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WP 6, Task 6.4
Hydrological modelling and data assimilation

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Task overview

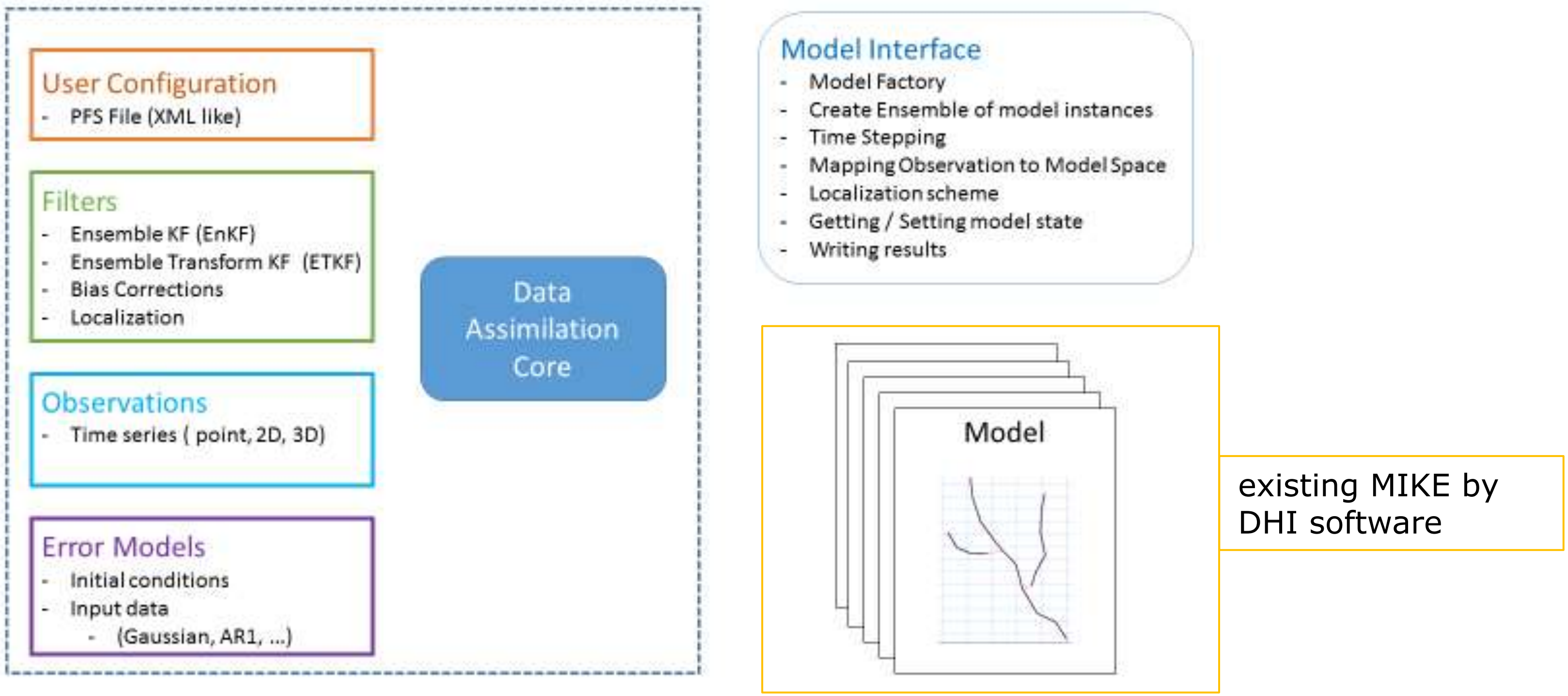
Task objectives

The objective of this task was to develop and demonstrate a catchment-scale hydrological and hydrodynamic modelling and data assimilation approach using SAR altimetry data.

Activities

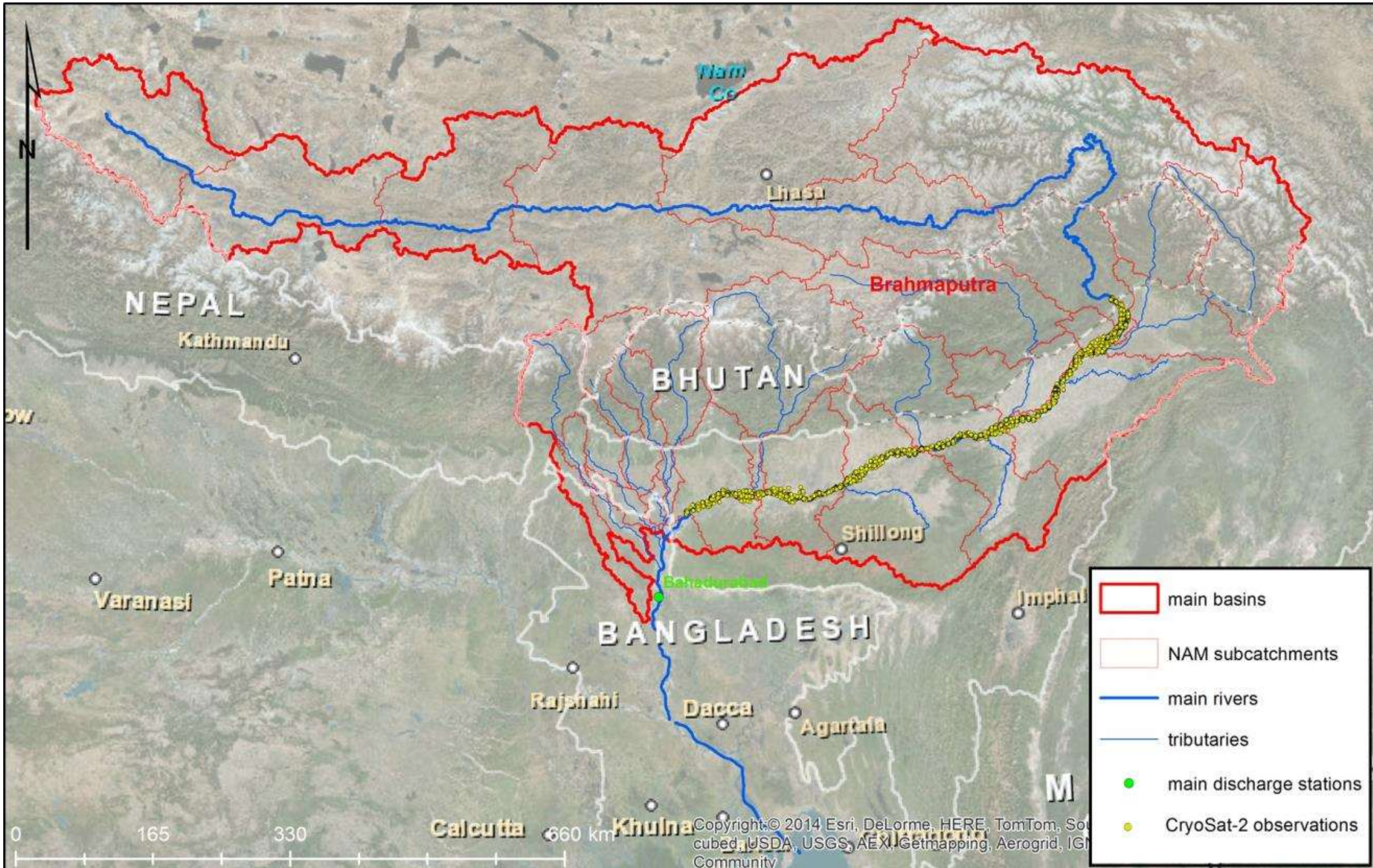
- Development of data assimilation capabilities in the MIKE 11 hydrological-hydrodynamic modelling system tailored for assimilation of drifting-orbit altimetry data (CryoSat-2).
- Demonstration of the hydrological-hydrodynamic modelling and data assimilation approach for the Brahmaputra River basin using CryoSat-2 altimeter data.
- Processed CryoSat-2 Level 2 data for the Brahmaputra River basin were provided by DTU Space.

