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Updating river basin models with radar altimetry

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PhD Thesis
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The synopsis part of this thesis is available as a pdf-file for download from the DTU research database ORBIT: http://www.orbit.dtu.dk

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PREFACE

The work presented in this PhD thesis was conducted at the Department of Environmental Engineering of the Technical University of Denmark (DTU) under the supervision of Associate Professor Peter Bauer-Gottwein. The work was conducted from October 2009 to January 2013. The PhD project was funded by Danida, Danish Ministry of Foreign Affairs (project number 09-043DTU).

The PhD thesis is based on three scientific journal papers, of which one is published and two have been submitted.

I. Michailovsky, C.I., McEnnis, S., Berry, P.A.M., Smith, R., and Bauer-Gottwein, P.: River monitoring from satellite radar altimetry in the Zambezi River basin. Hydrology and Earth System Sciences, 16 (7), 2181-2192, 2012.

II. Michailovsky, C.I., Milzow, C., Bauer-Gottwein, P.: Assimilation of Radar Altimetry to a Routing Model of the Brahmaputra River. Submitted.

III. Michailovsky, C.I., and Bauer-Gottwein, P.: Operational reservoir inflow forecasting with radar altimetry: The Zambezi case study. Submitted.

The papers are referred to by their roman numerals throughout the thesis (e.g.: Paper **I**).

In this online version of the thesis, the papers are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from:

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ABSTRACT

Hydrological models are widely used by water managers as a decision support tool for both real-time and long-term applications. Some examples of real-time management issues are the optimal management of reservoir releases, flood forecasting or water allocation in drought conditions. Long term-applications include the impact analysis of planned hydraulic structures or land use changes and the predicted impact of climate change on water availability.

One of the obstacles hydrologists face in setting up river basin models is data availability, whether because the datasets needed do not exist or because of political unwillingness to share data which is a common problem in particular in transboundary settings. In this context, remote sensing (RS) datasets provide an appealing alternative to traditional in-situ data and much research effort has gone into the use of these datasets for hydrological applications. Many types of RS are now routinely used to set up and drive river basin models.

One of the key hydrological state variables is river discharge. It is typically the output of interest for water allocation applications and is also widely used as a source of calibration data as it presents the integrated response of a catchment to meteorological forcing. While river discharge cannot be directly measured from space, radar altimetry (RA) can measure water level variations in rivers at the locations where the satellite ground track and river network intersect called virtual stations or VS.

In this PhD study, the potential for the use of RA over rivers for hydrological applications in data sparse environments is investigated. The research focused on discharge estimation from RA as well as the use of RA for data assimilation to routing models with the objective of improving river discharge forecasts.

In the first paper included in this PhD study, the potential for using altimetry for level and discharge monitoring in the Zambezi River basin was assessed. Altimetric levels were extracted using a detailed river mask at 31 VS located on rivers down to 80 m wide. Root mean square errors relative to in-situ levels were found to be between 0.32 and 0.72 m. Discharge was estimated from the altimetric levels for three different data availability scenarios: availability of an in-situ rating curve at the VS, availability of one pair of simultaneous measurement of cross-section and discharge and availability of historical discharge data. For the few VS where in-situ data was available for comparison,

the discharge estimates were found to be within 4.1 to 13.8% of mean annual gauged amplitude.

One of the main obstacles to the use of RA in hydrological applications is the low temporal resolution of the data which has been between 10 and 35 days for altimetry missions until now. The location of the VS is also not necessarily the point at which measurements are needed. On the other hand, one of the main strengths of the dataset is its availability in near-real time. These characteristics make radar altimetry ideally suited for use in data assimilation frameworks which combine the information content from models and current observations to produce improved forecasts and reduce prediction uncertainty.

The focus of the second and third papers of this thesis was therefore the use of radar altimetry as update data in a data assimilation framework. The approach chosen was to simulate reach storages using a simple Muskingum routing scheme driven by the output of a rainfall-runoff model and to carry out state updates using the Extended Kalman Filter.

The data assimilation approach developed was applied in two case studies: the Brahmaputra and Zambezi River basins. In the Brahmaputra, data from 6 Envisat VS located along the main reach was assimilated. The assimilation improved model performance with Nash-Sutcliffe model efficiency increasing from 0.78 to 0.84 at the outlet of the basin.

In the Zambezi River basin, data from 9 Envisat VS located within 2 distinct watersheds was assimilated. Because of the presence of the large Barotse floodplain in the area, the routing scheme was coupled to a simple floodplain model. Overall model performance was improved through assimilation with Nash-Sutcliffe model efficiencies increasing from 0.21 to 0.65 and 0.82 to 0.88 at the outlets of the 2 watersheds.

The results from both the Zambezi and the Brahmaputra showed that the low temporal resolution of the data could be compensated in part by the use of multiple VS which will acquire data on different days over the 35-day repeat period. This highlights the benefits which could be obtained from radar altimeter missions with denser spatial resolution allowing for more, narrower rivers to be monitored. In both case studies, the simple error model specification used was found to be one of the weak points of our approach and further research is suggested in this direction.

DANSK SAMMENFATNING

Hydrologiske modeller bruges i vid udstrækning som beslutningsværktøj under forvaltningen af vandressourcer i både realtid og i langsigtet planlægning. Som eksempler på anvendelse i realtid kan nævnes optimal styring af reservoirer, forudsigelse af oversvømmelser og allokering af vand under tørke. Til langsigtet planlægning bruges hydrologiske modeller blandt andet til at vurdere påvirkninger af planlagte hydrauliske anlæg og ændringer i arealanvendelse samt til at forudsige effekter fra klimaændringer på vandressourcerne.

En af hydrologernes udfordringer under udfærdigelsen af afstrømningsmodeller er tilgængeligheden af data. Manglen på data kan skyldes, at data simpelthen ikke eksisterer, eller at der fra politisk side ikke er vilje til at dele denne, hvilket ofte ses ved grænseoverskridende problemstillinger. Her viser teledetektion sig ofte som et attraktivt alternativ til traditionel in situ data og der er forsket meget i brugen af disse datasæt i hydrologiske sammenhænge. Mange typer af teledetektion bruges nu regelmæssigt i afstrømningsmodeller.

Afstrømningen af vand er et af de centrale elementer i de hydrologiske modeller. Den er typisk den mest styrende parameter i forbindelse med allokering af vand, og bruges ofte til kalibrering, da den repræsenterer afvandingsområdets samlede respons på det aktuelle klima. Afstrømning kan ikke direkte måles fra rummet, men radar altimetri (RA) kan vise variationen i floders vandstand på virtuelle stationer (VS), som er de lokaliteter, hvor satellitten krydser henover den pågældende flod. I dette PhD projekt blev potentialet for at bruge RA over floder i hydrologiske sammenhænge i områder med mangel på data undersøgt. Forskningen fokuserede på at estimere afstrømning ud fra RA, ligesom RA blev brugt i data assimilering til routing modeller med det formål at forbedre forudsigeler af floders afstrømning.

I den første artikel inkluderet i dette PhD studie blev potentialet for at anvende RA højdemålinger til overvågning af vandstanden og afstrømningen i floden Zambezi vurderet. Med et detaljeret kort over floden, blev RA højdemålinger for 31 VS med en flodbredde på mindst 80 m identificeret. Mindste kvadraters metode (RMSE) relativt til in situ vandstanden blev fundet til at være mellem 0,32 og 0,72 m. Afstrømningen blev estimeret fra RA højdemålingerne for tre forskellige scenarier med varierende datagrundlag; først med en in situ afstrømningshydrograf ved den virtuelle station, dernæst med en samtidig in situ måling af flodens tværsnit og afstrømning og sidst med tilgængelig historisk afstrømningsdata. Den estimerede gennemsnitlige årsafstrømning for de få VS med tilgængelig in situ data blev fundet til at være imellem 4,1 og 13,8% af den målte gennemsnitlige afstrømning.

Et af hovedproblemerne med at bruge RA i en hydrologisk sammenhæng er den relativt lave målingsfrekvens, som indtil nu har været på mellem 10 til 35 dage. Dertil skal lægges, at den VS ikke nødvendigvis er placeret på det punkt, hvor der er brug for målinger. På den anden side er en af de største fordele ved datasættet dets tilgængelighed i tæt ved realtid. Disse egenskaber gør RA ideelt til brug i dataassimilering, hvor information fra modeller kombineres med realtidsobservationer for dermed at kunne producere forbedrede forudsigelser og reducere usikkerheder ved forudsigelser.

Fokus i anden og tredje artikel af denne afhandling var derfor brugen af RA til at opdatere data gennem dataassimilering. Den valgte metode var at simulere lagring i vandløb med en simpel Muskingum routing metode drevet af en afstrømningsmodel, samt at opdatere tilstandsvariablerne ved at benytte det udvidede Kalman filter.

Den udviklede metode til data assimilering blev anvendt i to studier: oplandene for floderne Brahmaputra og Zambezi. For Brahmaputrafloden blev data fra 6 Envisat VS langs hovedløbet af floden assimileret. Assimileringen øgede modellens ydelse, hvor Nash-Sutcliffe effektiviteten (NSE) steg fra 0,78 til 0,84 ved oplandets udløb.

I Zambezifloden blev data fra 9 Envisat VS lokaliseret i to adskilte vanddistrikter assimileret. På grund af tilstedeværelsen af den store flodslette Barotse i området, blev routing metoden koblet til en simpel flodslettemodel. Den overordnede ydelse af modellen blev med dataassimileringen øget og NSE steg fra 0,21 til 0,63 og 0,82 til 0,78 ved udløbet fra de 2 afvandingsområder.

Resultaterne fra både Zambezifloden og Brahmaputrafloden viste, at der delvist kan kompenseres for den lave opdateringsfrekvens af data ved at bruge flere VS. Derved vil man kunne få data fra forskellige dage igennem den 35 dages cyklus. Dette fremhæver de fordele, man vil opnå med RA data med en højere rumlig opløsning og dermed muliggøre overvågning af flere, mindre floder. I begge studier viste den anvendte simple fejlmodel sig at være et af de svage punkter ved vores metode, og yderligere forskning i denne retning anbefales.

