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MONASH ENGINEERING

Optimizing SAR-based Flood Extent Assimilation for Improved Flood Inundation Forecasts

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Accurate Forecasts Needed to Mitigate Flood Risk

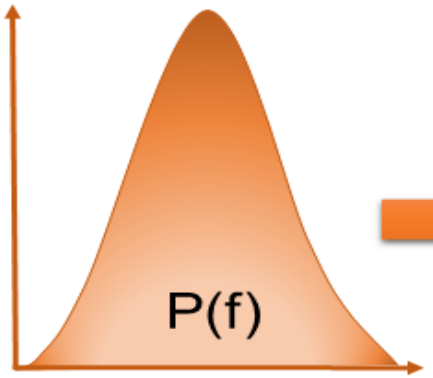
Monsoon floods, Maharashtra, Western India, 2019

Floods in Evesham, River Avon, UK, 2019

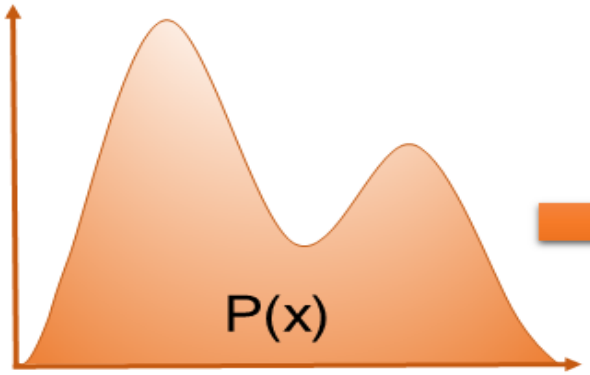
Source: Image #1News 18 (https://www.news18.com/photogallery/india/maharashtra-floods-dramatic-visuals-of-monsoon-fury-2214801-1.html); Image #2 BBC (https://www.bbc.com/news/uk-england-50430743)

Flood Data Assimilation for Improved Forecasts?

