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COMBINING ENVISAT AND CRYOSAT-2 ALTIMETRY TO INFORM HYDRODYNAMIC MODELS

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ABSTRACT

Decreasing availability of in-situ river monitoring data can be met with increasing availability and quality of satellite altimetry data over rivers. CryoSat-2 is an altimeter mission launched in 2010 by the European Space Agency (ESA). With its unique drifting orbit, common procedures of working with satellite altimetry data over rivers cannot be easily applied. This work presents a way of informing a hydrologic-hydrodynamic model of the Brahmaputra River with CryoSat-2 altimetry. For one, CryoSat-2 data with its high spatial resolution was used to calibrate water levels in the 1D hydrodynamic model. For the other, a data assimilation framework was developed and applied, showing promising results for assimilation experiments with real and synthetic CryoSat-2 data.

1. INTRODUCTION AND BACKGROUND

The objective of this work is to show how altimetry data from the CryoSat-2 mission can be used over rivers. The drifting orbit of CryoSat-2 challenges common ways of processing satellite altimetry data over rivers and incorporating it into hydrologic-hydrodynamic models. However with its orbit, together with the new Synthetic Aperture Interferometric Radar Altimeter (SIRAL) sensor on board, data from CryoSat-2 can provide water level measurements along rivers at unpreceded spatial resolution. The potential for this has been shown e.g. in [1] and [2]. This is one of the first works combining CryoSat-2 altimetry data with a hydrologic-hydrodynamic river model. In cooperation with the Danish Hydrologic Institute (DHI), a data assimilation (DA) framework has been developed which is capable of assimilating observations of water level (or discharge) with practically any distribution in time and space. This framework was then used to assimilate CryoSat-2 altimetry data to a hydrodynamic model of the Brahmaputra River in South Asia.

A record of satellite altimetry data over inland water bodies of ever increasing quality and density has become available, while, at the same time, the amount of publically available in-situ river monitoring data is decreasing in recent years, despite growing pressure on water resources through population and economic growth and also climate change. This shows the importance of making satellite altimetry data usable for hydrologic applications.

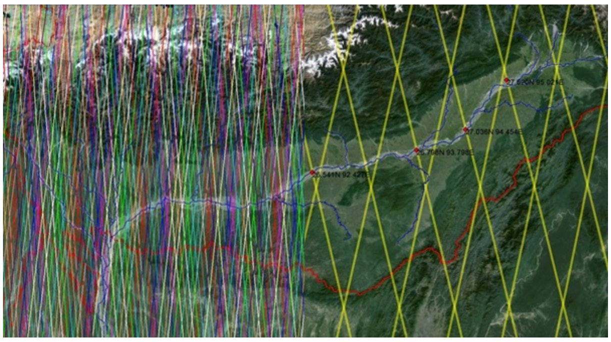

Figure 1: The Assam Valley, India with the Brahmaputra River. The left half is shown with the ground tracks of one full 369-day cycle of the drifting orbit of CryoSat-2, The right half with the the 35-day repeat orbit of Envisat, including virtual stations along the river.

Commonly those satellites are on repeat orbits with cycles between 10 and 35 days, allowing to derive so called virtual station time series of water levels at points where the satellite's ground track crosses a river regularly. CryoSat-2 however uses a drifting orbit (with a full repeat cycle of 369 days; ground tracks shown in Fig. 1) which does not allow to directly derive virtual station time series of river water levels with useful temporal resolution and thus calls for new ways of processing satellite altimetry data over rivers and incorporating it into hydrologic-hydrodynamic models.

2. CASE STUDY: BRAHMAPUTRA RIVER

A number of studies have evaluated satellite radar altimetry data over the Brahmaputra River. One reason for this is the river's large size, especially in its downstream part, the Assam Valley in India, and its favourable direction of flow in that part in relation to the satellites' orbits, from east to west. Besides that, this transboundary river is only poorly covered by in-situ measurements, at least when it comes to publically

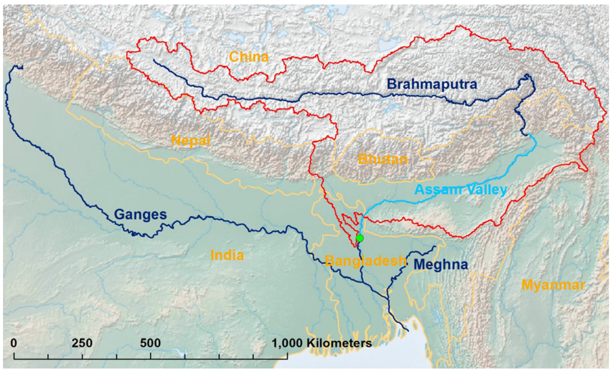

Figure 2: Basemap of the Brahmaputra basin model and its surroundings. National borders in yellow, model boundaries in red. The focus part of this work, the Brahmaputra River in the Assam Valley, is marked in light blue. The green dot marks the in-situ discharge station Bahadurabad.

