Satellite-based altimetry data for hydrological assessments: two case studies

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Authors
J.E. Hunink, J.P.C. Eekhout, J. de Vente, S. Contreras, G. Simons

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NL-RIA

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FutureWater
Costerweg 1V
6702 AA Wageningen
The Netherlands

+31 (0)317 460050

info@futurewater.nl

www.futurewater.nl

Summary

A Dutch consortium has joined in the project "Dutch network on small spaceborne radar instruments and applications (NL-RIA)", led by TU Delft. The objective is to bundle the radar-related knowhow available in The Netherlands, and fill the knowledge gaps, in order to boost SmallSat radar-based Earth Observation technology. The task of FutureWater in this project is to study challenges and requirements for applications of altimeter data for water resources assessments. This report presents a short literature review, existing databases that are currently used for this type of studies, two case studies performed by FutureWater in which altimetry data was used. Based on these case studies in the final chapter, a few recommendations and requirements are put forward on revisit frequency and accuracy for the design of an altimetry mission.

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1 Introduction

1.1 Background

Since its beginning, the space sector has been dominated by space agencies and large corporations acting as large-scale integrators (LSI), with smaller stakeholders contributing specialized subsystems. Dutch technology has been particularly successful in implementing and supplying optical remote sensing instruments for air quality and pollution monitoring, but also in the field of Radio Frequency (RF) technology and instruments: Dutch parties are world players in the areas of antenna technology, micro-electronics, and radar instrumentation.

In the last couple of decades, there is an increasing focus on small spacecrafts, light weight and agile development cycles, and dramatically reduced costs. There are several successful missions recently both for optical imaging as well as in the field of microwave remote sensing. This development is likely to strengthen further: commercially driven light-weight missions emphasizing the delivery of high-resolution data with very short revisit times over specific areas of interest. This type of missions provides a new level-field, with lower technological and financial entry barriers, for the development of miniaturized microwave Earth Observation systems and their exploitation.

A large Dutch consortium has joined in the project “Dutch network on small spaceborne radar instruments and applications (NL-RIA)”, led by TU Delft. The objective is to bundle the radar-related knowhow available in The Netherlands, and fill the knowledge gaps, in order to boost SmallSat radar-based Earth Observation technology. The focus of the project is on microwave remote sensing.

A key advantage of microwave remote sensing compared to optimal imagery is the all-weather/day and night observation capability, which greatly enhances the observation opportunities. This includes the ability to observe through clouds. Microwave remote sensing system include passive (radiometers) and active ones (radar altimeters, Synthetic Aperture Radars, precipitation radars, scatterometers, etc). This study will focus on altimeters and thus on active radar.

Satellite-based applications of altimeter technology have been operationally used for several decades. Altimeters are used to measure wave height and wind over oceans, resulting in information on sea-level rise, ocean currents, eddies, and the El Niño effect. Innovative systems which are currently under development are expected to measure also water levels over inland waterbodies. The challenge is here to designate the waterbody from surrounding uprising landmasses which are at shorter distances and have far higher backscatter.

Continuous monitoring of fresh water bodies like rivers, lakes and artificial reservoirs, is important for water resources management, and thus for the principal water users in river basins, such as domestic, industrial and irrigation demands. Also, potentially there can be applications of this information for flood early warning, renewable energy (hydropower) and for the transport sector (shipping).

The SWOT (Surface Water and Ocean Topography) is a mission being developed by NASA and other agencies and is planned to be launched in 2020, having as a key purpose to measure inland water bodies using the latest radar technology. This mission is relatively expensive and will have a limited revisit capability. There may be an opportunity for smaller low-cost missions with less accuracy but higher update rate.

For the management of fresh water resources at the basin level, information on the status of surface water bodies is critical. In many areas in the world however, this information is scarce. Especially in developing countries, water level measurements of lakes and reservoirs are hardly available. In Europe, ground-based measurements are more common but sometimes performed by the entity operating the reservoir or river abstraction, and thus not available to water resources managers for the purpose of water resources planning. Also in transboundary (international) river basins, ground-based information is often not shared, so satellite-based information can be of high value for certain end-users (Zhang et al., 2014).

Altimeter measurements of rivers, lakes and artificial reservoirs and be used for two purposes:

- Strategic planning of water resources, which requires water resources assessments to support for example river basin management plans
- Operational management of water resources, for example for the hour-by-hour operational management of water release from reservoirs for hydropower.

Figure 1. Water levels of the Fuensanta reservoir, Segura river basin, Spain, in 2015 (left) and 2017 (right). Source: La Verdad

This study focuses on the first type of applications: strategic planning and decision making on the long-term. Especially for this purpose, satellite-based altimeter data has the potential to fill an important information gap. For the second type of applications: operational water management and short-term decision making, typically ground-level water level sensors are more cost-effective than satellite-based solutions[1].

The following section presents a few related applications and summarizes the key challenges of using altimetry data for water resources assessments.

[1] https://www.futurewater.nl/projects/intogener-chile-3/

1.2 Current challenges of using altimetry data for water resources assessments

Up to today, ground-based measurements of water level data for water resources assessments are more commonly used than satellite-based measurements. Streamflow gauges typically measure water levels, from which streamflow is derived using a stage-discharge relationship. Ground-based equipment to measure water levels of lakes and reservoirs are used to establish water balances of these water bodies and assess inflows and outflows.

However, in many areas in the world, ground-based measurements are not available. Especially in mountainous areas, but often also in downstream areas, especially in developing countries, information on the status of water bodies is scarce. This is problematic as for water resources planning this information is essential to calibrate models and build decision support tools.

Increasingly, satellite-based altimetry datasets are becoming a useful resource to fill the data gaps for this type of studies. Over the last decade, several researchers are developing methodologies to derive streamflow from satellite-based altimetry of water levels in rivers (Kim et al., 2019a; Sichangi et al., 2016). Kim et al. (Kim et al., 2019b) provides an overview of the methods used for this purpose. For assessing streamflow, certain information on the local river conditions is necessary to establish a relationship between river level and flows. This, next to the challenges in terms of accuracy of the water level measurements, has limited so far its use for a few wide rivers like the Amazon (e.g. da Silva et al., 2010). Few studies have been dedicated so far to narrower rivers; e.g. Domeneghetti et al. (2015) show that their may be potential for radar altimetry to contribute to the calibration of hydraulic models.

The use of altimetry data on lake and reservoir levels is closer to operational use in actual user-oriented applications, as will be discussed afterwards. The accuracy of these data are typically in the order of 5 to 50 cm (Politi et al., 2016). The disadvantage of altimeters is that they can only return measurements from along their track, which does not cover the globe. As a result, only specific water bodies (that fall into the satellite's track) can be detected. Laser altimeters such as the Geoscience Laser Altimeter System (GLAS) on- board ICESat (Ice, Cloud, and land Elevation Satellite) are more suitable for relatively small water bodies due narrower footprint size (~100 m) compared to radar altimeters (several kilometers).

Rather than lake water level, the actual variable of interest for water resources assessments is lake water storage, or storage fluctuations. Lake water storage cannot be measured directly from altimetry data. Water level information needs to be combined with bathymetric information of the water body in order to produce volumetric estimates. To replace the need for bathymetric predictions, new techniques that make use of visible and IR-based lake surface area estimations have been developed for the retrieval of lake water volume (e.g. Duan and Bastiaanssen, 2013).

Duan and Bastiaanssen (2013a) tested four global altimetry datasets and proposed a method for estimating water volume changes in lakes and reservoirs from these databases in combination with satellite imagery data, and without any in-situ measurements and bathymetry maps. Three lakes/reservoirs with different characteristics were studied. Two of the three lakes provided accurate estimates, while for one lake the method showed poor performance when comparing with in-situ water levels.

Zhang et al. (Zhang et al., 2014) developed a novel classification algorithm in order to improve the accuracy of water surface area estimations for reservoirs with areas in the order of 100 km^2.

They smartly combine data from the ICESat/GLAS with relatively high spatial resolution (70 m) and the MODIS-derived data (several kilometers). This takes away a disadvantage of the ICESat data which is its short life- time (2003–2010) and low repeat frequency (91 days). The satellite-based reservoir elevation and storage were validated by gauge observations over five reservoirs. The storage estimates were highly correlated with observations (i.e., coefficients of determination larger than 0.9), with normalized root mean square error (NRMSE) between 10 and 25%.

In short, the use of altimetry data so far is limited for water resources planning: decision support tools and models need data with sufficient observations and accuracy. The key challenges and/or requirements are:

- Data needs to be available at least on a monthly timestep. Some altimetry datasets have a lower frequency, which limits their usefulness for this purpose.
- The footprint of satellite-based altimeter data is nowadays at least 100m, but most platforms have in fact much larger footprints (several km^2). This limits their usefulness for water bodies that are in the order 1-10 km^2. In many river basins, reservoirs are typically in that order of magnitude, summing a substantial part of the water stored in the basin (see Figure 2 for all reservoirs in Spain).
- Related to the footprint is the accuracy in the water level measurement: the error can be up to several decimeters. Depending on the depth-storage relationship, this can limit its usefulness for a sufficiently accurate estimate of water volume and inflows and outflows. Case study II provides more insight in this issue.

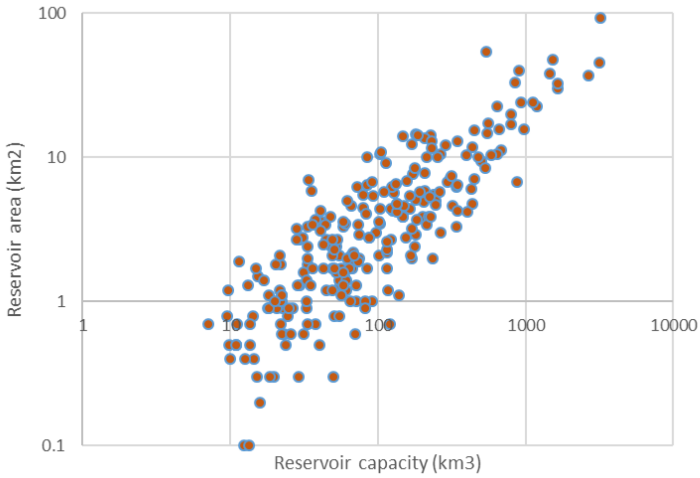

Figure 2. Reservoir capacity versus reservoir area of all reservoirs in Spain

1.3 Existing altimetry databases

Several radar altimeters are currently operational, for example the ERS Radar Altimeter (RA) and Envisat RA-2, the Poseidon sensors on-board of TOPEX/Poseidon, Jason-1 and Jason-2 (or Ocean Surface Topography Mission, OSTM), and GeoSat FellowOn (GFO) Radar Altimeter. Data from these sensors were used to create several databases that include water body level estimates. This section provides a short summary of the most relevant databases available today.