"True" flood extent + Measurement errors =



Uncertain forcings/parameters

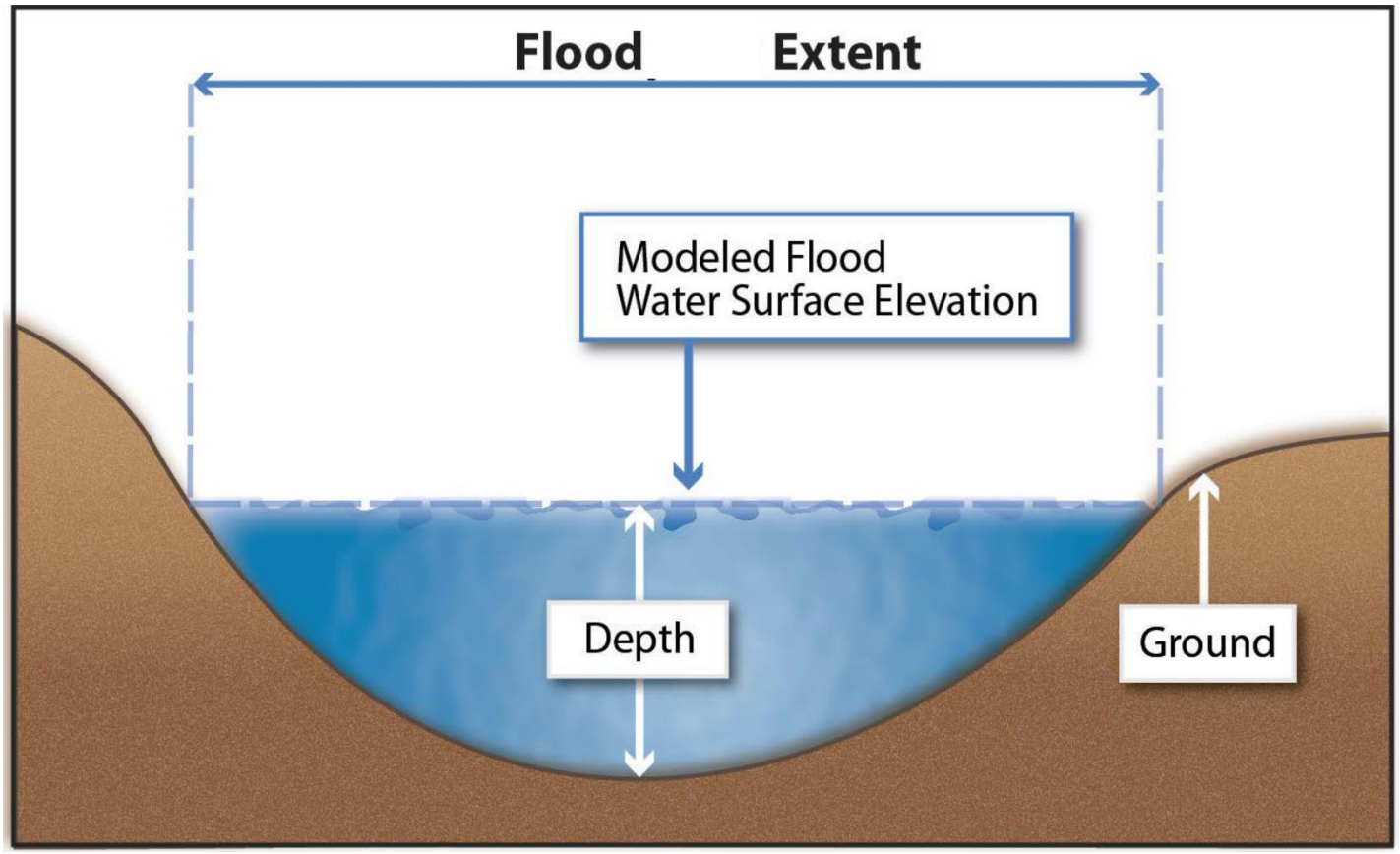


"Open loop" model states

Data Assimilation

Updated model states

Optimizing Flood Extent Assimilation

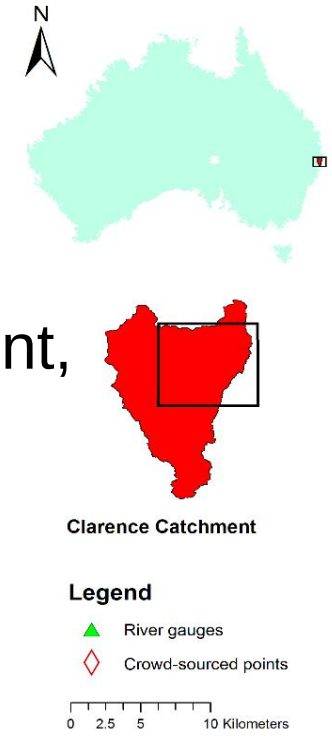


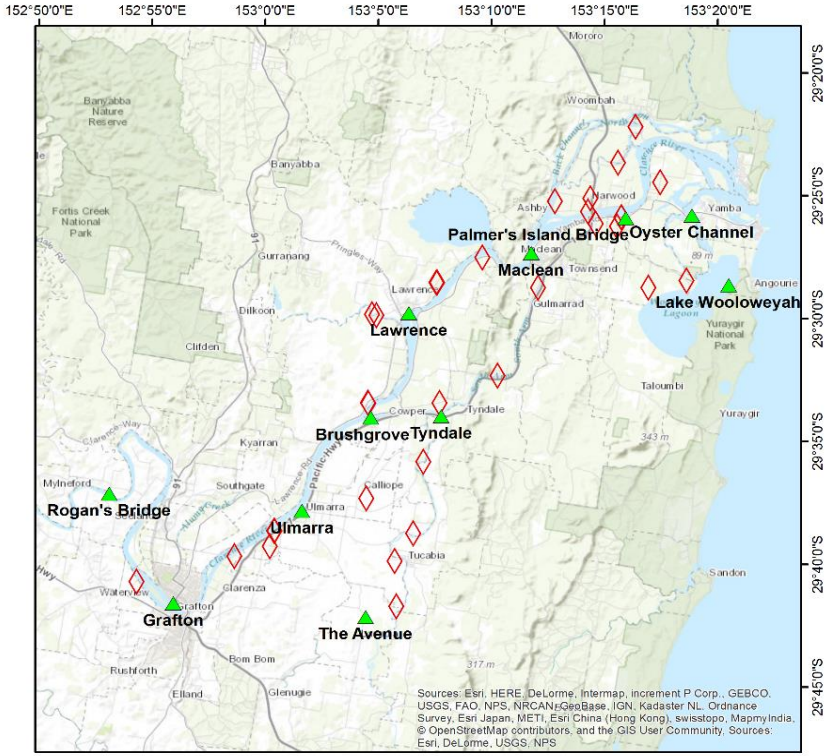
Where, when, and how often should RS data be acquired for flood extent assimilation to be most effective?

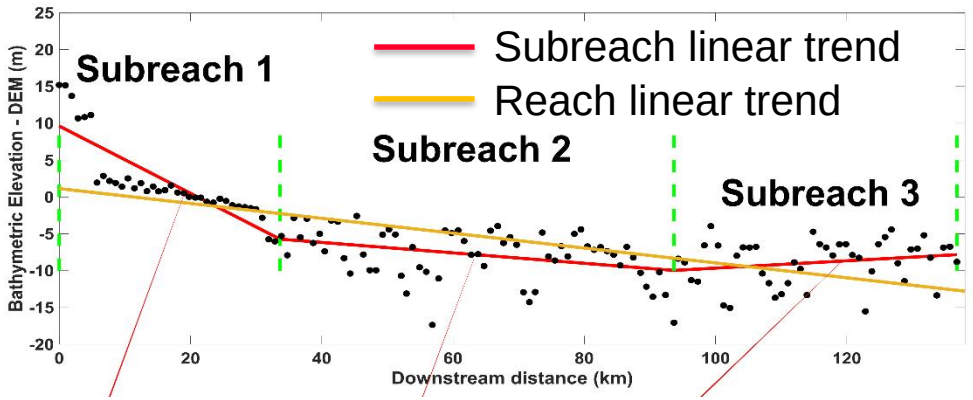
Source: FEMA, USA (https://www.fema.gov/media-library-data/1523562952942-4c54fdae20779bb004857f1915236e6c/Flood_Depth_and_Analysis_Grids_Guidance_Feb_2018.pdf)

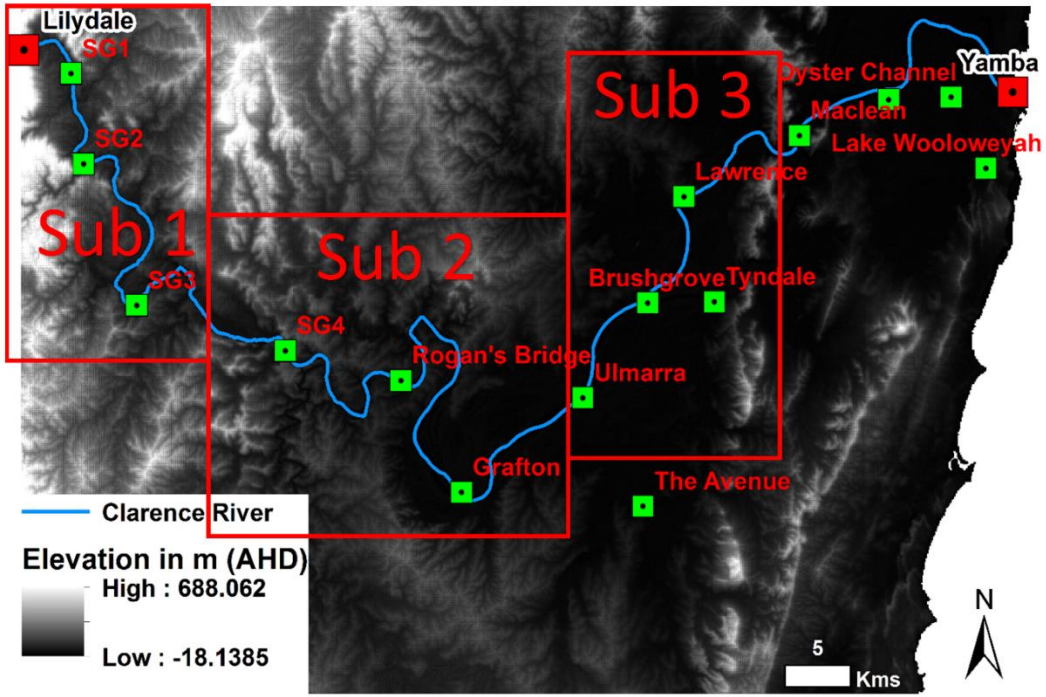
Study Site, Data Summary, and Experimental Setup