accessible data: The three riparian countries China, India and Bangladesh have no data sharing agreements or similar [3]; India considers the Brahmaputra a “confidential” basin [4]. This makes efficient water resource management in the basin hard. The downstream country Bangladesh in the Ganges-Brahmaputra-Meghna Delta (see an overview map in Fig. 2), that has 90% of its surface water generated outside the country [5], is challenged by this, experiencing devastating floods regularly. Improving flood forecasting capabilities – without relying on in-situ measurements – is crucial, and has for example been a focus of [5]. There are more examples for the use of conventional, i.e. virtual station type altimetry data over the Brahmaputra ([6], [7], or [8]).

3. DATA AND METHODS

3.1. CryoSat-2 altimetry data over the Brahmaputra River

We used CryoSat-2 Level 2 altimetry data that were processed and provided by The National Space Institute, Technical University of Denmark. The basis for the data is the ESA baseline-b L1b 20 Hz product. This was retracked by [2] using a primary peak threshold retracker. Most of the study area is covered in the Synthetic Aperture Radar Interferometric (SARIn) mode of CryoSat-2. This provides data that can be off-nadir corrected [9] with an along-track resolution of approximately 300 metres [10]. For this work, data from the beginning of the mission in mid 2010 until the end of 2013 have been used.

CryoSat-2 altimetry data do not provide any metadata or similar to easily determine whether an echo originates from land surface or a small inland water body such as a river. A common solution to this is to use river masks derived from remote sensing imagery.

The Brahmaputra River in the Assam Valley has a dynamic, continuously changing braided river bed. See

Figure 3: Landsat-7 image of a section of the Brahmaputra River in the Assam Valley showing the dynamic river bed. Left: 2010. Right: 2011.

one example for river channels changing significantly between the years 2010 and 2011 in Fig. 3. This requires a high-resolution, dynamic river mask. For this task Landsat-7 and 8 NDVI imagery [11] with a spatial resolution of 30 metres and a (theoretical) temporal resolution of 16 days was chosen The availability of this optical imagery is however severely limited by cloud cover. From this imagery, one individual river mask for each year was created, representing low-flow conditions in the river. These masks were used to filter the relevant altimetry data. To map the data into the model space of the 1D hydrodynamic model the filtered data points subsequently were projected onto the model river line.

As mentioned, for DA in this work only data from the downstream Assam Valley (see Fig. 2) are used, however a relevant amount of data also could be extracted over the more narrow upstream parts of the Brahmaputra River. Tab. 1 provides an overview over the number of points and overflights that were extracted with the mentioned river masks over the different sections of the Brahmaputra River.

3.2. Synthetic CryoSat-2 altimetry data

To evaluate and prove the capability of the DA framework described in section 3.4, controlled synthetic DA experiments were conducted. For this, a model realisation was run with perturbed runoff forcing which served as a hidden truth model. Simulated water levels

Table 1: Overview over the number of individual outlier-filtered CryoSat-2 returns (data points) over the river mask and the number of overflights. Note that for the DA experiments only data from the Assam Valley have been used.

	Assam Valley		**headwaters**		**entire Brahmaputra**	
	returns over water	over-flights	returns over water	over-flights	returns over water	over-flights
2010	270	42	198	60	468	102
2011	1005	151	613	195	1618	346
2012	657	145	687	219	1344	364
2013	887	148	625	203	1512	351
Total	2819	486	2123	677	4942	1163

were sampled from the hidden truth run of the model at the exact same locations and times as the real CryoSat-2 observations occurred. A defined standard error was added to these water levels to account for measurement uncertainties. Those synthetic CryoSat-2 observations then were assimilated to the original model, and the performance of the DA method could be evaluated in comparison to the hidden truth model.

