Real-time remote sensing driven river basin modeling using radar altimetry

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Abstract

Remote sensing (RS) data are an alternative to in-situ hydrometeorological data in remote and poorly monitored areas and are increasingly used in hydrological modeling. This study presents a lumped, conceptual, river basin water balance modeling approach based entirely on RS data: precipitation was obtained from the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA), temperature from the European Centre for Medium-Range Weather Forecast (ECMWF) global reanalysis dataset and evapotranspiration was derived from temperature data. The Ensemble Kalman Filter was used to assimilate radar altimetry data.
(ERS2 and Envisat) measurements of reservoir water surface elevations. The modeling approach is applied to the Syr Darya River Basin, a primarily snowmelt driven basin with large topographical variability and scarce meteorological data that is shared between 4 countries with conflicting water management interests. Assimilation of radar altimetry data improved model results significantly. Without data assimilation, model performance was limited, probably because of the size and complexity of the model domain, simplifications inherent in model design, and the uncertainty of RS data. Data assimilation reduced the mean of the reservoir water surface level residuals from 19.5 to 4.5 meters, and model root mean square error from 16.7 meters to 6.4 meters. By providing an impartial source of information about the hydrological system that can be updated in real time, the modeling approach described here could provide useful hydrological forecast information that could be updated at time scales appropriate for decision-making. The approach has potential to facilitate cooperation in transboundary basins with conflicting management objectives.

**Keywords**

Data assimilation, Radar altimetry, River basin modeling, Syr Darya, Ensemble Kalman Filter
Introduction

Hydrological models are constructed for two main purposes: improved hydrological process understanding and practical decision support for water resources management. One of the main tasks in planning and management of water resources is to identify and characterize the properties of the resources in a basin and their interactions (Loucks et al., 2005). The hydrological assessment becomes more challenging when the basin is shared between political units, either at the intra- or interstate level, with conflicting upstream and downstream interests in time and space.

Hydrology is a discipline limited by data availability. Many hydrological variables are hard to measure, and those that can be measured are only available for limited intervals in space and time. This situation is improving due to the increasing availability of RS techniques and automatic ground sensors. Hydrological modeling in remote or data-scarce areas must often rely on RS data only. Satellite-based data with high temporal resolution have the potential to fill critical information gaps in such ungauged basins (e.g. Grayson et al., 2002; Lakshmi, 2004).

Remote sensing data can be used in hydrological models in two ways (Brunner et al., 2007): as input parameters (or forcing data) and as model constraining data during calibration. The most popular remote sensing data sources for hydrological applications are multispectral imagery for the determination of actual evapotranspiration (e.g. Bastiaanssen et al., 1998; Jiang et al., 2001; Stisen et al., 2008b), active microwave sensors for the mapping of the soil moisture distribution (e.g. Parajka et al., 2006), total water storage change estimates from GRACE (e.g. Hinderer et al., 2006; Winsemius et al., 2006), and river and lake level variations from radar altimetry (e.g. Birkett, 2000; Alsdorf et al., 2001) and interferometric SAR (e.g. Alsdorf et al., 2001; Wdowinski et al., 2004). Several previous studies have used
remote sensing data in the context of river basin water balance modeling (e.g. Campo et al., 2006). Andersen et al. (2002) built a distributed hydrological model of the Senegal River Basin using precipitation derived from METEOSAT data and leaf area index (LAI) estimated from the normalized difference vegetation index (NDVI) from NOAA AVHRR data. Stisen et al. (2008a) developed a distributed hydrological model of the same catchment using potential evapotranspiration (PET) estimated from global radiation, precipitation from satellite-derived cold cloud duration, and LAI calculated from NDVI. Boegh et al. (2004) used RS-data to derive PET and LAI as input to a distributed agro-hydrological model. Francois et al. (2003) used Synthetic Aperture Radar (SAR) estimates of soil moisture in a lumped rainfall-runoff model. Distributed, physically based hydrological models represent the hydrological processes at a specific resolution in space and time. However, such models require accurate spatially resolved input data, computational loads for large systems are high and sometimes prohibitive, and for some hydrological processes (such as overland flow, actual evapotranspiration and infiltration), parameterization and/or effective parameter values can be scale dependent (Bloschl et al., 1995; Sivapalan, 2003). For all these reasons, lumped hydrological modeling remains an attractive and widely used method for river basin water balance simulations (Reed et al., 2004; Carpenter et al., 2006).

In this study, we use RS-data exclusively as inputs to a lumped conceptual hydrological model. Precipitation is obtained from the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al., 2007); daily temperature is obtained from the European Centre for Medium-Range Weather Forecast (ECMWF) global reanalysis dataset (Molteni et al., 1996); and potential evapotranspiration is derived from temperature using Hargreaves equation
The water level in a cascade of reservoirs is simulated in the model, and satellite radar altimetry data (Berry et al., 2005) are used to update the state of the reservoirs using data assimilation techniques.

Research in data assimilation (DA) has led to the development of a set of statistical methods to infer the most likely state of a system using all sources of information available. These methods were first used for oceanography and meteorology applications, but have been used in hydrology since the 1990’s (McLaughlin, 1995; Evensen, 2003). Previous studies using data assimilation techniques on hydrological modeling included land surface models (e.g. Reichle et al., 2002), surface water models (e.g. Madsen et al., 2005) and groundwater models (e.g. Franssen et al., 2008).

DA has proved to be a very valuable tool for hydrological modeling because it can improve operational forecasts and also allow the model to adapt to changes after calibration. In our case study, satellite altimetry measurements over four reservoirs are assimilated into a hydrological model, reducing the deviation of model predictions from the “true” state of the system. Several DA techniques are available, including the Particle Filter (Arulampalam et al., 2002) and the Reduced Rank Square Root Filter (Verlaan et al., 1997); The Ensemble Kalman Filter (Evensen, 2003) is used here because it has a simple conceptual formulation, it is easy to implement and is computationally feasible.