DHI MIKE 1D Data Assimilation framework

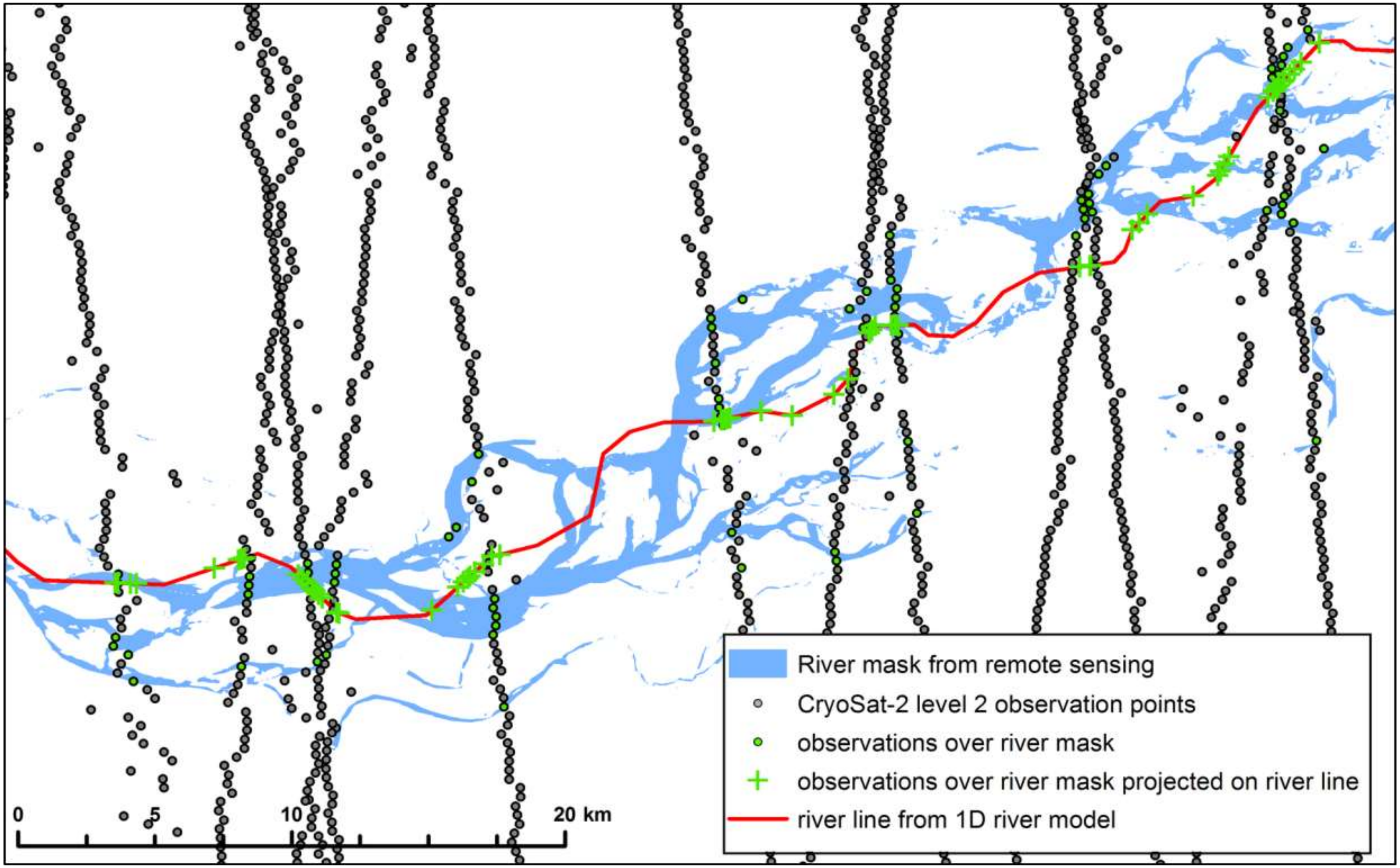


- Assimilation of spatially and temporally distributed observations of discharge and water level
- Projection of observation data onto model river network
- Flexible model error description (perturbation of model forcing or model states, with spatial and temporal correlation of error)
- Different filters and localization
- …

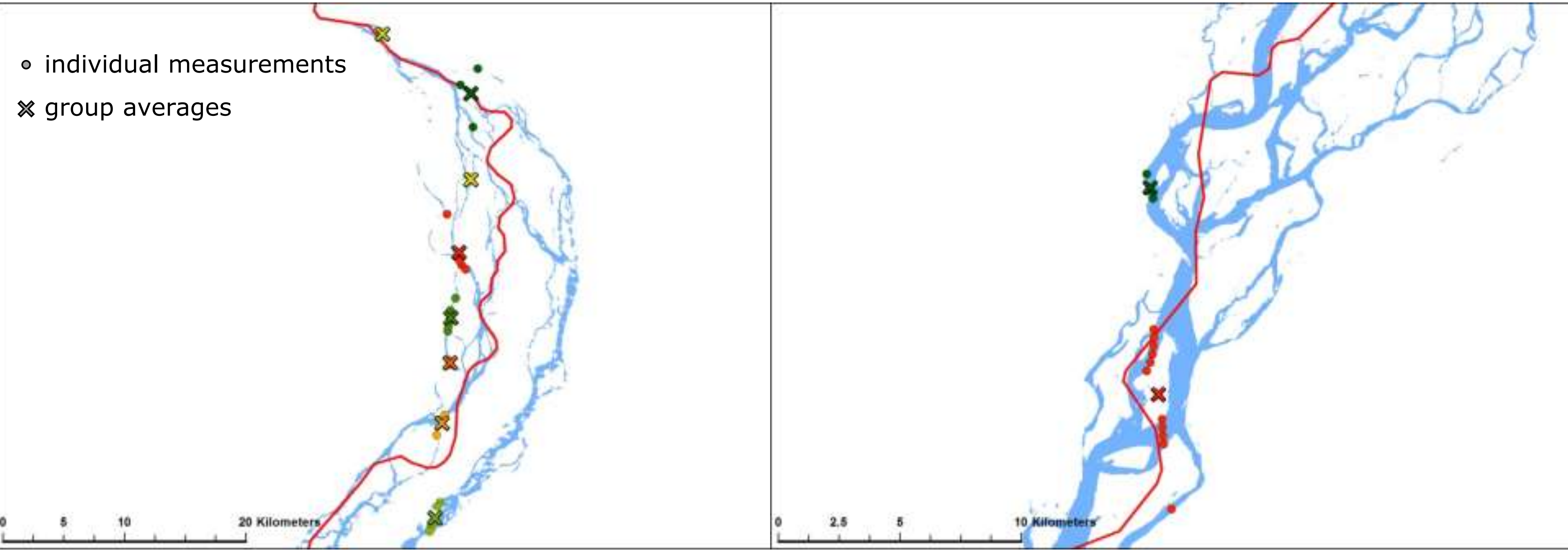
Brahmaptura case



CryoSat-2 data processing – river mask filtering



CryoSat-2 data processing - clustering



Observations of one transect are not assimilated individually

→ Aggregation into clusters based on their location. No. of cluster groups determined based on distance threshold (e.g. 5 km)