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1 INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

While fresh water is a vital resource, the quantity of globally available water in lakes, rivers, wetlands and reservoirs as well as its temporal and spatial variations are not well known (Alsdorf et al., 2007). Knowledge and prediction of the quantities of water flowing in rivers is of great importance in order to improve water allocation efficiency, reservoir and hydropower operation or in order to mitigate floods and droughts. The total amount of fresh water flowing in rivers and to the ocean is also an important unknown of global circulation models which are used to drive weather and climate models (Alsdorf et al., 2007).

In order to keep track of and predict water availability, both in-situ river gauges and hydrological model forecasts are widely used. However, in-situ monitoring density varies greatly between different geographical areas and in many regions of the globe in-situ data is either inexistent or available with considerable delays due to poor accessibility, costs or political unwillingness to share data (Calmant and Seyler, 2006; Alsdorf et al., 2007).

With the development of satellite remote sensing, many new datasets are available to monitor different parts of the water cycle which allows hydrologists to rely less heavily on in-situ data. Remote sensing data is now widely used either as forcing to hydrological models or as calibration/validation datasets. The types of data available are varied and include precipitation (e.g. Stisen and Sandholt, 2010), temperature, reference evapotranspiration (e.g. Schmugge et al., 2002), topography (Farr et al., 2007), total water storage from gravimetry (e.g. Tapley et al., 2004), surface soil moisture (e.g. Wagner et al., 1999), inundation extent form synthetic aperture radars (e.g. Matgen et al., 2007) etc. We refer the reader to e.g. Tang et al. (2009) for a review of the use of remote sensing in hydrological applications.

While these remote sensing datasets help with the understanding and quantification of the inland water cycle, no remote-sensing technique is currently capable of measuring river discharge which is usually the variable of interest in hydrological applications and is a useful quantity for model calibration/validation as it presents the integrated basin response to meteorological forcing.

Traditional discharge monitoring relies on the monitoring of river levels and their conversion to discharge through a rating curve which is a site-specific relationship between level and discharge. Rating curves are typically established by fitting a power-law through a number of points corresponding to simultaneous measurements of discharge and level.

In order to measure discharge from space, the most promising technology is radar altimetry. Radar altimetry is a technique to measure height and with repeat measurements over a surface water body temporal level variations in lakes, wetlands and rivers can be tracked (Koblinsky et al., 1993; Birkett, 1995; Birkett, 1998). The location of the intersection between the satellite ground track and a water body at which the measurement is made is commonly referred to as a *virtual station* or *VS*.

While altimetry data does not suffer from the same restrictions in coverage or distribution as in-situ data, the use of radar altimetry in hydrological studies is not widespread due to several specific challenges.

Firstly obtaining level time-series from altimetry over rivers can be difficult because radar altimetry was initially designed, and is optimized, for operation over oceans. The response over rivers, due to the absence of waves as well as the inclusion of response from the surrounding terrain in the altimeter footprint, is complex and requires detailed analysis of individual returns (e.g. Berry et al., 2005).

Secondly, the spatial resolution, with for example one measurement every 369 m along-track for the Envisat RA-2 altimeter, make current altimetry missions unsuitable for the monitoring of narrow rivers.

Thirdly, the temporal resolution is low, with a repeat time of between 10 and 35 days for the different satellite missions which is much longer than what is needed in particular for real-time optimization problems such as flood mitigation or reservoir operation.

And finally, because where VS do not coincide with in-situ gauges, no rating curves are available. Thus, other methods, for example relying on models or bathymetry, need to be developed and used in order to obtain discharge.

1.2 RESEARCH OBJECTIVES

In this context, the PhD research has focused on the use of river altimetry for hydrological applications in large data sparse river basins. The first portion of the work focused on the generation of level and discharge time-series at VS locations and the second portion focused on the assimilation of river altimetry to large-scale routing models in data sparse regions.

The main objectives of the research were:

- Precise semi-automatic selection of data for narrow rivers (Paper **I**)
- Development of rating-curves with minimal in-situ data to obtain discharge from level (Paper **I**)
- Assimilation of radar altimetry to large scale routing models (Paper **II** and Paper **III**)

This thesis is based on the three papers written as part of the PhD study. Chapter 2 presents a literature review of previous work on the research topic, chapter 3 presents the two case studies, and chapter 4 presents the methods used for the study. The main results from the papers are summarized in chapter 5 and chapters 6 presents the conclusions. Finally, the three papers can be found in chapter 8.

2 CONTEXT

2.1 RADAR ALTIMETRY FOR INLAND WATER MONITORING

Radar altimetry is a technique to measure height. A radar pulse is emitted by the satellite in the nadir direction and analysis of the echo returned from the surface of the Earth allows for the determination of different characteristics of the underlying terrain. The time taken for the signal to bounce back to the satellite is used to determine the *range* which is the distance between the satellite and the surface. The signal is assumed to travel at the speed of light and corrections need to be applied to the range due to deceleration of the electromagnetic waves in the atmosphere. These corrections are out of the scope of this study and we refer the reader to e.g. Calmant et al. (2008) or Rosmorduc et al. (2011) for further details.

After correction of the range and with precise knowledge of the satellite position, the land or water surface elevation relative to a terrestrial reference (for example the ellipsoid) can be calculated. The elevation of the underlying surface is then equal to the satellite altitude relative to the reference surface minus the range (see Figure 1 for illustration).

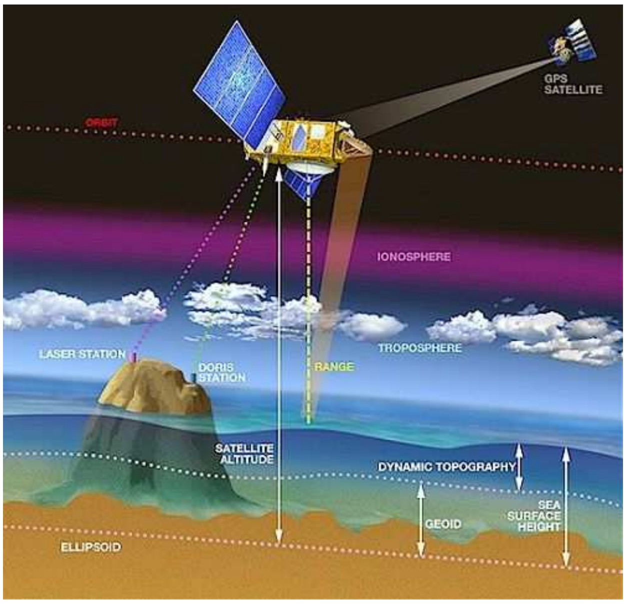

Figure 1: Illustration of satellite altimetry (Figure: CNES/D. Ducros in Rosmorduc et al. (2011))

Due to bandwidth limitations and in order to reduce noise, for all past missions, the returned echoes were averaged on board before being transmitted from the satellite. For example, for the Envisat satellite, the pulse was emitted with a frequency of 1800 Hz but 100 echoes were averaged on board to produce the 18 Hz waveforms which were sent from the satellite.

While satellite based radar altimetry was initially designed for ocean monitoring, the different satellite missions have been collecting data over continental surfaces and in particular over surface water bodies (Calmant et al., 2008). The first studies concerning the use of radar altimetry for inland water monitoring focused on large lakes and reservoirs for which the returned signal to the altimeter is "ocean-like". This is an important feature as the shape of returned echoes over oceans fits a Brown model (Brown, 1977) from which the extraction of range is well established.

Some of the first applications over lakes include Morris and Gill (1994) who used the TOPEX/Poseidon (T/P) Geophysical Data Records (GDR) data over the Great Lakes and found root mean square (rms) errors of 3 cm and Birkett (1995) who showed that the T/P GDR heights could be used to monitor lakes with a surface area > 300 km^2 with high accuracy (~4 cm rms).

Birkett (1998) showed that T/P data was also able to track river and floodplain levels for rivers > 1.5 km wide and found rms errors relative to gauged levels in the Amazon of 60 cm.

Over smaller water bodies, the returned echoes do not have "ocean-like" shapes. This is due to their smooth very reflective nature. The altimeter footprint, which is of about 2-10 km over oceans but is significantly smaller over land surfaces, will also typically not only contain information from the water surface but also from the surrounding terrain. While a water body within the footprint will usually dominate the return signal due to the much higher reflectivity of water compared to land, this will lead to more complex waveforms which need post processing. This processing is called *retracking* (e.g. Koblinsky et al., 1993; Birkett, 1998; Berry et al., 2005).

By retracking Geosat altimetry data at four VS locations on the Amazon River, Koblinsky et al. (1993) showed that water level variations could be tracked in large rivers using satellite radar altimetry. Their results showed a 70 cm rms error which was due in large part to errors in the orbit determination. Further studies over the Amazon using Envisat data have found rms errors less than 30 cm (e.g. Frappart et al., 2006).

Berry et al. (2005) showed that by retracking individual echo shapes, altimetry levels could be retrieved from smaller surface water bodies than was previously considered feasible. Birkinshaw et al. (2010) used such data in a study of the Mekong River and found rmse values between 44 and 65 cm for retracked Envisat data over rivers down to 400 m in width.

One of the main obstacles to the use of altimetry data for hydrological applications is their coarse temporal resolution. For satellites which have carried radar altimeters in the past, the repeat period has been of between 10 days (for the TOPEX/Poseidon satellite) and 35 days (for the Envisat satellite).

Roux et al. (2008) proposed a method to overcome the temporal resolution limitation. By using linear models exploiting nearby gauging stations, they were able to generate daily water level time series at a VS from the 35-day repeat Envisat data.

2.2 Estimating river discharge from radar altimetry

Measuring river discharge from space remains an important research question in the hydrological community and the most promising technology for this purpose is radar altimetry.

In traditional discharge monitoring, a rating curve relating water levels to discharge is established by fitting a power-law to multiple simultaneous measurements of level and discharge. Water levels are then recorded, typically on a daily basis, and converted to discharge using the rating curve.

Obtaining river discharge from radar altimetry requires the establishment of such rating curves at each VS location, often in the absence of in-situ discharge measurements.

If an in-situ rating curve is available at a VS location, obtaining river discharge is fairly straightforward, the one remaining task being to find a common reference level between the in-situ rating curve and the altimetry levels. Another similar approach which avoids the leveling issue is to develop a rating curve based directly on altimetry measurements and coincident in-situ discharge measurements (e.g. Kouraev et al., 2004; Zakharova et al., 2006; Papa et al., 2010). While this method yields good results, its application is limited to VS locations where altimetry and in-situ discharge data are available for overlapping time periods.