We present a river basin modeling approach to the Syr Darya River Basin (SDRB) that can be used for real time modeling. In this basin, the four riparian nations face a complicated trans-boundary water resources management problem. Real-time hydrological modeling can support the decision makers in adaptive management as forecasts of, for instance, water availability can be updated continuously as new data become available.
Methods and Data

Case study

The Syr Darya River is located in the Central Asian republics of Kyrgyzstan, Uzbekistan, Tajikistan, and Kazakhstan and, along with the Amu Darya River, is one of two principal tributaries to the Aral Sea (Figure 1). About 22 million people in the region depend on irrigated agriculture for their livelihoods, and 20% to 40% of GDP in the riparian countries is derived from agriculture, most of which is irrigated (Bucknall et al., 2003). Much of the region has an arid climate, with strongly seasonal precipitation and temperature patterns. The extensive development of irrigation in the basin is associated with a number of environmental problems including desiccation of the Aral Sea, which has lost up to 90% of its pre-1960 volume and has received international attention as an environmental disaster area (Micklin, 2007).

The Syr Darya River originates in the Tien Shan Mountains of Kyrgyzstan and is formed by the confluence of the Naryn and Karadarya rivers near the border of Kyrgyzstan and Uzbekistan. The population of the basin is approximately 20 million, with an area of about 400,000 km². Annual precipitation averages about 320 mm and ranges from 500-1500 mm in the mountain zones to 100-200 mm in desert regions near the Aral Sea. The bulk of runoff comes from melting snow and glaciers in the mountains of Kyrgyzstan. Because of the combined effects of snowmelt and glacial runoff, about 80% of runoff in the basin occurs between March and September. The onset of the snowmelt period shifts from early spring to early summer with increasing elevation, distributing snowmelt runoff over a period of several months. In the summer months, glacial ablation peaks and prolongs the period of peak runoff. Annual runoff averages about 39 km³/year, and approximately 90% of the river’s mean annual flow is regulated by reservoirs (Savoskul et al., 2003).
The Syr Darya River was extensively developed for irrigation and hydropower during Soviet times, particularly after 1960, with the primary goal of producing cotton. Total irrigated area in the Aral Sea basin increased from 5 million hectares in 1965 to 7.9 million hectares in 2000 (Micklin, 2007). About 1.7 million hectares are currently irrigated directly from the Syr Darya River (Siegfried et al., 2007). Cotton is an important source of foreign exchange in Uzbekistan, and continued production through irrigated agriculture is a priority for the government (World Bank, 2004).

A significant change to the natural hydrological pattern of the basin occurred with the construction of the Toktogul Reservoir in 1974. Because the timing of the March-September natural runoff peak coincides with the irrigation season, substantial reservoir storage is not required to regulate seasonal runoff. However, the aggressive expansion of irrigation during Soviet times created a need for multi-year storage to store excess flows in wet years to supplement dry year flows. Toktogul Reservoir was constructed on the Naryn River (the principal tributary to the Syr Darya) to serve this purpose. The reservoir is the largest storage facility in the Aral Sea basin and has a total capacity of 19.5 km$^3$ (14 km$^3$ active storage). The construction of the reservoir was accompanied by the building of four smaller downstream reservoirs and power plants to maximize electricity generation from reservoir releases. The five facilities, commonly called the Naryn Cascade, have a combined generation capacity of 2870 MW (World Bank, 2004).

Toktogul Reservoir and the Naryn Cascade are at the heart of a dispute over management of the Syr Darya River that has existed since the downfall of the Soviet Union in 1991. In the Soviet system, the reservoir was operated to benefit irrigated agriculture and power was produced incidentally as flows were released to meet downstream demands. In 1992, the Central Asian riparian states agreed to continue
Soviet water allocation policies and established the Interstate Commission for Water Coordination (ICWC) to oversee the allocation process. However, the new system immediately came under strain as the competing interests of the newly independent states emerged. Toktogul Reservoir came under the control of Kyrgyzstan, which is less dependent on irrigated agriculture and lacks fossil fuel resources for energy generation. Kyrgyzstan had been supplied with fossil fuels under the Soviet system but found itself in the position of having to purchase energy supplies on world markets after 1991. Kyrgyzstan turned to hydropower for its own energy needs, which peak in winter because of heating demands, placing the country’s operational objectives in direct opposition to those of its downstream neighbors; Kyrgyzstan would prefer to store summer peak flows for winter power generation, while the downstream countries would like winter releases minimized to conserve water for the summer season (Biddison, 2002; World Bank, 2004; Siegfried et al., 2007). Increased winter releases also cause flooding, as many of the downstream irrigation works are not built to handle high flows and ice in the river bed reduces winter flow capacity (Biddison, 2002).

Under these new conditions, the Soviet allocation pattern proved to be infeasible, and the riparian countries entered into a series of annual agreements in which downstream countries agreed to purchase hydropower from Kyrgyzstan during the summer irrigation period in order to ensure summer releases. These agreements were essentially barter transactions in which the downstream states agreed to compensate Kyrgyzstan for summer releases by delivering electricity, oil, coal, and gas during the winter months. In practice, the downstream countries did not always deliver the agreed amounts of energy, forcing Kyrgyzstan to make additional winter releases. In addition, the ad hoc nature of the annual agreements meant that multi-year storage
considerations, which were the original purpose of Toktogul Reservoir, were not
given adequate consideration in the allocation process. As a result of increased year-
round pressure and a lack of long-term planning, Toktogul storage declined to a
previously unsurpassed low of 7.5 km$^3$ 1998 (World Bank, 2004).