1.3.1 Global Reservoir and Lake Monitor (G-REALM)

The U.S. Department of Agriculture's Foreign Agricultural Service (USDA-FAS), in co-operation with the National Aeronautics and Space Administration, and the University of Maryland, are routinely monitoring lake and reservoir height variations for many large lakes around the world. The program utilizes NASA/CNES/ESA/ISRO radar altimeter data over inland water bodies in an operational manner. The surface elevation products are produced via a semi-automated process and placed online[1]. Monitoring height variations will greatly assist the USDA/FAS Office of Global Analysis to quickly locate regional droughts, as well as improve crop production estimates for irrigated regions located downstream from lakes and reservoirs. Reservoir and Lake height variations may be viewed in graphical and text format by placing the cursor on and clicking the continent and lake of interest. River Lake Hydrology (RLH)

The project currently utilizes near-real time data from the Jason-3 mission, and archive data from the Jason-2/OSTM, Jason-1, Topex/Poseidon, and ENVISAT missions. Data processing procedures closely follow methods developed by the NASA Ocean Altimeter Pathfinder Project (see references). When fully operational, updated products are delivered within 7-10 days after satellite overpass. The resulting time series of height variations are expected to be accurate to better than 10cm rms for the largest (and more open) bodies of water such as The Great Lakes, USA, Lakes Victoria and Tanganyika in Africa etc. Smaller lakes or those that experience more sheltered (from wind) conditions can expect to have accuracy's better than 20cm rms (e.g. Lake Chad, Africa). Satellite passes that cross over narrow reservoir extents in severe terrain will push the limits of the instruments with resulting rms values of many tens of centimeters.

1.3.2 Hydroweb (GOHS)

The Hydroweb[2] project provides continuous, long-duration time-series of the levels of large lakes with surface areas over 100 km2, reservoirs and the 20 biggest rivers in the world. The operational measurement series are updated no later than 1.5 days after a new altimetry measurement becomes available. They cover about 80 large lakes and 300 measurement points along about 20 major rivers.

The database is based on various altimetry satellites: ERS-1 (1991-1996), Topex/Poseidon (1992-2006), ERS-2 (1995-2011), GFO (2000-), Jason-1 (2001-2013), Envisat (2002-2012), Jason-2 (2008-) and Saral/Altika (2013-). The dataset is developed by the GOHS (Géophysique, Océanographie et Hydrologie Spatiales) group of LEGOS (Laboratoire d'Etudes en Géophysique et Océanographie Spatiales) in Toulouse. This dataset has been used for example previously for an irrigation potential study in the Nile basin, see (Droogers et al., 2012)

1.3.3 ICESat-GLAS level 2 Global Land Surface Altimetry data (ICESat-GLAS)

Although the main objective of the Geoscience Laser Altimeter System (GLAS) on the ICESat (Ice, Cloud, and land Elevation Satellite) mission is to measure the elevation changes of polar ice sheets between 2003 and 2009, ICESat-GLAS derived water levels in lakes have shown a high accuracy of around 10 cm (Bhang et al., 2007). The ICESat-GLAS level 2 Global Land Surface Altimetry data (GLA14) was recently used to derive water levels for lakes (Phan et al., 2012; Swenson & Wahr, 2009; Zhang et al., 2011a, 2011b). The main strength of the satellite laser altimeter ICESat is that it can measure at 172 m intervals along-track with a narrower footprint size of about nominal 70 m compared to the radar altimeters with a footprint size of several kilometers (Zwally et al., 2002).

1.3.4 Database for Hydrological Time Series of Inland Waters (DAHITI)

The DAHITI (Database for Hydrological Time Series of Inland Waters) dataset has been used successfully for flooding, lake and wetland studies previously (Schlaffer et al., 2016; Schwatke et

[1] https://ipad.fas.usda.gov/cropexplorer/global_reservoir/
[2] http://hydroweb.theia-land.fr/

al., 2015b; Singh et al., 2015). DAHITI was developed by the Deutsches Geodätisches Forschungsinstitut der Technischen Universität München (DGFI-TUM) in 2013. DAHITI provides water level time series of lakes, reservoirs, rivers, and wetlands derived from multi-mission satellite altimetry for hydrological applications. For the estimation of water heights, multi-mission altimeter data are used, such as Topex (NASA, CNES), Jason-1 (NASA, CNES), among others. The processing strategy of DAHITI which is described in detail in Schwatke et al. 2015 is based on an extended outlier detection and a Kalman filtering.

A global study on the use of DAHITI for lake storage evaluation was performed by Busker et al. (2018). An area-specific application of the DAHITI database for water resources assessments is presented as case study I in this report.

1.4 Objective

To understand better the potential for small-scale low-cost altimetry missions, this study aims at showcasing the use of these data for water resources assessments and assessing how the uncertainty of satellite altimetry product affects the calibration of a hydrological model, and thus influences the usefulness of these data for being used in water resources planning. Based on this study, a few recommendations and requirements were extracted to support the design of such a mission.

The study consists of two case studies. Case study I shows how altimetry data can be used in a real-world application, in which this type of data was essential to derive the water balance of a wetland, and to support an NGO in directing their efforts towards better conservation of the wetland.

Case study II investigates how altimetry data could potentially be useful for calibrating hydrological models: revisit frequency and accuracy (related to footprint and mixed pixels) are changed by generating datasets of synthetic altimetry products, to assess this factor affects the performance of the model.

2 Case study I: water balance of a large swamp

2.1 Introduction

Swamps are ecological systems that provide critical ecosystem services in many areas in the world. Their dynamics are often difficult to grasp and data on the hydrological processes taking place is often scarce. To evaluate the relevance of these complex system, data on the water stored in the wetland can be an essential variable which is in many places in the world not available.

This case study shows how altimeter data of the large Lukanga swamp (1850 km^2) in the Kafue basin, Zambia, was used to establish the water balance of this highly complex system. The study was performed for the NGO The Nature Conservancy, in order to demonstrate the importance of this system in the overall hydrological and ecological functioning of the river basin.

2.2 Methods

2.2.1 Approach

The Lukanga Swamp is a large wetland that functions like a sponge, absorbing water that comes in during the wet season, or from the periodically flooding of the Kafue through overflow. It buffers water and releases the water slowly during the dry period.

Figure 3 shows a map with the Lukanga Swamp, the Kafue river in the north-east, the Lukanga River and the Mufukushi River that are part of the Lukanga watershed. The blue arrows indicate the water received from the Lukanga watershed. The red arrow the water leaving the swamp to the Kafue river. The yellow arrows indicate areas with occasional overflow during flood events. It is important to note that these flows do not occur only as surface flows, but also as sub-surface flows: the floodplain and the Lukanga swamps are probably well connected through the sub-surface. However, no data are available on this connection.

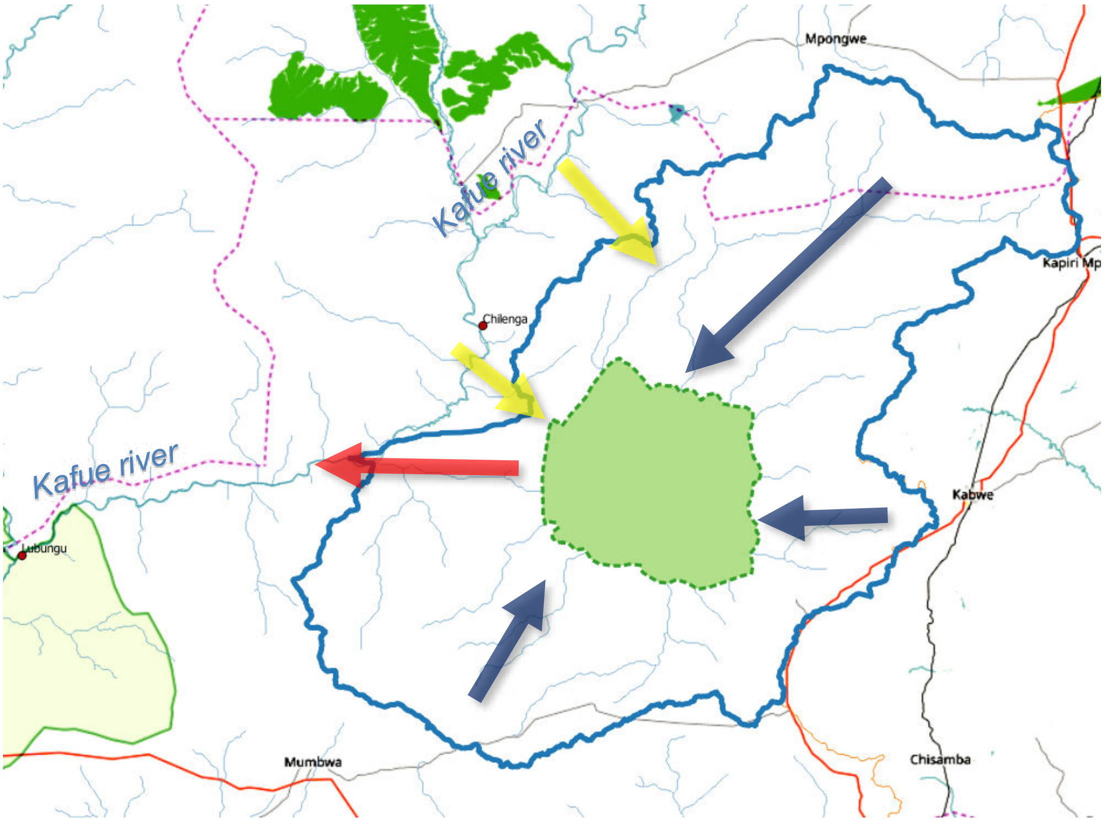

Figure 3. Schematic diagram of the study area showing water balance components and the tools used

To resolve the water balance of the swamp, a combination of tools is used:

- Optimal imagery from satellites to assess the flood dynamics, based on flood area estimates;
- A hydrological model (SWAT) to assess the hydrological flows to the swamp, and precipitation/evapotranspiration;
- Altimeter data to validate the storage level fluctuations and the water storage variability of the swamp;
- A water resources system model (WEAP) to integrate all data from observations and the SWAT model, to assess the water balance.

The water balance is resolved on a monthly timestep for a period of 16 years (2000-2015).

In this report, no detailed descriptions are given of the modelling components of this study. More details on that can be found in (Hunink et al., 2017a).

The following water balance was established for the system:

$$P + Qin + Qov - ET - Qout = dS$$

For an explanation of these variable see Table 1.