→ Average (location and elevation) of each group used as measurement to be assimilated

→ Standard deviation of elevations within one group can be used as observation standard deviation for DA

Data assimilation setup

Model error description

Via temporally and spatially correlated perturbation of forcing (runoff from NAM subcatchments)

Observation error

Standard error taken from standard deviations of elevations within each cluster group

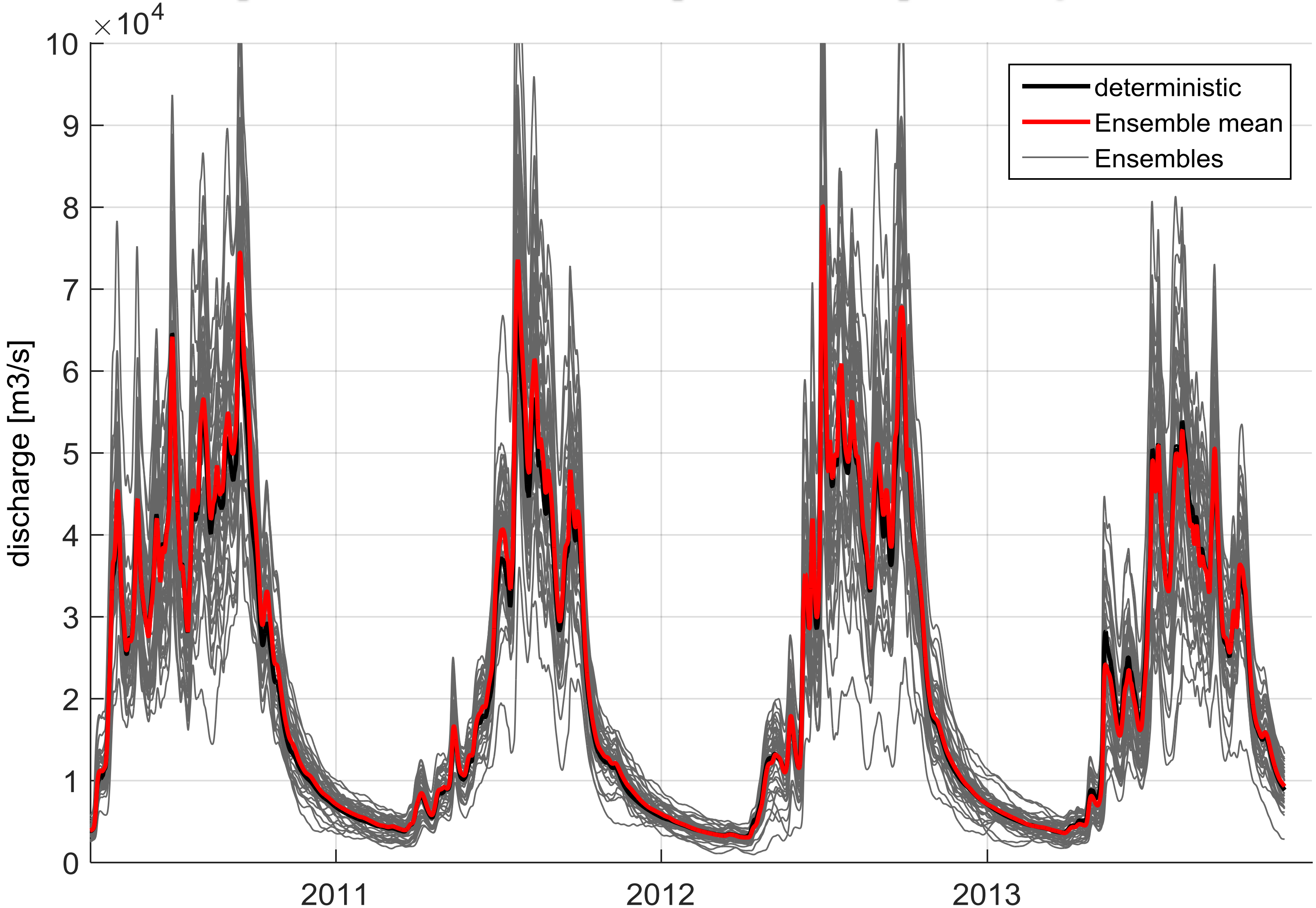
Localization

Localization needed as otherwise spurious correlations across the long river network give unreasonable updates