Kyrgyzstan, Uzbekistan, and Kazakhstan attempted to reform the ad hoc system that
developed after 1991 by entering into a framework agreement in 1998. The new
agreement recognized the need to provide compensation for lost generating capacity
and expressed an intention to move away from a barter system towards cash
transactions for water and power. The agreement also recognized the need for multi-
year regulation of the river (World Bank, 2004). Although considered an
improvement over the ad hoc arrangements that existed previously, the 1998
agreement has not resolved the upstream-downstream conflict and today it appears
that the agreement has essentially been abandoned and the riparian countries have
reverted to an ad hoc allocation system (Abdukayumov, 2008). On a visit to the
region in May 2008, the authors observed that storage in Toktogul had dropped to
about 6.5 km$^3$, only slightly above dead storage (5.5 km$^3$). The riparian states appear
to be pursuing national solutions, with Kyrgyzstan attempting to build new
hydropower facilities upstream of Toktogul Reservoir and Uzbekistan and Kazakhstan
seeking to construct new storage facilities to capture winter releases. These facilities
are expensive and inefficient, and considerable resources could be saved by basin-
wide cooperation (Biddison, 2002).

In these circumstances of mutual distrust between the up- and downstream countries,
remote sensing and data assimilation hold great promise for increasing transparency,
reducing forecast uncertainty, and increasing the speed at which forecasts can be
developed and updated. Because remotely-sensed data products are available to all,
their increased use in the region has the potential to reduce distrust by providing a common base of information. The increasing availability of these products in real-time also has the potential to accelerate the forecasting process so that water allocation plans can be agreed upon earlier in the irrigation season. Statistical methods like the Ensemble Kalman Filter offer a way to fine-tune forecasts as new data become available, giving the countries more flexibility to respond to changing conditions at the seasonal scale.

**River Basin water balance modeling**

The river basin model is implemented using the commercial software package DHI Mike Basin (DHI, 2009). The model consists of a rainfall-runoff component, a river network component that includes the reservoirs and an irrigation component that simulates the major irrigation water users in the basin. The simulation is run in 1 day timesteps from January 1st, 2000 to December 31st, 2007.

**Rainfall-runoff model**

The runoff processes in the catchment were simulated through a lumped conceptual hydrological model. The NAM (Nedbør – Afstrømningsmodel, Danish for rainfall-runoff model) is a modeling system consisting of mass balance equations that account for the water content in four different storages representing processes occurring in the land phase of the hydrological cycle: snow storage, surface storage, lower soil zone storage and groundwater storage (DHI, 2000). The minimum data requirements of the modeling system are precipitation, potential evapotranspiration and observed discharge. Daily mean temperature is also required if snowmelt contributes to runoff. A comparison of data requirements and performance of NAM with other hydrological models is provided by Refsgaard et al. (1996). The four storage are typically
described using a set of 17 parameters, about 10 of which are commonly used for model calibration.

Due to the limited amount of observed in-situ river discharge data, it was impossible to achieve a unique and stable calibration based on 10 free model parameters. Instead a more robust version of NAM was developed using only two free calibration parameters: one describing soil moisture storage and the other groundwater response times. The structure of this simplified version of NAM is shown in Figure 2. Table 1 lists the parameters chosen to enforce this model structure. Because of its simplicity, the modeling approach is robust and appropriate given the general scarcity of observation data in the SDRB.

Precipitation falls as snow if the temperature is below 0 degrees Celsius. Each single catchment is divided into 10 separate elevations zones of equal area and the precipitation discrimination is done for each individual elevation zone using temperature lapse rates based on Tsarev et al. (1994). Snow melt is modeled using a simple degree-day approach:

$$SM_{pot} = \begin{cases} M \times T, & T > 0 \\ 0, & else \end{cases}$$

$$SM = \min(SS, SM_{pot})$$

**Equation 1**

where $SM_{pot}$ is the potential snowmelt (mm day$^{-1}$), $T$ is the temperature in degrees Celsius, $SS$ is the snow storage (mm day$^{-1}$), and $M$ is a seasonally variable degree day factor (mm day$^{-1}$ deg$^{-1}$) based on a parameterization proposed by Shenzis (1985) for the Central Asian Mountains. Snowmelt parameters are shown in
Table 2. Snow melt is calculated for each elevation zone separately. Snow melt and precipitation enter the soil storage. Water in the soil storage is depleted by evapotranspiration. Actual evapotranspiration is calculated as a function of potential evapotranspiration and soil wetness:

\[
AET = ET_{ref} \times \frac{L}{L_{\text{max}}}
\]

**Equation 2**

where \(ET_{ref}\) is the reference ET calculated using Hargreave’s equation (mm day\(^{-1}\)), \(L\) is the soil storage (mm) and \(L_{\text{max}}\) is the maximum soil storage (mm). \(L_{\text{max}}\) is a calibration parameter. Percolation from the soil storage to the groundwater storage is calculated using the following parameterization:

\[
PER = (P + SM) \times \frac{L}{L_{\text{max}}}
\]

**Equation 3**

where \(P\) is the precipitation in mm day\(^{-1}\). Baseflow from the groundwater reservoir to the river is calculated using a linear reservoir approach:

\[
BF = \frac{1}{CKBF} \times GS
\]

**Equation 4**

where \(GS\) is the groundwater storage in mm and \(CKBF\) is the response time of the groundwater (days). This is the second calibration parameter. Rainfall-runoff processes are thus simulated in a very simple approach with two calibration parameters only: \(L_{\text{max}}\) and \(CKBF\).

An automatic calibration module is available for NAM (Madsen, 2000). The module is based on the Shuffled Complex Evolution (SCE) algorithm, and it allows the
optimization of multiple objectives: (1) overall water balance; (2) overall RMSE, (3) peak flow RMSE and (4) low flow RMSE. The catchments were classified into calibration, validation, prediction and inactive catchments, based on the discharge data provided by the Operational Hydrological Forecasting Department (UzHydromet) in Tashkent, Uzbekistan. Catchments with continuous discharge records of 8 years or more were used for calibration, while those with 3-7 years of discontinuous data were used for validation. Prediction catchments are defined as those where no discharge data are available, but topography and land cover suggest considerable runoff. Areas were no runoff is expected were considered inactive. In total there were 32 prediction catchments (excluding those used for calibration and validation) and 60 inactive catchments.