Clarence Catchment, NSW, Australia



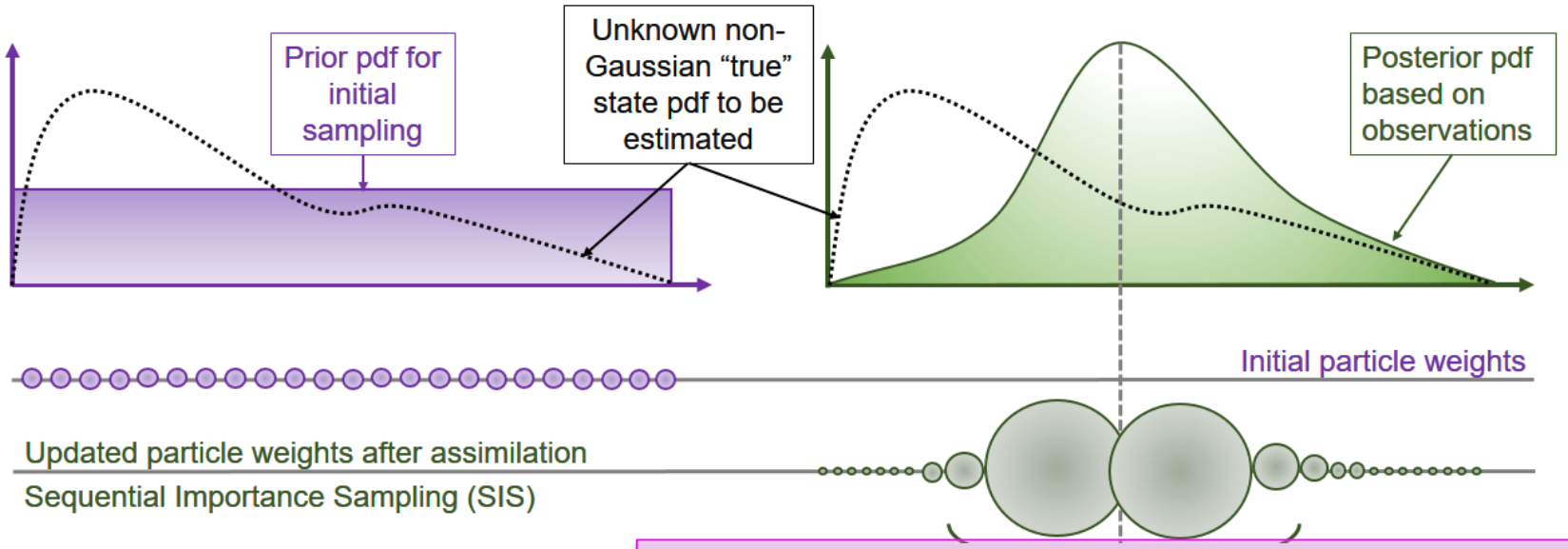


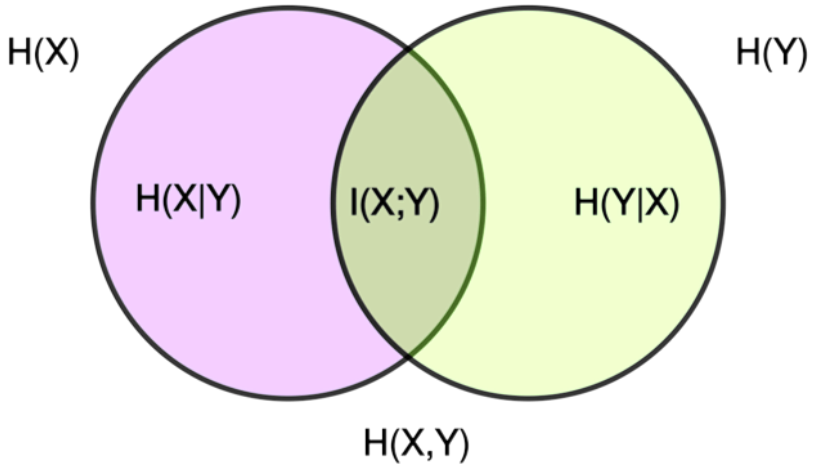




- Subreach identification using interpolated + surveyed bathymetric data.
- LiDAR DEM at 90m (±30cm), inflow hydrograph for 2011 floods (~ARI 27) + forecast inflow uncertainties, downstream tidal levels Lisflood-FP Full2D.
- Impacts on channel and floodplain water depth evaluated.