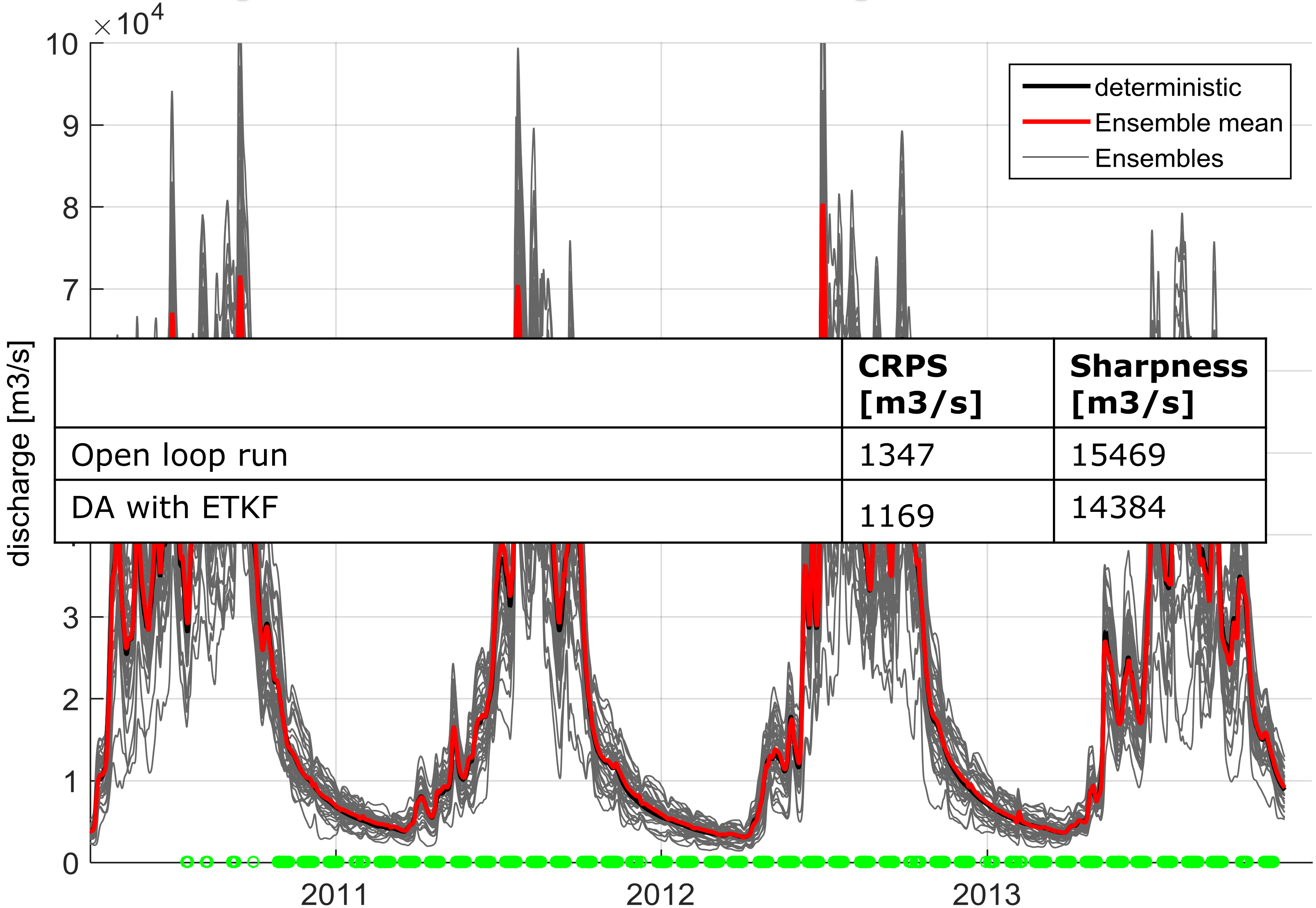
Virtual window

To spread out measurements over several simulation timesteps

Brahmaputra case – open loop run, no DA

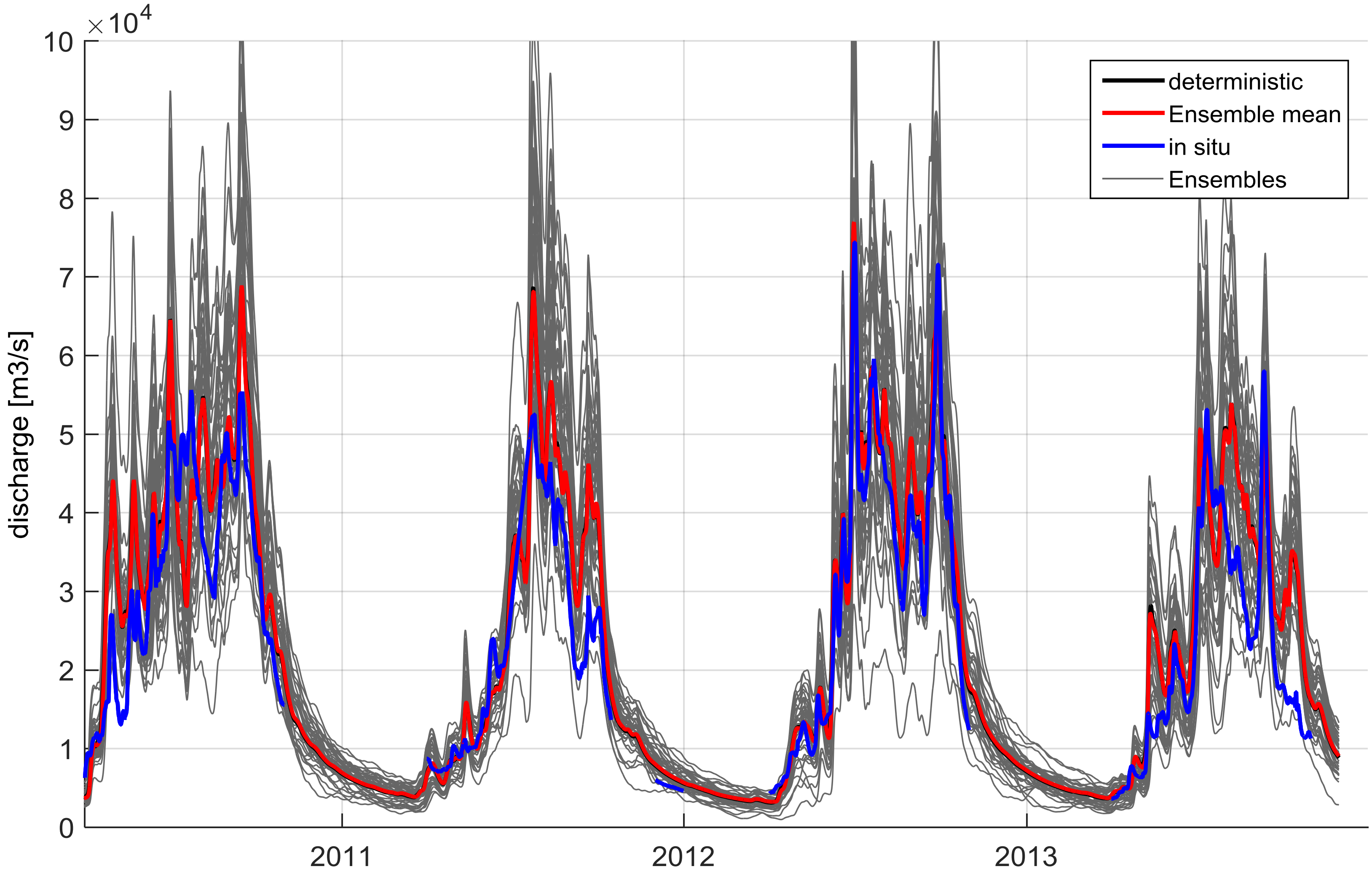


Brahmaputra case – DA of synthetic data

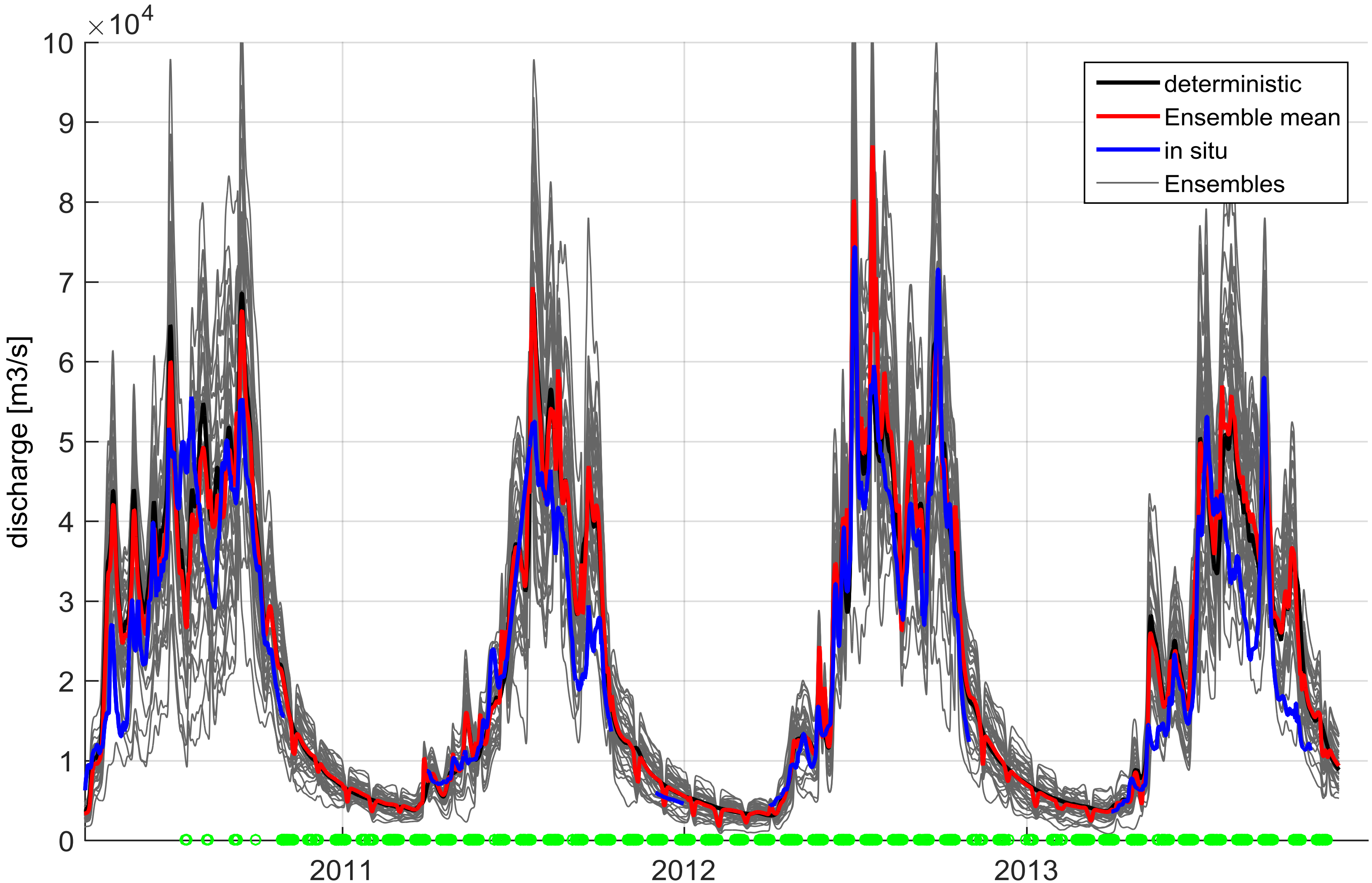


	CRPS [m3/s]	Sharpness [m3/s]
Open loop run	1347	15469
DA with ETKF	1169	14384

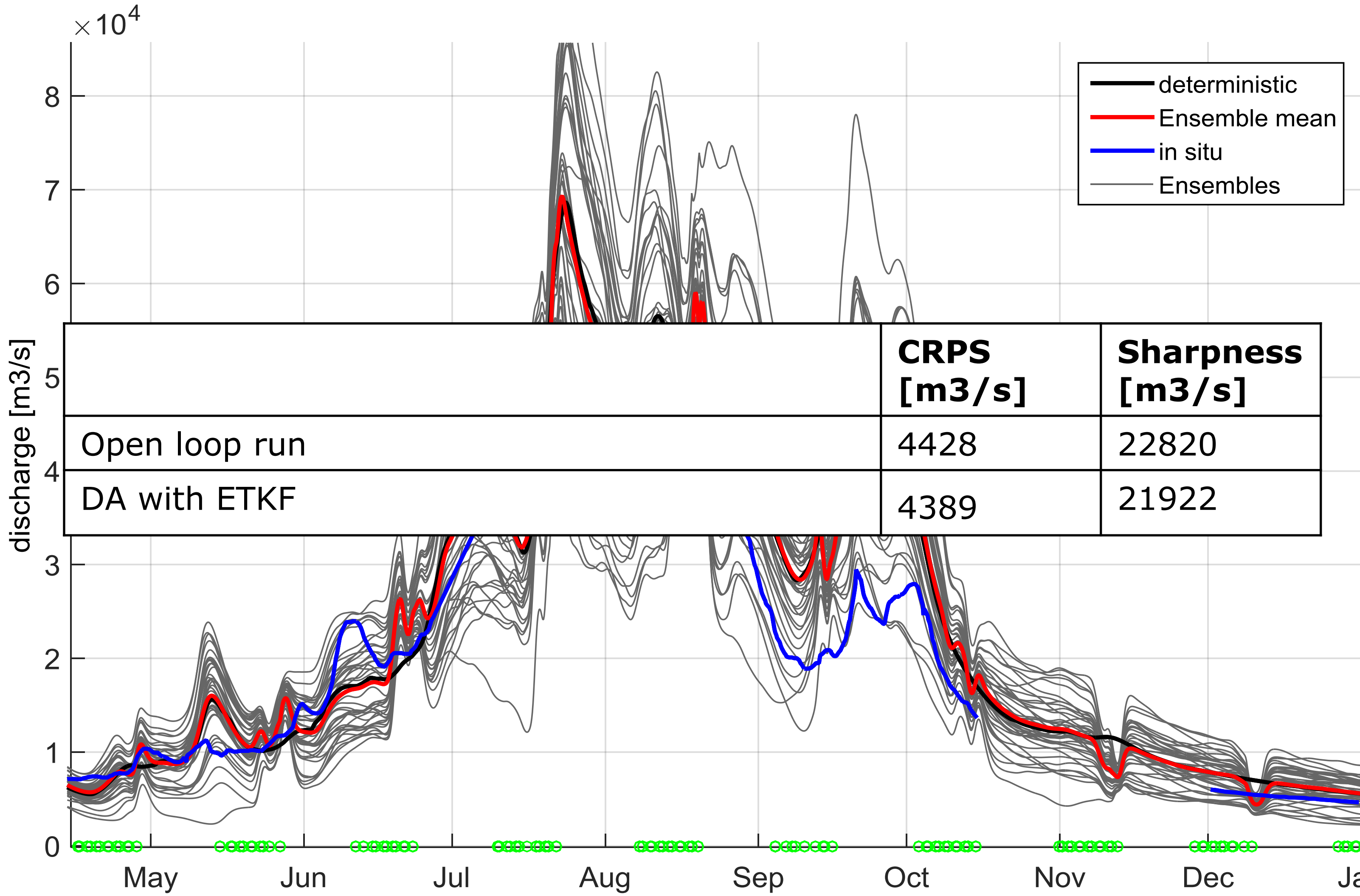
Brahmaputra case – open loop run in comparison to in-situ discharge



Brahmaputra case – DA of CryoSat-2 data



Brahmaputra case – DA of CryoSat-2 data



	CRPS [m3/s]	Sharpness [m3/s]
Open loop run	4428	22820
DA with ETKF	4389	21922

Assimilation of real CryoSat-2 data

Challenges

- Only very limited in-situ data available (one location, high-flow season only)
  → impact of observations far away from in-situ station is small
- Performance of deterministic model without DA:

	NSE	bias
Calibration period (2002 – 2007)	0.921	1.0 %
Calibration period high-flow (2002 – 2007)	0.876	2.5 %
Validation period (DA) high-flow (2010 – 2013)	0.751	16.0 %

- Short memory of updates → updating not only of water levels, but also of rainfall-runoff models

- CryoSat-2 observation error assessment

Conclusions

Further tuning of and gaining insight into **Brahmaputra DA**

- optimize localization and virtual window
- different model error description (to allow global updating?)
- different filtering of CryoSat-2 data and measurement error description
- different retracking or off-nadir correction of CryoSat-2 data

DA framework is working in principle

→ Very flexible framework that can be used for wide variety of observations and models

→ Comparison of value of (synthetic) data from different missions (CryoSat-2 vs AltiKa vs Sentinel-3 …) possible

→ Comparison of value of CryoSat-2 data with different water masks, different retrackers, different off-nadir corrections…

Some thoughts on evaluation of operational hydrologic forecasting

We always have two forecasts "for free":

- Climatology, i.e. (mean of) observations from past years
- Persistence, i.e. "tomorrow = today"

→ A meaningful hydrologic model should beat these forecasts!