For this analysis, the principal unknown variable is Qov: an overflow that occurs occasionally from the main river system towards the swamp in case of high flooding events in the Kafue river. This variable depends on the coupling of both systems and is parameterized in the WEAP model. No data are available on this coupling, so the parameters need to be assessed by inverse modelling ("calibration"). The inverse modelling is done by matching the water levels as simulated by the WEAP model, with the water levels from altimetry data.

Table 1. Description of the water balance terms

Abbreviation	Variable	Description	Tool used
P	Precipitation	Rainfall falling directly on the swamp	Station data
Qin	Streamflow	Water inflow from the Lukanga watershed	SWAT
Qov	Overflow	Occasional surface overflow from Kafue during flood events, and subsurface flow from the Kafue river floodplain to the Lukanga swamps	Remote Sensing
ET	Evapotranspiration	Evapotranspiration from swamp (assumed to be at its potential rate)	SWAT
Qout	Outflow	Flow leaving swamp through exit channel to Kafue and subsurface flow between Kafue alluvial subsurface and swamp subsurface	Water balance / WEAP
dS	Storage difference	Difference in water stored in Lukanga swamps	Altimeter data

2.2.2 Data

Satellite-based altimeter data has been collected from the DAHITI database ("Database for Hydrological Time Series over Inland Waters") (http://dahiti.dgfi.tum.de/en/) (Schwatke et al., 2015a), previously summarized. The database provides water level data from July-2002 to October-2010 (Figure 4).

Lukanga Swamp Africa, Zambia Public Realtime

GENERAL INFO

Target Name:	Lukanga Swamp
Continent:	Africa
Country:	Zambia
Target Type:	Wetland
Basin:	Zambezi
Longitude:	27.7954 °E
Latitude:	-14.4054 °N
Period:	2000-01-01 - 2015-11-03
Data Points:	220
Min./Max./Avg. Height:	1115.25 m / 1118.25 m / 1116.44 m
Height Variations:	3.01 m
Last Update:	2016-09-12 09:47:01
Software-Version:	4.4

ALTIMETER DATA

The data of the following altimeter missions and corresponding passes have been used for the estimation of the water level time series. An additional "*" indicates that an additional retracking of the altimeter measurements was performed.

Mission	Pass No.
Envisat	0156, 0543
SARAL/AltiKa	0156*, 0543*

Figure 4. Lukanga swamp data profile in the DAHITI database.

2.3 Results

2.3.1 Validation of the intra-annual and inter-annual dynamics of the altimetry data

The altimetry data for the Lukanga swamp is shown in Figure 5. For the period with available data, three periods with interannual trends in water levels can be distinguished:

- September-2002 to December-2006 was a period with an overall decrease of water levels. Based on an approximate level-volume relationship, this corresponds to a decrease in volume of approx. 4,000 MCM
- In 2007 water levels started to increase. The interannual positive trend was maintained up to October-2010. This increase corresponds to an additional volume of about 7,000 MCM. Optical satellite imagery confirms that the open water surface is also relatively high during this period.
- The third period with available data ranged from March-2013 to November-2015. As in the first period, this was characterized by a declining interannual trend.

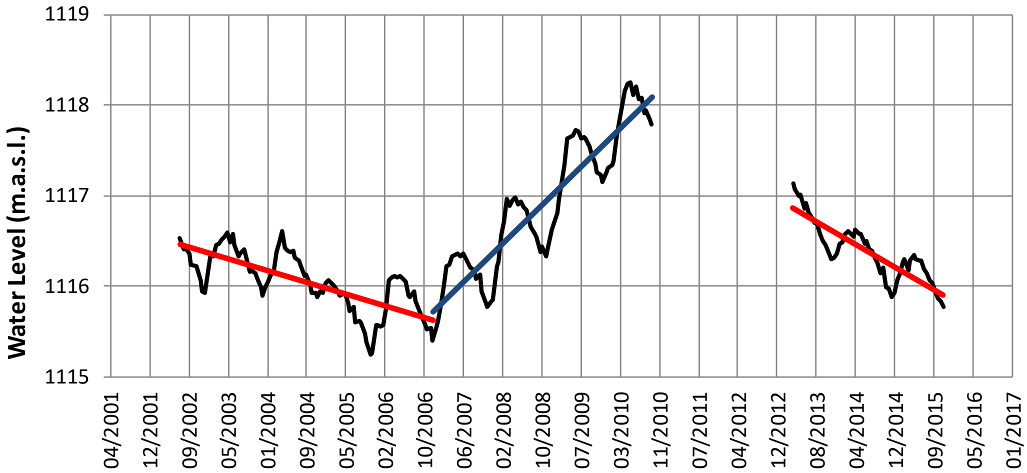

Figure 5. Altimetry data of the Lukanga swamp

To verify the verify intra-annual and interannual dynamics, the altimetry data were compared with historic in-situ data of the water level of the swamp, available between the years 1961 and 1987 (see Figure 6).

Table 2 shows three statistics: the mean annual amplitude, the length of the inter-annual periods and the standard deviation of the altimetry dataset versus the in-situ dataset. As can be seen, the statistics are rather similar. This suggests that, in spite of the mixed pixels in the wetland, the altimetry data are sufficiently accurate to be used for the purpose of establishing the water balance.

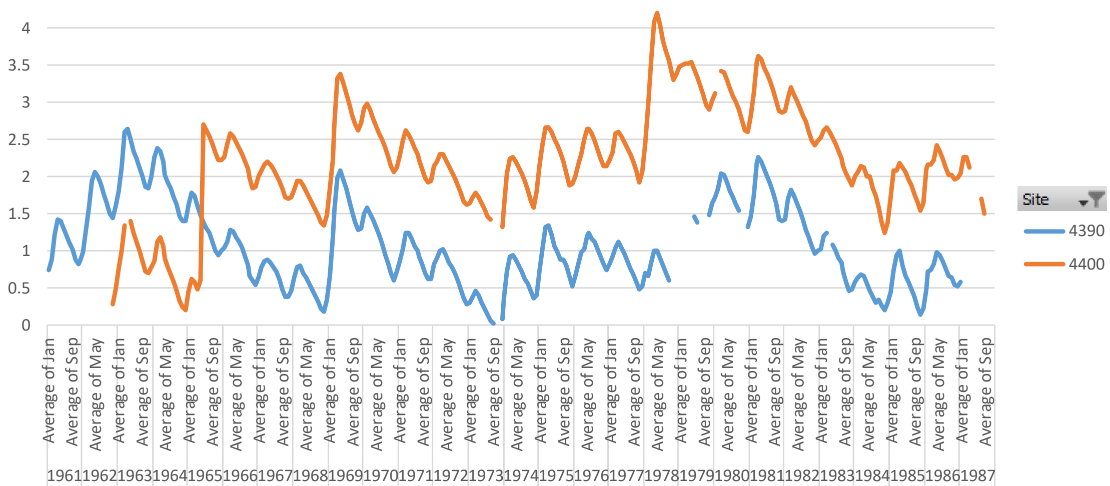

Figure 6. Surface water level at Chilwa Island and at Twenty Village in the Lukanga Swamp, from 1961-1987.

Table 2. Statistics of the altimetry data and in-situ water level data of the swamp

Statistic	Altimetry data (2002-2015)	In-situ data (1961-1978)
Mean annual amplitude (m)	0.8	1.2
Interannual periods (years)	4 – 5	4 - 5
Standard deviation (m)	0.71	0.65

2.3.2 *Inverse modeling based on altimetry data*

The WEAP model was used to assess the water balance. By means of inverse modeling, the parameters were established that define the coupling between the Kafue system and the swamp. The parameters that describe this coupling are (1) minimum flow in the Kafue system, and (2) maximum flow from the Kafue system towards the swamp.

The goal of the inverse modeling is to make sure that there is an adequate match between simulated swamp levels and observed (altimetry) levels. Figure 7 shows both time series. From the figure it can be observed that the interannual trends are well captured by the model (decreasing between 2002-2005, increasing 2006-2010, decreasing 2013-2015). Also, the annual dynamics (the months in which the lake starts filling and emptying) are well captured. The correlation between both series is relatively high, giving confidence in the model outcomes (Pearson correlation coefficient = 0.77). A less adequate fit is seen in the annual amplitude. This is most likely due to the poor information on the lake bathymetry. This demonstrates the need for having accurate data to establish the depth-volume curve.

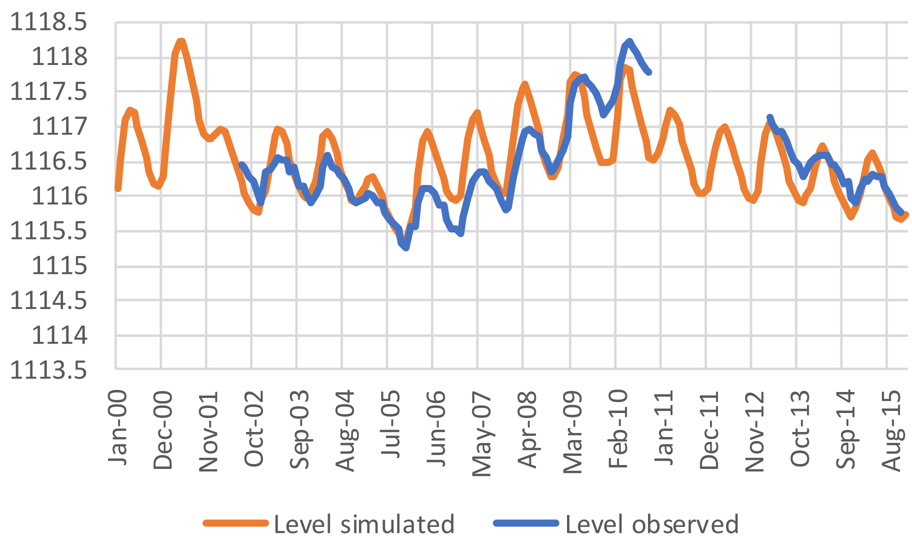

Figure 7. Simulated versus observed (remote sensing) water levels in the swamp

2.3.3 *The water balance of the swamp*

Using all information sources, simulations and the altimetry data, the dynamics of the water balance was assessed for the 15-years period, see Table 3, Figure 8 and Figure 9.

Table 3. The annual water balance for the swamp, based on the water balance equation used in this study (see section 2.1). All values in MCM per year.