The input data of calibration catchments were duplicated and only the second half of the duplicated record was used for calibration, while the first half was used to drive a model warm-up period. The two parameters $L_{\text{max}}$ and $CKBF$ were adjusted through the automatic calibration module, minimizing overall root mean squared error. The maximum number of iterations was set to 1000, which was never exceeded. It was noted that while $CKBF$ was relatively stable, the results for $L_{\text{max}}$ were either very high (median of 3510 mm) or very low (median of 32 mm); the latter was generally associated with a significantly negative water balance. The validation procedure showed that low $L_{\text{max}}$ values performed substantially better in windward-facing catchments, whereas high $L_{\text{max}}$ values resulted in a better fit in leeward-facing catchments. This could be due to underestimation of orographic precipitation by the TMPA product. However, there were too few precipitation stations to substantiate this. The median $L_{\text{max}}$ values were used in prediction catchments (Table 6, in Results).
River network and water allocation model

The Mike Basin river network consists of nodes and reaches. The catchments dewater into the river network at catchment nodes. The water transfer from one node to the next is instantaneous, i.e. at every node a simple water balance equation is solved. The only nodes that can store water temporally are the reservoir nodes. Irrigation sites are introduced into the model as water demand nodes. Figure 1 shows the Mike Basin river network layout.

Information on the reservoirs was obtained from the Scientific Information Council of the Interstate Commission for Water Coordination in Central Asia (ICWC, 2009). The reservoirs in the Syr Darya River Basin are implemented as rule curve reservoirs. The reservoir water balance is calculated from inflow, outflow and losses. The level-area-volume curve is used to convert volume to water level. This information was provided by UzHydromet. Once the water level reaches the flood control level, all additional water is instantaneously routed downstream. Observed release time series are available from the ICWC (2009). The observed releases were prescribed as minimum downstream release time series for the various reservoirs. In a real-time application mode of the model, these releases would be replaced by planned/projected releases.

The irrigation areas in the Syr Darya River Basin are lumped into 6 major demand sites, following Raskin et al., 1992. These are High Naryn, Fergana, Mid Syr, Chakir, Artur and Low Syr. Irrigation areas and crop distributions were taken from Raskin et al. (1992). Irrigation water demand was calculated using the FAO-56 methodology (Allen, 2000). Growing season time periods were estimated based on FAO-56. During the growing season, the soil water balance is calculated on a daily time step from precipitation, crop evapotranspiration and irrigation for each demand site.
Precipitation is taken from the TMPA product (see below), crop evapotranspiration is calculated using the FAO dual crop coefficient approach and reference ET and irrigation is calculated using the standard FAO-56 irrigation model. This model assumes that irrigation is triggered if the soil water content decreases below 50% of the readily available water. Soil water contents at field capacity and wilting point were uniformly set to 0.15 and 0.05 respectively. A total loss fraction of 0.3 was generally assumed for all demand sites.

**Data Assimilation**

The Ensemble Kalman Filter (EnKF) has become a popular data assimilation technique within several fields because of its ease of implementation and its computational feasibility (Evensen, 2003). In the EnKF, the covariance matrix used in a traditional Kalman Filter is replaced by an ensemble of model states. The mean of the ensemble is assumed to be the “truth” and the model error (or covariance) is represented by the sample variance of the ensemble members. The ensemble members are then updated according to model and observation errors, as it would be done in a traditional Kalman Filter. Let $X^f$ be the model forecast $ns \times ne$ matrix containing all model states for every ensemble member, where $ns$ is the number of state variables and $ne$ is the number of ensemble members.

$$X^f = (x^f_1, ..., x^f_{ne})$$

**Equation 5**

where $x^f_1$... $x^f_{ne}$ are the forecast vectors containing all state variables for each ensemble member. The model error covariance $P^f$ is
where the overbar denotes an average over the ensemble. The model states of every member are then updated through the traditional update equation

\[
\mathbf{x}^a_i = \mathbf{x}^f_i + \mathbf{K}_i (y_i - H \mathbf{x}^f_i),
\]

Equation 7

where \(\mathbf{x}^a\) is the vector of updated model states for the \(i\)th ensemble member, \(H\) is an \(n_o \times n_s\) operator (\(n_o\) is the number of observations) that transforms the states into observation space and \(y\) is a \(n_o \times 1\) vector that contains the observations for every state variable. The Kalman gain \(\mathbf{K}\) is denoted by

\[
\mathbf{K} = \mathbf{P} \mathbf{H}^\top (\mathbf{H} \mathbf{P} \mathbf{H}^\top + \mathbf{R})^{-1}
\]

Equation 8

where \(\mathbf{R}\) is the \(n_o \times n_o\) error covariance matrix of the observations. The observations \(y_i\) (in Eq. 7) must be treated as random variables having a distribution with mean \(y\) and a covariance \(\mathbf{R}\) (Evensen, 2003). A normally distributed, uncorrelated distribution is assumed.

Because Mike Basin does not have a DA module, the assimilation algorithm described in Verlaan (2003) was adapted to run a set of Mike Basin models automatically and to assimilate water level measurements over several reservoirs. Since the only input to the Mike Basin water allocation model is runoff and irrigation, the ensemble of models was produced by stochastically perturbing the area of irrigation districts and the runoff timeseries of active catchments. The average standard deviation of the runoff residuals from the validation process (
Table 6, in Results) was used as the standard deviation for the runoff perturbations; while an uncertainty factor of ± 0.2 was assigned to the irrigation area. This was implemented as:

$$Q_i = Q_0 \pm \sigma_Q$$

where $Q_i$ is the specific runoff for the $i$th ensemble member, $Q_0$ is the estimated specific runoff for every catchment and $\sigma_Q$ is the runoff uncertainty and has zero mean and a standard deviation equal to the runoff standard error. An uncertainty factor of ± 0.2 was assigned to the irrigation area. Since this uncertainty could not be estimated, it was used as filter tuning parameter, as described below. The irrigation uncertainty was implemented as follows:

$$IWD_i = IWD_0 \cdot (1 \pm \sigma_{IWD})$$

where $IWD_i$ is the irrigation water demand for the $i$th ensemble member, $IWD_0$ is the water demand estimated from Raskin et al. (1992), and $\sigma_{IWD}$ is the uncertainty about the current area of the irrigation districts. This approach was chosen for $IWD$ because it prevents the fictitious generation of water demand during non-growing periods, when $IWD_0$ is zero.