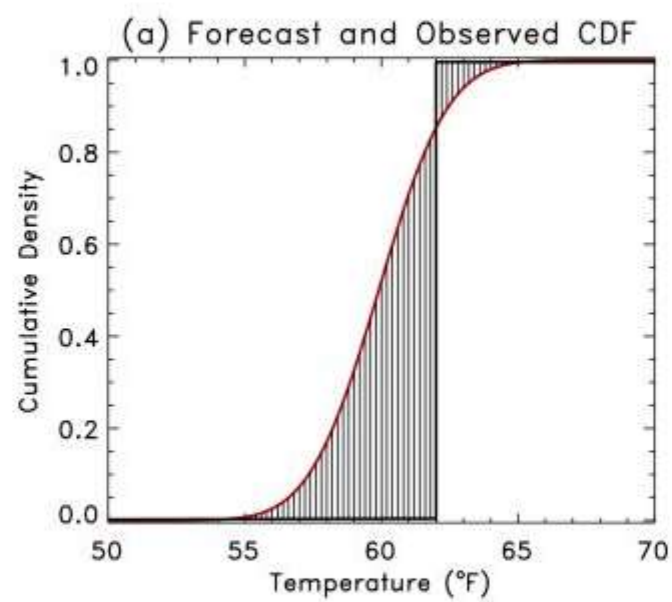
Indicator?: **Continuous Rank Probability Score (CRPS)**

$$CRPS = \frac{1}{k} * \sum_{i=1}^{k} \int_{x=-\infty}^{x=\infty} \left(F_i^f(x) - F_i^0(x)\right)^2 dx$$

where k forecast cases (timesteps)

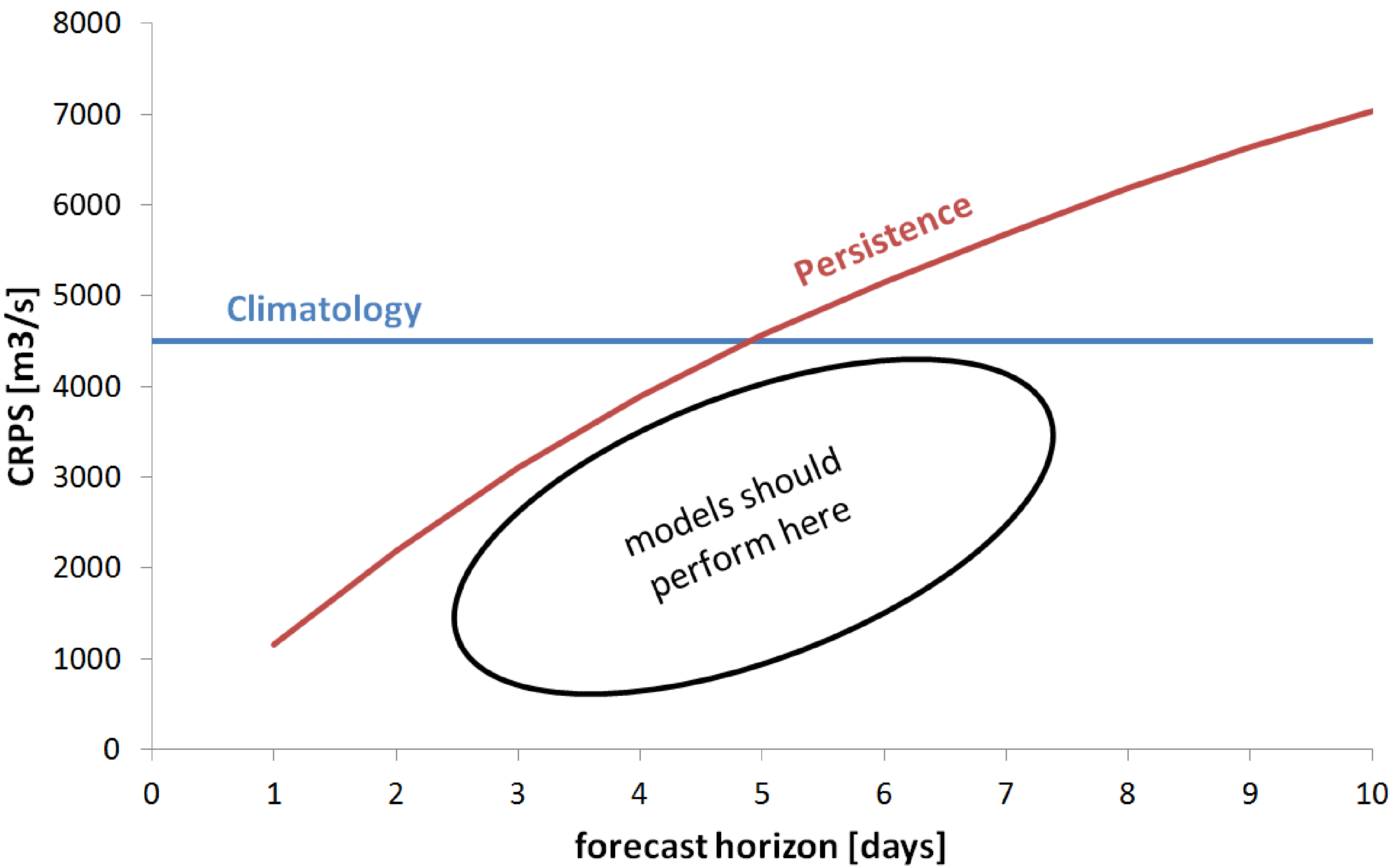
$F_i^f(x)$ forecast probability cdf of k