Year	Inflow watershed Qin	Evapot. - Precipitation ET - P	Overflow Kafue Qov	Outflow to Kafue Qout	Storage diff. Swamp dS
2000	5124	345	0	-3545	-1233
2001	7149	310	205	-5317	-1726
2002	1796	1260	0	-3258	2722
2003	4166	794	0	-3106	-266
2004	3625	688	0	-2994	58
2005	1617	1625	0	-1601	1609
2006	4850	616	52	-2785	-1501
2007	4367	455	262	-3376	-799
2008	5118	690	210	-4267	-370
2009	5293	760	414	-4678	-268
2010	5282	551	446	-4797	-380
2011	3188	1021	28	-3691	1497
2012	3512	724	352	-3176	36
2013	3858	1039	50	-3196	326
2014	3018	1078	0	-2535	595
2015	3031	1118	0	-2306	393
Mean	4062	817	126	-3414	43

To understand better the swamp´s role as a regulating buffer – retaining water in dry periods and dry years – and providing water to the Kafue river, the following flows were included in one figure (Figure 8):

- Kafue flow at Chilenga (observed flows), 20 km upstream of Lukanga swamps
- Inflow into the swamp, from the Lukanga watershed
- Overflow from the Kafue river to the Lukanga swamps during flood periods
- Outflow from the Lukanga swamp to the Kafue river

Figure 8 shows the monthly balance for all years, and Figure 9 shows the annual totals, and the mean monthly values.

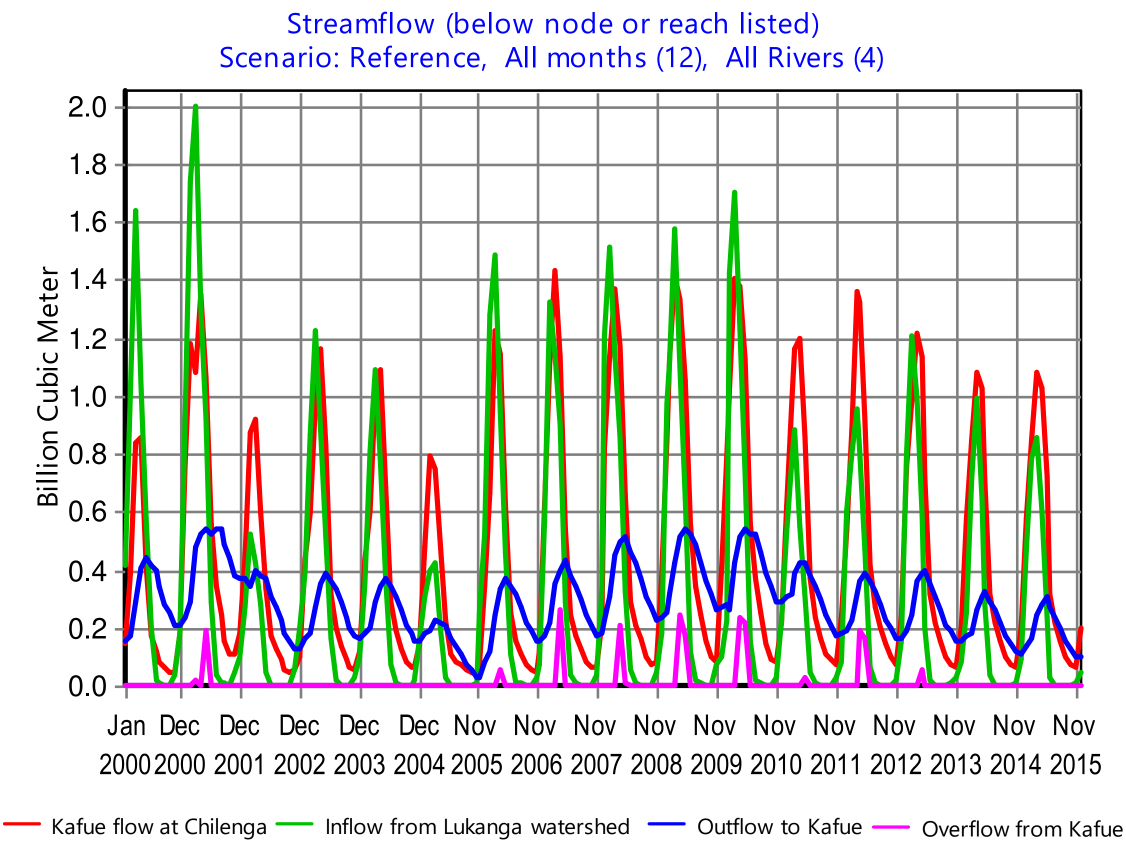

Figure 8. Monthly water balance (2000-2015) of the Lukanga swamp

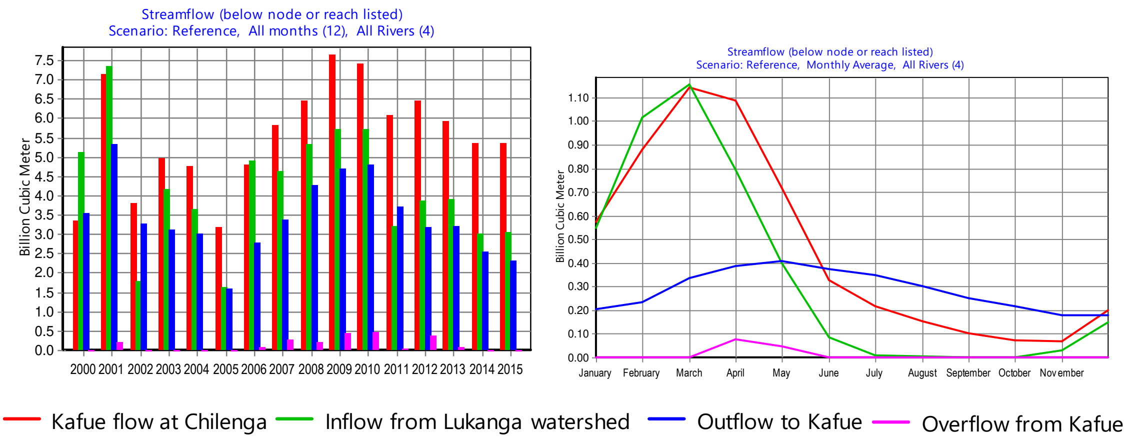

Figure 9. Annual and mean monthly water balance (2000-2015) of the Lukanga swamp

Based on this assessment, two key outcomes were found especially relevant for demonstrating the importance of the swamp:

- The Lukanga watershed is a key water provider to the Kafue river basin, both in terms of quantity as quality. The swamp regulates the inflow into the Kafue basin to a large extent, and is thus critical for downstream dependent water users as irrigation and the environment.
- The principal unknown factor: overflow during high floods occurs in about half of the years, although in some years this overflow is quite limited. Maximum amounts are approximately 500 MCM (in 2010). On average this component is about 7% of the flow

in the Kafue river. This suggests that during such a wet year, about 7% of the polluted load from mining activity upstream in the Kafue is filtered and deposited in the swamp.

2.4 Discussion

From this case study, a few key messages can be extracted related to the use of altimetry data:

- The use of the satellite-based altimetry data to assess the water balance of this system was critical: without this historic and recent altimetry data, it is not possible to reproduce the storage dynamics and the water balance.
- For this particular system with inter-annual trends of about 5 years, a time series of altimetry data of approximately **10 years** is recommendable to be able capture the dynamics sufficiently well. In case no inter-annual trends are apparent, a period of 5 years can be sufficient.
- Data with a **monthly** timestep is sufficient for this analysis. Lower frequencies (for example two months) would reduce the accuracy of the analysis as for the inverse modeling it is essential to capture well the inflection point where inflow starts to exceed outflow or outflow exceeds inflow.
- Given the annual variability of the water level and the related water volumes in this water body, it can be assumed that an accuracy of approximately **10 cm** is at least necessary to assess the water balance of this system well enough. In other words, with an error of around 20 cm, the annual pattern would not be captured sufficiently well to be able to use the altimetry data for this purpose.

These points and requirements were roughly inferred from this case study, but not quantified using for example a sensitivity analysis. This is done in case study II, presented in the next section.

3 Case study II: water balance of an artificial reservoir

3.1 Introduction

In this case study, we assess how satellite altimeter data can be utilized to calibrate a hydrological model, and specifically how the frequency and data accuracy of the altimeter data affect model results. The case study uses the open-source SPHY model (Terink et al., 2015), a spatially distributed hydrological model developed by FutureWater and several partners. Ground-based reservoir level measurements were used to generate synthetic altimeter data for this modeling experiment, with different revisit frequencies and measurement errors.

The case study is performed for a sub-humid catchment in the Segura basin, southeastern Spain with a complex hydrology. This catchment can be considered one of the “water towers” of this area: crucial for the water provision and water security in the region. Water resources assessments are thus essential to support decision making and develop water resources management plans.

For this catchment, data on the reservoir levels are available, retrieved from ground-based sensors. The data are available online on the website of the River Basin Authority. However, very often these data are not available, and the elaboration of water resources assessments are hampered by the lack of data on the status of surface water bodies.

3.2 Methods

3.2.1 Approach

Hydrological modeling for water resources assessments requires:

1. Spatial information on the biophysical attributes of the landscape: topography, soil, land use, which can be often obtained from remote sensing information, e.g. Hunink et al. (2016);
2. Meteorological data of a representative period, for example 30 years, for example from local weather observations or global reanalysis data;
3. Observed data on the surface water bodies and streamflows in the catchment to calibrate the model.

Often, especially requirement 3 is a challenge: data on the surface water flows and state variables are scarce, have gaps, or are only available for a part of the catchment. Mostly, streamflow data are only available for downstream areas, but not for more upstream locations due to difficult accessibility or lack of economic activities upstream. If there are surface water bodies in these upstream areas, the model should account for changes in the state of that water body. Satellite-based altimeter data which accurately reflects water level fluctuations in the water body can potentially be useful for assessing these state changes.

This analysis consists of three steps:

1. To show how important it is to have such information on the water balance of an upstream water body, the first step in this analysis is to use a model which is calibrated with a streamflow time series of one single downstream gauge, in order to assess the inflow of an upstream water body;

2. Then, a second model is calibrated, but with information on the outflow of the surface water body and water level changes (which could be from satellite-based altimeter data), and thus the water balance of the water body;
3. As a third step, the quality and frequency of this water level data is altered to assess how this influences the performance of the calibrated model.

Satellite altimeter data can be utilized directly in the calibration procedure when the reservoir operations can accurately be simulated by the hydrological model. Often this may not be the case, for example because the reservoir operation rules are complex and based on downstream water demand in a large catchment.