A MutualInformation-based Particle Filter for Flood Extent Assimilation





$$L_i = I(y;x) = H(x) - H(x|y)$$

Quantify likelihood of model given the observation

Particle weight calculation

$$w_i = \frac{\left(L_i - \min_i L\right)}{\left(\max_i L - \min_i L\right)} \times \left(\frac{L_i}{\max_i L}\right)^{\vartheta}$$

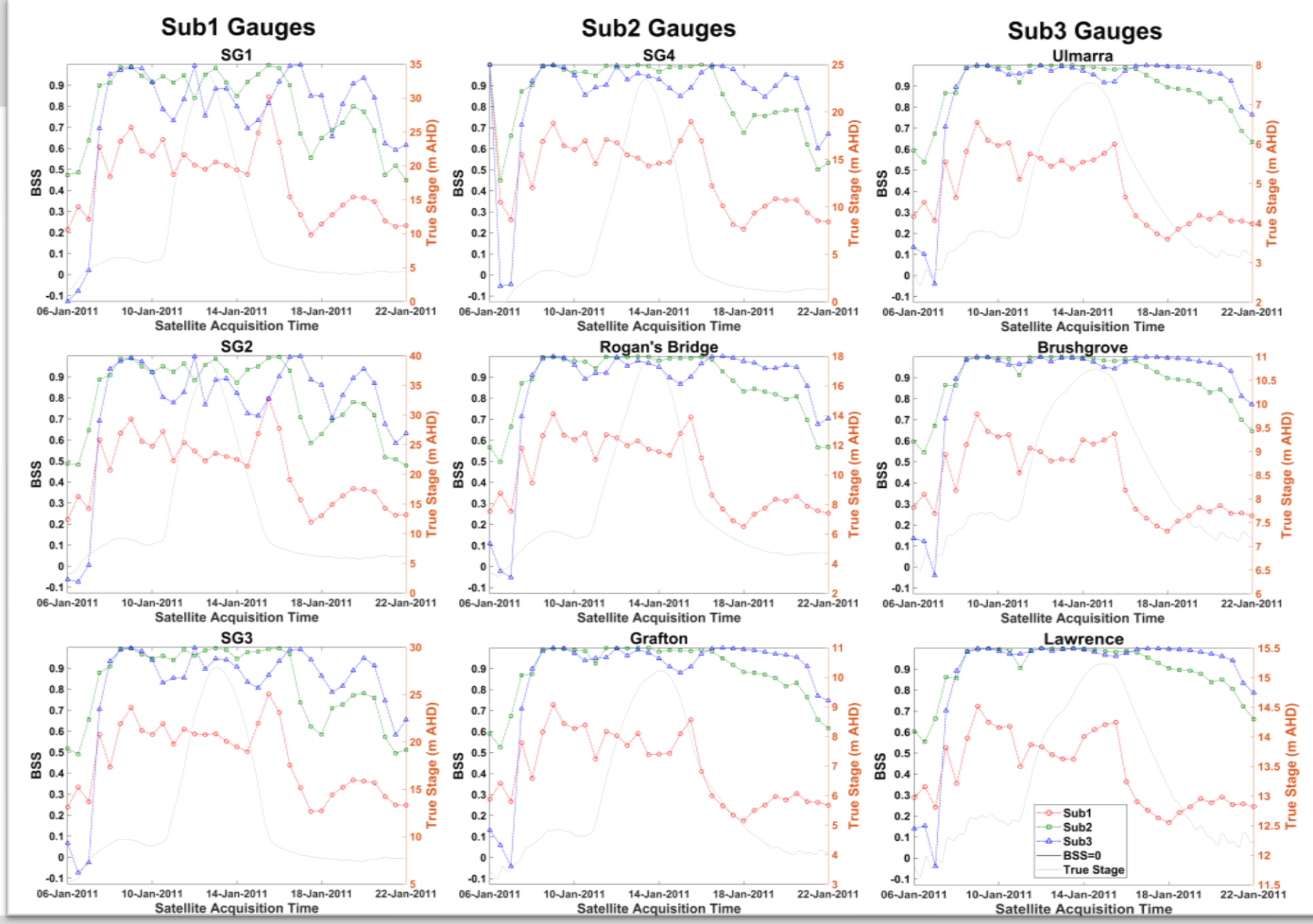
Calculate probabilities based on the agreement, by rescaling from 0 to 1

$$W_i = \frac{w_i}{\sum_{i=1}^{N} w_i}$$

Normalize so weights sum up to 1 as in a PDF

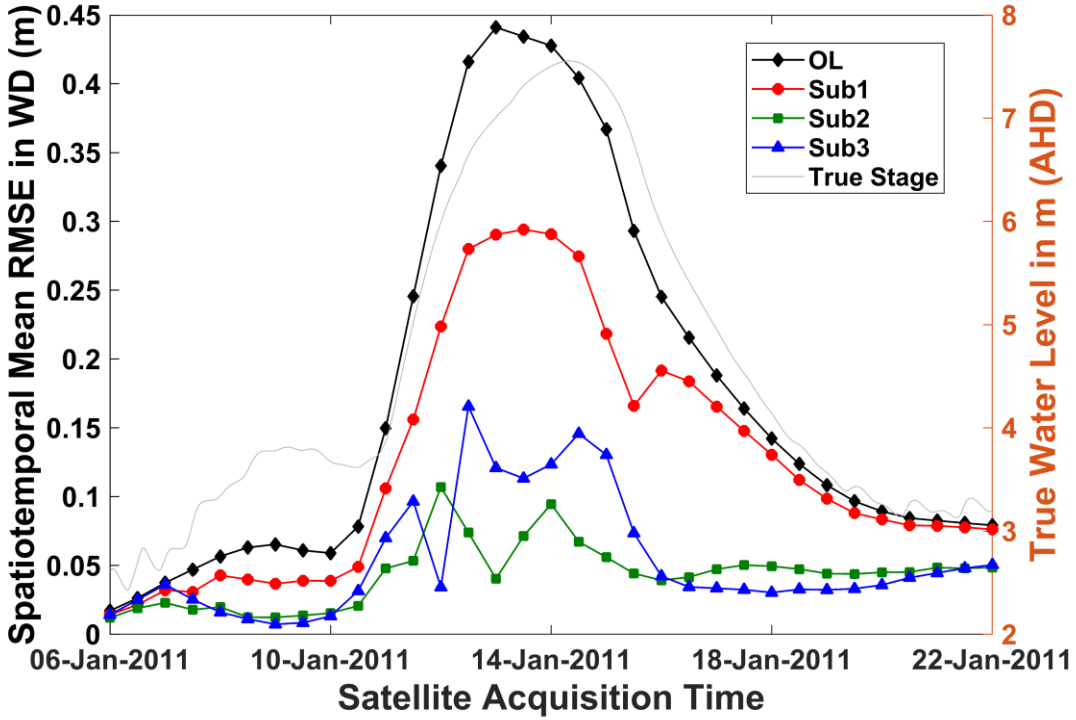
Q: When and where is a single image most helpful for the next assimilation time step?