3.3. Hydrologic-hydrodynamic Brahmaputra basin model

The red outline in Fig. 2 shows the extent of the Brahmaputra basin hydrologic-hydrodynamic river model that was set up in DHI MIKE HYDRO River software (previously MIKE 11). The model is almost entirely forced and parameterized with the help of remote sensing and other global data because of the mentioned restrictions to data access in the region.
The hydrologic part consists of 33 subcatchments, which are modelled as conceptual, lumped NAM rainfall-runoff models [12]. The focus of this work however is the hydrodynamic model of the Brahmaputra River. MIKE HYDRO River uses a 1D dynamic wave routing based on the Saint-Venant equations for unsteady flow [13]. This model was forced by the runoff simulated in the 33 subcatchments. Discharge calibration of the entire model was performed against in-situ discharge at Bahadurabad station close to the outlet of model (see Fig. 2)
The use of virtual station altimetry requires water levels and water-level discharge relationships only to be accurate in the actual virtual stations, or relies on using water level amplitudes only, like for example done by [6]. When assimilating distributed data such as the CryoSat-2 altimetry data however, it is crucial that the hydrodynamic model is able to reproduce accurate water levels and water level-discharge relationships across the entire model. Hence, water level profiles and water level-discharge relationships across the entire Brahmaputra River in the Assam Valley were calibrated to CryoSat-2 and Envisat virtual station altimetry data. This is necessary as no precise DEM or bathymetry is available for the study region, making it impossible to directly parameterize a hydrodynamic model to accurately simulate water levels in the entire system.

3.4. Data Assimilation Framework

For the DA experiments, the DHI Data Assimilation Framework for their hydrologic-hydrodynamic modelling suite MIKE HYDRO River was used. An overview is given in Fig. 4: The framework provides various filters, error models for description of model error, and observation mapping methods to assimilate different datasets to MIKE models. It is written in .NET/C# to directly communicate in memory with the MIKE models. Provided filters are for example the

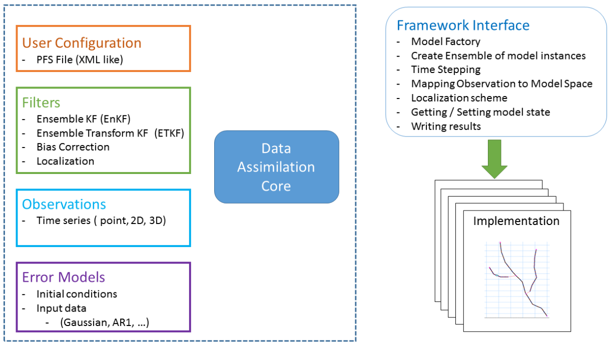

Figure 4: Scheme of the DHI Data Assimilation Framework. In this case, the implementation was made into the MIKE HYDRO River modelling system.

Ensemble Kalman Filter (EnKF), the Ensemble Transform Kalman Filter (ETKF) or a defined gain method. Besides that, methods for local analysis are provided.

Provided a hydrodynamic model that accurately reproduces water levels (see section 3.3), one can use this flexible framework to assimilate CryoSat-2 altimetry data to the model.
For this work, the ETKF was used based on [14]. Due to spurious correlations across the large model space (the model spans approximately 1000 km), localisation has been used based on the local analysis by [15], limiting the update to 200 km upstream and downstream of the observation. The model state vector consists of water levels in all calculation points of the hydrodynamic model. Model uncertainty was to be assumed to be dominated by the uncertainty of the forcings, primarily rainfall. Hence, model uncertainty was described by perturbing the runoff forcings (from the subcatchments) of the hydrodynamic model. This perturbation had to be modelled with temporal AR1 correlation, and spatial correlation, as otherwise the effects of the perturbations aggregated across the entire model space would cancel each other out.
Each crossing of the river usually yields in several individual data points. Those were aggregated, and then assimilated using the mean elevation. Observation uncertainty was taken from the standard deviations of the elevations within each of the aggregated groups.

4. RESULTS AND DISCUSSION

4.1. Assimilation of synthetic CryoSat-2 data

DA experiments with synthetic CryoSat-2 data as described in section 3.2 were performed. The results generally look promising. One popular indicator for the skill of ensemble forecasts is the continuous rank probability score (CRPS), combining sharpness and reliability [16]. Tab. 2 shows sharpness and CRPS for the synthetic DA experiment compared to an open loop run; all performance was evaluated against the

Table 2: Results of the synthetic DA experiment (shown in Fig. 5) and one with real CryoSat-2 data in terms of discharge at Bahadurabad station. Sharpness is given as the width of the 90% confidence intervals

		CRPS [m^3/s]	sharpness [m^3/s]
synthetic data	open loop run	5475	16369
	DA with ETKF	3444	10658
real data	open loop run	4198	14893
	DA with ETKF	3557	10957

discharge from the hidden truth model where the synthetic observations were extracted from. In the open loop run the ensemble was run with the exact same description of model uncertainty, only without any assimilation. DA can improve the CRPS in terms of discharge at Bahadurabad station by approximately 37%. The run is shown in Fig. 5. The positive results from this controlled synthetic experiment show i) the potential value of CryoSat-2 altimetry data for hydrodynamic models and ii) that the data assimilation framework developed is able to assimilate distributed data like the CryoSat-2 data.