For the second and third step of this analysis, the water balance of the water body (in this case an artificial reservoir) needs to be assessed. The unknown variable of the water balance is the reservoir inflow, which can be estimates with the following equation:

$$Q_{in} = Q_{out} + \Delta vol - ET$$

With Q_{in} the reservoir inflow (m^3 day^{-1}), Q_{out} the reservoir outflow (m^3 day^{-1}; observed), Δvol the change in reservoir storage (m^3 day^{-1}; observed from altimeter data) and ET the open water evaporation (m^3 day^{-1}; simulated).

In this equation, the change in reservoir storage is obtained from the satellite altimeter data and a relationship between reservoir water level and reservoir volume.

Reservoir water level and outflow timeseries were obtained from the local water authority (Confederación Hidrográfica del Segura) and open-water evaporation was determined with the Hargreaves equation from the SPHY model. Changes in reservoir volume were obtained from a fitted power-law relationship between the observed reservoir level and volume, see Figure 10. We have fitted the following power law function to the data to determine the reservoir volume from water level:

$$RES_{vol} = \left(\frac{RES_{level} - c}{a}\right)^{\frac{1}{b}}$$

Where RES_{vol} is the reservoir volume (m^3 day^{-1}), RES_{level} is the water level in the reservoir (m amsl), and a, b and c are parameters. The power law equation was fitted to the observed data and we obtained the following values for the three parameters: a = 0.054757, b = 0.40285, c = 864.06.

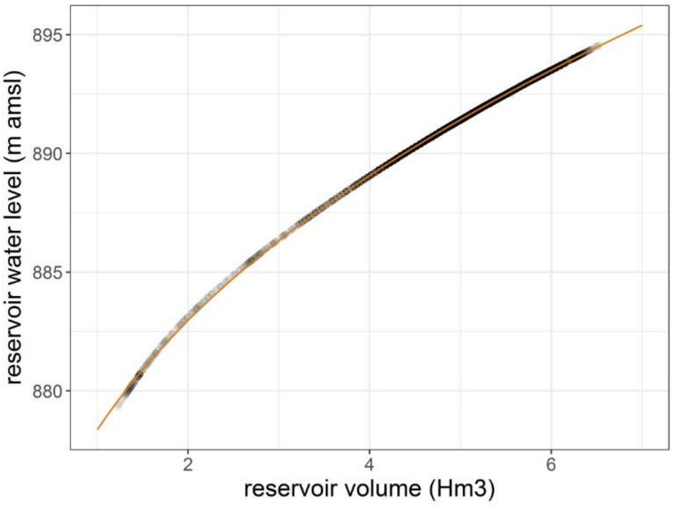

Figure 10. Power-law relationship between reservoir volume (Hm^3) and reservoir water level (m amsl).

The open water evaporation can be obtained from the following equation:

$$ET = kc_{open-water}ET_{ref}$$

With $kc_{open-water}$ the crop coefficient for open water, which can be assumed at 1.2 (Allen et al., 1998), and ET_{ref} the reference evapotranspiration, which can be obtained from the Hargreaves equation (G.H. Hargreaves and Z.A. Samani, 1985).

For the third step in the analysis, we test the sensitivity of the model performance for

- revisit frequency (i.e. 1 day, 2 days, 7 days, 1 month) and
- measurement error (i.e. 25%, 50%, 100%, 200%) of the altimeter data.

The model is applied on a cell-by-cell basis, with a fixed resolution of 200 m and a daily time step. The SPHY model simulates most relevant hydrological processes, i.e. interception, evapotranspiration, surface runoff, and lateral and vertical soil moisture flow. We use the SPOTPY python library (Houska et al., 2015) to calibrate the model, using the Simulated Annealing algorithm with 500 iterations and the Nash-Sutcliffe model efficiency (Nash and Sutcliffe, 1970).

We optimize two model parameters, i.e. a routing parameter (kx) and a model parameter that affects surface runoff (alpha), which both affect the discharge hydrograph. All calibration results are compared with a set of model performance indicators, that include daily and monthly Nash-Sutcliffe model efficiency, percent bias (PBIAS) and Normalized Root-Mean-Square Error (NRMSE).

3.2.2 Study area

The study was performed in the headwaters of the Segura River catchment in SE Spain (Figure 11). The first step in the analysis is performed for the Fuensanta catchment. The Fuensanta catchment covers an area of 1189.7 km^2 and elevation ranges between 580 and 2040 m amsl. Upstream of the Fuensanta reservoir there are two other reservoirs: the Anchuricas and La Vieja reservoirs.

The second and third step in the analysis is performed for the Anchuricas subcatchment. The Anchuricas reservoir was constructed in 1955, with the function to generate hydropower. The reservoir has a capacity of 6 Hm^3. The Anchuricas subcatchment covers an area of 234.3 km^2 and elevation ranges between 900 and 1920 m amsl. The landuse in the Anchuricas subcatchment is dominated by natural vegetation, i.e. forest (67.5%) and shrubland (29.2%). Cropland only covers 3% of the surface area.

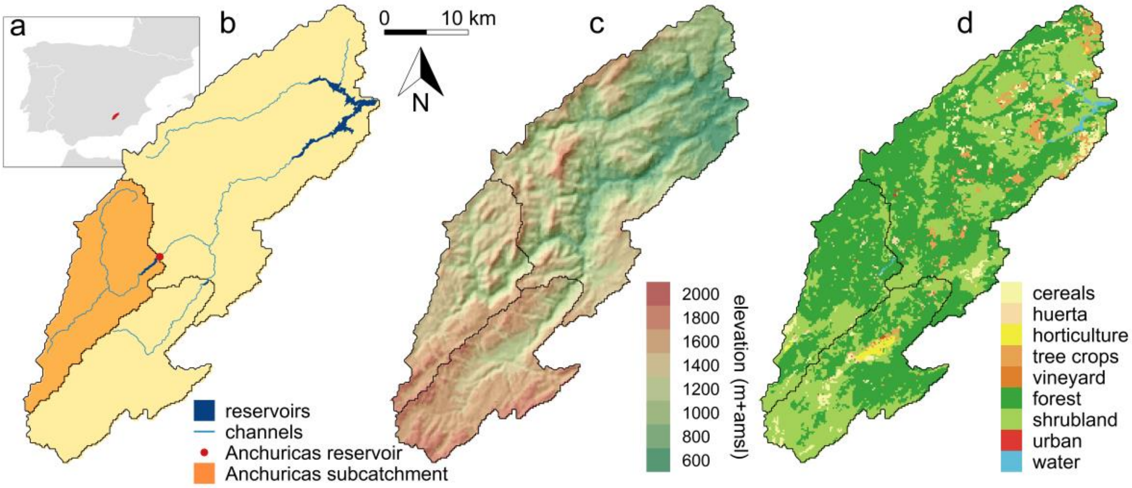

Figure 11. The study area, with (a) the location of the study area in Spain, (b) the delineation of the subcatchment, the location of the rivers and reservoirs, (c) the digital elevation model, and (d) the landuse.

3.2.3 Data

An overview of the datasets that were used for the SPHY model is summarized in Table 4. All spatial data were prepared at a 200 m resolution.

Table 4. Input data for the SPHY model

Dataset	Detail, resolution, scale	Source
Digital Elevation Model	30 m resolution	Shuttle Radar Topography Mission (NASA)
SoilGrids	250 m resolution	ISRIC
Precipitation	Daily 2000-2010, 5 km resolution	SPREAD (Serrano-Notivoli et al., 2017)
Temperature	Daily 2000-2010, 10 km resolution	SPAIN02 (Herrera et al., 2016)
NDVI	16-day temporal resolution, 250 m resolution	MODIS (MOD13Q1v6)
Landuse	1:50 000	Mapa de Cultivos y Aprovechamientos de España 2000-2010 (MAPAMA, 2010)

Reservoir timeseries (inflow, outflow, volume and level)	Daily 2000-2010 at Anchuricas and Fuensanta reservoir	Confederación Hidrográfica del Segura

Digital elevation data were obtained from the Shuttle Radar Data Topography Mission (SRTM) of the NASA's Space Shuttle Endeavour flight on 11-22 February 2000 (Farr et al., 2007). Texture (sand, clay, silt) and soil organic matter data were obtained from the SoilGrids database (Hengl et al., 2017) at 250 m resolution. Pedotransfer functions (Saxton and Rawls, 2006) were applied to prepare the soil hydraulic properties maps used in the SPHY model.

Daily meteorological data were obtained from the SPREAD dataset (precipitation) (Serrano-Notivoli et al., 2017) with a 5 km resolution and from the SPAIN02 dataset (temperature) (Herrera et al., 2016) with a 10 km resolution. In the SPHY model, NDVI is used to determine actual evapotranspiration, interception and canopy storage.

NDVI data were obtained from the MODIS database (Didan, 2015). We used each of the individual NDVI images, after gap-filling (mainly due to cloud cover) with the long-term average 16-day period NDVI for the period 2000-2010. More details on the approach can be found in Hunink et al. (2016). A local landuse map was used as input for the SPHY model, which distinguishes 14 landuse classes in the study area (MAPAMA, 2010).

Daily reservoir data were obtained from the Anchuricas and Fuensanta reservoirs from the local water authority (Confederación Hidrográfica del Segura). These data included reservoir inflow, outflow, water level and volume.

3.3 Results

3.3.1 Water balance calibration

The water balance calibration was performed in the Fuensanta catchment, i.e. the entire study area as shown in Figure 11 (a). The average annual reservoir inflow, measured by the local water authority (Confederación Hidrográfica del Segura), was compared to the total runoff from the SPHY model. The water balance calibration mainly focused on the soil hydraulic properties. We applied a multiplication factor to the saturated hydraulic conductivity (1.25) and field capacity maps (1.35), which resulted in a percent bias (PBIAS) of -0.24 (Table 5).

Table 5. Water balance, individual runoff components and model efficiency of the water balance calibration

Water balance (mm)	
Precipitation	737.71
Interception	129.14
Actual ET	441.14
Total runoff	147.94
Individual runoff components (mm)	
Snow runoff	99.58

Surface runoff	3.97
Rootzone drainange	32.2
Baseflow	12.2
Observed runoff (mm)	148.29
PBIAS	-0.23658

3.3.2 Calibration with reservoir inflow data

Next, we calibrated the model with daily reservoir inflow data from the Fuensanta reservoir. In the Fuensanta catchment, daily discharge is affected by reservoir operations from 2 reservoirs, i.e. the Anchuricas reservoir and the La Vieja reservoir. The SPHY model is equipped with a simple reservoir module that includes 1 calibration parameter (i.e. K_r). Apart from parameters kx and alpha, we also included the K_r parameters from both reservoirs in the calibration procedure.