$F_i^0(x)$ observation at timestep k

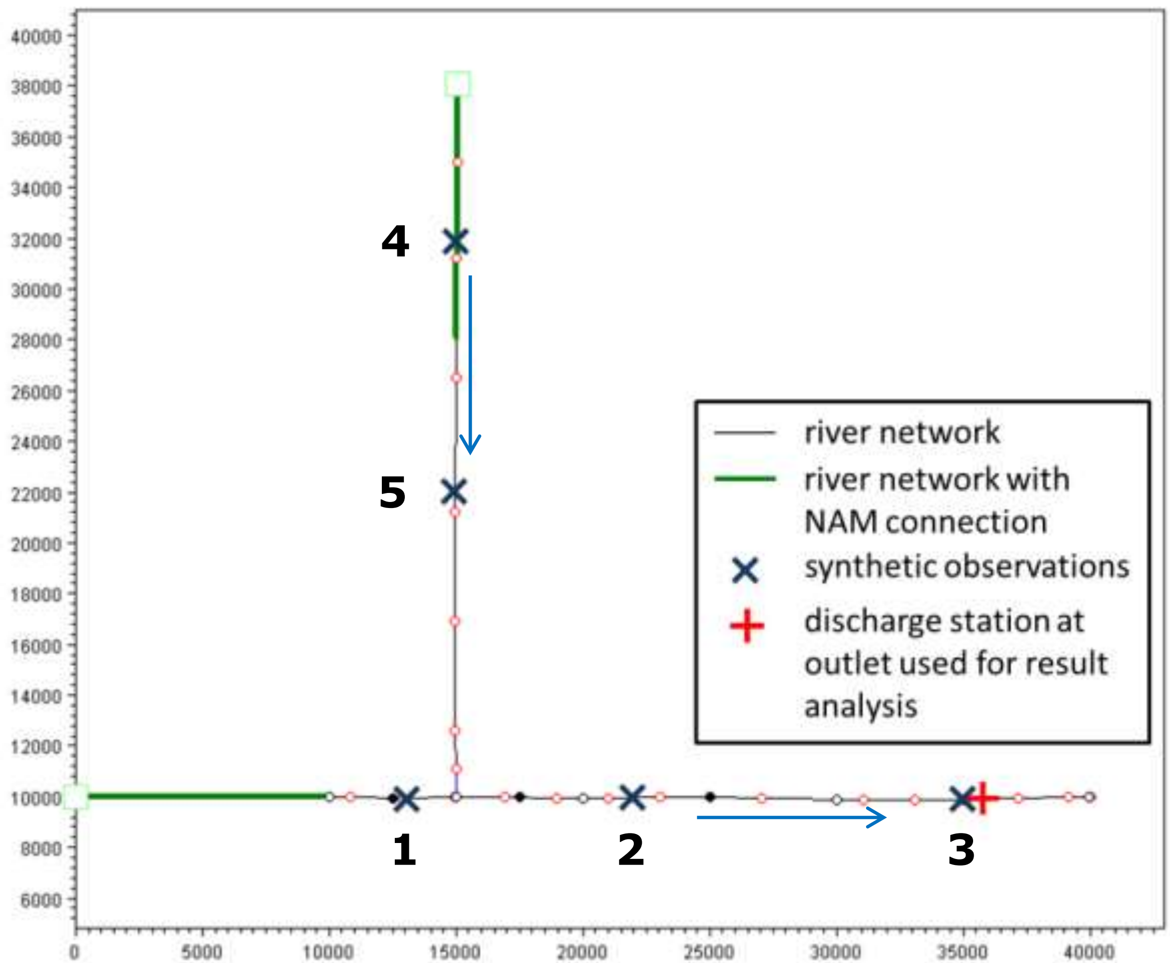


- combines reliability and sharpness
- For deterministic forecast: CRPS = MAE

CRPS for Bahadurabad on the Brahmaputra



Synthetic test case



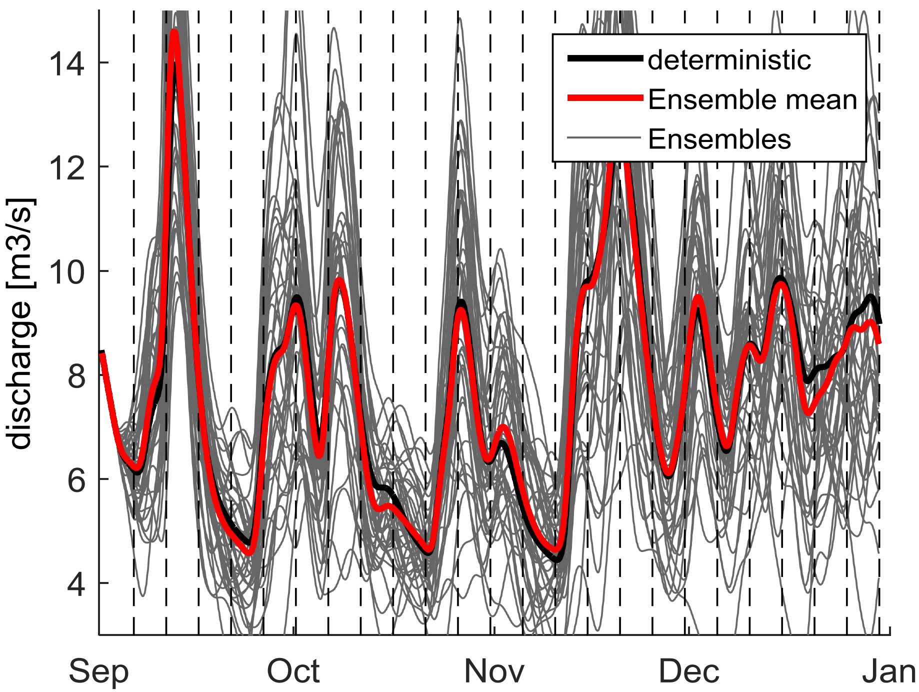
Test case with

- 2 river branches
- 2 NAM catchments for runoff forcing
- Synthetic observations distributed in space and time
- Model error description by runoff forcing perturbation

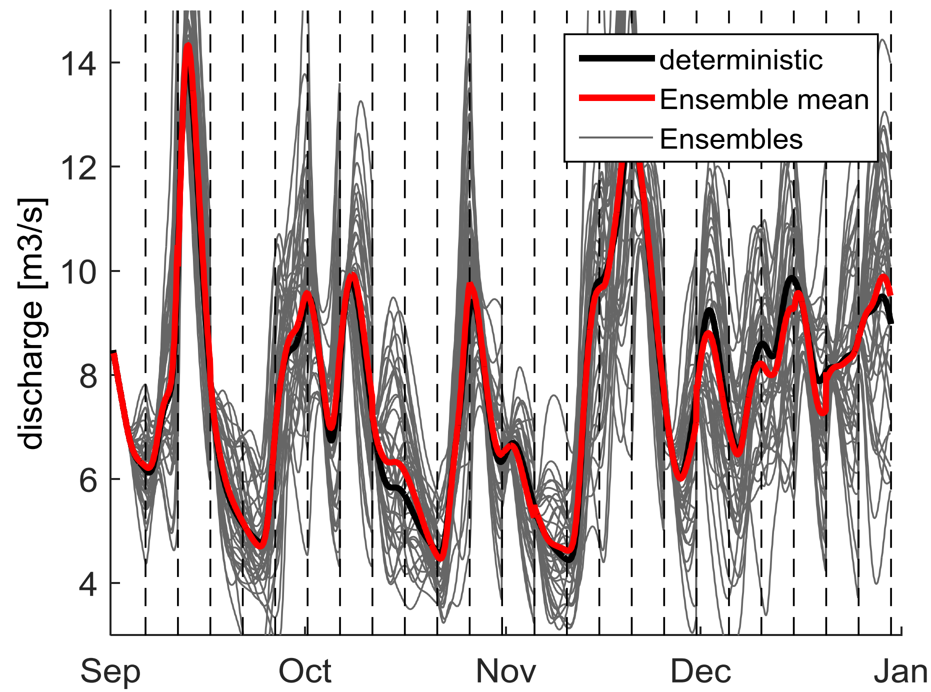
…similar as in real study case

Synthetic test case – assimilation of non-perturbed data

Results of DA using synthetic observations from non-perturbed deterministic model, evaluated for discharge at outlet