The DA scheme was practically implemented in Mike Basin by running one model time step $n_e$ times and storing the evolution of the state variables for every ensemble member. The appropriate ensemble size, runoff and $IWD$ perturbation levels were chosen by running a series of experiments (Table 3).

**Input, Forcing and Calibration/Validation datasets**

All input, forcing and calibration/validation datasets were obtained from remote sensing data sources.
Table 4 provides an overview of the various data sources used in this study.

Catchment delineation

The digital elevation model (DEM) of the area was obtained from the Shuttle Radar Topography Mission (SRTM). The mission is described by Rabus et al. (2003), and an assessment of its results is provided by Rodriguez et al. (2006). The data with a 3 arc second (90 meter) resolution was resampled to 1 km spatial resolution. The 1 km DEM was used to delineate the river network and the catchments.

Rainfall

The Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al., 2007) has been used as the data source for precipitation in the Syr Darya basin. The 3B42 research product was found suitable because of its temporal and spatial resolution (3 hours and 0.25°, respectively) and the incorporation of surface observation data. The TMPA rainfall estimates have been validated in diverse regions, e.g. USA (Villarini et al., 2007), Argentina (Su et al., 2008) and Brazil (Collischonn et al., 2008). The 3-hourly data were accumulated over one day periods and area-averaged over the different catchments. The precipitation product was not altitude-corrected because it has already been adjusted to match observations of a global gauge network. The global bias of the 3B42 product relative to the available station data was calculated as minus 20%. This bias was corrected by multiplying the 3B42 precipitation by a factor of 1.25.

Mean temperature

Snowmelt modeling requires daily mean temperature inputs. Therefore, the decadal (10-day) ground observations provided by the RCHT could not be used. An ECMWF operational dataset that includes 2-meter temperature was used (ECMWF, 2009).
data is available in near real time and has a temporal resolution of 6 hours (0000, 0600, 1200 and 1800 UTC) and a spatial resolution of 0.5° up to 2006, and 0.25° thereafter. The temperature fields were averaged over daily periods, with the time for this procedure corrected by the median longitude of the Syr Darya basin (70° E), i.e. UTC + 0600. The pixel-wise daily mean temperature was then area-averaged over the catchments. The mean catchment elevation was used as the reference elevation when extrapolating the temperature to the different elevation zones in the catchment.

**Reference evapotranspiration**

Input data for reference ET calculation based on the Penman-Monteith equation were not available. Reference ET was therefore computed from the temperature data using Hargreaves equation (Allen et al., 1998):

\[
ET_a = 0.0023(T_{\text{mean}} + 17.8)(T_{\text{max}} - T_{\text{min}})^{0.5} \cdot R_a ,
\]

*Equation 11*

where \( T_{\text{mean}} \) is defined as the average of \( T_{\text{max}} \) and \( T_{\text{mean}} \) (not the average of all available temperature measurements) and \( R_a \) is the extraterrestrial radiation (converted to mm day\(^{-1}\) through the latent heat of vaporization) for the corresponding Julian day and latitude. Hargreaves et al. (2003) present a comprehensive evaluation of the performance of Equation 11. A temperature averaging period above 5 days is recommended; although some water resource studies (e.g. the IWMI World Climate Atlas) use 10-day temperature averages (Hargreaves et al., 2003). The PET fields were calculated over 10-day periods and then area-averaged over the different catchments.
Satellite radar altimetry was initially used in order to study the marine geoid and ocean dynamics (Rapley, 1990). However, over the past two decades different research groups have derived inland water heights from space-based radar altimetry (e.g. Cazenave et al., 1997; Berry et al., 2005; Cretaux et al., 2006). In this study, altimetry data re-tracked by the Earth and Planetary Remote Sensing Laboratory (EAPRS) over four large reservoirs was assimilated into the MIKE BASIN model in order to update the water level of the reservoirs. The data used is derived from the ERS and ENVISAT satellites, which cover 82° N to 82° S and have repeat cycles of 35 days. The altimetry data retracted by the EAPRS lab provide a large number of inland water bodies. In total, 39 ERS2 targets and 37 ENVISAT targets were identified over rivers and lakes in the basin; but only those over the Toktogul, Chardara, Kayrakkum and Charvak Reservoirs (Figure 1) were assimilated into the model. Frappart et al. (2006) reports an accuracy of 0.25-0.53 m for the Radar Altimeter 2 (on board of ENVISAT) over lake targets in the Amazon basin.

Results

Validation of Remote Sensing Dataset versus Ground Observations

Precipitation and Temperature

The tendency of the TMPA product to underestimate precipitation has been successfully corrected, although there is still a mismatch between the observed and the RS-based precipitation data (Figure 4). Figure 5 compares the temporal variability of observed precipitation and temperature with corresponding RS-based products on three selected stations (shown in Figure 1). While RS temperature fits well with observed dekadal data, the (corrected) monthly RS-precipitation estimates largely underpredict rainfall.
Radar altimetry targets were obtained over four of the main reservoirs in the area. For these reservoirs, the altimetry data were found to have an average actual precision of 0.86 m (Table 5), below the accuracy of 0.25-0.53 reported in Frappart et al. (2006) for ENVISAT over lake targets.