We optimized the routing parameter kx to a value of 0.964, alpha to a value of 0.1721 and Kr to 0.06232 (Anchuricas) and 0.00407 (La Vieja). At the Fuensanta reservoir, this resulted in a Nash-Sutcliffe model efficiency (NSE) of 0.45 for daily discharge, a NSE of 0.67 for monthly discharge, a PBIAS of -7.30 and a normalized RMSE (NRMSE) of 73.90. Figure 12 shows the resulting observed and simulated timeseries of reservoir inflow at the Fuensanta reservoir.

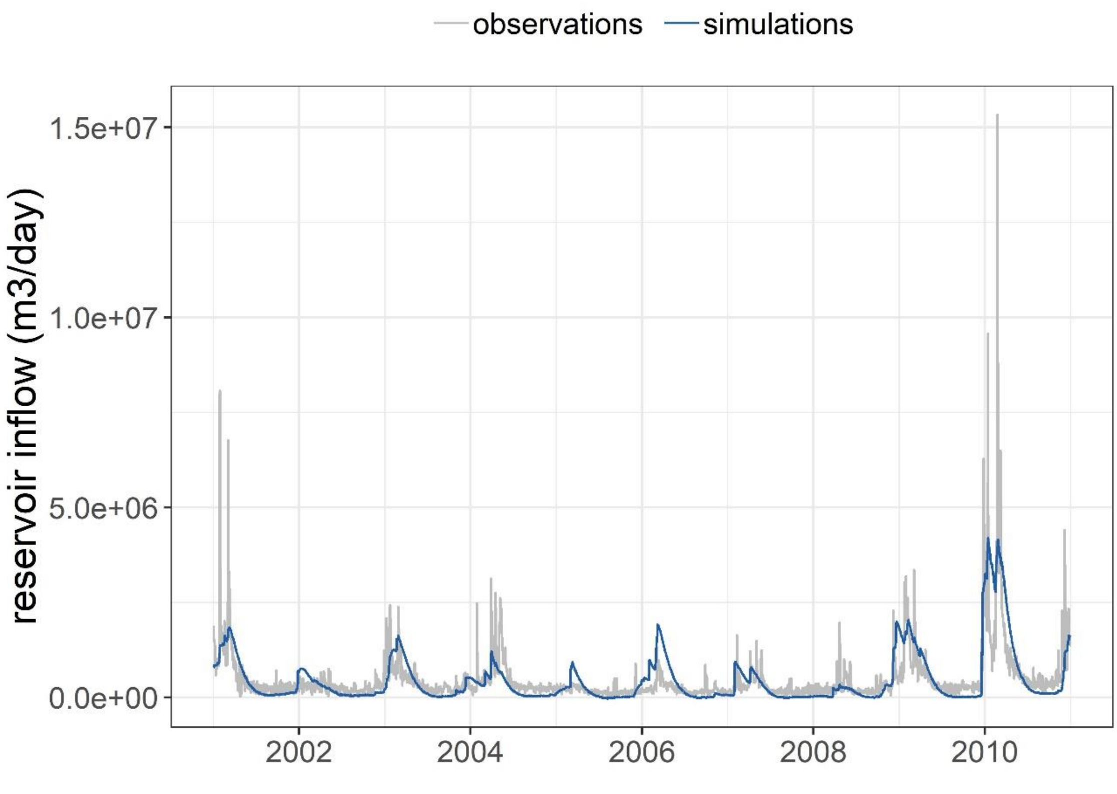

Figure 12. Reservoir inflow timeseries at the Fuensanta reservoir of the observations (grey) and simulations (blue) after reservoir inflow calibration

The obtained parameter set was applied to the Anchuricas catchment, where reservoir parameter K_r does not affect the model results. At the Anchuricas reservoir, this resulted in a NSE of 0.23

for daily discharge, a NSE of 0.36 for monthly discharge, a PBIAS of -26.40 and a NRMSE of 87.50. Figure 13 shows the resulting observed and simulated timeseries of reservoir inflow at the Anchuricas reservoir. The figure clearly shows that low flows in the Anchuricas cathcment are poorly simulated when the model is optimized at the Fuensanta reservoir.

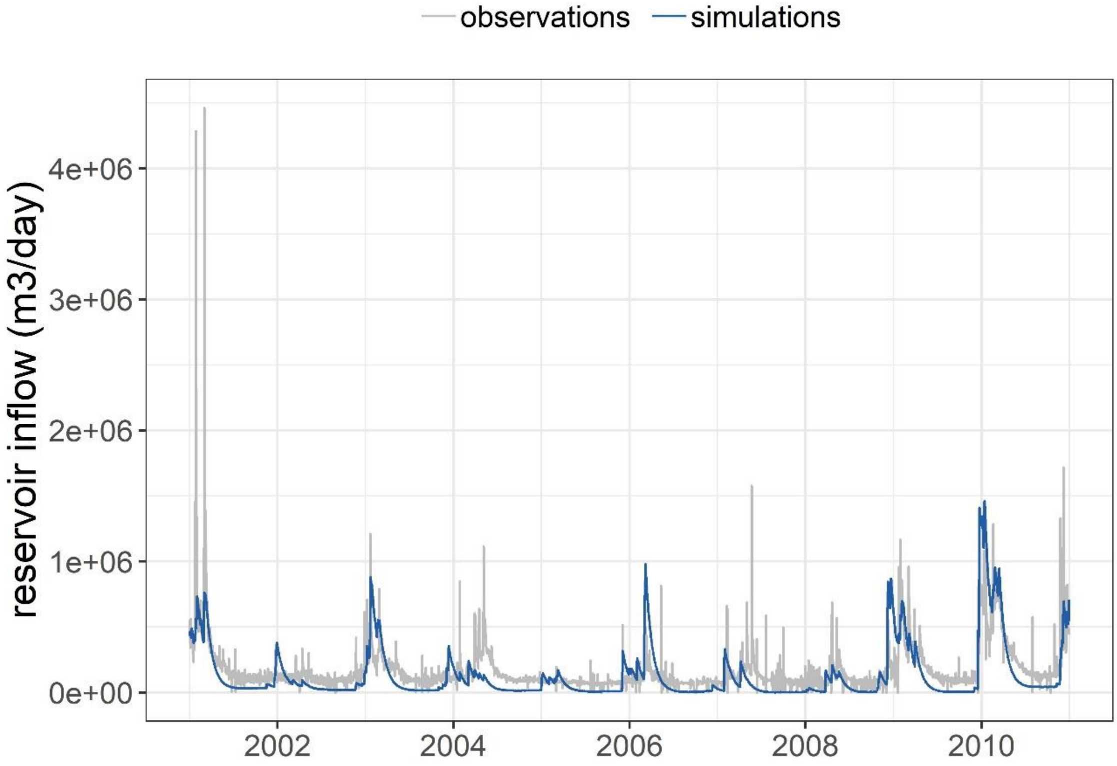

Figure 13. Reservoir inflow timeseries at the Anchuricas reservoir of the observations (grey) and simulations (blue) after reservoir inflow calibration

3.3.3 Calibration with altimeter data

As stated before, we determined reservoir inflow at the Anchuricas reservoir from observed reservoir outflow and water level and simulated open-water evaporation. The derived reservoir inflow time series is subsequently used to calibrate the model.

We first calibrated the model with the highest temporal resolution (i.e. 1-day frequency) and without error (i.e. 0%). We optimized the routing parameter kx to a value of 0.987 and alpha to a value of 0.999, which resulted in a NSE of 0.43 for daily discharge, a NSE of 0.71 for monthly discharge, a PBIAS of -2.70 and a NRMSE of 75.50. Figure 14 shows the resulting simulated timeseries of reservoir inflow at the Anchuricas reservoir from the calibration with reservoir inflow data from altimeter data. These results show that calibration with altimeter data has improved the model performance as compared to calibration with data from the downstream Fuensanta reservoir only (Table 6).

SPHY is able to accurately simulate the monthly discharge of the Anchuricas catchment, while daily fluctuations are not fully captured by the model. This may be caused by inaccuracies of the observations or by processes that are not well captured by the SPHY model. Hence, these model and observation uncertainties should be considered when evaluating the results below.

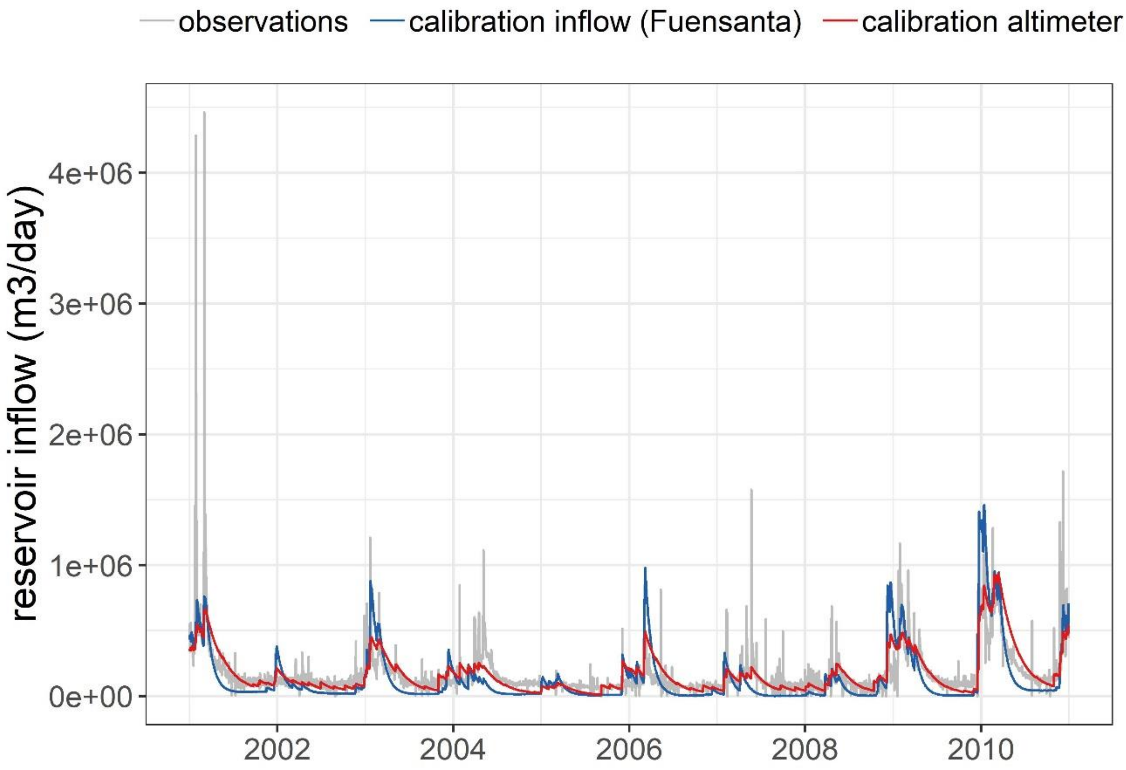

Figure 14. Reservoir inflow timeseries at the Anchuricas reservoir of the observations (grey), simulations based on inflow data (blue) and simulations based on altimeter data (red)

Table 6. Model parameters and model performance of the calibration with inflow data and altimeter data in the Anchuricas and Fuensanta catchments

	Model parameters		Model performance			
	kx	Alpha	NSE daily	NSE monthly	PBIAS	NRMSE
Inflow (Fuensanta)	0.964	0.1721	0.45	0.67	-7.30	73.90
Inflow (Anchuricas)	0.964	0.1721	0.23	0.36	-26.40	87.50
Altimeter (Anchuricas)	0.987	0.999	0.43	0.71	-2.70	75.50

3.3.4 Impact of revisit frequency

The revisit frequency may be an important variable when considering satellite data. Therefore, we varied the revisit frequency and assessed the sensitivity of the revisit frequency to the model results. We used the same approach as discussed before, but here we neglected part of the reservoir inflow timeseries, depending on the revisit frequency. We have tested this with the following frequencies: 2 days, 1 week and 1 month.