- Assimilation impact on next 12h after the assimilation evaluated



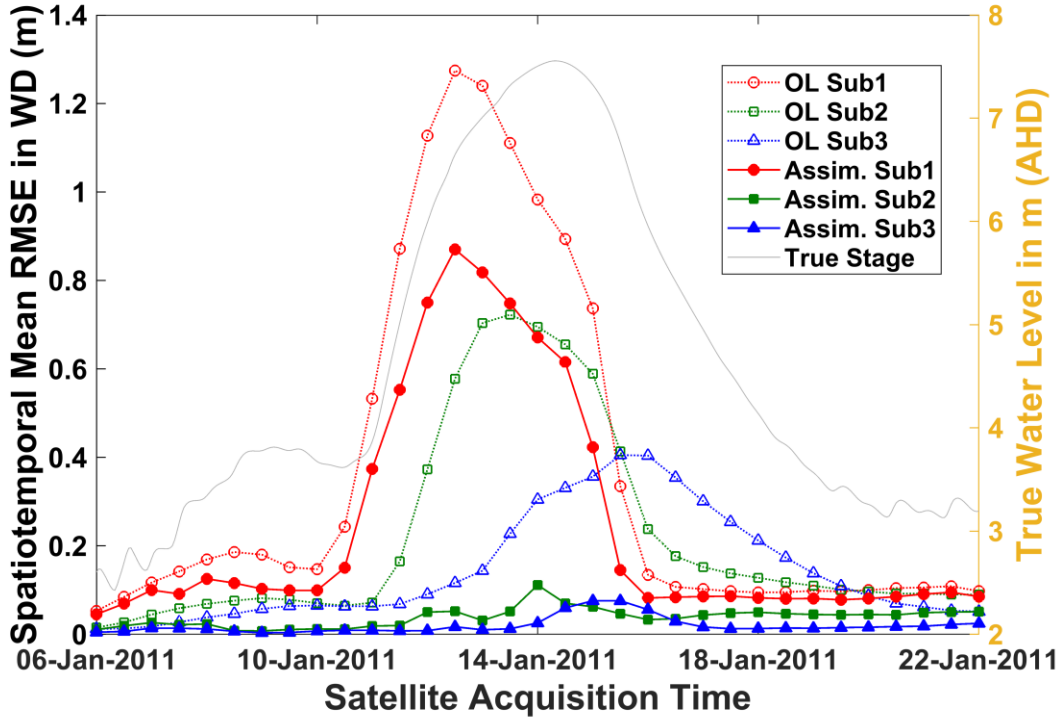
Impact on Floodplain Water Depth Simulation

GLOBAL



(a)

LOCAL



(b)

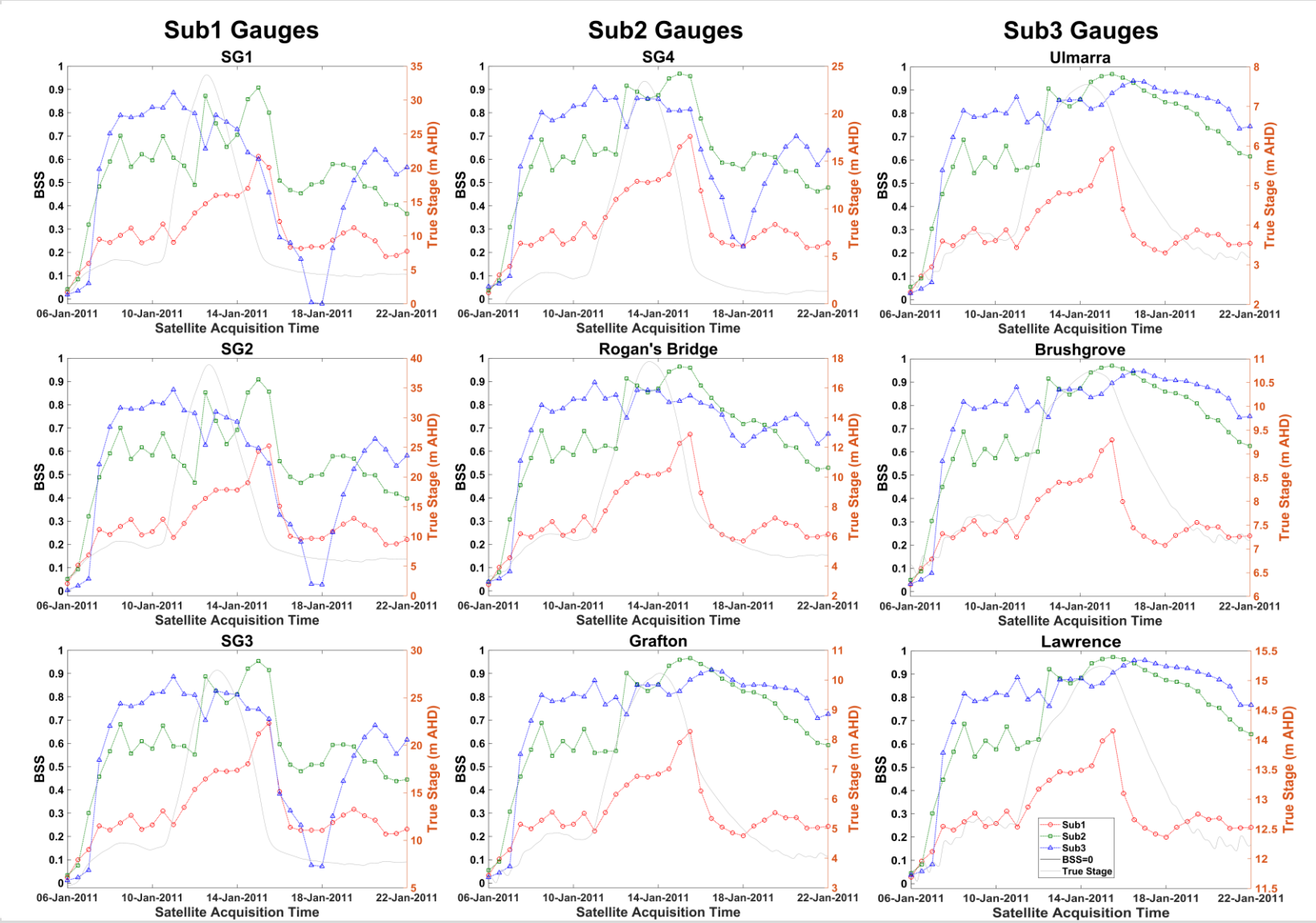
- Spatial impact on next 12h after the assimilation evaluated
- RMSE averaged across whole model domain – Global case
- RMSE averaged across assimilation sub-domains – Local case