Open loop run, no DA



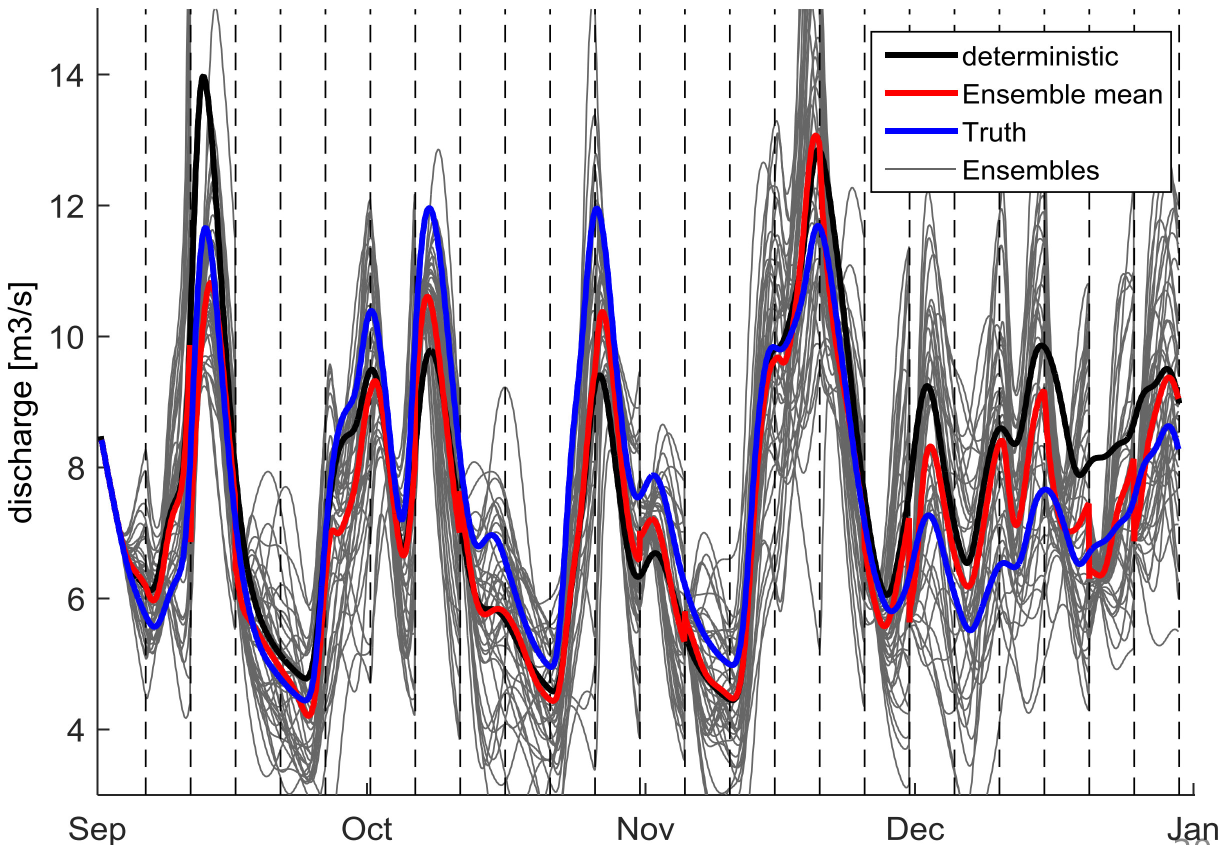
DA with ETKF

	CRPS [m3/s]	Sharpness [m3/s]
Open loop run	0.3936	4.3154
DA with ETKF	0.2984	3.1401

Synthetic test case – assimilation of perturbed data

Results of DA using synthetic observations taken every 5th day from perturbed model (i.e. deterministic run≠ truth)

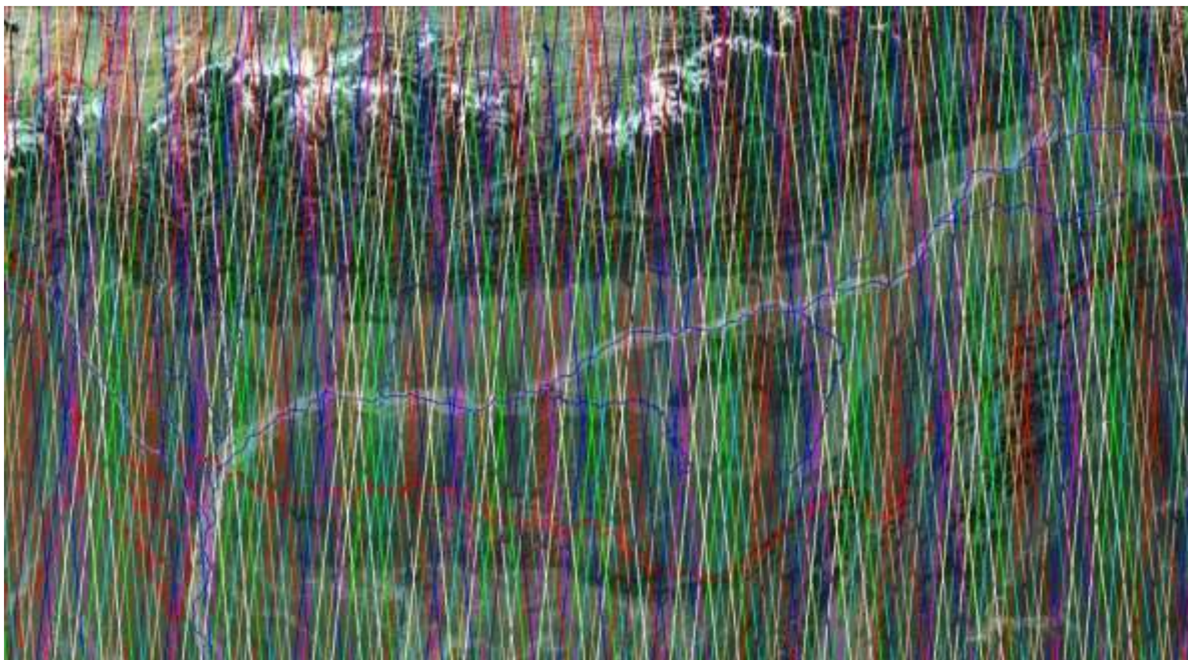
	CRPS [m3/s]
Open loop run	1.0090
DA with ETKF	0.5091



How to use "new type" altimetry data in hydrological modelling?

Task:

Use CryoSat-2 altimetry data (or in general from multiple missions) to update water levels in a hydrodynamic river basin model



CryoSat-2 ground tracks for one 369-day cycle over the Assam Valley, India

Envisat 35-day repeat tracks over the Assam Valley, India, with virtual stations along Brahmaputra