Bjerklie et al. (2003) studied the potential for estimating river discharge from remote sensing data only, including radar altimetry. They proposed a method which relies on the measurement of hydraulic data from remote sensing and multiple regression analysis of discharge measurements to derive rating curves and found that discharge could be determined with an average uncertainty of less than 20%.

Leon et al. (2006) and Getirana et al. (2009) used discharge estimates from calibrated hydrological models at VS locations in order to develop rating curves. While this method removes the need for in-situ stations at the VS, the quality of the rating curve will be directly related to the quality of the calibrated model which will typically depend on availability of in-situ data elsewhere in the basin for the calibration/validation of the model.

2.3 RIVER ALTIMETRY FOR HYDROLOGICAL MODELING

Hydrological models are widely used as decision support tools by water resources managers for long-term planning applications, such as analyzing the consequences of the construction of a new reservoir, as well as to deal with real-time management issues such as flood and drought mitigation.

Models can be broadly split into rainfall runoff (RR) models, which simulate land processes, and hydrodynamic models, which simulate water routing in reaches. Both RR and hydrodynamic models are used from local to global scales with varying degrees of simplification and conceptualization.

Hydrological model predictions are subject to high uncertainties which stem from many different sources including model forcing, structure, parameterization, initial conditions and uncertain or lack of calibration/validation datasets (e.g. Liu and Gupta, 2007).

Because many parameters in models are either not directly related to measurable quantities or need to be representative of large areas, hydrological models rely on the calibration/validation process where model parameters are tuned to fit simulated and observed states and fluxes. Calibration is commonly carried out using in-situ discharge (for RR models) and levels or both (for hydrodynamic models) as calibration data and lack of such datasets can be a major obstacle in modeling of remote areas.

Getirana (2010) showed that using Envisat altimetry data with a 35-day repeat period for the automatic calibration of a model in the Branco River basin yielded similar results to using daily gauged discharge provided knowledge of the rating curves at the VS. Getirana et al. (2013) further demonstrated the potential for calibrating a large-scale flow routing scheme of the Amazon basin without using in-situ data.

Using altimetry in combination with other remote sensing data sources (surface soil moisture and gravity), Milzow et al. (2011) successfully calibrated a model of the poorly gauged Okavango catchment.

Even when models are well calibrated, flow predictions are still subject to uncertainties due to errors in forcing data, model parameters and model formulation. For real-time applications, one solution to reduce these uncertainties is the integration of observations into the model framework using data assimilation.

Data assimilation is the process through which a model is updated using observations of the modeled system in order to improve predictions. It can be used to update model inputs, states, parameters or output variables and has been used in the field of hydrology since the 1980s (Kitanidis and Bras, 1980a; Kitanidis and Bras, 1980b).

For real-time applications which rely on accurate relatively short-term predictions, knowledge of the current state of the hydrological system is paramount. Sequential data assimilation in which an update is carried out whenever a new measurement becomes available is therefore well adapted to these types of applications.

While many difficulties remain, in particular in relation to the specification of model and measurement uncertainties, the updating of states in rainfall runoff and hydrodynamic models using in-situ water level and stream flow measurements has been successfully used to update states in hydrodynamic (e.g. Refsgaard, 1997; Madsen and Skotner, 2005; Vrugt et al., 2005) and rainfall runoff models (e.g. Pauwels and De Lannoy, 2006; Clark et al., 2008). Liu et al. (2012) present a comprehensive review on the current state of data assimilation for hydrological applications.

As far as the use of remotely-sensed river level or discharge is concerned, it has been shown that assimilating water levels derived from synthetic aperture radar imagery and high resolution digital elevation models to hydrodynamic models improved model predictions (Neal et al., 2009; Giustarini et al., 2011) but unfortunately, high resolution DEMs are not currently available on a global scale.

Studies preparing for the launch of the Surface Water Ocean Topography (SWOT) mission, which is scheduled to be launched in 2019 and has a swath altimeter on board, have used synthetic swath altimetry data as assimilation data to update hydrodynamic models and found that, provided knowledge of the bathymetry at the VS, modeled depth and discharge were improved through assimilation (Andreadis et al., 2007; Biancamaria et al., 2011).

Using altimetry levels over reservoirs, Pereira-Cardenal et al. (2011) showed that the assimilation of altimetry from Envisat improved modeled reservoir levels in the Syr Darya River Basin, but no studies have reported the use of nadir altimetry over rivers in a data assimilation framework.

3 CASE STUDIES

3.1 THE ZAMBEZI RIVER BASIN

The Zambezi River is the largest water resource in Southern Africa draining a basin of $1.37 \cdot 10^6$ km^2 and discharging an average 130 km^3/year to the Indian Ocean (The World Bank, 2010). Eight countries have land areas in the Zambezi River Basin: Angola, Botswana, Malawi, Mozambique, Namibia, Tanzania, Zambia and Zimbabwe (Figure 2).

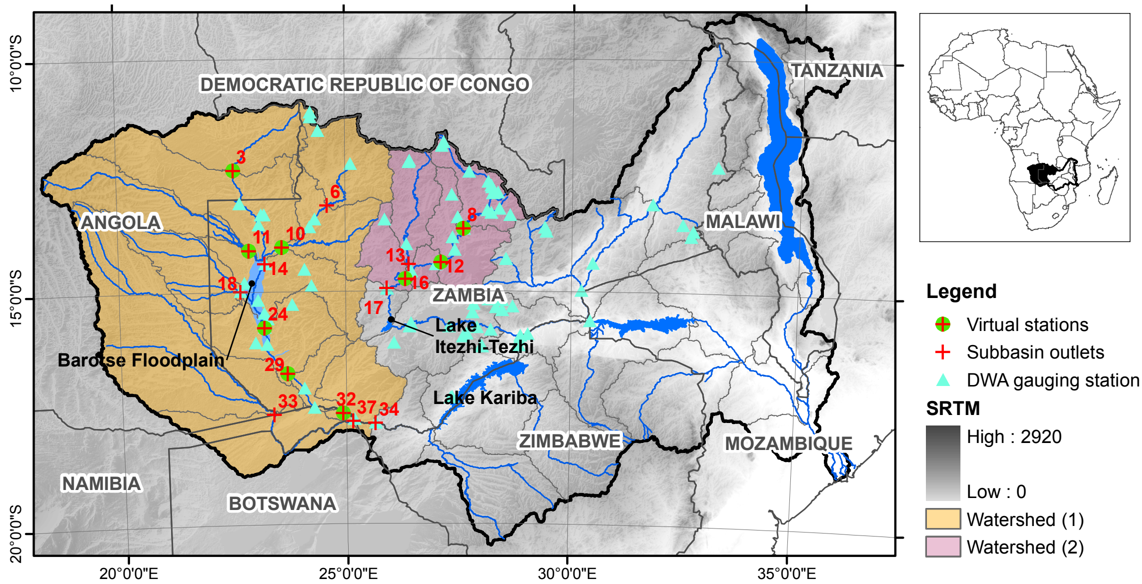

Figure 2: The Zambezi River Basin with location of the modelled watersheds

Water availability in the basin is highly spatially and temporally variable. Most of the water in the basin comes from the northern regions where precipitation is high with up to 1400 mm/year while in some of the southern areas the value declines to 500 mm/year (The World Bank, 2010). Most of the rainfall occurs in the rainy season between the months of October and March.

The major water resources management issues in the basin are related to the operation of the large hydroelectric dams (lakes Kariba and Cahora Bassa are the largest, but many smaller dams are also present in the basin) and the timing of reservoir releases relative to water requirements for irrigation. While the current area equipped for irrigation is low (less than 0.15% of the total basin area), currently planned irrigation projects if realized would triple this area (The World Bank, 2010).

Discharge data for the basin is available from the Global Runoff Data Centre (GRDC) but of the 98 stations reported in the database, only 34 have data up to the year 2000 and the latest reported data point overall is from 2006. More recent data for Zambian gauging stations was obtained from the Department of Water Affairs (DWA). The dataset made available for this project contains level and discharge up to the year 2008 for the most recent data. The dataset is not complete and the location of the gauging stations with data after the year 2001 is shown in Figure 2.

For the Zambezi case study, Envisat altimetry data was retracked by the Earth and Planetary Remote Sensing Lab (E.A.P.R.S) over the whole of the basin. The first part of the study focused on extraction of data points corresponding to rivers in order to produce level time series at all VS locations identified as useable (Paper **I**). The potential for discharge monitoring at the VS was studied using different approaches for different data availability scenarios (Paper **I**).

Paper **III** focused on the use of altimetry data in two distinct watersheds in the Zambezi River basin (see Figure 2) for assimilation to a routing model and improved inflow prediction to the Itezhi-Tezhi and Kariba reservoirs.

3.2 THE BRAHMAPUTRA RIVER BASIN

The Brahmaputra River is located in South Asia and drains a basin of $580 \cdot 10^3$ km^2. It flows through China, India and Bangladesh and discharges an average $19.3 \cdot 10^3$ m^3/s into the Ganges-Brahmaputra Delta where it merges with the Ganges before flowing to the Bay of Bengal (Figure 3).

The largest portion of Rainfall in the basin (about 90%) occurs during the monsoon between the months of June and October. In the summer, snowmelt contributes to river discharge. The river flows in braided channels for most of its course.

The main water management challenge in the Brahmaputra basin is flood mitigation. Floods are common during the monsoon season, with peak flows typically occurring during July and August, and the flooding often poses a threat to human lives and livelihoods.