River Basin Water Balance Modeling Results

The modeling approach captures the dominance of snowmelt in the hydrological cycle: precipitation is accumulated during the winter and released throughout the melting season (Figure 6). However, the calibration-validation process shows that model results are uncertain and tend to underestimate runoff (Table 6). This is not surprising considering the size and complexity of the model domain and the uncertainty associated with remotely-sensed data. Model uncertainty can be significantly reduced through the assimilation of radar altimetry measurements of reservoir water surface elevations.

Data assimilation results

Figure 8 compares the reservoir levels predicted by the assimilation scheme and the corresponding no-assimilation setup. When altimetry measurements were available, their assimilation considerably improved the results of the model (Table 8). However, when all ensemble models incorrectly simulate an empty or full reservoir (e.g. Kayrakkum in September/2000 or Toktogul in July/2005) the model does not react to the assimilation of altimetry measurements, because the current model error covariance $P$ for that particular state variable becomes zero.

The accuracy of the EnKF estimates improve proportionally to the square root of the ensemble size $N$ (Evensen, 2007), although in practical applications this is limited by the number of ensemble members that are computationally feasible to run. A series of
experiments were run in order to determine tuning parameters that would optimize model performance (Table 3).

An ensemble size of 50 was chosen because it significantly reduced the mean and the standard deviation of the residuals in relation to running the model with only 5 ensemble members. An ensemble size of 100 (not plotted) did not show any improvement. A runoff perturbation of 20 L km\(^{-2}\) s\(^{-2}\) and an irrigation area uncertainty of 40% yielded the best results for all four reservoirs (Figure 10).

The data assimilation approach described here could benefit the annual water allocation process in the Syr Darya basin by providing an efficient and transparent technology for updating hydrological forecasts in real time. In the current management setup, the riparian states are supposed to agree on an allocation plan at the beginning of April; however, agreement is often delayed until well into the growing season, creating significant uncertainties for irrigation planning and increasing tensions on both sides of the conflict. An obstacle to co-operation is the deteriorated state of the hydro-meteorological monitoring network that existed in Soviet times (Schar et al., 2004). In addition, national hydro-meteorological agencies now responsible for data collection are reluctant to share data and the annual process of data collection and forecasting can also be delayed by poor communications infrastructure (Biddison, 2002). A model driven by remotely sensed data that could be updated in real-time would minimize forecast uncertainties and delays, potentially accelerating the annual allocation process. Although the approach described here uses historical remotely sensed data, it could easily be adapted to forecasted data.

Figure 12A shows how the model prediction deviates from the “true” state of the system when no altimetry data is available. Figure 12B shows the average forecast
error when predicting water levels at Toktogul 1-5 months in advance and assimilating altimetry data until the previous 1-4 months. Predictions one and two months ahead (April and May) are significantly improved as more recent altimetry measurements are assimilated. However, model predictions three or more months in advance are poor, and the impact of data assimilation much less significant.
Discussion

A modeling approach using only remotely-sensed data has been developed and applied to the Syr Darya River Basin. The ability of the river basin model to predict reservoir water surface levels without data assimilation was moderate at best. The general underprediction of reservoir levels might be due to inaccuracies in the RS input data, to the simplification inherent in model structure (e.g. monthly snowmelt coefficient, lack of individual modeling of glacial accumulation/ablation), or to unmodeled changes in the hydrology of the basin (e.g. variation of irrigation water demand or dominance of snowmelt and glacial ablation compared to snow and glacial accumulation).

Limited availability of in-situ discharge data for model calibration required that high resolution RS data to be aggregated over very large areas (sometimes as large as 37 000 km$^2$). If more discharge stations were available, smaller subcatchments could be used and the fine resolution of the data products would have been better exploited. Although estimates of river discharge from radar altimetry have been reported, (e.g. Coe et al., 2004; Kouraev et al., 2004; Zakharova et al., 2006) these techniques are still under development, have limitations in mountainous areas and require in-situ stage-discharge data. Distributed hydrological models can incorporate high resolution RS data without averaging over sub-catchments but have higher data and computational requirements. Model results showed that RS data alone cannot substitute for ground observations because of calibration needs and the limited accuracy of RS data.

Considering the limitations imposed by the lack of ground observations and the uncertainty of RS data, the assimilation of satellite altimetry of reservoir surface elevations can reduce deviations between predicted and observed water levels. Even
though the mean accuracy of the altimetry data was 0.86 m, it was sufficient to improve the performance of the model. Without such data, reservoir levels would diverge over time from the “true” state of the system. More frequent and higher precision altimetry data would improve the accuracy of the system’s states.

The ensemble Kalman filter is a reasonable method for incorporating satellite altimetry data into the Mike Basin modeling package. An ensemble size of 50 resulted in a good trade-off between model performance and computation time. A mean runoff perturbation of 20 L km\(^{-1}\) s\(^{-1}\) and an irrigation area uncertainty of 40% provided the model enough flexibility to assimilate altimetry measurements.

The hydrological system in the SDRB has been analyzed in the past: Raskin et al. (1992) simulated water supply and demand in the basin, Antipova et al. (2002) showed an optimization approach for the water and energy systems in the Naryn-Syr Darya cascade of reservoirs and Cai et al. (2002) presented a framework for sustainability analysis of the water resources in the SDRB. Although the studies have identified benefits from cooperation among the riparian countries, they appear to have had little impact on real-world decision-making. Both national agencies and donors have expressed a desire for concrete tools to improve the water management in the basin (Biddison, 2002), and the approach presented here is an important step in this direction.

The combined use of remotely sensed data to drive hydrological models and satellite altimetry data to update model states has considerable potential to provide impartial information about the hydrological system. The application of this approach in a (near) real time mode could help facilitate adaptive management of water resources in the region. Additionally, the annual allocation process carried out by the national
authorities of the riparian states could benefit from a transparent, freely-available information base. Implementing this modeling approach in real time basis will require using the real time precipitation product (3B42RT) instead of the research product (3B42). The RT product does not incorporate gauge data, but becomes available ca. 6 hours after observation (see Huffman et al., 2007; Huffman, 2008, 2009). The temperature data are available 7 hours after observation, and reservoir release policies could be simulated using trends in historical release data. Considering that the model timestep is 1 full day, the model could be ready to run 7 hours after the end of every day (i.e. 0700 UTC). Near RT altimetry data is provided 3 days after observation [Philippa: we need a reference here]. This means that the model could be re-run when measurements of any of the reservoirs become available.