4.2. Assimilation of real CryoSat-2 data

When assimilating the actual CryoSat-2 data, and comparing the results to in-situ data of discharge at Bahadurabad station results look less good, but still an improvement of CRPS of 15% compared to the open loop run was achieved (see Tab. 2).

Various reasons can exist why the performance of the DA of real CryoSat-2 data is poorer than the one of the synthetic test case. Further tuning of the DA setup, including model uncertainty description, observation uncertainty description, and other parameters such as localisation may be needed. Another possible reason is also the quality of the in-situ data, which furthermore only was available for the high-flow season. And of course the processing and extraction of the CryoSat-2 data, be it different ways of filtering and projecting the data, or also other retracking methods, can be discussed.

5. CONCLUSION

CryoSat-2 altimetry data for one of the first times could be used in combination with a hydrodynamic river model. A hydrodynamic model of the Brahmaputra River in South Asia was set up, based almost entirely on remote sensing and other global data owing to the restricted access to data in the study region.

CryoSat-2 altimetry data was filtered over a dynamic river mask extracted from Landsat imagery. The spatially dense distribution of CryoSat-2 data, owing its drifting orbit, could be used, in combination with virtual station altimetry, to calibrate water levels in a 1D hydrodynamic model of the Brahmaputra River.

A model prepared in such a way can be informed by basically any kind of altimetry information, including CryoSat-2 altimetry data. To perform the DA, a flexible data assimilation framework has been developed to work together with the DHI MIKE HYDRO River software. DA experiments show promising results, suggesting that such distributed data indeed can be used beneficially to improve performance of a hydrologic-hydrodynamic model. Still, there is more work to be done evaluating the low performance improvements of assimilating real CryoSat-2 data.

In conclusion, this study succeeded in informing a hydrodynamic model by altimetry data, without relying on the concept of virtual stations as common for conventional altimetry data.

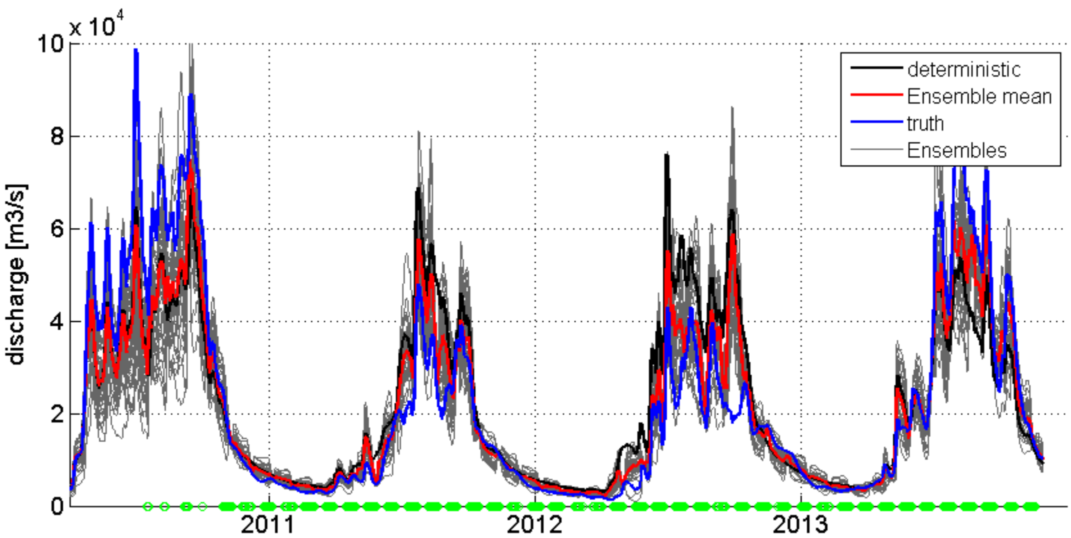

Figure 5: DA results in terms of discharge at Bahadurabad station. Assimilation of synthetic data, compared to discharge of the hidden truth model.