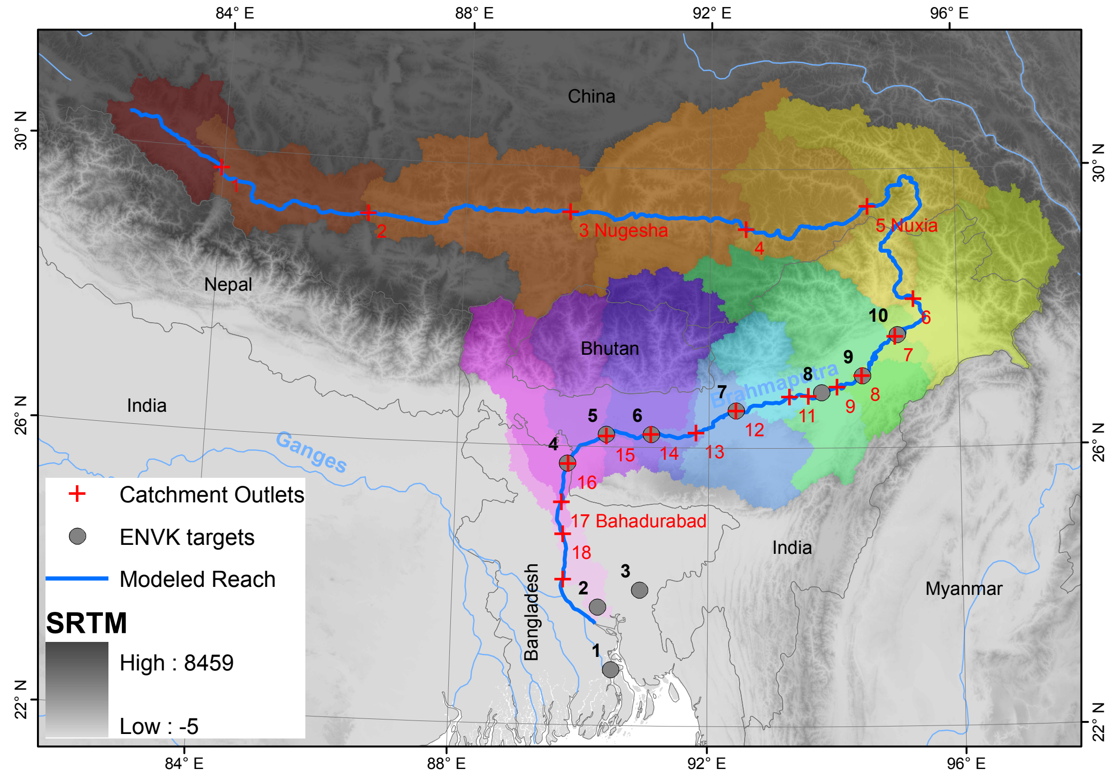

Figure 3: The Brahmaputra River Basin

In-situ data was available at three locations on the Brahmaputra River: the Nuxia and Nugesha stations in Tibet and the Bahadurabad station in Bangladesh. No recent low-flow data is available at these stations. Historical data at Bahadurabad was used to evaluate model performance during dry months.

For the Brahmaputra study, the River Lake Hydrology (RLH) data product was used. Six VS were found to be located on the main river stretch and Paper **II** focused on the assimilation of the data from these VS to a routing model of the Brahmaputra River.

4 METHODS

4.1 RADAR ALTIMETRY TIME-SERIES

The altimetry data used in the PhD study was from the Envisat RA-2 instrument. The satellite emitted a pulse in the nadir direction with a frequency of 1800 Hz which corresponds to one data point approximately every 3.69 m along-track. However, due to bandwidth limitations and in order to reduce noise, averaging of 100 echoes was carried out on board to produce the 18 Hz waveforms which were sent from the satellite.

The altimetry data used in Paper **I** and Paper **III** was the 18 Hz retracked waveforms, called the Radar AlTimetry product (RAT) (Berry et al., 2005). The data was provided by the Earth and Planetary Remote Sensing Lab (E.A.P.R.S.) over the whole of the Zambezi River Basin and data points corresponding to rivers had to be selected. This was done geographically, based on the distance between each RAT data point and the river. The location of rivers was determined by calculating the Normalized Difference Vegetation Index (NDVI). NDVI values for open water are typically between -1 and -0.1 and a threshold was set after visual inspection of the Landsat imagery for each VS. This extraction method can be compared to the semi-automatic method described in Roux et al. (2010).

Further selection was carried out based on the backscatter coefficient which is a function of the power reflected from the surface and will vary based on the nature of terrain and wind conditions (Birkett, 1998). The backscatter coefficient is noted sigma0 (σ^0). It is expressed in dB and is included for each data point in the RAT product. Its value is typically of about 10dB over oceans and has values from approximately 20 to over 40dB over rivers and wetlands (Birkett, 1998). The selection was therefore carried out by keeping only data from waveforms where $\sigma^0 \geq 20$ dB.

VS were then classified according to quality based on their rms errors relative to in-situ water levels. Because many VS did not coincide with gauging stations but were located along the same reach as one, varying cross-sectional area and travel time were taken into account in order to evaluate VS quality (see Paper **I** for details on the procedure).

The altimetry data used in Paper **II** is the River and Lake Hydrology (RLH) product (Berry et al., 2005). The RLH data is also computed from the 18 Hz retracked waveforms. However, fewer retrackers are used than for the RAT product and complex echo shapes are flagged and not further processed. The extraction is based on predefined "boxes" centered on the river and all retracked waveforms within a box will be used to produce a single data point per satellite pass.

RLH data is freely available online on the European Space Agency River and Lake Project homepage (http://tethys.eaprs.cse.dmu.ac.uk/RiverLake/shared/main).

4.2 Discharge from altimetry

In Paper **I**, three methods to obtain discharge from altimetry for different data availability scenarios were tested. The three methods relied on obtaining a rating curve and some reference level. Because of the coarse temporal and spatial resolutions considered in this study and the fact that no looped rating curves were observed in the in-situ data, the kinematic wave approximation was assumed valid for all discharge computations.

4.2.1 Method 1 - In-situ rating curve method

For VS locations where rating curves were available, they were directly used to estimate discharge once a common reference was established for the altimetric and in-situ level time series. This common reference was established by shifting the altimetry levels by the difference between the in-situ and altimetric time series' means.

4.2.2 Method 2 - Field data method

The second method was based on field work carried out in Zambia in May and June of 2010. Over the course of the field work, 12 VS were visited. At each VS, one coincident measurement of discharge and cross-section was made. For narrow rivers (up to 120 m wide), the measurements were carried out using a tagline, weight and propeller (USGS Type AA-MH current meter). Depth was sampled every 5 to 10 meters and velocity measurements were taken at 0.8 and 0.2 times the total depth at each point. The velocities were then averaged and integrated over the cross sectional area to obtain discharge (see full description of the velocity area method in Dingman, 2002).

For wider rivers an Acoustic Doppler Current Profiler (ADCP, RiverRay, Teledyne RD Instruments) was used.

The objective of the field work was to gather enough information in order to apply Manning's equation and calculate discharge values from altimetry measurements. Manning's equation is a widely used empirical method to determine turbulent open channel flow from the physical characteristics of the channel (Chow et al., 1988). The equation reads:

$$Q = \frac{A^{5/3}}{P^{2/3} \cdot n} \cdot \sqrt{S_f} \tag{1}$$

where Q is the river discharge [m^3/s], A is the cross sectional area [m^2], P is the wetted perimeter [m], n is Manning's roughness [s/m$^{1/3}$] and S_f is the friction slope which is equal to the bed slope S_0 in the kinematic wave approximation (Chow et al., 1988).

The common difficulty in applying Manning's equation is the determination of n. Manning's equation at the time of measurement reads:

$$Q_m = \frac{A_m^{5/3}}{P_m^{2/3} \cdot n_m} \cdot \sqrt{S_{0,m}} \tag{2}$$

Where the m index indicates values measured in the field. Assuming n and S_0 constant, Manning's equation can then be rewritten as:

$$Q = Q_m \cdot \left(\frac{A}{A_m} \right)^{5/3} \cdot \left(\frac{P_m}{P} \right)^{2/3} \tag{3}$$

Having measured cross-sections in the field, A and P can then be expressed as functions of river depth. All other terms on the right hand of the equation are known. Altimetry level (h) to depth (d) conversion was carried done by using the measured field depth and the closest altimetry measurement as references:

$$d_{alti} = h_{alti} - \left(h_{meas} + d_{meas} \right) \tag{4}$$

4.2.3 Method 3 - Historical flow data method

Dingman and Sharma (1997) showed that the following rating curve which has the advantage of relying only on measurable morphological characteristics of the river, could be used to obtain a good estimate of discharge for a wide range of rivers:

$$Q = 1.564 \cdot A^{1.173} \cdot R^{0.4} \cdot S^{-0.0543 \cdot \log10(S)} \tag{5}$$

Where A is the cross-sectional area [m^2], R is the hydraulic radius [m] and S is the water-surface slope which is equal to bed slope in the kinematic wave approximation (Chow et al., 1988).

Bjerklie et al. (2003) pointed out that while most of the variables needed in the equation can be measured from remote sensing, depth cannot. As little inter-annual variation in dry-season flows is observed in the uncontrolled reaches of the Zambezi, our approach consisted in using historical average low flows in order to derive a reference depth.

The reference depth was obtained by assuming a rectangular cross section and injecting the average annual low flow in equation (5):

$$Q_{low} = 1.564 \cdot \left(W \cdot d_{low}\right)^{1.173} \cdot \left(\frac{W \cdot d_{low}}{W + 2 \cdot d_{low}}\right)^{0.4} \cdot S_0^{-0.0543 \cdot \log 10(S_0)} \tag{6}$$

Where Q_{low} is the average annual low-flow [m^3/s] and d_{low} is the reference low-flow depth [m]. The average altimetry height for the driest month, h_{low}, was then extracted and the altimetry to depth conversion carried out:

$$d = h - \left(h_{low} - d_{low}\right) \tag{7}$$

Channel width was determined from Landsat imagery and bed slope was obtained by extracting elevation data from the Shuttle Radar Topography Mission (SRTM) along 20 km reach stretch and performing a linear regression.

4.2.4 UNCERTAINTY

Uncertainties on the variables used in the three discharge computation methods were estimated and the impact on the discharge values determined using Monte Carlo simulations. All variables were assumed normally distributed with a mean equal to the measured value and the standard deviations were estimated as described in Table 1. 1000 Monte Carlo runs were carried out for each method.

Table 1: Uncertainties on discharge calculation parameters (STD values are only indicated if a common value/percentage was used for all VS)

Method		STD	Comments
1	Rating curve	--	none: in-situ rating curves used as benchmark
2 (tagline)	depth	5 cm	estimated from field procedure
	distance	50 cm	estimated from field procedure
	velocity	5 mm/s	estimated from field procedure
2 (ADCP)	discharge	--	output from measurement
3	slope	--	determined from linear regression
	width	20% of measured width	estimated from measurement procedure
	reference low flow	--	computed from sample of average dry flows

4.3 Assimilation strategy

Reliable short-term river discharge predictions are highly valuable for water managers. In order to improve forecasts and reduce their typically high associated uncertainties, data assimilation merges model and observations to obtain the best possible estimate of the current state of a system.