Future research work includes an assessment of the structural errors inherent in the rainfall-runoff (RR) model, the error assumptions and their impact on the assimilation scheme. The ensemble of models was generated by perturbing runoff and irrigation forcing in the water allocation model (Mike Basin) instead of perturbing meteorological input data in the RR model because the structural error of the RR model is expected to be much larger than the error of the input data. Furthermore, the model errors were assumed normally distributed and uncorrelated, even though the residuals from the calibration-validation process are temporally correlated.

Other future areas of research include the implementation of a dual state-parameter optimization approach (e.g. Moradkhani et al., 2005) in order to improve overall model performance. The issue of averaging RS data over subcatchments could be overcome by using satellite altimetry to estimate river discharge. The performance of the hydrological model could also be improved through an improved representation of
snowmelt processes, as well as representation of glacial processes. Glacial processes were not modeled due to lack of ground data. However, a representation of glacial processes is particularly important, as long term trends and estimates of future conditions indicate that glacial storage is being lost (Hagg et al., 2007; Niederer et al., 2008). Reduced glacial storage could have impacts on the annual runoff pattern in the basin by concentrating runoff in the spring snowmelt season and reducing summer runoff, much of which results from glacial melting. A long-term loss of glacial storage could reduce the resilience of the water resources system because glacial melting compensates for reduced snow melt runoff during hot, dry years. These issues are important for water resources planning at inter-annual and decadal time scales.

Conclusions

Hydrological models driven by remotely sensed data alone may not be able to provide reasonable simulations of large and complex river basins with scarce calibration data. New remotely sensed data sources such as satellite radar altimetry measurements have potential to improve simulation results by updating model states using data assimilation techniques. Radar altimetry provides the hydrological community with a periodical and impartial source of data. The inclusion of such data into science-based decision support systems has potential to induce cooperation in transboundary river management by providing a basis for the development of operational modeling tools from a transparent and readily-available information base.
Acknowledgements

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References


Figure 1. Base map of the Syr Darya River Basin (SDRB)
Figure 2: Structure of the rainfall-runoff model
Figure 4 Comparison of precipitation datasets: TRMM-3B42 versus RCHT. Monthly averages
Figure 5. ECMWF average monthly temperature TS versus RCHT at three locations (see Figure 1 for locations).
Figure 6. Rainfall-Runoff modeling results
Figure 8. Reservoir level simulation: data assimilation (black), without data assimilation (red), and observed water levels (blue) for an ensemble size of 50, runoff perturbation of 20 L km$^{-2}$ s$^{-1}$ and irrigation area perturbation of 40%. The shaded area indicates the 2.5 and 97.5% quantile range of the sample, and the crosses are altimetry measurements. For interpretation of the color reference in this figure, the reader is referred to the electronic version of this article.
Figure 10. Impact of ensemble size, runoff perturbation and irrigation area perturbation. The experiments are described on Table 3. A (○), B (△), C (□), D (◇), E (●), F (▲) and G (■).
Figure 12. (A) Average absolute residuals of reservoir level after assimilation of altimetry data. (B) Average (2000-2007) reservoir level residual in April, May, June and August when data assimilation is interrupted in March, February, January and December (within the same hydrological year).
### Parameters used in the rainfall-runoff model (NAM)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Units</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Umax</td>
<td>Maximum water content in surface storage</td>
<td>mm</td>
<td>1</td>
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<tr>
<td>CQOF</td>
<td>Overland flow runoff coefficient</td>
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<td>CKIF</td>
<td>Time constant for interflow</td>
<td>hours</td>
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</tr>
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<td>CK1,2</td>
<td>Time constants for routing overland flow</td>
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<td>TIF</td>
<td>Rootzone threshold value for inter flow</td>
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<td>TG</td>
<td>Rootzone threshold value for groundwater recharge</td>
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*For a detailed description of these parameters and their interaction the reader is referred to DHI (2000).*
### Table 2. Snowmelt parameters used in the rainfall-runoff model (NAM)

<table>
<thead>
<tr>
<th>Lapse rate [deg 100m⁻¹]</th>
<th>Degree day coefficient (M) [mm deg⁻¹ day⁻¹]</th>
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<td>wet</td>
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<td>-0.7</td>
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Table 3 Ensemble Kalman Filter tuning parameters

<table>
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<th>Experiment</th>
<th>Ensemble size</th>
<th>Runoff uncertainty [L km$^2$ s$^{-1}$]</th>
<th>Irrigation area unc. [%]</th>
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<tr>
<td>A</td>
<td>5</td>
<td>5</td>
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</tr>
<tr>
<td>B</td>
<td>5</td>
<td>20</td>
<td>0.4</td>
</tr>
<tr>
<td>C</td>
<td>50</td>
<td>5</td>
<td>0.05</td>
</tr>
<tr>
<td>D</td>
<td>50</td>
<td>5</td>
<td>0.4</td>
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<td>E</td>
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<td>0.05</td>
</tr>
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<td>F</td>
<td>50</td>
<td>15</td>
<td>0.2</td>
</tr>
<tr>
<td>G</td>
<td>50</td>
<td>20</td>
<td>0.4</td>
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Table 4 Source and spatio-temporal resolution of the various datasets used in the model