Q: When and where is a single image most helpful for the whole forecast?

- Single images every 12h start 6 Jan
- Images assimilated only at given subreach
- Impact from first visit to 22 Jan evaluated

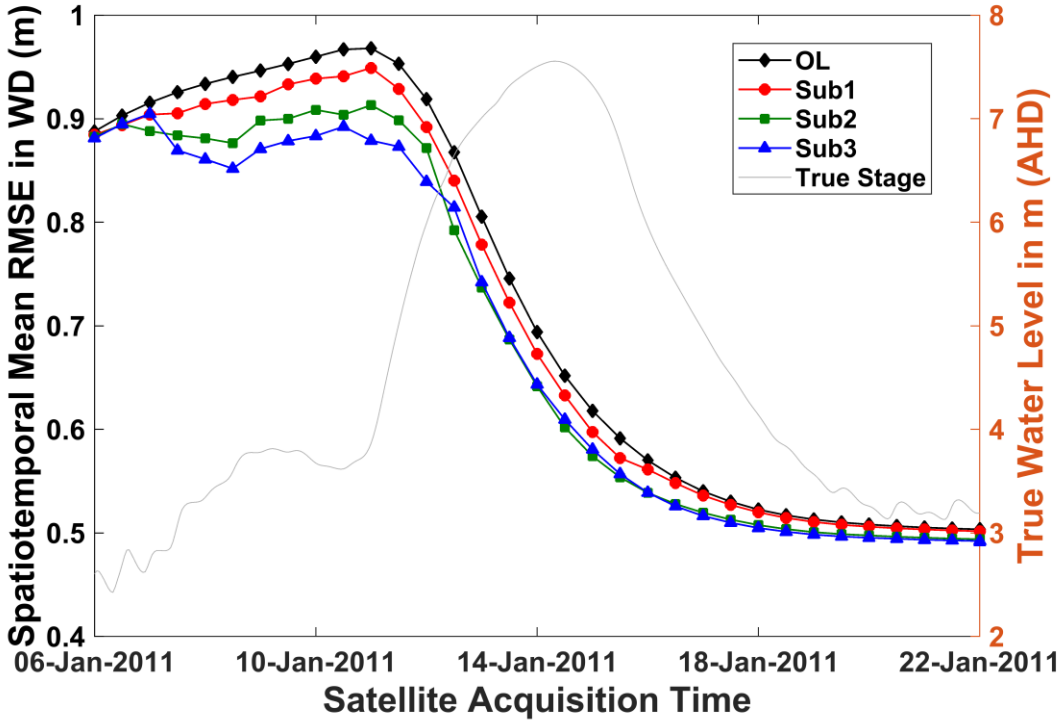
$$\mathrm{BSS} = 1 - \frac{\overline{(\mathbf{Assim.} - \mathbf{Truth})^2}}{\overline{(\mathbf{OL} - \mathbf{Truth})^2}}$$

- BSS=0 – no impact
- BSS<0 – -ve impact
- BSS>0 – +ve impact



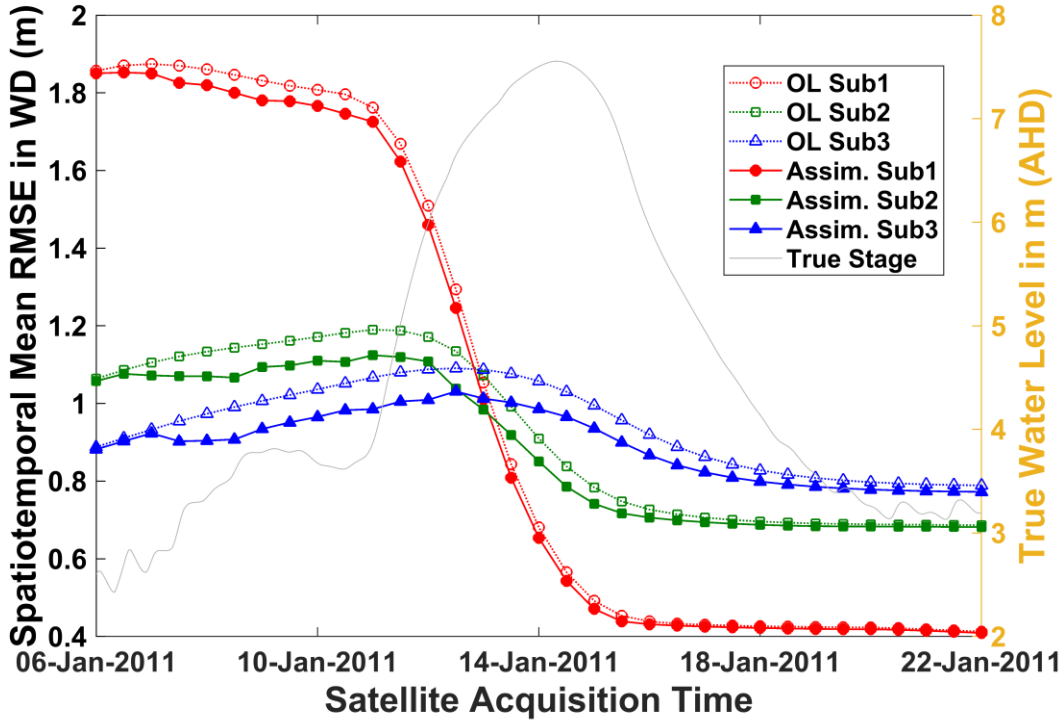
Impact on Floodplain Water Depth Simulation