Paper **II** and Paper **III** focus on the assimilation of radar altimetry levels to update states in a routing model in order to improve modeled flows in the Brahmaputra and Zambezi where reliable discharge forecasts have the potential to help with flood mitigation and reservoir operation respectively.

4.3.1 Modeling

In any data assimilation problem, one of the first questions to answer is which model states to update. In this study, the decision was made to decouple the land phase (the rainfall-runoff model or RR model) from the routing phase. The output from the RR model was then used as forcing to the routing model and the updates were carried on the volume of water routed.

This choice was made because of the complex relationship and time-lags between the measured value, level, and the inner states of the RR model, such as soil or aquifer storage. Updating the RR states would therefore require an ensemble based assimilation procedure which would greatly increase the computational burden, in particular for large-scale applications which are the focus of this study.

The assimilation strategy used in Papers **II** and **III** is based on a Muskingum routing scheme driven by the output of calibrated rainfall runoff (RR) models.

Expressing the Muskingum routing scheme in terms of storage yields:

$$s_{N,j+1} = A_N \cdot \sum_{i=0}^{N-1} \left[\left(M_{N-i,j+1} + M_{N-i,j} \right) \cdot \prod_{k=N-i}^{N-1} C_{1,k} \right] + 4 \cdot A_N \cdot \sum_{i=1}^{N-1} \left[\frac{s_{N-i,j}}{2 \cdot K_{N-i} \cdot (1 - X_{N-i}) + \Delta t} \cdot \prod_{k=N-i+1}^{N-1} C_{1,k} \right] + C_{3,N} \cdot s_{N,j} \tag{8}$$

where $s_{N,j}$ is the storage in reach N at time step j [m^3] and $M_{N,j}$ is the runoff inflow to reach N at time step j [m^3/s]. X_N [-], a weighing factor and K_N [days], the travel time of the flood wave through the reach, are assumed constant for each reach N and Δt is the model time step [days] (Chow et al., 1988). Reaches are numbered in ascending order from the furthest upstream to the furthest downstream.

A_N is defined as:

$$A_N = \frac{\Delta t \cdot K_N}{\Delta t + 2 \cdot K_N \cdot (1 - X_N)} \tag{9}$$

and C_{1N} and C_{3N} are defined as in Chow et al. (1988):

$$C_{1,N} = \frac{\Delta t - 2 \cdot K_N \cdot X_N}{2 \cdot K_N \cdot (1 - X_N) + \Delta t} \tag{10}$$

$$C_{3,N} = \frac{2 \cdot K_N \cdot (1 - X_N) - \Delta t}{2 \cdot K_N \cdot (1 - X_N) + \Delta t} \tag{11}$$

For the Brahmaputra model (Paper **II**), the output of a Budyko type (Zhang et al., 2008) RR model of the Brahmaputra was used to drive the routing model. The RR model was forced using direct precipitation and snowmelt. In order to obtain snowmelt, a simple temperature index method was used to model snow storage and snow melt (Hock, 2003). The model was calibrated using in-situ flows at 3 gauging stations located at the outlets of subbasins 3, 5 and 17 assuming constant calibration parameters within the upstream and (reaches 1 to 6) and downstream (reaches 7 to 9) portions of the model (for a detailed description of the RR model see Finsen et al.: Using radar altimetry to update a large-scale hydrological model of the Brahmaputra River Basin, submitted to *Hydrology Research*, 2012). The meteorological forcing is described in Table 2.

For the Zambezi model (Paper **III**), the RR model was built using the Soil and Water Assessment Tool (SWAT). The general setup for the SWAT model including landcover and soil datasets was modeled after Schuol et al.(2008) and the meteorological forcing used is described in Table 2. Calibration was carried out manually and focused primarily on groundwater parameters.

Table 2: Meteorological datasets used for the RR models. (*****) This dataset starts in 2008 and was extended to cover the whole period (see Paper II for details).

	Precipitation	**Temperature**
Brahmaputra	Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) 3B42RT real-time product**(*)**	European Centre for Medium range Weather Forecast (ECMWF) Operational Surface Analysis Data Set
Zambezi	Famine Early Warning Systems Network (FEWS-Net) rainfall estimate product (RFE)	European Centre for Medium Weather Forecast (ECMWF) ERA-Interim product

Because of the presence of the Barotse floodplain in the study area, a simple floodplain model was coupled to the routing model. The floodplain model was built using an approach similar to Dincer et al. (1987). Two processes were modeled: water transfers between the main reach and floodplain driven by head differences and evaporation from the floodplain (Figure 4). Direct precipitation to the floodplain was not considered as it is already taken into account in the SWAT model. Open water evaporation rate was assumed equal to potential evaporation which was computed in the RR model using the Hargreaves method.

The equations for the floodplain processes were then:

$$\frac{dV_{fp}}{dt} = coeff \cdot \left(h_{rc} - h_{fp}\right) - A_{fp} \cdot ET_0 \tag{12}$$

$$\frac{ds_{rc}}{dt} = msk(s, M) - coeff \cdot \left(h_{rc} - h_{fp}\right) \tag{13}$$

where V_{fp} is the floodplain volume [m^3], *coeff* the transfer coefficient for the 1st order exchange between reach and floodplain [m^2/s], h_{rc} and h_{fp} the water levels in the reach and floodplain respectively, A_{fp} the floodplain area [m^2], ET_0 the potential evaporation [m/s], s_{rc} the water stored in the reach [m^3], *msk* the Muskingum routing operator as presented in equation (8), *s* the state vector of volumes in all reaches and *M* the input from the RR model [m^3/s].

A one-day time step was used for modeling and this was assumed small relative to the time-scale of the floodplain processes. The floodplain equations were therefore solved assuming mean daily volume in the floodplain equal to the volume at the end of the previous day, minus evaporation. Evaporation was assumed to be removed before any transfers take place. The explicit solution is then:

$$V_{fp,k} = V_{fp,k-1} - coeff \cdot \left(h_{rc,k*} - h_{fp,k-1}\right) - A_{fp,k-1} \cdot ET_0 \tag{14}$$

$$s_{rc,k} = msk(s_{k-1}, M_{k-1}, M_k) - coeff \cdot \left(h_{rc,k*} - h_{fp,k-1}\right) \tag{15}$$

Where $h_{rc,k*}$ is the level in the reach after the addition/subtraction of volume from the Muskingum routing but before any transfers with the floodplain in the time step.

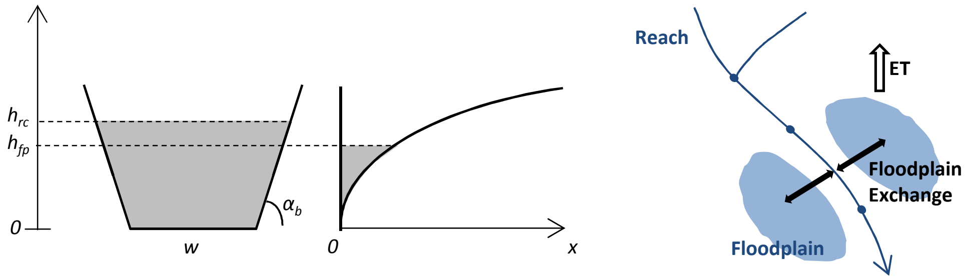

Figure 4: Reach and floodplain cross-section geometry and illustration of floodplain processes.

The reach cross sections were assumed trapezoidal with constant bank slope, α_b, and the bottom of the floodplain was assumed to rise with distance from the reach following:

$$h_{fp} = (\beta \cdot x)^m \tag{16}$$

Where β and *m* are shape parameters and *x* is the distance from the side of the floodplain closest to the reach (see Figure 4). The relative values of the shape parameters were fixed based on literature values for floodplain extent (770 000 ha) and storage (average annual storage of 8.5 km^3) (Beilfuss and dos Santos, 2001).

In both case studies, reach width and bank slope were determined based on Landsat imagery. Bank slope was estimated by measuring low and high flow widths as well as high and low flow altimetric heights from the same location:

$$\alpha_b = \tan^{-1}\left(\frac{alti_{high} - alti_{low}}{\left(w_{high} - w_{low}\right)/2}\right) \tag{17}$$

The base width of the reaches was assumed equal to measured low flow widths.

Muskingum's *K* as well as the floodplain exchange coefficient, *coeff*, and shape parameter, *m*, were calibrated using both in-situ flows and altimetric levels.

4.3.2 Measurement operator

In order to carry out data assimilation of radar altimetry derived river levels, a measurement operator which maps the model states to be updated (reach storages) in the measurement space (altimetric levels) needs to be defined.

Reaches were assumed trapezoidal with bottom width *w*, bank slope α_b and length *L*. The reach storage can be expressed as a function of depth, *d*:

$$s = L \cdot \left(w \cdot d + \frac{d^2}{\tan(\alpha_b)}\right) \tag{18}$$

Solving for depth yields:

$$d = \frac{-wL + \sqrt{\left(wL\right)^2 + 4L/\tan(\alpha_b) \cdot s}}{2L/\tan(\alpha_b)} \tag{19}$$

Because the altimetric observations are measurements of water surface elevation rather than depth, a common reference was set to obtain:

$$h\left(s\right) = \frac{-wL + \sqrt{\left(wL\right)^2 + 4L/\tan(\alpha_b) \cdot s}}{2L/\tan(\alpha_b)} + \frac{\sum_{t=t1}^{t=tn}(d_{model}(t) - alti(t))}{n_t} \tag{20}$$

Where *(alti)* are the altimetric height measurements and *h* is the measurement operator.

4.3.3 The Extended Kalman Filter

The Extended Kalman Filter (EKF) was chosen for assimilation in Papers **II** and **III**. The EKF is the non linear extension of the linear Kalman filter (KF) which is a widely used sequential data assimilation strategy. The EKF is used when the model operator, the measurement operator or both are non-linear. The basic idea is then to replace the non-linear operators with their first order Taylor approximations at the forecasted state.