The results (Figure 15 and Table 7) show that the revisit frequency does not substantially influence the simulated hydrologic response of the model. The flow dynamics obtained are similar, which leads finally to similar estimates of water resources availability. It is important to note, that the model captures the monthly dynamics rather good which is essential for water resources assessments; however, the daily dynamics are poorly represented by the model. This is due to a combination of data limitations of the soil, landcover and meteorological data, next to also limitations in the model structure itself. For this reason, even with a monthly frequency, the model still performs as reasonably well as in the reference simulation.

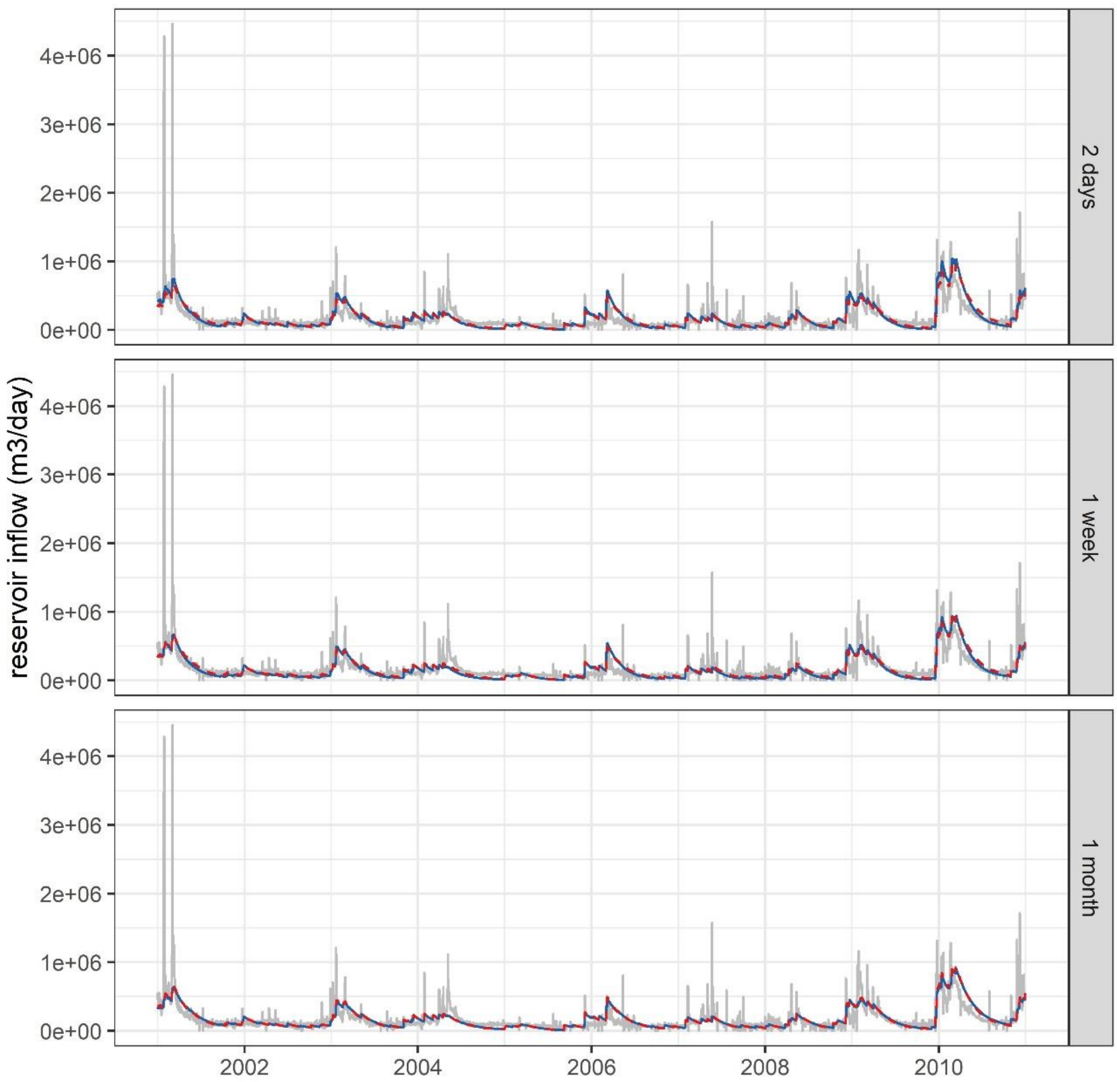

Figure 15. Reservoir inflow timeseries at the Anchuricas reservoir of the observations (grey), simulations based on 1 day frequency (red dashed) and simulations based on variation of revisit frequency (blue)

Table 7. Model parameters and model performance of the calibration with altimeter data with variation in revisit frequency for the Anchuricas reservoir.

	Model parameters		Model performance			
dt (days)	kx	Alpha	NSE daily	NSE monthly	PBIAS	NRMSE
1	0.987	0.999	0.43	0.71	-2.70	75.50
2	0.9834	0.999	0.43	0.69	-2.20	75.70
7	0.9844	0.7534	0.42	0.69	-11.00	76.00

30	0.988	0.999	0.43	0.71	-2.90	75.70

3.3.5 Impact of measurement error

Satellite altimeter data are most likely subject to a measurement error. Similar to the assessment of the impact of revisit frequency, we assessed here the sensitivity of the error to the model results. We considered 4 different errors, i.e. 25%, 50%, 100% and 200%. The errors are a percentage of the standard deviation of the reservoir water level timeseries and correspond, respectively, to an error of 0.46 m, 0.91 m, 1.82 m and 3.65 m. Subsequently, the errors are added as gaussian noise to the reservoir inflow timeseries.

The results (Figure 16 and Table 8) show that measurement error does not substantially affect the model performance up to an error of 100%. With an error of 200%, the model performance decreases. With an error of 200%, the model overestimates the discharge peaks and underestimates the low flow periods.

The fact that model performance is unaffected by measurement error up to 100% may be due to a similar effect as with the revisit frequency. The model is not able to simulate the high frequency variation at daily scale. The addition of an error to the data has a similar effect on the timeseries that are used to calibrate the model, i.e. high frequency fluctuations are added to the timeseries. However, the running average is unaffected by these small fluctuations. The running average is well simulated by the model (as shown by a high NSE for monthly time steps), so the model performs equally well at monthly time steps.

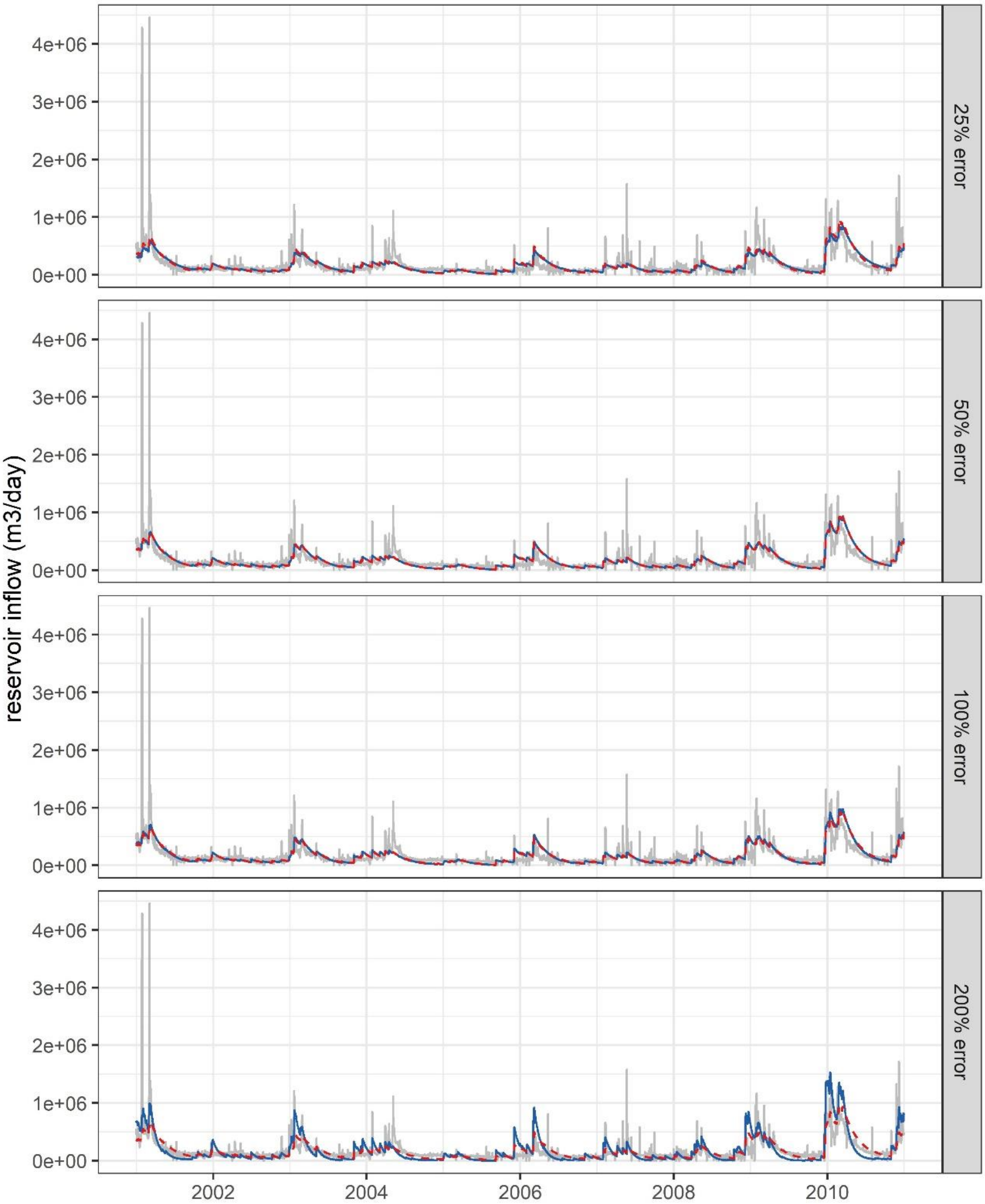

Figure 16. Reservoir inflow timeseries at the Anchuricas reservoir of the observations (grey), simulations without error (0%; red dashed) and simulations variation in measurement error (blue)