GLOBAL



(a)

LOCAL

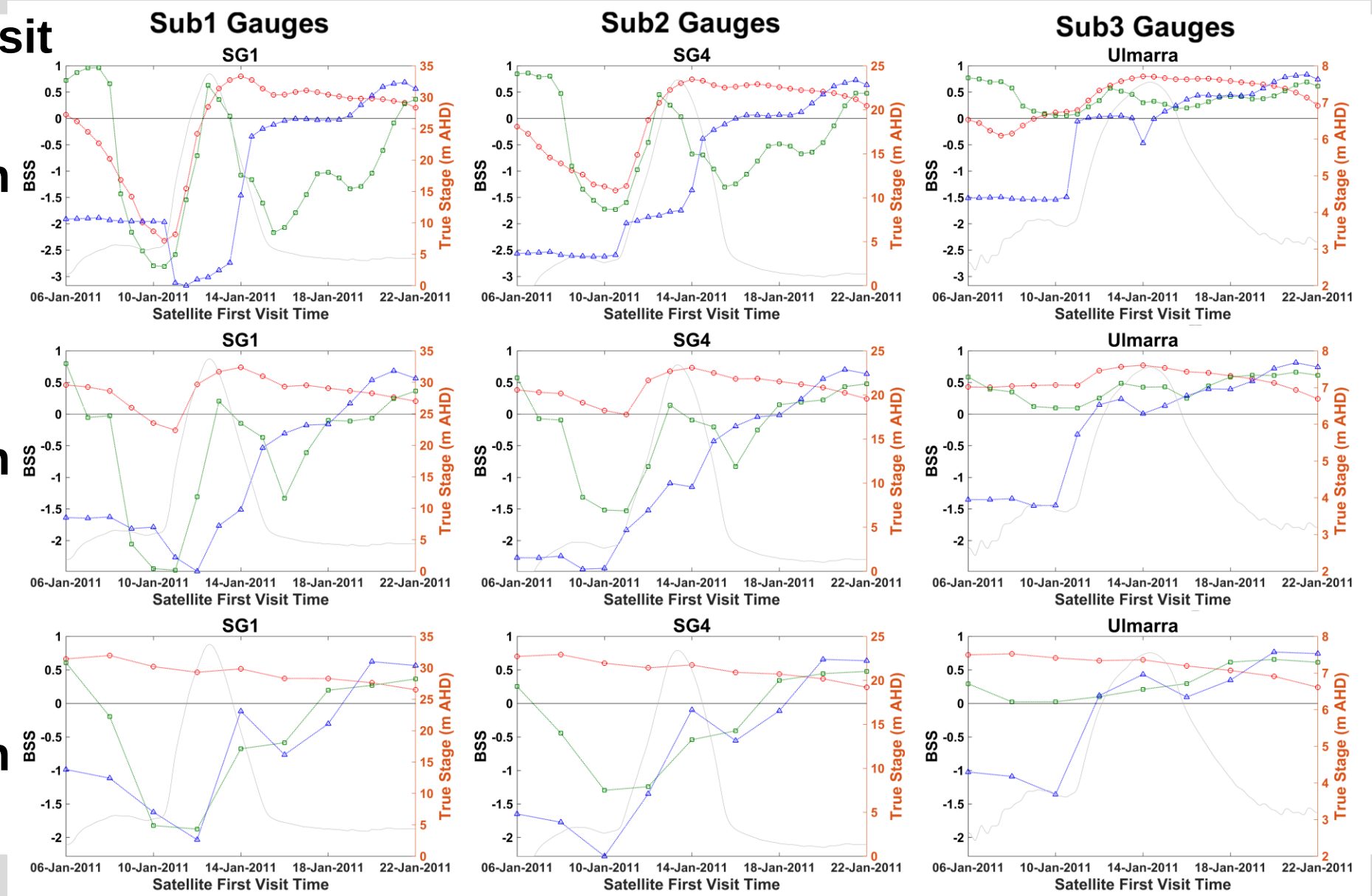


(b)

- Spatial impact on entire forecast duration evaluated
- RMSE averaged across whole model domain – Global case
- RMSE averaged across assimilation sub-domains – Local case