Equations (21) to (25) present the basic KF equations, in these equations, the '*f*' superscript indicates a forecasted state or covariance and the '*a*' exponent indicates an analysis (or updated) state or covariance.

The propagation equations are:

$$\boldsymbol{s}_{k+1}^{f} = \mathbf{F}_{k+1} \cdot \boldsymbol{s}_{k}^{f} + \mathbf{G}_{k+1} \cdot \boldsymbol{u}_{k+1} + \boldsymbol{\Gamma}_{k+1} \cdot \boldsymbol{w}_{k} \tag{21}$$

$$\mathbf{P}_{k+1}^{f} = \mathbf{F}\mathbf{P}_{k}^{f}\mathbf{F}^{T} + \boldsymbol{\Gamma}_{k+1}\mathbf{Q}_{k}\boldsymbol{\Gamma}_{k+1}^{T} \tag{22}$$

Where $\boldsymbol{s^f}$ is the forecasted state vector, $\boldsymbol{u}$ is the model forcing, $\boldsymbol{w}$ is a sequence of white Gaussian noise with covariance **Q**, **F** is the state transition matrix, ***G*** the control input matrix, $\boldsymbol{\Gamma}$ the noise input matrix and **P** is the state covariance matrix.

The state and its covariance are propagated until a time step *m* when an observation of the system is made. The state and covariance at time step *m* are then updated using the new measurement:

$$\boldsymbol{s}_{m}^{a} = \boldsymbol{s}_{m}^{f} + \mathbf{P}_{m}^{f} \cdot \mathbf{H}_{m}^{T} \cdot \left(\mathbf{H}_{m} \cdot \mathbf{P}_{m}^{f} \cdot \mathbf{H}_{m}^{T} + \mathbf{R}_{m}\right)^{-1} \left(\boldsymbol{y}_{m} - \mathbf{H}_{m} \cdot \boldsymbol{s}_{m}^{f}\right) \tag{23}$$

$$\mathbf{P}_{m}^{a} = \left[\mathbf{I} - \mathbf{P}_{m}^{f} \cdot \mathbf{H}_{m}^{T} \cdot \left(\mathbf{H}_{m} \cdot \mathbf{P}_{m}^{f} \cdot \mathbf{H}_{m}^{T} + \mathbf{R}_{m}\right)^{-1} \cdot \mathbf{H}_{m}\right] \cdot \mathbf{P}_{m}^{f} \tag{24}$$

Where **H** is the measurement operator which is defined as:

$$y_{m} = \mathbf{H}_{m} \cdot s_{m}^{t} + v_{m} \tag{25}$$

Where *y* is the measurement, $\boldsymbol{s}^t$ is the true state and *v* is a sequence of white Gaussian noise with covariance $\mathbf{R}_m$. The difference $(y_m - \mathbf{H}_m \cdot s_m^f)$ is called the innovation or measurement residual.

In case of non-linear model and measurement operators equations (21) and (25) use the non-linear model and measurement operators directly. For all other instances of **F** and **H** in equations (21) through (24), the first order Taylor approximations of the non-linear operators around the forecasted model state are used:

$$\mathbf{H} = \left.\frac{\partial h}{\partial s}\right|_{s=s^f} \qquad \text{and} \qquad \mathbf{F} = \left.\frac{\partial f}{\partial s}\right|_{s=s^f}$$

For the Brahmaputra case study, only the measurement operator was non-linear, while for the Zambezi case study, the inclusion of the Barotse floodplain made the model operator non-linear as well.

4.3.4 Error model

In order to perform data assimilation with the EKF, model and measurement error need to be specified.

Measurement errors on altimetry data points were assumed normally distributed with zero mean. In previous studies, Envisat altimetry levels over different rivers were found to have standard errors between 20 and 80 cm (see e.g. Frappart et al., 2006; Birkinshaw et al., 2010; Papa et al., 2010; Michailovsky et al., 2012).

In the Zambezi, the error estimates from Paper **I** were used as a basis to determine standard errors at the different VS. The errors used were between 34 and 74 cm over the basin and in the Brahmaputra the standard error on the measurements was assumed to be of 70 cm.

The quantification of model error is a very complex task due to the difficulty to isolate and quantify the different sources of error and simplifying assumptions are usually made. In this study, we assumed that the dominant source of error stemmed from the RR forcing to the routing models (e.g. Andreadis et al., 2007; Biancamaria et al., 2011).

The magnitude of the error on RR model outputs is typically proportional to the magnitude of the modeled runoff and the model error was therefore implemented as a multiplicative error term applied to the forcing. In order to quantify the uncertainty of the RR model, the normalized runoff calibration residuals were analyzed.

In the Zambezi to obtain in-situ measurements of runoff, gauged flow was assumed equal to runoff for upstream catchments. For catchments located further downstream gauged runoff from a given area was assumed equal to the difference between downstream and upstream gauged discharge.

In the Brahmaputra, only the data from Bahadurabad could be used and the normalized discharge residuals were therefore used and the error assumed to stem in equal proportions from all subbasins.

The residuals in both cases showed a high temporal correlation. In order to obtain a model error term in equation (21) closer to the assumption of white Gaussian noise, the autocorrelation was explicitly taken into account in the assimilation scheme. This was done by assuming a first-order auto-regressive (AR1) representation for the residuals:

$$\boldsymbol{w}_k = a \cdot \boldsymbol{w}_{k-1} + \boldsymbol{\varepsilon}_k \tag{26}$$

where a is the AR1 parameter and $\boldsymbol{\varepsilon}$ is a sequence of white Gaussian noise with covariance Q'.

The Kalman Filter equations can then be applied by augmenting the state vector with the correlated noise term (see e.g. Jazwinski, 1970). By setting:

$$\boldsymbol{S} = \begin{bmatrix} \boldsymbol{s} \\ \boldsymbol{w} \end{bmatrix},\ \mathbf{F'}_{k+1} = \begin{bmatrix} \mathbf{F}_{k+1} & \boldsymbol{\Gamma}_{k+1} \\ 0 & a \cdot \mathbf{I} \end{bmatrix},\ \mathbf{G'}_{k+1} = \begin{bmatrix} \mathbf{G}_{k+1} \\ 0 \end{bmatrix},\ \text{and}\ \boldsymbol{\Gamma'}_{k+1} = \begin{bmatrix} 0 \\ \mathbf{I} \end{bmatrix}$$

where all matrices and vectors are as defined previously and $\mathbf{I}$ is the identity matrix. Equation (21) can then be rewritten as:

$$\boldsymbol{S}_{k+1} = \mathbf{F'}_{k+1} \cdot \boldsymbol{S}_k + \mathbf{G'}_{k+1} \cdot \boldsymbol{u}_{k+1} + \boldsymbol{\Gamma'}_{k+1} \cdot \boldsymbol{\varepsilon}_k \tag{27}$$

And equations (22) to (24) can then be applied replacing $\boldsymbol{s}$, $\mathbf{F}$, $\mathbf{G}$ and $\boldsymbol{\Gamma}$ by $\boldsymbol{S}$, $\mathbf{F'}$, $\mathbf{G'}$ and $\boldsymbol{\Gamma'}$.

4.3.5 Model evaluation criteria

In order to assess the performance of the deterministic and assimilation model runs both in terms of accuracy and precision, the following measures were used:

- Coverage: the percentage of observations which fall within the predicted nominal confidence interval (this measure is also referred to as *reliability*).
- Nash-Sutcliffe Efficiency (NSE)
- Root Mean Square Error (RMSE)
- Sharpness: the width of the predicted nominal confidence interval

Because the choice of one prediction model over another typically requires tradeoffs between sharpness and reliability, a criteria combining both was used: the interval skill score (ISS) which is defined as follows (Gneiting and Raftery, 2007):

$$ISS_\alpha = \sum_i iss_\alpha \left(l, u, x_i\right) \tag{28}$$

and

$$iss_\alpha(l,u,x) = \begin{cases} (u-l) & \text{if } \; l < x < u \\ (u-l) + 2/\alpha \cdot (l-x) & \text{if } \quad x < l \\ (u-l) + 2/\alpha \cdot (x-u) & \text{if } \quad x < u \end{cases} \tag{29}$$

where x is the observed value and l and u the upper and lower confidence bounds at significance level α. The ISS should therefore be minimized as a high value will indicate wider confidence bounds and/or more observations falling outside of the confidence bounds.

5 RESULTS

In this chapter, the main findings of the research will be highlighted. The first two sections present results for the monitoring of levels and discharge in the Zambezi river basin (Paper **I**). The third section presents the results from the assimilation of radar altimetry data to routing models of the Brahmaputra (Paper **II**) and Zambezi (Paper **III**) rivers. The main results obtained were the following:

- Radar altimetry level time series were successfully extracted at 31 VS in the Zambezi for rives between 80 and 400 m wide with rms errors between 0.32 and 0.72 m
- Discharge at the good quality VS in the Zambezi was determined within 4.1 to 6.5% of mean annual in-situ gauged amplitude using in-situ rating curves and from 6.9 to 13.8% using the field and historical data methods.
- Assimilation of radar altimetry to simple routing models provided improved predictions in both case studies with NSE improvements from 0.78 to 0.84 in the Brahmaputra and from 0.21 to 0.65 and 0.82 to 0.88 in the Zambezi.
- There is a need for better error modeling as shown by the lack of robustness in terms of model reliability
- The low temporal resolution of the altimetry dataset can be overcome by using multiple VS depending on data availability

5.1 LEVEL MONITORING IN THE ZAMBEZI RIVER BASIN

A total of 423 crossings between the river network and the satellite ground track were identified in the Zambezi river basin. After removing crossings over small rivers where no data could be acquired and those located over floodplains, lakes or reservoirs, 31 virtual stations were identified as useable (see Figure 5).

The rivers at the retained VS had widths from 40 to 400 m, with the majority of them being between 100 and 250 m wide. For the 4 VS located at an in-situ gauging station, rms errors relative to in-situ levels were found to be between 32 and 72 cm which is within range of literature reported values for the Envisat altimeter over different rivers though previous studies focused on rivers of minimum 450 m width (e.g. Frappart et al., 2006; Birkinshaw et al., 2010; Papa et al., 2010).

For the classification of VS shown in Figure 5, VS with an rms error of less than 40 cm were classified as "good", those with an rms error of less than 70 cm classified as "moderate" and the rest classified as "bad" quality. A table detailing the results at each VS is included in Paper **I**.