<table>
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<th>Data Source</th>
<th>Resolution</th>
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<td></td>
<td></td>
<td>Space</td>
<td>Time</td>
<td></td>
</tr>
<tr>
<td><strong>Remotely sensed</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>Precipitation</td>
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<td>3 hrs</td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>ECMWF</td>
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<td>6 hrs</td>
<td></td>
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<tr>
<td>PET</td>
<td>Func. of Temp</td>
<td>0.5°-0.25°</td>
<td>6 hrs</td>
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<td>Lake altimetry</td>
<td>ERS/ENVISAT</td>
<td>76 targets</td>
<td>35 days</td>
<td></td>
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<td>DEM</td>
<td>SRTM</td>
<td>1000x1000m</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discharge</td>
<td>RCHT</td>
<td>18 stations</td>
<td>daily</td>
<td></td>
</tr>
<tr>
<td>Reservoir release</td>
<td>ICWC</td>
<td>5 reservoirs</td>
<td>monthly</td>
<td></td>
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<tr>
<td><strong>Comparison data</strong></td>
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<td></td>
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<td></td>
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<td>RCHT</td>
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<td>10 days</td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>RCHT</td>
<td>5 stations</td>
<td>10 days</td>
<td></td>
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<td>Reservoir levels</td>
<td>RCHT</td>
<td>4 reservoirs</td>
<td>daily</td>
<td></td>
</tr>
</tbody>
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Table 5. Altimetry targets over each reservoir. The altimetry error is reported here as the RMSE between the timeseries after the mean of each has been removed.

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>Satellite</th>
<th>RMSE [m]</th>
</tr>
</thead>
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<tr>
<td>Chardara</td>
<td>ERS</td>
<td>0.63, 0.85</td>
</tr>
<tr>
<td></td>
<td>ENVISAT</td>
<td>0.37, 0.48</td>
</tr>
<tr>
<td>Toktogul</td>
<td>ERS</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>ENVISAT</td>
<td>0.89</td>
</tr>
<tr>
<td>Charvak</td>
<td>ERS</td>
<td>1.81</td>
</tr>
<tr>
<td></td>
<td>ENVISAT</td>
<td>1.42</td>
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<tr>
<td>Kayrakkum</td>
<td>ERS</td>
<td>0.61</td>
</tr>
</tbody>
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### Table 6. Results of the rainfall-runoff model calibration.

<table>
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<tr>
<th>Catchment</th>
<th>Station ID</th>
<th>Wind orientation</th>
<th>Lmax [mm]</th>
<th>CKBF [hr]</th>
<th>$R^2$</th>
<th>WBE [%]</th>
<th>Mean runoff [L km$^{-2}$ s$^{-1}$]</th>
<th>Runoff error [L km$^{-2}$ s$^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>2</td>
<td>16055</td>
<td>W</td>
<td>1600</td>
<td>1201</td>
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<td>-3.3</td>
<td>8.86</td>
</tr>
<tr>
<td></td>
<td>47</td>
<td>16169</td>
<td>W</td>
<td>2090</td>
<td>2575</td>
<td>0.66</td>
<td>-2.6</td>
<td>9.59</td>
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<tr>
<td></td>
<td>55</td>
<td>16176</td>
<td>W</td>
<td>2280</td>
<td>1445</td>
<td>0.73</td>
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<td>11.67</td>
</tr>
<tr>
<td></td>
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<td>16193</td>
<td>W</td>
<td>9220</td>
<td>947</td>
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<td>8.24</td>
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<tr>
<td></td>
<td>145</td>
<td>16198</td>
<td>L</td>
<td>86.8</td>
<td>1552</td>
<td>0.41</td>
<td>-26</td>
<td>10.97</td>
</tr>
<tr>
<td></td>
<td>148</td>
<td>16279</td>
<td>L</td>
<td>23.4</td>
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<td>-27</td>
<td>14.85</td>
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<td>Validation</td>
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<td>1100</td>
<td>0.37</td>
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<tr>
<td></td>
<td>12</td>
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<td>32</td>
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<td>0.55</td>
<td>6.8</td>
<td>8.5</td>
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<tr>
<td></td>
<td>14</td>
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<td>L</td>
<td>32</td>
<td>1100</td>
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<td></td>
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<td>L</td>
<td>32</td>
<td>1100</td>
<td>0.45</td>
<td>-4.1</td>
<td>9.04</td>
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<td></td>
<td>16</td>
<td>16135</td>
<td>L</td>
<td>32</td>
<td>1100</td>
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<td>-36</td>
<td>8.15</td>
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<td></td>
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<td>L</td>
<td>32</td>
<td>1100</td>
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<td>8.62</td>
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<td></td>
<td>9</td>
<td>16146</td>
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<td>1100</td>
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<td></td>
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<td>W</td>
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<td>1100</td>
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<td>8.3</td>
<td>13.52</td>
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<tr>
<td></td>
<td>49</td>
<td>16510</td>
<td>W</td>
<td>3510</td>
<td>1100</td>
<td>-1.7</td>
<td>-3.8</td>
<td>8.25</td>
</tr>
</tbody>
</table>

*a* W: winward; L: leeward.

*b* Water balance error
Table 8. Reservoir water level residuals with and without assimilation of radar altimetry data

<table>
<thead>
<tr>
<th></th>
<th>Toktogul</th>
<th>Chardara</th>
<th>Kayrakkum</th>
<th>Charvak</th>
<th>Mean*</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>mean(res)</td>
<td>2.72</td>
<td>0.99</td>
<td>-8.20</td>
<td>-6.19</td>
</tr>
<tr>
<td></td>
<td>std(res)</td>
<td>2.82</td>
<td>1.16</td>
<td>8.50</td>
<td>13.14</td>
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<tr>
<td>No</td>
<td>mean(res)</td>
<td>-4.55</td>
<td>0.68</td>
<td>-15.38</td>
<td>-57.72</td>
</tr>
<tr>
<td>DA</td>
<td>std(res)</td>
<td>14.61</td>
<td>2.59</td>
<td>10.01</td>
<td>39.78</td>
</tr>
</tbody>
</table>

*: Mean of absolute residuals across all reservoirs.