6. REFERENCES

1. Bercher, N., Dinardo, S., Lucas, B. M., Fleury, S., Calmant, S., Crétaux, J.-F., Femenias, P., Boy, F., Picot N. & Benveniste, J. (2013). Applications of CryoSat-2 SAR & SARIn modes for the monitoring of river water levels. In *Proceedings of CryoSat Third User Workshop, 12 - 14 March 2013, Dresden, Germany*.

2. Villadsen, H., Andersen, O. B., Stenseng, L., Nielsen, K., & Knudsen, P. (2015). CryoSat-2 altimetry for river level monitoring - Evaluation in the Ganges-Brahmaputra basin. *Remote Sens. Environ.*, **168**, 80–89. doi:10.1016/j.rse.2015.05.025

3. Biancamaria, S., Hossain, F., & Lettenmaier, D. P. (2011). Forecasting transboundary river water elevations from space. *Geophys. Res. Lett.*, **38**, L11401. doi:10.1029/2011GL047290

4. Central Water Commission. (2009). *Integrated Hydrological Data Book (non-classified river basins)*. New Delhi.

5. Hossain, F., Maswood, M., Siddique-E-Akbor, A. H., Yigzaw, W., Mazumdar, L. C., Ahmed, T., Hossain, M., Shah-Newaz, S. M., Limaye, A., Lee, H., Pradhan, S., Shresta, B., Bajracahrya, B., Biancamaria, S., Shum, C. K. & Turk, F. J. (2014). A promising radar altimetry satellite system for operational flood forecasting in flood-prone bangladesh. *IEEE Geosci. Remote Sens. Mag.*, **2**(3), 27–36. doi:10.1109/MGRS.2014.2345414

6. Michailovsky, C. I., Milzow, C., & Bauer-Gottwein, P. (2013). Assimilation of radar altimetry to a routing model of the Brahmaputra River. *Water Resour. Res.*, **49**(8), 4807–4816. doi:10.1002/wrcr.20345

7. Papa, F., Frappart, F., Malbeteau, Y., Shamsudduha, M., Vuruputur, V., Sekhar, M., Ramilien, G., Prigent, C., Aires, F., Pandey, R. K., Bala, S. & Calmant, S. (2015). Satellite-derived surface and sub-surface water storage in the Ganges–Brahmaputra River Basin. *J. Hydrol.: Reg. Stud.* **4**, 15-35. doi:10.1016/j.ejrh.2015.03.004

8. Papa, F., Durand, F., Rossow, W. B., Rahman, A., & Bala, S. K. (2010). Satellite altimeter-derived monthly discharge of the Ganga-Brahmaputra River and its seasonal to interannual variations from 1993 to 2008. *J. Geophys. Res.*, **115**, C12013. doi:10.1029/2009JC006075

9. Armitage, T., & Davidson, M. (2014). Using the Interferometric Capabilities of the ESA CryoSat-2 Mission to Improve the Accuracy of Sea Ice Freeboard Retrievals. *IEEE Trans. Geosci. Remote Sens.*, **42**(1-2), 529–536. doi: 10.1109/TGRS.2013.2242082

10. European Space Agency & Mullar Space Science Laboratory. (2012). *CryoSat Product Handbook* (Vol. DLFE-3605).

11. NASA Landsat Program. (2015). Landsat 7 and 8 NDVI 32-day composites, as available at https://earthengine.google.com/.

12. Nielsen, S. A., & Hansen, E. (1973). Numerical simulation of the rainfall runoff process on a daily basis. *Nord. Hydrol.*, **4**, 171–190.

13. MIKE by DHI. (2009). MIKE 11 - A Modelling System for Rivers and Channels - Reference Manual. Hørsholm, Denmark.

14. Sakov, P., & Oke, P. R. (2008). Implications of the Form of the Ensemble Transformation in the Ensemble Square Root Filters. *Mon. Weather Rev.*, **136**(3), 1042–1053. doi:10.1175/2007MWR2021.1

15. Sakov, P., & Bertino, L. (2011). Relation between two common localisation methods for the EnKF. *Comput. Geosci.*, **15**(2), 225–237. doi:10.1007/s10596-010-9202-6

16. Gneiting, T., Raftery, A. E., Westveld, A. H. & Goldman, T. (2005). Calibrated Probabilistic Forecasting Using Ensemble Model Output Statistics and Minimum CRPS Estimation. *Mon. Weather Rev.*, **133**(5), 1098–1118. doi:10.1175/MWR2904.1