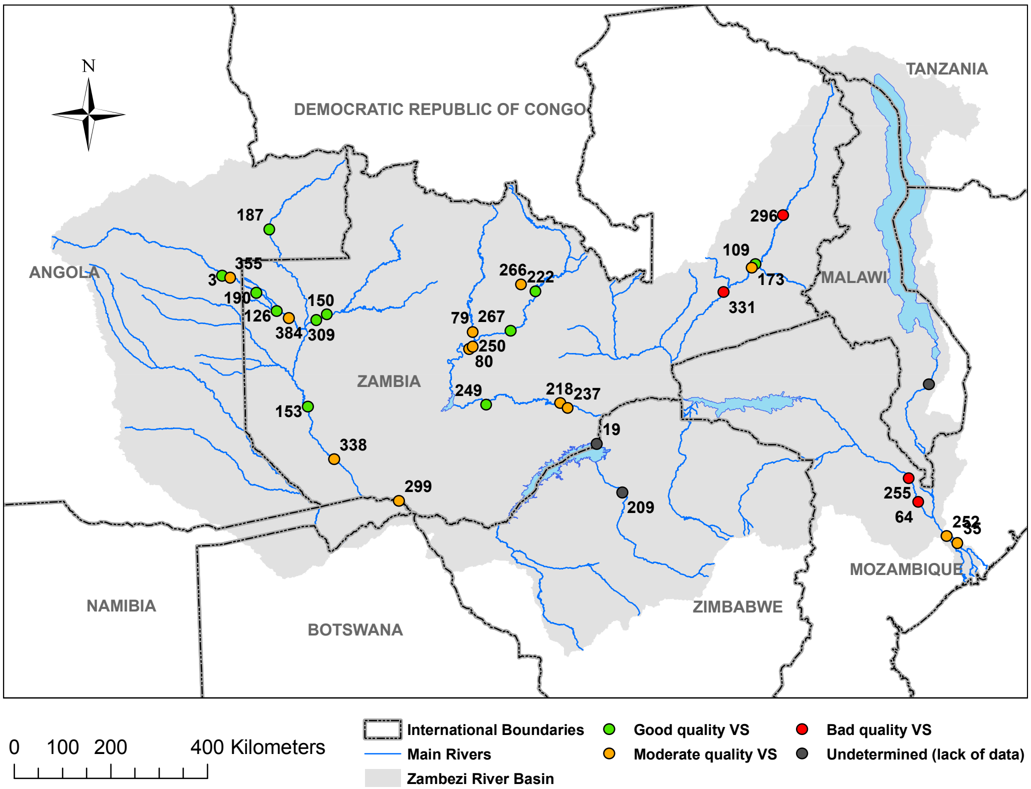

Figure 5: Location and quality classification of VS in the Zambezi River basin

No unique characteristic of a VS was identified as predicting the quality of the altimetric data in this study.

5.2 Discharge monitoring in the Zambezi River Basin

Of the VS identified in the Zambezi River Basin, only four were at the location of an existing gauge with an available rating-curve. The rating curves used in method 1 were the same as those used to produce the in-situ discharge data and the computed discharge at the three VS classified as "good" (109, 150 and 222) were therefore predictably found to be in very good agreement with the in-situ values with rms errors between 4.5 and 7.2% of mean amplitude and standard deviations (std) on the estimate within the same range (Table 1).

Table 3: Discharge calculation results using method 1

VS	RMSE [m3/s]	RMSE % of mean amplitude	STD [m3/s]	STD % of mean amplitude	Nb. of points of compari son	Hist. mean amplitude [m3/s]	Hist. mean flow [m3/s]
109	69.4	7.2	64.6	6.7	8	957.8	181.6
150	48.5	6.1	57.1	7.2	14	796.0	242.2
222	19.9	4.5	25.4	5.7	6	445.6	144.8
237	299.4	44.1	331.2	48.9	35	677.3	1030.3

Three of the rating curves built using the field method (method 2) were found to be close to the in-situ rating curves (at VS 109, 150 and 222), and the discharge results were similar to those obtained using method 1(Table 4).

The results at the fourth VS, however, were inconclusive. While flows estimated using the field data were systematically underestimated compared using the gauging station's rating curve, the field rating curve was found to be similar to an older rating curve from the same gauging station. Being unable to determine which in-situ rating curve to use, we chose to exclude the results from this VS.

Table 4: Discharge calculation results using method 2

VS	RMSE [m3/s]	RMSE % of mean amplitude	STD [m3/s]	STD % of mean amplitude	Nb. of points of compari son	Hist. mean amplitude [m3/s]	Hist. mean flow [m3/s]
150	59.9	7.5	69.5	8.7	14	796.0	242.2
222	49.8	11.2	42.2	9.5	6	445.6	144.8
309	42.9	5.4	54.5	6.8	11	796.0	242.2

The results using only remote sensing and historical low flow data (method 3) were found to have higher errors but they remained well within acceptable errors for discharge measurements with rmse values between 6.9 and 13.8% of mean amplitude for VS located at gauge locations.

Table 5: Discharge calculation results using method 3. Entries on a grey background signal VS location not coinciding with that of the gauge used for comparison.

VS	RMSE [m3/s]	RMSE % of mean amplitude	STD [m3/s]	STD % of mean amplitude	Distance from gauge [km]	Hist. mean amplitude [m3/s]	Hist. mean flow [m3/s]
79	88.9	34.7	121.2	47.3	90	256.1	68.4
109	132.5	13.8	113.5	11.8	0	957.8	181.6
150	55.2	6.9	70.6	8.9	0	796.0	242.2
173	297.4	31.1	154.8	16.2	20	957.8	181.6
222	54.0	12.1	57.9	13.0	0	445.6	144.8
266	33.0	76.3	24.1	55.7	40	43.2	17.9
267	82.8	19.8	61.8	14.8	15	418.6	158.5
299	538.0	15.9	478.2	14.1	80	3383.3	2720.8
309	47.3	5.9	74.2	9.3	25	796.0	242.2

5.3 Altimetry assimilation

5.3.1 Brahmaputra River case study

Six VS were used for assimilation in the routing model of the Brahmaputra River. The VS are located at the outlets of subbasins 7, 8, 12, 14, 15 and 16. The results are presented at the outlet of subbasin number 17 which coincides with the Bahadurabad gauging station, the only location in the basin for which recent discharge data was available. The location of the VS and gauging station is shown in Figure 3.

Analysis of model residuals yielded the following parameters for the AR1 error model:

$$\alpha = 0.9562 \text{ and } \sigma(\varepsilon) = 0.098$$

The results at Bahadurabad are presented in Table 6 and Figure 6. Model fit was found to improve significantly through assimilation. However, model reliability was strongly degraded with the number of observations within the 95% falling from 92% for the deterministic run to 76% for the assimilation run leading to a deterioration of the interval skill score.

Table 6: Assimilation Results at Bahadurabad. .Coverage, sharpness and ISS refer to a significance level of 0.05.

		Validation Period			Calibration Period (Deterministic Run)
		Deterministic Run	Assimilation Run	% change	
Coverage %	α = 0.95	91.96	76.30		93.15
	α = 0.70	91.54	85.90		93.81
NSE	α = 0.95	0.777	0.840		
	α = 0.70	0.777	0.844		
RMSE m^3/s	α = 0.95	10045	8510	-15.3	
	α = 0.70	10045	8396	-15.9	
Sharpness m^3/s	α = 0.95	22725	14129	-37.8	
	α = 0.70	21793	17117	-21.5	
ISS m^3/s	α = 0.95	$42{\cdot}10^3$	$55{\cdot}10^3$	29.6	
	α = 0.70	43.10^3	42.10^3	-4.0	

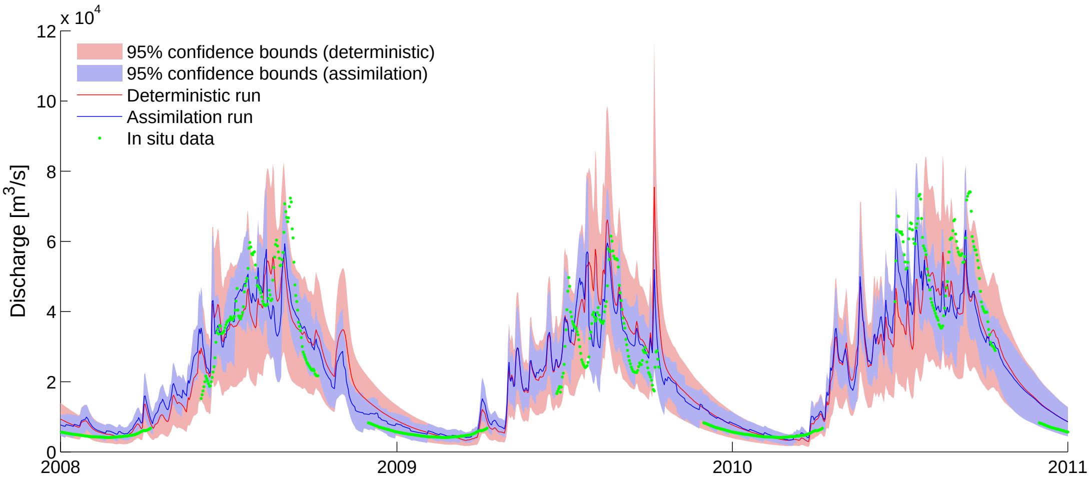

Figure 6: Assimilation results at Bahadurabad (AR1 parameter: 0.9562)

The influence of the error model was tested by running the assimilation again with a lowered AR1 parameter which may have been overestimated in the residual analysis due to the smoothing effect of the river routing. The σ(ε) parameter was adjusted to obtain the same coverage for high flows in the calibration period as in the previous run.

The results show that while the NSE and rms errors were only slightly affected, the coverage was largely improved (Table 6). This sensitivity to the error representation is a weakness of the assimilation scheme used as there is no agreed upon method to determine model error and a functioning error model parameterization will not be transferrable to a new case study.

While the Envisat satellite has a 35-day repeat period, the shifted reading times at the 6 VS used meant that, provided no missing data points, a measurement was acquired every 3 to 9 days. This proved to be an important factor in the success of the assimilation over the Brahmaputra River as improvements from the assimilation tended to wash out 6 to 10 days after a measurement (Figure 7).

