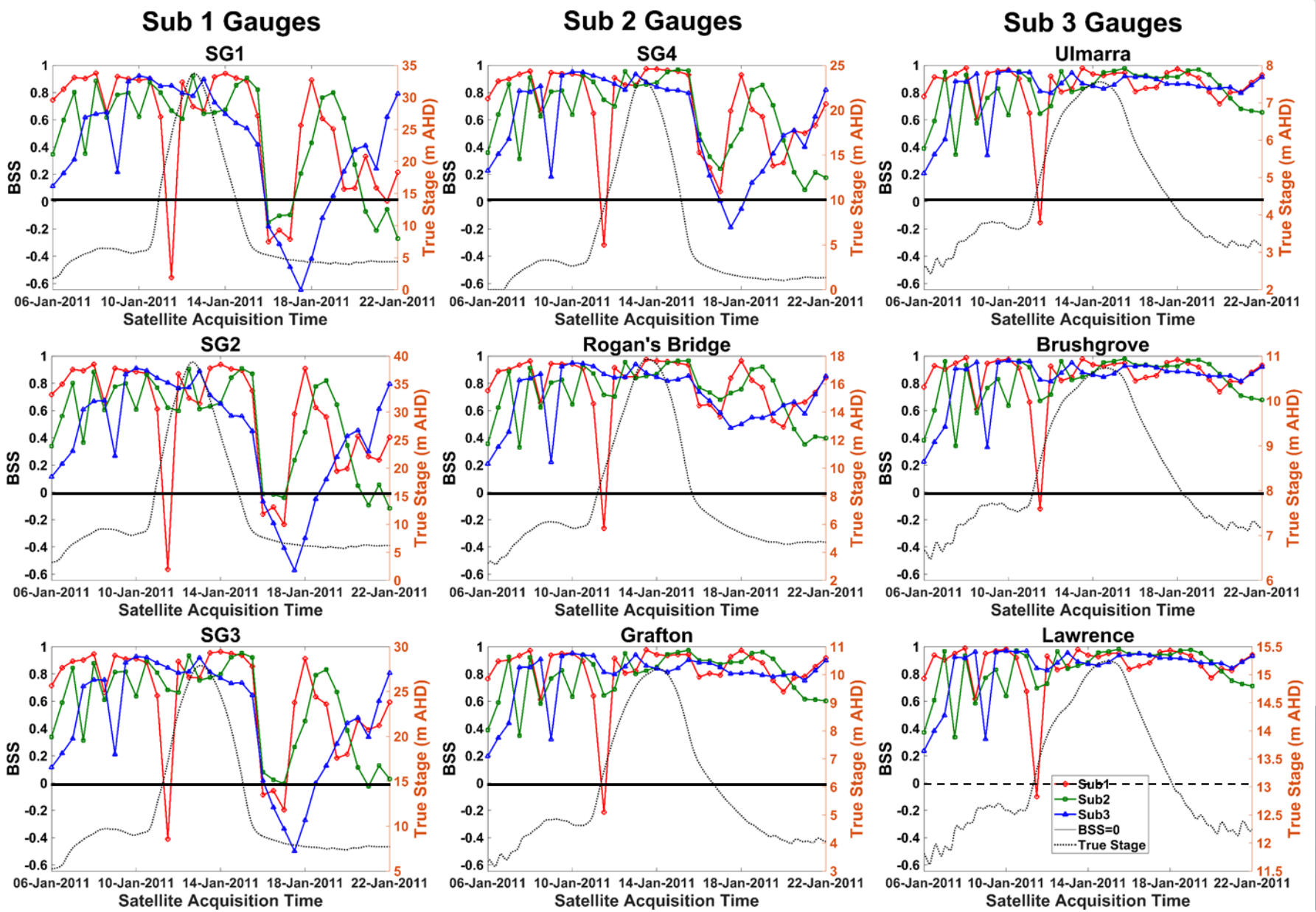
Flat gentle valley, dominant backwater



# Key Results

Brier Skill Scores showing the improvement in the forecast with the assimilation as compared to the forecast without the assimilation

**BSS=1 means 100% improvement!!!**



# The Way Forward



# Outlook

Develop observation  
localization strategy in  
space and time

Scale for global  
implementation and  
integration with GloFAS

Test for different  
catchment  
characteristics and real  
cases



**Feedback/Questions:**

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