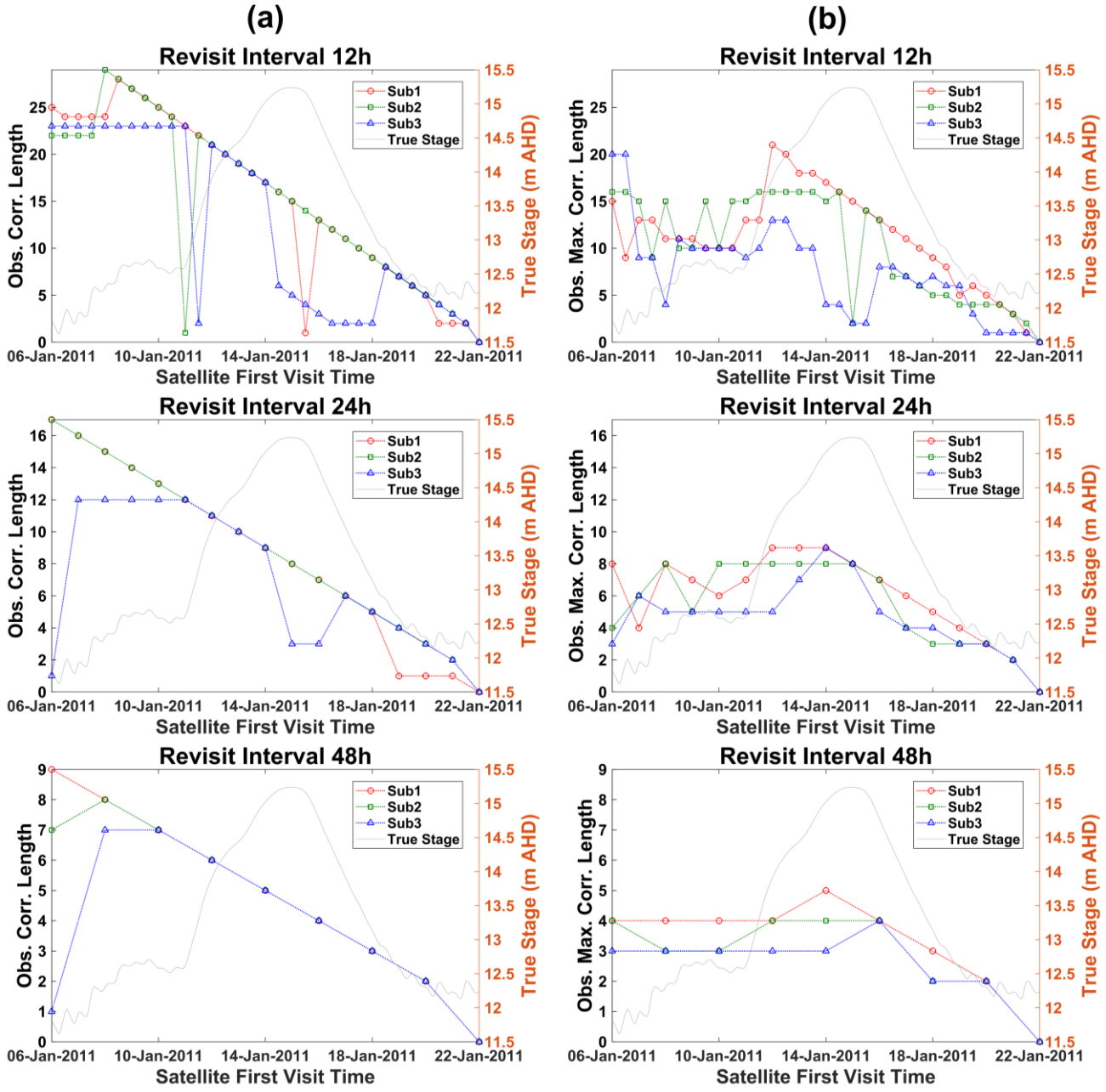
Q: How do first visit time and revisit frequency impact assimilation efficiency?

- Multiple images assimilated with first visit times starting 6 Jan
- First visit times are lagged by one revisit interval each time
- Impact from first visit to 22 Jan evaluated



Q: How many observations together have a positive impact?

- Weights were multiplied forward
- Impact evaluated from each assimilation time step to next
- Each point on each curve shows the number of images showing positive impacts with weight multiplication (y-axis) w.r.t the first visit time (x-axis)
- (a) shows number of images with positive impact while (b) shows number of images resulting in maximum positive impact vs. first visit time



Maximum Improvements Possible

Sub-reach	Reach Hydraulic Behaviour	Dominant Flow Control	Revisit	Max. BSS	First Visit	Time of Max. Imp.	No. of Images Assimilated
I	Kinematic	Topography	12h	0.9996	08-01-2011 12:00	14-01-2011 00:00	11
			24h	0.9825	10-01-2011 00:00	16-01-2011 00:00	6
			48h	0.8536	10-01-2011 00:00	18-01-2011 00:00	4
			Single	0.6516	15-01-2011 12:00:00	Full forecast	1
II	Hydrodynamic	Inflows during the rising limb and flood propagation during the falling limb	12h	0.9992	09-01-2011 00:00:00, 10-01-2011 00:00:00	14-01-2011 00:00:00, 15-01-2011 00:00:00	11
			24h	0.9988	12-01-2011 00:00	20-01-2011 00:00	8
			48h	0.9929	14-01-2011 00:00	22-01-2011 00:00	4
			Single	**0.9529**	**15-01-2011 00:00:00**	**Full forecast**	**1**
III	Hydrodynamic	Tidal backwater effects	12h	0.9994	10-01-2011 12:00	14-01-2011 12:00	8
			24h	0.9979	11-01-2011 00:00	17-01-2011 00:00	7
			48h	0.9955	06-01-2011 00:00	12-01-2011 00:00	7
			Single	0.8846	11-01-2011 00:00	Full forecast	1

Conclusions

- Assimilation efficiency was sensitive to image location and timing with respect to reach hydraulic characteristics and flood wave arrival time.
- Maximum local improvements in the channel were observed when assimilating images at and after the peak arrival time in the particular sub-reach, while most floodplain water depth improvements resulted from images just before and after the inflow peak.
- Assimilation efficiency increased from upstream to downstream for the gauges, due to the errors being added through the inflow boundary
- First visit time and observation correlation length critical for multiple image assimilation and found to be a function of the reach hydraulics.
- Assimilating a single image at the right place and right time could yield improvements comparable to multiple images.