Table 8. Model parameters and model performance of the calibration with altimeter data with variation in measurement error

	Model parameters		Model performance			
error (%)	kx	Alpha	NSE daily	NSE monthly	PBIAS	NRMSE
0	0.987	0.999	0.43	0.71	-2.70	75.50
25	0.9893	0.938	0.41	0.69	-5.20	76.50

50	0.987	0.987	0.43	0.71	-3.10	75.50
100	0.9854	0.982	0.43	0.70	-3.00	75.40
200	0.9673	0.999	0.27	0.39	-1.10	85.70

3.3.6 Impact of revisit frequency and measurement error

We also assessed the impact of both the revisit frequency and measurement error on the model performance. In the subsequent calibration runs, we set the revisit frequency to 1 month and varied the error as shown in the previous section, i.e. 25%, 50%, 100% and 200% error.

In contrast to the results of the previous section, the model performance significantly reduces when considering a revisit frequency of 1 month and variations in measurement error. While the model still performed reasonably well with an error of 100% and a revisit frequency of 1 day, here error of 50% already shows a decrease of NSE and other model performance indicators. The NSE even becomes negative with an error of 100% and higher (both daily and monthly).

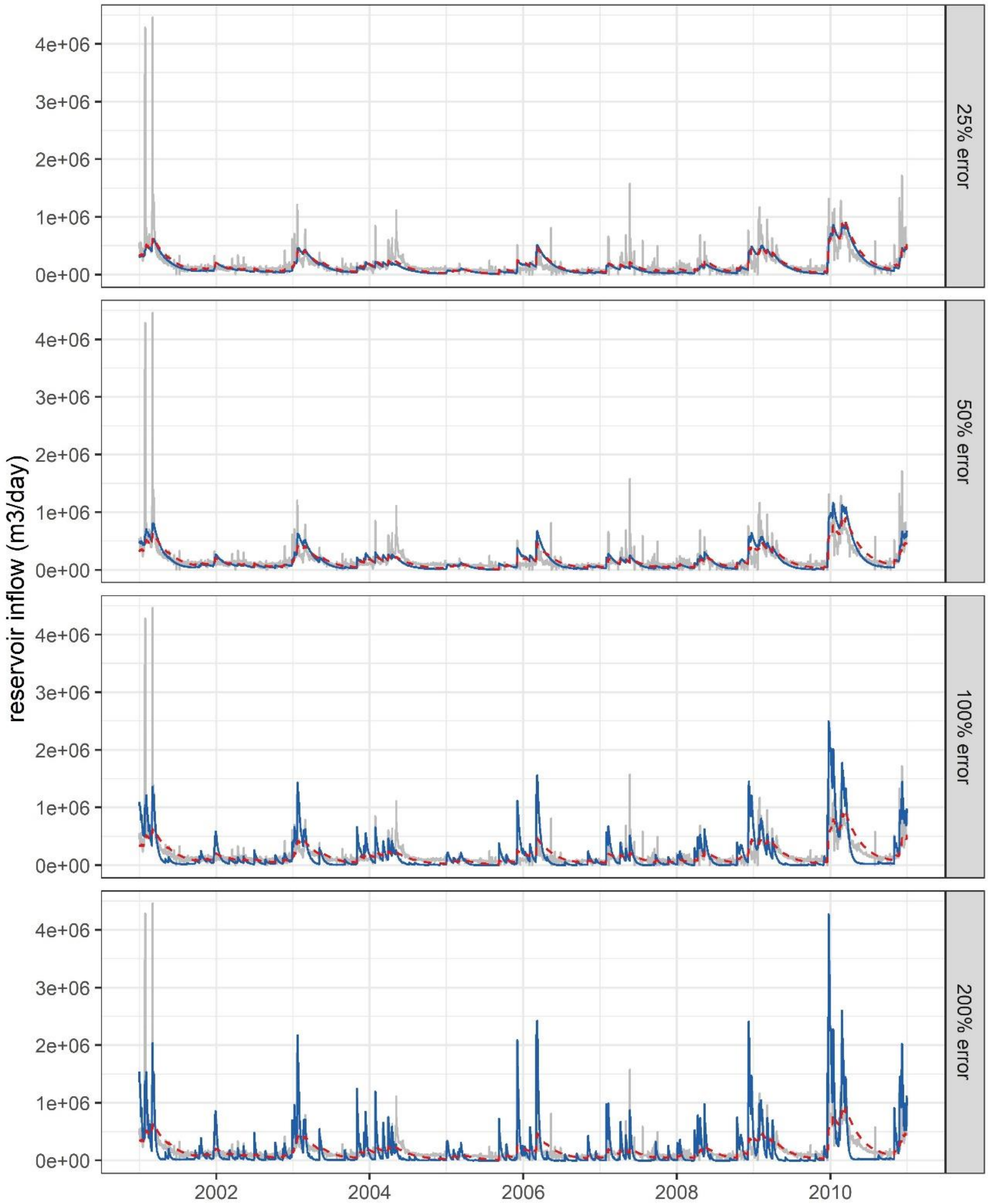

Figure 17. Reservoir inflow timeseries at the Anchuricas reservoir of the observations (grey), simulations without error (0%; red dashed) and simulations variation in measurement error (blue), with a revisit frequency of 1 month

Table 9. Model parameters and model performance of the calibration with altimeter data with variation in measurement error with a revisit frequency of 1 month

	Model parameters		Model performance			
error (%)	kx	Alpha	NSE daily	NSE monthly	PBIAS	NRMSE
0	0.988	0.999	0.43	0.71	-2.90	75.70
25	0.9854	0.641	0.41	0.67	-15.40	76.80

50	0.979	0.905	0.40	0.63	-5.00	77.50
100	0.9326	0.999	-0.17	-0.15	-0.10	108.20
200	0.871	0.999	-0.89	-0.56	0.20	137.30

3.4 Discussion

In this case study, we tested the feasibility of the use of satellite altimeter data to calibrate hydrological models, and specifically how the frequency and data accuracy of the altimeter data affect model results. A prerequisite of utilizing satellite altimeter data for calibrating hydrological models is that a discharge station is available downstream of the water body where the altimeter data are obtained. These discharge data are needed to assess the water balance of the water body. However, even if no streamflow station is installed, useful reservoir outflow data can sometimes be derived from data on hydropower generation, in case the reservoir is used for this purpose (Hunink et al., 2017b).

Using altimeter data to support model calibration resulted in significantly better prediction accuracy for the Anchuricas reservoir as compared to a situation where the model was calibrated with discharge from the downstream Fuensanta reservoir (Table 3). The model is able to accurately simulate the monthly discharge of the Anchuricas catchment, while daily fluctuations are not fully captured by the model due to data and model limitations. For water resources assessments, monthly timesteps are often sufficient.

The analysis showed that the revisit frequency does not substantially affect the model performance, with respect to the calibration run with a 1-day frequency. This may be caused by the fact that the model performs well simulating the monthly variation in discharge, but high frequency variation is not well captured. The model performance is unaffected by measurement error up to 100% of the standard deviation, which may be due to a similar effect as with the revisit frequency. The model is not able to simulate the high frequency variation at daily scale. The addition of an error on the data has a similar effect on the timeseries that are used to calibrate the model, i.e. high frequency fluctuations are added to the timeseries. However, the running average is unaffected by these small fluctuations. The running average is well simulated by the model (as shown by a high NSE for monthly time steps), so the model performs equally well at monthly time steps.

The model performance reduces significantly when considering a revisit frequency of 1 month and variations in measurement error. While the model still performed reasonably well with an error of 100% and a revisit frequency of 1 day, at a 1 month revisit frequency an error of 50% already shows a strong decrease of NSE and other model performance indicators. The NSE even becomes negative with an error of 100% and higher (both daily and monthly).

4 Take-home messages

From the work presented here and based on literature review, the following key considerations are proposed for shaping a low-cost altimetry mission useful for assessing inland water bodies and water resources planning:

- Altimetry information can be extremely useful for complex systems as for example swamps, where data on surface water levels and flows are scarce, as often the case in developing countries. Altimetry data can support the management and conservation of these systems that provide key ecosystem services for people and the environment.
- To build hydrological models for water resources assessments, historic data is required to calibrate and validate the tools. To capture the variability in water resources systems and thus perform a successful validation, a period of around **10 years** of altimetry data is recommendable.
- A revisit frequency of **1 month** is typically sufficient for water resources assessments. Higher frequencies are normally not necessary as they may only lead to minor improvements in the performance of the modeling tools. Lower frequencies (e.g. two months) are not sufficient to capture the seasonal pattern adequately.
- The required accuracy is highly dependent on the characteristics of the water body and is a function principally of the annual dynamics in storage, and the depth-storage relationship. In case study I, with a very large but shallow water body, an accuracy of approx. **10 cm** was considered necessary. For case study II, with a smaller and deeper water body, it was found that up to an error of **180 cm** the performance of the model was not significantly affected.
- The accuracy requirement can possibly also be expressed as a percentage of the annual variability in water levels, of a particular water body of interest. For example:
    - In case study I, annual increases of approximately 1 m are common. The accuracy requirement is approximately 10% of this (10 cm)
    - In case study II, water level increases or decreases within a year of around 15 m are possible. Also here, the accuracy requirement is in the order of 10-15% of this annual variability.
- Finally it has to be noted, that the usefulness of the altimetry data is also dependent on the availability and quality of other datasets necessary for the hydrological modeling. These datasets are primarily the depth-volume relationship, ideally from in-situ measurements but possibly extracted from satellite data (Duan and Bastiaanssen, 2013b); as well as discharge data upstream or downstream of the water body. Without these data sources it is not possible to establish a reliable water balance of the water body.

5 References

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