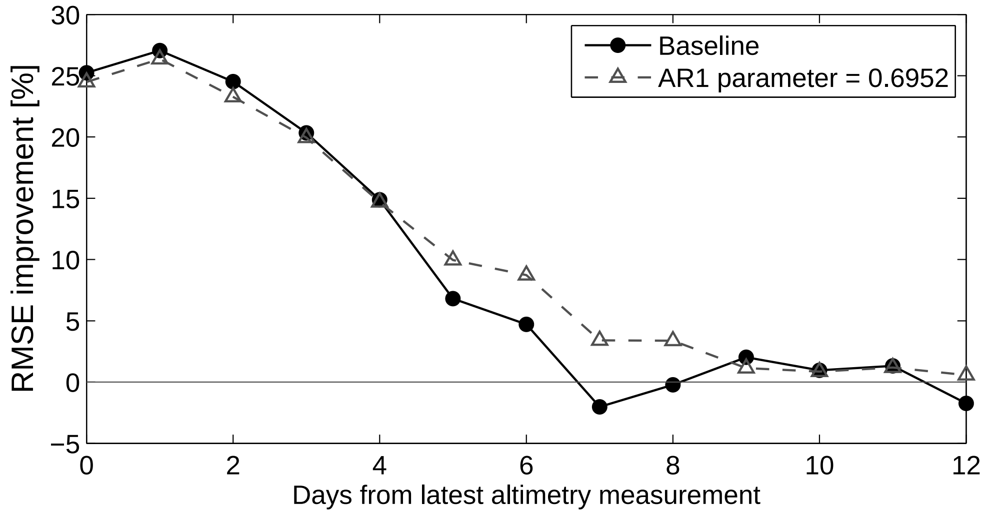

Figure 7: RMSE improvement as a function of the time since the last altimetry measurement

5.3.2 ZAMBEZI RIVER CASE STUDY

Assimilation of altimetry in the Zambezi River basin was carried out in the western part of the basin: upstream of Lake Kariba (watershed 1) where 6 VS were available and upstream of Lake Itezhi-Tezhi (watershed 2) where 3 VS were available (see Figure 2 for the location of watersheds and VS).

The results show improvements in all measures at all subbasins except for a slight loss of coverage for subbasin 17 (<3%) and a large loss of coverage for subbasin 24 (~14%) which led to a degradation of the ISS at this subbasin.

Table 7: Assimilation results in the ZRB. Coverage, sharpness and ISS refer to a significance level of 0.1. Shaded backgrounds indicate a degraded indicator.

Id	Coverage		RMSE			NSE		Sharpness			ISS		
	det [%]	assim [%]	det [m³/s]	assim [m³/s]	diff [%]	det [-]	assim [-]	det [m³/s]	assim [m³/s]	diff [%]	det [m³/s]	assim [m³/s]	**diff [%]**
14	83.8	80.0	596.8	351.7	-41	0.42	0.80	1398	810	-42	1938	1359	**-30**
24	79.9	66.0	503.0	343.2	-32	0.58	0.81	1091	569	-48	1611	1814	**+13**
32	54.4	72.8	784.9	459.6	-41	0.18	0.72	1413	594	-58	2732	2631	**-1**
34	54.0	70.9	896.5	598.6	-33	0.21	0.65	1211	545	-55	4252	3958	**-7**
12	73.5	81.8	76.7	55.1	-28	0.72	0.86	153	93	-40	374	304	**-19**
17	86.7	84.3	121.5	99.0	-19	0.82	0.88	227	174	-23	306	288	**-6**

Figure 8a shows that the improvements from assimilation were unevenly spread over time as can be seen for example in the difference in performance between the years 2005 and 2007.

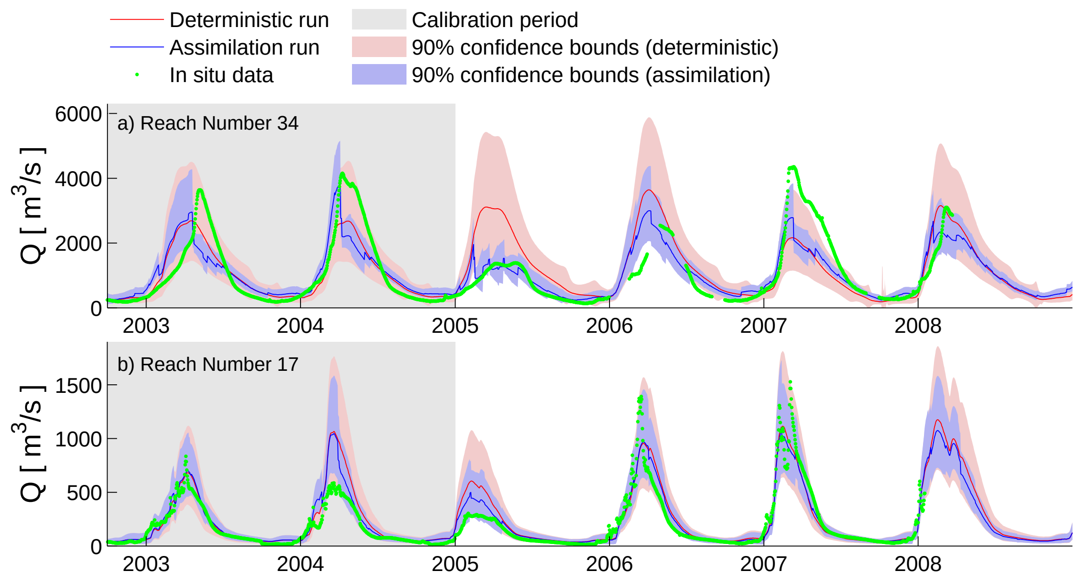

Figure 8: Assimilation and deterministic runs at the outlets of watershed 1 (a) and 2 (b).

Inspection of the altimetric time series revealed that in 2007, a large gap existed in the dataset with only one value available over a period of 67 days, between the 9th of February and the 17th of April and that the update carried out on that day decreased the model performance. The maximum delay between 2 satellite passes over one of the VS in watershed (1) is of 16 days which means that even in the best case scenario, the altimetry dataset may not be able to capture sharp peaks in the hydrograph. The fact that the VS were located on narrow reaches increased the risk of the altimeter not being able to lock on to the water surface leading to a missing data point, or of contamination by other surfaces leading to an erroneous measurement.

In watershed (2), the same problem occurred because only 3 VS were available to perform the update and the 3 VS are all visited by the satellite within 6 days of each other over the 35-day satellite repeat period.

6 Conclusions

The objective of this PhD study was to study the use of radar altimetry for hydrological monitoring and modeling in large river basins.

The analysis of Envisat altimetry over the Zambezi has shown that with precise geographical selection, water level time series can be extracted for rivers much narrower than the 369 m along-track resolution of the data product would suggest, with good results being obtained for rivers between 80 and 400 m wide.

Two methods were developed and tested to produce discharge time-series from altimetry in the absence of in-situ rating curves. The results for the Zambezi suggest that a virtual discharge gauging station can be set up at a VS location using data from a single field visit or using historical datasets to determine a reference low-flow depth. However, the methods could only be tested at a limited number of locations and further studies are needed in order to determine whether they are widely applicable. In many regions of the globe, river monitoring has declined since the 1980s and the use of historical data to set up virtual gauging stations at or near decommissioned in-situ gauging stations therefore has great potential.

A simple data assimilation method to update the states of a routing model using radar altimetry was developed. The method is suited to large river basins with minimal in-situ data and was designed as an add-on to be easily coupled with any rainfall-runoff model. Data assimilation was carried out using this method in the Brahmaputra and Zambezi river basins. Model performance in terms of accuracy was greatly improved through the assimilation in both case studies, but the issue of model reliability remained unsolved due to the difficulty in accurately representing model errors, in particular for the more complex Zambezi case study.

The results in the Zambezi showed that for areas where river dynamics are complex, representing model error by a multiplicative factor on rainfall-runoff forcing is inadequate and further work should focus on quantifying and taking into account the uncertainty of the routing scheme itself. Another option would be the use of more detailed hydrodynamic model which would diminish the routing model error, and potentially make the initial assumption of a runoff-dominated model error valid. This would however involve switching to an ensemble based assimilation strategy due to the more complex routing equations and the added computational burden may need to be considered for large-scale applications.

The Zambezi case study also highlighted the limitations linked to the low temporal resolution of the Envisat data in areas where only few VS are available, in particular if the VS are located on narrow rivers where missing/erroneous data points are more likely. However, future satellite-based altimetry missions, in particular the Surface Water Ocean Topography (SWOT) mission scheduled to be launched in 2019, will provide data at a higher spatial and temporal resolution and over narrower rivers than is currently possible. This will enhance the value of radar altimetry in data assimilation applications. The limitations linked to the resolution of the dataset could also be mitigated by jointly assimilating altimetry and other remote-sensing data types in a more integrated approach.

In conclusion radar altimetry is a valuable dataset for hydrologists, in particular for applications in data-sparse regions, and while it is not in a position to replace in-situ gauging networks, methods to integrate the use of radar altimetry jointly with other remote-sensing and in-situ data types and hydrological models have the potential to greatly improve knowledge and prediction of freshwater availability.

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8 PAPERS

The following papers are included in the thesis:

I. Michailovsky, C.I., McEnnis, S., Berry, P.A.M., Smith, R., and Bauer-Gottwein, P.: River monitoring from satellite radar altimetry in the Zambezi River basin. Hydrology and Earth System Sciences, 16 (7), 2181-2192, 2012.

II. Michailovsky, C.I., Milzow, C., Bauer-Gottwein, P.: Assimilation of Radar Altimetry to a Routing Model of the Brahmaputra River. Submitted.

III. Michailovsky, C.I., and Bauer-Gottwein, P.: Operational reservoir inflow forecasting with radar altimetry: The Zambezi case study. Submitted.

In this online version of the thesis, the papers are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from:

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The Department of Environmental Engineering (DTU Environment) conducts science-based engineering research within four sections:
Water Resources Engineering, Urban Water Engineering,
Residual Resource Engineering and Environmental Chemistry & Microbiology.

The department dates back to 1865, when Ludvig August Colding, the founder of the department, gave the first lecture on sanitary engineering as response to the cholera epidemics in Copenhagen in the late 1800s.

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